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Evaluating the Internal and External Usability of Mobile Technologies in Facilitating Knowledge Transfer

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Abstract

A worker's performance and productivity depend on a variety of factors including knowledge, to be essential for self-effectiveness and self-efficacy. In the literature, knowledge transfer is argued to enhance the quality of work, and therefore, its value. When addressing this issue, the latest studies have considered and evaluated the use of mobile technologies, which are evidenced to improve a worker's capacity and skills. However, only a few have investigated the impact of the internal and external usability of mobile technologies in facilitating knowledge transfer. This study draws upon evidence from a survey (n= 237) which shows that both internal and external usability positively influence knowledge transfer. The results of this research shed new light on the importance of mobile technology acceptance by employees, providing a better understanding of how and why rich usability facilitates knowledge transfer and eventually impacts their performance and productivity.

Keywords: Usability, Technology Acceptance, Knowledge Transfer, Mobile Technologies.

Introduction

As a strategic asset, knowledge plays a significant role in worker performance and productivity (Wang and Yang 2016). Recently, several authors have studied the impact of knowledge transfer on work productivity which supports socioeconomic development (Shujahat et al. 2019). Knowledge transfer is defined as the transmission of knowledge (experience, know-how, lessons learned) and the use of transmitted knowledge, namely transmission and absorption between the knowledge owner (who possesses knowledge) and the knowledge perceiver (who acquires knowledge). The use of information and communication technologies (ICT) among organizational members, plays a transparent role in transferring explicit knowledge (Borchert and Heisel 2021). In the last decade, the observed digital innovations (Kowal and Paliwoda-Pękosz 2017) as shift from desktop to mobile settings has empowered knowledge transfer by eliminating location and power supply requirements (Becker et al. 2015), while at the same time, increasing the accessibility and utilization of knowledge resources (Zhang and Jasimuddin 2015). With the increasing adoption of mobile technology, the interest in "knowledge transfer" and "mobile technology" is often determined by the fact that organizations are both "knowledge intensive" and "mobile" (Attour and Barbaroux 2016). While many studies consider the impact of mobility on knowledge transfer capacity (Becker et al. 2015; Leber et al. 2014; Pirker et al. 2014), there is a lack of empirical research to consider the impact of usability in this setup.

In the recent studies, usability has been proofed to be a significant factor in accepting mobile technology in knowledge transfer (Kuciapski 2017). Moreover, the notion of usability has been distinguished and analysed in two separate dimensions, namely internal and external. While the former strictly concerns the mobile application, the latter is considered in terms of its environment, and comprises the hardware device and the built-in operating system. It is worth noting here, that the hardware limitations of any mobile device still concern bandwidth, computing power, screen size and storage (Karadimce and Davcev 2013), despite the many enhancements implemented in recent years (Weichbroth 2018). In order to meet these strict requirements, a new class of operating systems has been designed, developed from scratch (Khanna and Singh 2016). Both dimensions constitute the new executable environment that imposes different user requirements on software applications. Therefore, the need emerged to deliberately study these two aspects in order to gain a better understanding of the usability phenomenon in the context of mobile applications facilitating knowledge transfer. The study intends to contribute to fill this research gap by investigating three research questions:

1. Does internal usability (IU) influence the intention to use mobile technologies for facilitating knowledge transfer?
2. Does external usability (EU) influence the intention to use mobile technologies for facilitating knowledge transfer?
3. Does external usability influence the perceived internal usability of mobile technologies for facilitating knowledge transfer?

Thus, the contribution of this study is to frame and evaluate the usability of mobile technologies, split into these two separate dimensions, in the act of knowledge transfer. To the best of our knowledge, the findings extend the literature of both knowledge management (KM) and human-computer interaction (HCI) by providing a new two-fold perspective on the factors that impact the adoption of mobile technologies for knowledge transfer. The rest of the paper is structured as follows. Section 2 presents theoretical background and study motivation. Section 3 shows the research methodology. Section 4 analyses and discusses the results obtained from the study. Section 5 is a follow-up discussion. Finally, the conclusions of this paper are provided in Section 6.

