Intention to use business intelligence tools in decision making processes: applying a UTAUT 2 model

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Abstract
The pressure on the speed of information processing ranks business intelligence technologies among the fastest growing decision support tools. The main goal of this article is, applying the UTAUT 2 (the unified theory of acceptance and use of technology), to verify the factors determining the implementation of business intelligence tools in business processes, especially decision-making, and their subsequent optimal use in business practice. The researched scheme was modified according to the specifics of business intelligence tools and was supplemented by user behaviour in decision-making. The verification was performed using a questionnaire survey based on UTAUT 2 theory and 152 respondents were included in the analysis. According to the results, the most important variable of influence on both the behavioural intention and the users’ behaviour itself in decision-making was the factor of habit. And surprisingly, some previously recognised links were not confirmed, especially the factors influencing the intention of behaviour (effort expectancy, social influence, facilitating conditions). So, there is room after almost 10 years and experience gained during the Covid-19 pandemic to modify the latest version of a model.

Keywords  Business intelligence · Technologic innovation · UTAUT (2) · Decision-making

JEL Classification  C380

Mathematics Subject Classification  62H30

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1 Introduction

The increasing need to satisfy changing customer requirements and desires pushes companies to create new organisational structures where business intelligence and decision-making methods are integrated into crucial processes closer to the operating units. Closed-loop decision-making, which results from a combination of continuous performance management with business intelligence, can lead to the immediate opportunity of an effective response depending on developing environmental conditions (Kale 2017). According to Statista, revenue in the business intelligence software segment has been projected to reach USD 22,798.15 m in 2021. Companies’ needs for data insights, customer analyses and all kinds of business processes have strongly increased due to digitisation and data that is collected online (Statista 2021). However, despite continuing growing investment in business intelligence, many organisations are still unable to achieve the required benefits from these systems due to insufficient and inefficient use (Arefin et al. 2015).

The main goal of the presented article is to verify the factors facilitating the implementation of business intelligence methods into the decision-making process. The model was compiled based on the UTAUT 2 theory—Unified Theory of Adoption and Use of Technology (Venkatesh et al. 2012) and the outputs obtained within the pilot research conducted in 2020. Subsequently, the procedure presented by Venkatesh et al. (2012) was used to verify the proposed model. A targeted questionnaire survey was conducted in April and May 2021 and the obtained data was processed using the SmartPLS program (https://www.smartpls.com/).

The integration of business intelligence into managerial decision-making should be the logical outcome of the entire implementation process. Appropriate use of data warehouses and data analysis facilitates business decision making. The whole process begins with a well-established data model infrastructure and data preparation, followed by the data analysis itself, integration, conversion of data into information and, finally, the actual use of the acquired knowledge (Surma 2011).

For the purposes of this article, the concept of business intelligence will be perceived and presented as a set of processes, applications and technologies that aim to provide useful and, above all, effective support to decision-making processes in organisations. Analytical and planning functions in the organisation are also supported. The foundations of these processes are based on the principles of multidimensional views of business data (Novotný et al. 2005).

The involvement of business intelligence techniques in the decision-making process often encounters the typically static nature of generally used decision-making principles, namely experience, the approach to the problem used thus far and the already implemented strategies. Furthermore, the discrepancy between these aspects and the ever-changing forms of information needs to be systematically eliminated so that these methods become natural support for the decision-making process (Misser et al. 2008). Organisations are often exemplary in software implementation (data warehouses, marketplaces and analytics), but other factors hinder successful integration into the decision-making process. These include a lack of understanding of the complexity of business intelligence projects and an unsatisfactory perception of these initiatives as company-wide decision support activities (Moss and Atre 2003).
For the research, the UTAUT 2 theory was chosen from the most frequently used models of technology innovation acceptance. The application of the model in its original version with the business intelligence implementation project has only been recorded in three studies (Grublješič and Jaklič 2015; Jaklič et al. 2018; Hou 2014) in the last 20 years (Ain et al. 2019). There is, therefore, the scope for verifying this model in relation to application in business processes.

The Unified Theory of Acceptance and Use of Technology (UTAUT) was designed as a combination of the previous eight theories dealing with acceptance and motivation to apply technology in order to create a unified theory (Venkatesh et al. 2003a). Like most other used models, this theory has been commented on, refined and modified over time. The last major update was published in 2012 (Venkatesh et al. 2012). So, the last nine turbulent years from the last UTAUT 2 update, ending with an unprecedented situation caused by Covid-19, could change the defined links and add or remove some critical factors.

In order to fulfil the objectives of this paper, its structure is as follows. After the short introduction, a brief literature review concentrating on the introduction of the most used models of technological innovation acceptance with an emphasis on business intelligence tools is presented. This part is finished by our own 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 is given at the end.

2 Literature review

Firstly, literary research explains key success factors typical for business intelligence in general. In the second part, the essential specifics of UTAUT 2 are characterised, and its connection with business intelligence tools is briefly described.

2.1 Business intelligence involvement in organisations

Visinescu et al. (2017) draw attention to the complexity of determining the real influence of the BI application in organisational management. On the one hand, the organisation can achieve a high return on investment by implementing this system; thus, the entire project will be evaluated as the right decision. On the other hand, it is complicated to determine whether even better results could not be achieved if other approaches and methods were used. To reveal the critical factors influencing the perceived quality of decision-making, Visinescu et al. tested a model based on the theoretical model developed by Clark and his colleagues (Clark et al. 2007). The study’s results confirmed the use of BI, the quality of information and the complexity of the solved problem as the main determinants of the perceived quality of decision-making in organisations (Visinescu et al. 2017).

It was also found that almost three-quarters of projects connected with business intelligence implementation fail due to poor communication between IT specialists and the end users of the implemented tools. Another essential aspect helping to reduce
the uncertainty associated with the (un)succesful use of BI tools is ensuring a sufficient level of management skills of selected employees. Their significant support in the given area can significantly influence the subsequent positive acceptance and inclusion of BI in business processes (Richards et al. 2019).

Other factors that BI system developers and administrators must consider concerning optimal use in the decision-making process include the type of decision-maker for whom the information obtained from the data is intended. The key is creating and applying such systems and methods that present a smaller volume of data but emphasise its significance, discover discrepancies and are specifically prepared for a given end user (Visinescu et al. 2017).

2.2 Business intelligence and UTAUT2

Business intelligence represents a complete and effective approach to working with data and information in the business environment. Outputs influence strategic decision processes. The basis of BI is to transform source data into knowledge, with which the right decisions are made. It can therefore be included among technological innovations, which are defined as a process in which technology (change, improvement) has been identified as a critical success factor for increasing market competitiveness (Jason 2013).

Research on the adoption of new technologies is most often based on several basic schemes (e.g. Ain et al. 2019; Lai and Lai 2017; Ani et al. 2019):

- DeLone and McLean information systems (IS) success model
- Technology acceptance model (TAM) and TAM 2
- Diffusion of innovation (IDT)
- Unified theory of acceptance and use of technology (UTAUT) and UTAUT 2

Furthermore, the concept of the latest theory will be introduced, which was used to build our own model. With regard to the revealed limitations of the first version of the UTAUT model, new aspects were integrated into the model, namely: the impact on consumers, automation and monetary costs. The UTAUT 2 framework covers four main areas: performance expectancy, effort expectancy, social influence and facilitating conditions (Ul-Ain et al. 2015). The study extends the theory to the study of the adoption and application of technology in the consumer context. It now includes three other constructs: hedonic motivation, price value and habit. Individual differences, namely age, gender and experience, are thought to mitigate the effects of these constructs on behavioural intent and the use of technology (Venkatesh et al. 2012).

Researchers then see hedonic motivation as a perceived pleasure and point out its impact on the positive acceptance of technology (Thong 2006). Over time, the continuous use of technology becomes an integral part of working time, which means that environmental stimuli can activate learned sequences, which can be repeated without conscious intention and become a habit (Bandyopadhyay and Fraccastoro 2007). In the consumer environment, the use of a product is affected by price, which indicates the perceived value of the product at a given price (Ul-Ain et al. 2015). The UTAUT 2 design scheme is shown in Fig. 1.
As mentioned above, the involvement of the UTAUT model in its original version with the business intelligence implementation project has only been recorded in three studies in the last 20 years (Ain et al. 2019). These studies are briefly presented below.

One of the models builds on previous empirical research and, at the same time, examines the determinant of compatibility based on a survey of coherence in predicting the intentions of using BI methods (Jaklič et al. 2018). The theories of IDT and UTAUT formed the basis for the development of the presented research scheme. It combines performance expectancy from UTAUT measurements of perceptions of social influence and behavioural intention (measurement of intentions of use) with provability of results and compatibility from IDT (ibid).