Theoretical Background and Motivation

As organizations strive to cut costs and remain competitive by becoming more efficient, they look for effective tools and solutions to achieve these goals (Gawin and Marcinkowski 2020; Korczak et al. 2019). Having said that, one might ask: how large a workforce can we try to make more productive through mobility? Entner (2012) found that mobile devices improve worker productivity in four ways: (1) reducing unproductive travel time, (2) improving logistics, (3) enabling faster and more efficient decision-making, and eventually, and (4) empowering small businesses and enhancing communications. In 2011, the wireless industry was estimated to increase productivity by \$ 33 billion in that year alone, while in 2022, it is projected to increase to \$ 220 billion. Indeed, early mobile implementations have revealed five authentic and verifiable ROIs, such as (Palumbo and Dyer 2008): higher efficiency in completing tasks, increased visibility into clients' needs, decreased operational costs, reduction of data error and loss, and client retention through better customer service. All of these require workers to bring together their experience, training, expertise and judgement, repeatedly updated by new incoming information and supplemented by their prior knowledge (Gawin and Marcinkowski 2019; Mach and Owoc 2008).

A central tenet which laid the foundations for this study is that mobile technologies facilitate knowledge transfer. In point of fact, the new paradigm of learning, in this case understood as the activity of obtaining knowledge has been defined as m-learning (Liu et al. 2010a). The explicit definition states that m-learning is "the acquisition of any knowledge and skills through the use of mobile technology, anywhere, and anytime" (Geddes 2004). Over the last two decades, m-learning has brought considerable research interest in a variety of facets of this domain (Elaish et al. 2019). Since m-learning delivers convenience, flexibility and mobility of time and place (Crescente and Lee 2011), organizations gain benefits that include, for example: instant communication and information sharing capacity (Ting 2005), enhancement of human-to-human interaction by reducing cultural barriers (Sarrab et al. 2013), improvement of worker productivity by providing on-the-job access to integrated and up-to-date information (Tokmakov and Mileva 2012). In spite of its great potential, there are a number of challenges regarding the adoption of m-learning (Liu et al. 2010b). Since, relatively, there are many studies in which different contexts (age, gender, education) were investigated, the relevance of usability has not been a major focus point. In view of this the motivation of the present research comprises our professional experience and prior knowledge, as well as evidence gathered from existing sources of scientific knowledge. The most frequent usability definition adapted to mobile settings (Weichbroth 2020) is that introduced in ISO 9241-11, where this term is defined as "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use" (ISO 2018). However, in the context of this study, perceived usability is measured in terms of user judgments on particular product properties (Hassenzahl and Monk 2010). Using, as a theoretical background, the technology acceptance model (TAM) (Davis et al. 1989), and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003), we have recognized and conceptualized particular usability attributes as likely predictors (variables) of the continuance intention to use mobile technologies for knowledge transfer.

Research methodology

Research model

In total, the structured literature review conducted let us identify technology acceptance variables regarding usability. The first stage of elaborating the research model was to select only those variables which have a unique meaning. A matching technique on the basis of variable definitions (Weichbroth and Kuciapski 2019) was applied to explore constructs with a convergent meaning. As a result, 12 variables were identified as expressing a significantly similar sense with other constructs. The variable selection process was based on the following exclusion criteria: *a*) with a less general character, or *b*) by design subjective or context-specific, and as a consequence, less referenced. An assessment of the citation level of particular variables in the subject matter literature was conducted only in the situation when it was not possible to determine which construct has a more narrow meaning (see Table 1).

Table 1. Variable selection process.

Omitted variable	Omit reason	Convergent variable
perceived control & skill (PCS) effort expectancy (EE) system functions (SF)	less general character	cognitive load (CL)
perceived self-efficacy (PSE)	less general character	performance expectancy (PE)
computer self-efficacy (CSE)	less general character	
self-efficacy (SE)	less general character	
perceived usefulness (PU)	less referenced in the literature	
satisfaction (S)	less referenced in the literature	
system satisfaction (SS)	less general character	perceived enjoyment (PEJ)

Eventually, 9 were excluded due to one or more of the following reasons: sparse frequency, low relevance, and non-conformity. In most of the cases, the reason was their less general character than one of the convergent variables. In particular, performance expectancy (PE) occurred to be a variable with many similar constructs. Moreover, the elaborated research model included the following technology acceptance factors: cognitive load (CL) (Hadie and Yusoff 2016)), facilitating conditions (FC) (Venkatesh et al. 2003), learnability (L) (Burney et al. 2017), memorability (M) (Burney et al. 2017), perceived enjoyment (PEJ)(Praveena and Thomas 2014), performance expectancy (PE) (Venkatesh et al. 2003), relative usability (RU) (Kuciapski 2017), system accessibility (SAC) (Park et al. 2012), system activities (SA) (Shujahat et al. 2019), and user autonomy (UA) (Kuciapski 2017). To sum up, the aim of the study is to evaluate the internal and external usability of mobile technologies in facilitating knowledge transfer, variables were grouped into such groups, where *a*) the internal perspective concerns the usability of the application, and *b*) the external perspective is connected with the usability of the environment used by the application, understood as the device and its operating system. Moreover, to determine which variables are appropriate to measure the influence of internal and external technology usability on the intention to use it, the consistency and explicitness of assertion statements from both internal and external usability contexts was examined for each construct (Table 2). Exemplary assertion statements were prepared in an analogous way as in referenced articles taking into account the IU and EU perspectives of mobile technologies.

According to Table 2, all variables have consistent and explicit assertion statements from both perspectives.

Table 2. Exemplary assertion statements for the internal and external usability context of variables.

Var.	Internal	External
CL	When using mobile applications, it is possible to conduct other activities.	When using mobile devices and their operating systems, it is possible to conduct other activities.
FC	Mobile applications are an easy solution to implement.	Mobile devices and their operating systems allow for the convenient use of mobile applications.
L	Learning how to use mobile applications is fast and easy.	Learning how to use mobile devices and their operating systems is fast and easy.
M	Even after a long time, it is still possible to use mobile applications efficiently.	Even after a long time, it is still possible to use mobile devices and their operating systems efficiently.
PE	The use of mobile applications increases efficiency in the realization of activities.	The use of mobile devices and their operating systems increases efficiency in the realization of activities.
PEJ	I enjoy utilizing mobile applications.	I enjoy utilizing mobile devices and their operating systems.
RU	The use of mobile applications is at least as convenient as with alternative solutions (e.g. desktop).	The use of mobile devices and their operating systems is at least as convenient as with alternative solutions (e.g. desktop).
SA	Mobile applications allow activities to be realized in a convenient way.	Mobile devices and their operating systems allow activities to be realized in a convenient way.
SAC	Access to resources with the use of mobile applications is easy.	Access to resources with the use of mobile devices and their operating systems is easy.
UA	Mobile applications allow activities to be conducted in a more individual way.	Mobile devices and their operating systems allow for conducting activities in an individual way.

Therefore, both groups – internal usability and external usability – contain all variables (see Fig. 1 below). Moreover, internal usability and external usability are introduced as grouping variables. Such an approach of proposing new technology acceptance determinants as a result of merging variables into constructs with a broader meaning was employed by (Venkatesh et al. 2003) during the elaboration of UTAUT. It allows constructs to be proposed which are characterized with a broad and universal application in explaining technology acceptance. The elaborated model includes connections between internal/external usability and the dependent variable (see Fig. 1 below).

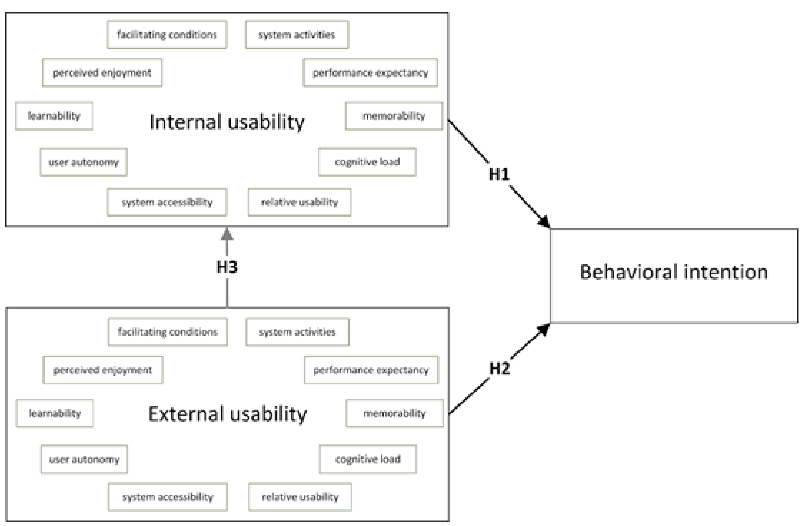

Figure 1. Model for evaluating the internal and external usability of mobile technologies in facilitating knowledge transfer.