Compatibility has specifically been shown to have a direct significant positive impact on the intentions to use BI techniques. By contrast, perception of performance, which consistently proves to be the strongest direct predictor of intentions for use (Venkatesh et al. 2003b; Li et al., 2013), only has an indirect impact on compatibility intentions in the BI context. Demonstrability of results and social impact positively

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Fig. 1 UTAUT 2. *Source* Own processing according to Venkatesh et al. 2012
strengthen the relationship between compatibility and intention to use (Jaklič et al., 2018).

The results of another study verifying users’ behavioural intention to use BI systems show that performance expectations, social impact, facilitating conditions and computer anxiety are important determinants of behavioural intention. While the expected effort was not included among these determinants, facilitation of conditions and intention of behaviour were confirmed as important user behaviour variables for BI users (Hou 2014).

The last theoretical model combines aspects of UTAUT with TAM and TAM 3 and is partially supplemented by the findings determined by the authors of a previous analysis of case studies on the adoption and use of BI systems (Grublješić and Jaklič 2015). The findings emphasise the importance of organisational factors as important determinants of user behaviour. These include social impact, result demonstrability, management support and management mechanisms for incorporating BI into business processes in line with business strategy. The model has also shown a strong impact of management facilitation on usage intensity and assigns a significant role to this factor in removing barriers to continued use. User confidence in the security of the organisational and technical infrastructure to support the use of BI systems was reported as the variable with the strongest impact on the intensity of use, and is a basic prerequisite for expanding the use and anchoring of BI into the work routine of employees (Jaklič et al. 2018).

3 Research model and hypothesis

Initial independent variables of performance expectations, indicating the degree to which individuals believe that technology will help them perform their tasks, and the expected effort associated with difficulties in using the system, are fundamental factors influencing the intention to leverage technological innovation (Escobar-Rodríguez and Carvajal-Trujillo 2014; Martins et al. 2018; Venkatesh et al. 2003b).

Many studies have also shown the importance of social influence in the adoption and implementation of a new technology (Alraja 2016; Brown and Venkatesh 2005; Mousa Jaradat and Al Rababaa 2013). Colleagues, as essential people from the closest working environment, can, according to the pilot research, significantly influence user behaviour connected with the decision-making process. System restrictions and overloading of the project team were seen by the majority of respondents as the main barriers to the success of the implementation of technological innovations. Indications of system constraints as the most common obstacles and technical constraints as the third in order can be included in the wording under the determinant of facilitating conditions (Kašparová and Průcha 2021).

The original UTAUT 2 model already predicts the direct influence of facilitating conditions and habit on user behaviour in general (Venkatesh et al. 2012). And since the pilot research has also revealed a key element for gaining a habit—experience as the most commonly used decision-making method and as the most frequently mentioned barriers to the implementation of these projects were linked to (non)providing
facilitating conditions, their crucial impact on the use of business intelligence in the decision-making process is likewise assumed.

Long-term research is devoted to the integration of business intelligence methods into decision-making processes. For this reason, the design of the model had been extended by one level, which will directly include the use of BI in decision-making in relation to behavioural intention and user behaviour. So, the first version of the proposed scheme contained two levels of user behaviour: the use of technological innovation (as it is in original version of UTAUT) and utilisation in the decision-making process. After obtaining data from the survey, these two levels were combined into one. They showed the same links and their internal consistency was close to 0.8.

This conclusion thus corresponds to the results obtained in the previous research. If respondents consider themselves as active users of business intelligence tools, they use their outputs in the decision-making process. There is therefore no need to extend the original version of the model to another level (Kašparová 2022). The final research model version based on the basics of UTAUT 2 and pilot research is shown in Fig. 2.

The constructs of performance expectancy (composed of 2 items in a questionnaire survey), effort expectancy (3), social influence (3) and facilitating conditions (3), which are based on the previous version, were preserved. From the newly added variables, habit (1) was included in the model as another key factor influencing both the intention (2) to use the new technology and the use itself in the decision-making process (2). The list below summarises hypothesised relationships tested in this study:

**H1** Performance expectancy (PE) has significant influence on behavioural intention (BeI) to use business intelligence.