It is likely that the environment of using the application, related to the utilized device and its operating system, influences the perceived usability of the application. Such a belief in a relation between the convenience of using a device and the desire to utilize applications available for it, has been supported in the studies of Fiks *et al.* (2018) in 2018, and one year later by Macis *et al.* (2019). Therefore, the connection between EU and IU is an integral part of the proposed model.

Model validation methodology

According to Fig. 1, the assumed relationships between grouped variables were verified by the three stated hypotheses, namely direct impact of internal **H1** and external **H2** usability on BI, and indirect impact of EU on IU. The validation of the stated hypotheses, and therefore the proposed model, was based on a survey among employees applying mobile technologies for knowledge transfer purposes. The questionnaire began with an explanation of key concepts, such as: m-learning, mobile devices, knowledge transfer, internal and external usability. Additionally, during face-to-face meetings, surveyed employees were introduced with key concepts and were able to ask questions. The crucial part of the survey included 71 statement assertions formulated in accordance with acceptance questionnaire rules, while also taking into account the context of mobile technologies and knowledge transfer – 3-5 statements for each variable in the elaborated model (Fig. 1). Each question was measured using a 7-point Likert scale.

Table 3. Research hypotheses.

Hypoth.	Connection	Description
H1	IU $\rightarrow$ BI	IU directly influences the intention to use mobile technologies for facilitating knowledge transfer.
H2	EU $\rightarrow$ BI	EU directly influences the intention to use mobile technologies for facilitating knowledge transfer.
H3	EU $\rightarrow$ IU	EU directly influences the perceived IU of mobile technologies for facilitating knowledge transfer.

The data was collected during a 6-month period, starting from January 2019. Because of the lack of a reliable sampling frame, it was difficult to conduct random sampling for all potential mobile technology users. Similar to Wang *et al.* (2009), this study adopted a non-random sampling technique (i.e. convenience sampling) to start collecting the sample data. Convenience sampling was used to conduct a pre-test so that the questionnaire might become more understandable, complete and with no ambiguous assertion statements. It was conducted among eight employees altogether, during individual face-to-face meetings. The participants were asked to fill out the survey and afterwards they were able to point out any doubts which were further discussed and eliminated. Surveys were received from many organizations in Poland from both the public and private sectors and with a diverse number of employees, representing 22 industries altogether. The survey was conducted among 318 employees, among whom 269 knew how to use mobile devices, applications and services also connected with m-learning, and were able to report on their experience. In total, 237 employees (157 females and 80 males) filled out the questionnaire, giving a response rate of 88%.

We employed structural equation modelling (SEM) to validate the research model. SEM has been widely tested in the field of technology acceptance. The advantage of SEM is that it considers both the evaluation of the measurement model and the estimation of the structural coefficient at the same time. A two-step modelling approach, recommended by Anderson and Gerbing (1988), as well as McDonald and Ho (2002), was followed in such a way that first a confirmatory factor analysis (CFA) was carried out to provide an assessment of convergent and discriminant validity. Inter-construct correlation coefficient estimates were examined along with a particular item's internal consistency reliability, by using Cronbach's alpha coefficient estimates. The model quality was measured with CFA fit indices, such as: $\chi 2$/d.f., Goodness of Fit Index (GFI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), Adjusted Goodness of Fit Index (AGFI), and Normed fit index (NFI). As CFA fit indices had values within the recommended range (Table 5), the stated hypotheses were verified through a regression analysis with SEM through significance levels and standardized β-coefficients. Due to a connection between the external variables, between EU and IU, the total effect was also measured. Bentler and Freemam (1983) define the total effect as the sum of the powers of the coefficient matrices. Calculating the total effect allowed a better determination of the extent to which particular variables impact BI.

Research results

A data validity test performed to reduce the possibility of receiving incorrect answers during the data collection period (Sekaran and Bougie 2016) showed that all 237 cases (questionnaires) were valid. The interconstruct correlation coefficient estimates were examined along with a particular item's internal consistency by using Cronbach's alpha (Cα) based on standardized items (Cα^*) coefficient estimates, depicted in Table 4.

Table 4. Data reliability.

Variable	Cα	Cα^*
IU	0.920	0.921
EU	0.938	0.939
BI	0.951	0.951

Reliability values greater than 0.7 are considered as acceptable in technology acceptance literature (Taber 2018). All items far exceeded the recommended level. The data was internally consistent and acceptable, with a total reliability equal to 0.964. The validity of the elaborated model was checked via CFA, an integral part of SEM. Consequently, the model meets the accuracy requirements of the fit indices, given in Table 5.