**H2** Effort expectancy (EE) has significant influence on behavioural intention to use business intelligence.

**H3** Social influence (SI) has significant influence on behavioural intention to use business intelligence.

**H4** Facilitating conditions (FC) have significant influence on behavioural intention to use business intelligence.

**H5** Habit (H) has significant influence on behavioural intention to use business intelligence.

**H6** Social influence has significant influence on the use of business intelligence in decision-making (UiDM).

**H7** Facilitating conditions have significant influence on the use of business intelligence in decision-making.

**H8** Habit has significant influence on the use of business intelligence in decision-making.

**H9** Behavioural intention has significant influence on the use of business intelligence in decision-making.
4 Methodology

A cross-sectional questionnaire survey was designed to examine the factors influencing the acceptance and use of the proposed solution. The research model contains five latent variables (PE, EE, SI, FC, H) and two dependant ones (BeI, UiDM). All variables are measured using scales adapted from Venkatesh (2012) and modified to reflect the specifics of using business intelligence in decision-making. Latent variables, or they are also called constructs or factors, are variables that are not directly observed or measured and, therefore, are derived from a set of variables that we measure using tests, surveys (Loehlin and Beaujean 2016).

The questionnaire was available to respondents on the web and consisted of several sets of questions. In the first part, basic information about each respondent was monitored both from a demographic point of view and about the nature of their employment: gender, age group, business sector, size of company and level of job position.
At the end of the first series of questions, the level of data processing in the organisation was determined and the next part of the questionnaire was answered by respondents after a positive answer to the question "I use business intelligence tools/outputs in my work."

The subsequent series of questions, in which only active business intelligence users were involved, was therefore specifically interested in the specific views of respondents on the implementation and application of business intelligence in their organisation and in their work process. The complete set of 14 questions was based on the recommended statements from the verification of the primary model UTAUT 2 defined by (Venkatesh et al. 2012). The statements were only partially modified according to the modification of the examined model. Finally, 152 responses were obtained in this part of the survey. The seven-point Likert scale was used, where respondents expressed the degree of agreement for individual statements: 7 stars represented absolute agreement, 1 star outright disagreement.

4.1 Sample

In order to verify the presented scheme through the defined hypotheses, a questionnaire survey was conducted in April and May 2021. The companies were selected using the Bisnode Magnusweb database, where companies were searched by legal form (active legal entities), valid email addresses and by business sector. Companies and workers from several industries were contacted. The following industries were selected according to the CZ-NACE classification: Information technology activities; Manufacture of motor vehicles (except motorcycles), trailers, semi-trailers; Finance and insurance, where a high degree of business intelligence involvement in decision-making processes is expected in all sectors.

For comparison, the survey also included fields where the use of business intelligence is rather in its infancy, but there is a potential for gaining a competitive advantage in the coming years: agriculture, forestry, fishing and accommodation in hotels and similar accommodation. The use of a large amount of data also has potential in these traditional sectors of the economy.

A total of 12,779 subjects from the total number of 45,642 active legal entities met the entered criteria after the inclusion of active legal entities with an available email address in the database. However, as the return was very low when applying random sampling, around 3%, a questionnaire was eventually sent to all 12,779 subjects to obtain the relevant number of responses. After the survey, 341 questionnaires were included in the analysis, of which 152 could be used to verify the model. These 152 respondents identified themselves as active users of business intelligence.

The original intention to obtain a representative sample by random sampling had to be modified during the course of the research. Due to the low return, a survey method was chosen to collect the corresponding sample, which is characterised by voluntary participation and the results cannot be generalised. The obtained picture of the researched situation can therefore only be indicative, but it can, despite some risks, provide relevant information about the researched problem (Šedlačík et al. 2016).
As part of the verification of similar models and ensuring a valid interpretation of the obtained data within the available sample of respondents, the use of the "10-times rule" is recommended across the studies. This is based on the assumption that its range should be at least 10-times the maximum number of internal or external model bonds to any latent variable (not directly measured but derived from observed variables) when determining the optimal sample size (Barclay et al. 1995). By its nature, this regulation is one of the so-called "rules of thumb", based on personal experience or general knowledge rather than on precise measurement or research. For this reason, authors and researchers are still discussing its application (Belle 2011).

Although this general rule does not take into account effect size, reliability, number of indicators and other factors influencing research results (Goodhue et al. 2012), Hair et al. (2011) nevertheless recommend this rule as a rough estimate of minimum sample size (Hair et al. 2011). Peng and Lai (2012) suggest the use of this rule to determine the appropriate sample size in similar analyses only if certain conditions are met, namely: significant strength of effects and high reliability of measured items (Peng and Lai 2012).

Regarding the application of this rule in the verification of UTAUT models, the authors frequently use it in their studies, but in most cases point out the risks associated with its application (Senyo and Osabutey 2020; Naranjo-Zolotov et al. 2018; Seethamraju et al. 2018). Due to the difficulty of obtaining similar data, this rule is also applied in the submitted article. The design of the model includes a total of 9 links, and the number of 152 complete questionnaires obtained meets the requirements of the above regulation.

4.2 Demographics

Out of the total number of 152 questionnaires, 113 were answered by men and 39 by women. Regarding distribution by age, the respondents were quite evenly distributed among all groups. The youngest group of employees aged 20–29 was the least represented (13). They probably do not yet have the competence to fill out a similar survey.

More respondents from smaller companies appeared in the presented questionnaire survey (110 out of 152). The distribution is likely given by targeting companies from specified sectors of the economy that were contacted by random selection. There was a greater willingness to answer and react among the employees of smaller companies. This is also connected to the higher involvement of members of the top management. In smaller companies, a similar type of questionnaire can also reach high-ranking employees (101 out of 152).

Regarding the distribution of respondents in individual fields of business, most of them worked in sectors that show the highest long-term involvement of decision-making methods based on data analysis (Statista 2018): automotive, information technology, finance and insurance (in total 102 out of 152). The basic characteristics of the respondents are summarised in Table 1.
### Table 1 Demographics

| Category                        | Frequency |
|---------------------------------|-----------|
| Gender                          |           |
| Male                            | 113       |
| Female                          | 39        |
| Age                             |           |
| 20–29                           | 13        |
| 30–39                           | 37        |
| 40–49                           | 37        |
| 50–59                           | 42        |
| 60–69                           | 23        |
| Business size                   |           |
| Micro and small enterprises     | 110       |
| Medium enterprises              | 21        |
| Large enterprises               | 21        |
| Job level                       |           |
| Top management, Board           | 101       |
| Middle management               | 24        |
| Operative management            | 10        |
| Specialists                     | 17        |
| Business sector                 |           |
| Automotive                      | 19        |
| Information technologies        | 72        |
| Finance and insurance industry  | 11        |
| Accommodation (hotels, etc.)    | 5         |
| Agriculture, forestry, fishing  | 45        |

*Source: Own processing*

### 4.3 PLS-SEM

This study aimed to examine the drivers of employees’ business intelligence usage behaviour, therefore, partial least squares structural equation modelling (PLS-SEM) was chosen to be an appropriate method as it helps to explain causal relationships among constructs (Tseng et al. 2019). This technique is used to construct predictive models, where many factors appear and are highly collinear. It reduces independent variables to a smaller set of uncorrelated components and performs least squares regression on these variables, not on the original data (Hair et al. 2016).

Evaluation requires checking internal consistency, convergent validity and discriminant validity. Composite reliability (CR) and Cronbach’s $\alpha$ are used to evaluate internal consistency reliability. Both composite reliability and Cronbach’s $\alpha$ values are recommended to be greater than 0.7 (Hair et al. 2016). Convergent validity is supported if all the standardised item loadings are greater than 0.70, and if the values of the average variance extracted (AVE) for every construct exceed 0.5 (Fornell and Larcker 1981).
5 Results

In the next chapter, obtained results are presented and briefly described.

5.1 Evaluation of the measurement model

Construct reliability and validity are assessed and provided in Table 2. All measured values meet the above criteria except for one Cronbach alpha value for effort expectancy. However, it only marginally fails to reach the recommended value of 0.7, and the other values for this variable meet the given recommendations, therefore their convergent validity can be considered good for all constructs.