Table 5. Fit indices of the model.

Fit indices	Recommended value	Result
χ2/d.f.	< 3	2.220
AGFI (Adjusted Goodness of Fit Index)	> 0.8	0.803
CFI (Comparative Fit Index)	> 0.9	0.942
GFI (Goodness of Fit Index)	> 0.8	0.837
NFI (Normed fit index)	> 0.8	0.903
RMSEA (Root Mean Square Error of Approximation)	< 0.08	0.071

Six fit indices satisfied by the elaborated model (Table 5) confirmed the model validity and allowed the path variances presented in Table 6 to be verified.

Table 6. Research hypotheses verification.

Hypoth.	Connection	Significance (p)	Standardized β-coefficient	Verification result
H1	IU $\rightarrow$ BI	< 0.001	0.539	Accepted
H2	EU $\rightarrow$ BI	0.03	0.320	Accepted
H3	EU $\rightarrow$ IU	< 0.001	0.932	Accepted

According Fig. 2, the results in Table 6 confirmed conceptual model which means that all three hypothesis can be accepted.

The total effects of particular variables on BI, calculated as the sums of the variables' direct and indirect impact on BI, are presented in Table 7.

Table 7. Total effects on behavioural intention

Variable	Direct effect	Indirect effect	Total effect
IU	0.539		0.539
EU	0.320	0.502	0.822

Discussion

Interpreting the outset of theoretical aspects, all stated hypotheses were supported, as H1-H3 were confirmed (Table 7). This means that both IU and EU influence the behavioural intention (BI) to use mobile

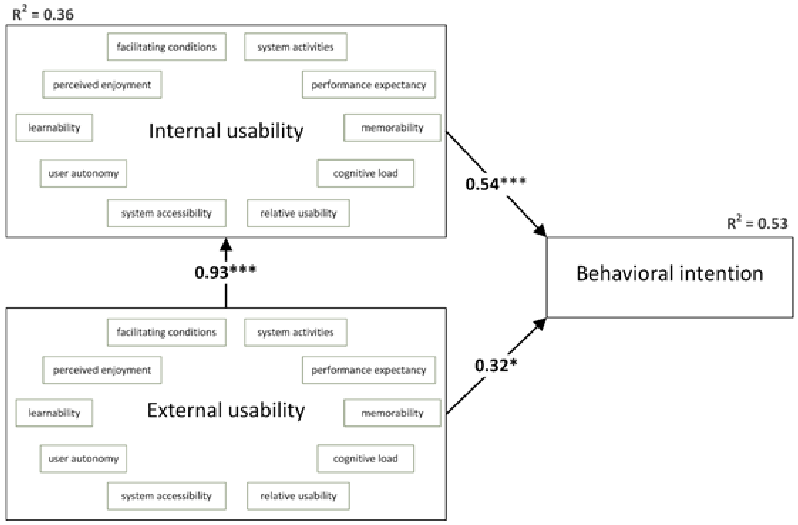

Figure 2. Model for evaluating the internal and external usability of mobile technologies in facilitating knowledge transfer - verification results.

technologies in facilitating knowledge transfer. This is consistent with findings in the studies of (Fiks et al. 2018; Kuciapski 2017; Liu and Huang 2015; Macis et al. 2019; Sung et al. 2016) who confirmed that various perspectives of usability impact the convenience and efficiency of technology use, as well as these (Becker et al. 2015; Zhang and Jasimuddin 2015) who supported that the use of mobile technologies positively influences knowledge transfer and therefore also employee productivity. IU occurred to very significantly (p<0.001) and strongly (β=0.539) influence BI (H1). Both the significance level (p=0.03) and the level of influence (β=0.320) were noticeably lower for the direct impact of EU on BI (H2), and should be considered as moderate. If only direct effects were measured, IU would be pointed out as a crucial factor in explaining the acceptance of mobile technologies in facilitating knowledge transfer. As EU has a very significant (p <0.001) and very strong (β=0.932) – nearly linear correlation exists – influence on IU, interpreting only the direct effects would be inappropriate. Therefore, the most important findings result from the total effects of IU and EU variables on BI (see Table 7). Even if there exists a strong total effect on BI from both variables, the β-coefficient value is far higher for EU (0.822) than for IU (0.539) due to the strong indirect influence of EU on BI (0.502) through the IU variable. This means that the usability of the mobile environments, not the mobile applications used, is a crucial factor influencing employee intention to utilize mobile technologies in facilitating knowledge transfer.