Discriminant validity is achieved if the square root of each construct’s AVE exceeds the squared correlation with any other construct (Hair et al. 2016). The square root of

| Construct                        | Cronbach’s alpha | Composite reliability | Average variance extracted (AVE) | Outer loadings |
|----------------------------------|------------------|------------------------|---------------------------------|----------------|
| Performance expectancy           | 0.865            | 0.937                  | 0.881                           |                |
| PE1                              |                  |                        |                                 | 0.943          |
| PE2                              |                  |                        |                                 | 0.934          |
| Effort expectancy                | 0.659            | 0.809                  | 0.586                           |                |
| EE1                              |                  |                        |                                 | 0.840          |
| EE2                              |                  |                        |                                 | 0.739          |
| EE3                              |                  |                        |                                 | 0.713          |
| Social influence                 | 0.933            | 0.957                  | 0.882                           |                |
| SI1                              |                  |                        |                                 | 0.945          |
| SI2                              |                  |                        |                                 | 0.935          |
| SI3                              |                  |                        |                                 | 0.937          |
| Facilitating conditions          | 0.788            | 0.866                  | 0.684                           |                |
| FC1                              |                  |                        |                                 | 0.871          |
| FC2                              |                  |                        |                                 | 0.826          |
| FC3                              |                  |                        |                                 | 0.782          |
| Habit                            | 1.000            | 1.000                  | 1.000                           | 1.000          |
| Behavioural intention            | 0.931            | 0.967                  | 0.936                           |                |
| BeI1                             |                  |                        |                                 | 0.969          |
| BeI2                             |                  |                        |                                 | 0.966          |
| Use in decision-making           | 0.795            | 0.907                  | 0.830                           |                |
| UiDM1                            |                  |                        |                                 | 0.904          |
| UiDM2                            |                  |                        |                                 | 0.918          |

Source Own processing
the AVE (ranging from 0.766 to 1), as shown in Table 3 (diagonal values) for each of the constructs, was also higher than its highest correlation with any other construct. Therefore, discriminant validity of the scales in this model was satisfied.

### 5.2 Structural model

As the construct measures were found to be reliable and valid, the structural model could be assessed. It involves examining the path coefficients, significance of the path coefficients and their relevance. The values of $R^2$ and the path coefficients are shown in Fig. 3.

As shown in Fig. 3, the influence of performance expectancy and habit explain 64.6% of the variance in the behavioural intention. Behavioural intention, social influence and habit explain 57.5% of the variance in the use in decision-making. $R$-squared values fall into the category $0.5 < R^2 < 0.7$, and these values are generally considered a moderate effect size. So, we may conclude that the model holds sufficient explanatory power and is capable of explaining the constructed latent variable (Henseler 2009). This research model contains five latent variables (PE, EE, SI, FC, H) and two dependent ones (BeI, UiDM).

Table 4 summarises t-statistic and $p$-values (significance level) for all the hypothesised relationships. Performance expectancy ($\beta = 0.400, T\text{-Statistics} = 4.143, p < 0.05$) and habit ($\beta = 0.261, T\text{-Statistics} = 2.142, p < 0.05$) positively influenced behavioural intention. Thus, H1 and H5 were supported. However, effort expectancy ($\beta = 0.143, T\text{-Statistics} = 1.792, p > 0.05$), social influence ($\beta = -0.018, T\text{-Statistics} = 0.223, p > 0.05$) and facilitating conditions ($\beta = -0.15, T\text{-Statistics} = 1.767, p > 0.05$) had no effect on behavioural intention. Thus, H2, H3 and H4 were not supported. Furthermore, social influence ($\beta = 0.266, T\text{-Statistics} = 2.923, p < 0.05$), habit ($\beta = 0.450, T\text{-Statistics} = 4.713, p < 0.05$) and behavioural intention ($\beta = 0.189, T\text{-Statistics} = 2.351, p < 0.05$) positively influenced behavioural usage in decision-making. Thus, H6, H8 and H9 were supported. Only facilitating conditions ($\beta = -0.033, T\text{-Statistics} = 0.343, p > 0.05$) had no effect on behavioural usage in decision making. Thus, H7 was not supported.
Fig. 3 Estimated structural model. Source Own processing

Table 4 Hypothesis testing

| Hypothesised relationships                           | T-statistics | P-value | Hypothesis   |
|-----------------------------------------------------|--------------|---------|--------------|
| Performance expectancy $\rightarrow$ Behavioural intention | 4.143        | 0.000   | Supported    |
| Effort expectancy $\rightarrow$ Behavioural intention  | 1.792        | 0.074   | Rejected     |
| Social influence $\rightarrow$ Behavioural intention  | 0.223        | 0.824   | Rejected     |
| Facilitating conditions $\rightarrow$ Behavioural intention | 1.767        | 0.078   | Rejected     |
| Habit $\rightarrow$ Behavioural intention            | 2.142        | 0.033   | Supported    |
| Social influence $\rightarrow$ Use in decision-making | 2.923        | 0.004   | Supported    |
| Facilitating conditions $\rightarrow$ Use in decision-making | 0.343        | 0.732   | Rejected     |
| Habit $\rightarrow$ Use in decision-making           | 4.713        | 0.000   | Supported    |
| Behavioural intention $\rightarrow$ Use in decision-making | 2.351        | 0.019   | Supported    |

Source Own processing
6 Conclusion

The UTAUT 2 model was adapted and extended to analyse the intention and utilisation of business intelligence tools in decision-making processes in Czech companies. Only two constructs in the model, performance expectancy and habit (with path coefficients 0.4 and 0.261 respectively significant at 5% level), were found to significantly and positively influence respondents’ intention to use these methods and they explained 64.6% of the total variance. Compared to previous studies using UTAUT theory to examine the adoption and successful use of business intelligence, social influence and facilitating conditions additionally showed a positive effect on behavioural intention (Jaklič et al. 2018; Hou 2014).

On the other hand, results confirmed the importance and correctness of the inclusion of the habit construct in the latest version of UTAUT 2. Previous studies dealing with business intelligence and UTAUT have not yet included this determinant in their models. The obtained results within the presented survey confirm its importance. It is also highly likely that the revealed changes in user behaviour may have been significantly affected by the consequences of the changes resulting from the ongoing Covid-19 pandemic. While before the pandemic, research determined the importance of providing facilitating conditions and social impact on behavioural intentions, as discussed above, current research has shown a significant impact of habit construct as an established work routine on user behaviour. Respondents are no longer dependent on management to provide facilitating conditions, nor are their intentions affected by the social environment, when they work mostly from home. Rather, they do not change their work habits and their intention is affected by the positive performance expectancy of the given technological innovation.

Social influence was subsequently revealed as a key determinant of user behaviour in the decision-making process. Thus, the obtained results show that the mere intention to use this type of technological innovation is not significantly influenced by the opinion of the immediate surroundings. However, the use itself in the decision-making process is already significantly influenced by social influence (with path coefficient 0.266 significant at 5% level). Other studies also presented survey points to the importance of social influence in the adoption and implementation of new technology (Alraja 2016; Brown and Venkatesh 2005; Mousa Jaradat and Al Rababaa 2013).

Overall, three out of four constructs in the model, behavioural intention, social influence, and habit (with path coefficients 0.189, 0.266 and 0.450, respectively, significant at 5% level), were found to significantly and positively influence respondents’ use in decision making and they explained 57.5% of the total variance. The confirmed link between the intention to use business intelligence and specific user behaviour means good news for management. If users express their intention to use the technology, they will use its advantages in the next work process and tend to implement it in the decision-making process. From the mentioned studies, this connection is also confirmed by Hou (2014).

Thus, the habit factor remains a challenge for managers considering the introduction of business intelligence into business processes. The pilot research, which preceded the presented study, already showed that the respondents most often rely on their own experience and intuition in their decision-making processes (Kašparová, 2020).
the run-up to the Covid-19 pandemic, this could be attributed to extreme pressure on performance in all areas of business. In the last two years, when the production of some researched industries has stopped completely (e.g. automotive) and other areas of human life have been marked by major changes as well, a significant effect of habit on user behaviour can be attributed to hunger after maintaining established processes in all areas where it was possible.

The research contains several limitations. First, as mentioned above and deeply described, the selection of respondents made on a voluntary basis could not ensure the required representativeness. However, the results may indicate certain contexts of behaviour.

The most recently modified version of the most widely used theories was used in the UTAUT 2 research. Nevertheless, a number of previously confirmed links in this study were not confirmed. After almost ten years and with regard to the changes caused by the Covid-19 pandemic, it is necessary to open the question of possible adjustments according to the achieved results. Last but not least, one of the limits of research is the generality of the presented theory. In order to obtain a more detailed overview of the selected topic, it would be appropriate to specify individual independent variables in the next phase of the research. The factors mentioned in this version of UTAUT 2 are general and their overview should be expanded for further analysis.

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**Declarations**

**Conflict of interest** The authors have no competing interests to declare that are relevant to the content of this article.

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