The relatively strong total impact of EU on BI translates also into its significant indirect influence on actual use, as the connection between behavioural intention and usage behaviour is positively verified in key technology acceptance models, such as TAM, TAM2, TAM 3, as well as UTAUT and UTAUT2. On the other hand, as the use of mobile technologies has been confirmed in the studies of (Becker et al. 2015; Chen and Hsiang 2007; Gururajan and Fink 2010; Jeno et al. 2019; Liu and Huang 2015; Sung et al. 2016; Zhang and Jasimuddin 2015) to positively impact various aspects of knowledge transfer processes, EU should be considered as a highly important factor and IU as an important indicator influencing the performance of knowledge workers. Moreover, Chen and Hsiang (2007) pointed out that knowledge transfer, if closely associated with the use of mobile technologies, can be extremely beneficial in the skills development of corporation employees.

Mobile devices and applications have been also confirmed by Jeno *et al.* (2019) to positively impact intrinsic motivation and perceived achievements in competence development from the viewpoint of Self-Determination Theory. Sung *et al.* (2016) highlighted that the use of mobile devices allows competence development processes to be conducted more effectively than when using only desktop computers. Liu and Huang (2015) positively verified that m-learning 2.0, in particular, plays a key role during knowledge transfer, as the use of mobile devices and applications can create a learning environment that is more authentic, collaborative, communicative, engaged and effective. The importance of including usability in technology acceptance models, and its division into internal and external perspectives, as proposed, is confirmed by a relatively high R^2 (0.53) value of BI (Fig. 2). This indicates that the elaborated model explains the 53 percent of behavioural intention to use mobile technologies in facilitating knowledge transfer by employees. IU is explained as being influenced 36 percent by EU, which is a moderate value and points out that several other determinants should be identified.

As IU and especially EU occurred to be important determinants in supporting employee intention to use mobile technologies for facilitating knowledge transfer, they have to be treated as factors for increasing hyper-connectivity and talent mobility in knowledge economies. The success of implementing mobile technologies for knowledge transfer is more related to the used environment – the device and its operating system – than the application itself (Table 7). As the performance of mobile devices occurred to be very important, software providers, when developing mobile applications, should select only technologies (frameworks, libraries, control sets) which are fully compliant with the hardware and operating systems of devices. In particular, the different types of mobile hardware devices have increased the risk of a decrease in the quality of the interaction between a user and an application. If a cross-platform approach is being used, developed mobile applications should not be identical for all platforms (operating systems) but separate convergent versions, fully adapted to the specifics of devices (size, native functions, peripherals, computing performance) and their operating systems (standard/typical: layout, typography, colours, data visualization, controls, interaction styles) should be created. There are software development frameworks available on the market that support application development in such a way. The stronger influence of EU on mobile technology acceptance utilized for facilitating knowledge transfer than in the case of IU, also means that if a mobile application has to be developed for a limited number of complementary platforms because of time or financial restrictions, platforms with a higher usability rating should be chosen first.

Conclusions

The primary outcome of the performed study is that even though both IU and EU were confirmed to strongly influence mobile technology acceptance in facilitating knowledge transfer by employees, the latter one is significantly more important. Therefore, when designing or choosing mobile solutions that should positively stimulate the performance of knowledge workers during knowledge transfer, the usability of the mobile environment, not mobile applications, should be first assessed. Moreover, the importance of including usability in technology acceptance models, and its division into internal and external perspectives, as proposed, is confirmed by the relatively high value of R^2 (0.53) of the dependent variable – behavioural intention to use devices and applications for knowledge transfer. Future research will cover this approach in a greater detail and also expand the model with additional variables. Further, the usability evaluation will cover a different context of the usage of mobile applications, which are pivotal in modern society across various spheres including business, communication, entertainment, finance and social media. In light of recent results, these research areas seem to be in the spotlight more than ever before due to the unprecedented conditions and constraints imposed by the COVID-19 pandemic. Ultimately, we also encourage other researchers to replicate and test our model on different sample sets, providing more evidence on its reliability and validity.

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