Applying Technology Acceptance Model (TAM) to Explore Users' Behavioral Intention to Adopt Wearables Technologies

Dan F. STĂNESCU
National University of Political Studies and Public Administration
Expozitiei Blvd. no.30a, Bucharest, RO
dan.stanescu@comunicare.ro

Marius C. ROMAȘCANU
National University of Political Studies and Public Administration
Expozitiei Blvd. no.30a, Bucharest, RO
marius.romascanu@comunicare.ro

Abstract
The popularity of wearable technologies increased dramatically in the last few years, wearable technologies are expected to become an indispensable part of our daily life shortly. Wearable technology is defined as any personal device worn on either the body or on clothing, or as an implant (more permanent and invasive) often with data collecting or motion-sensing capabilities. The study is based on a cross-sectional design, data being collected from a convenience sample of 261 participants (48 males, 213 females), aged between 18 and 29 years old (M=21,73, SD=3,70) through the following structured questionnaires: ATAS - Attitude Towards Automation Scale (Humphrey, 2018) and Technology Acceptance Model (Davis, 1989). The study applied the Technology Acceptance Model (TAM) to explore the behavioral intention of students in the adoption and use of wearables technologies. The results of the study suggest that both Perceived Ease of Use (r=.279, p<.01) and Perceived Usefulness (r=.386, p<.01) correlate with Actual System Use. Moreover, Perceived Ease of Use and Perceived Usefulness positively correlates with the Utility-scale of ATAS (r=.238, p<.01; r=.347, p<.01) and negatively with the Dystopia scale of ATAS (r=-.261, p<.01; r=-.266, p<.01). The reality is that the increased wearability of technology and the affordable prices of most of it has enabled individuals to access and interact with technology more often than ever, wearables technology becoming more and more an integral part of one's body, mind, and even the sense of self. Practical implications of the recent study are discussed as well as some directions for future research in the area.

Keywords
TAM; technology; wearables; Internet of Bodies; behavior.

Introduction

It has been well established that the interaction between humans and technology is influenced by several social and psychological factors and characteristics (Taiwo & Downe, 2013). Scholars developed several theoretical models to explain the acceptance behavior of end-users. One of the most cited and well-known models is the so-called Technology Acceptance Model (TAM) (Davis, 1986, 1989). TAM is considered the most influential and commonly employed theory for describing an individual's acceptance of information systems (Lee, Kozar, & Larsen, 2003). Chuttur (2009) argues that the wide acceptance of TAM is based on the fact that the model has a sound theoretical assumption and practical effectiveness.

During the last decade, the TAM model and its revised forms have gained considerable prominence, particularly due to its transferability to various contexts and samples, its potential to explain variance in the intention to use or the use of technology, and its simplicity of specification within structural equation modeling frameworks (King & He, 2006; Marangunić & Granić, 2015).

Fred Davis first developed this model in his doctoral studies at the Massachusetts Institute of Technology in 1986, starting from an adaptation of the more generalized Theory of Reasonable Action (TRA; Fishbein & Ajzen, 1975). In this model, Fishbein and Ajzen stated that individual behavior is driven by behavioral intentions. Behavioral intentions are a function of an individual's attitude toward the behavior and subjective norms surrounding the performance of the behavior.

They have defined "attitude" as the individual's evaluation of an object, the individual's positive or negative feelings about performing a specific behavior. Attitudes are formed by a series of beliefs and result in a value being placed on the outcome of the behavior (Ajzen, 2002). If the outcome or result of behavior is seen as being positive, valuable, beneficial, desirable, advantageous, or a good thing, then a person's attitude will be favorable with a greater likelihood of the person engaging in the behavior.

In addition to attitude, the intention is influenced by subjective norms. A subjective norm is the perceived social pressure to engage or not to engage in certain behavior. Subjective norm is defined as an individual's perception of whether people important to the individual, so-called relevant others, think the behavior should be performed.

Later on, Ajzen (1991) developed the Theory of Planned Behavior (Figure 1), which aims at explaining behavioral decision-making processes of human beings to better understand and predict their behavior. The first two factors are the same as the Theory of Reasonable Action (Fishbein & Ajzen, 1975). The third factor, the perceived behavioral control, is the degree of control that users perceive that may limit their behavior. It refers to the controllable degree that individuals feel when taking particular acts, which depends on three factors of capabilities, resources, and opportunities (Zhang, 2018). The more capacities, resources, and opportunities individual think they own in taking particular acts, the less expected obstacles and the stronger the perceived behavior control individuals have (Ajzen, 1985).

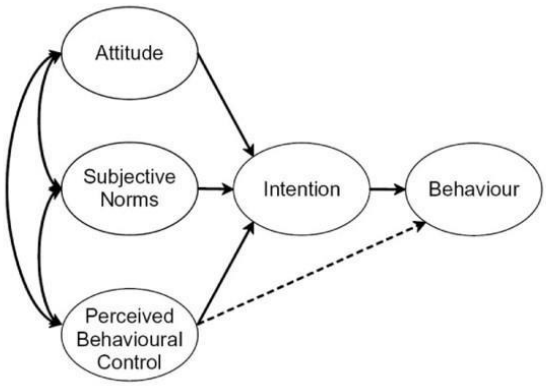

Figure 1. The Theory of Planned Behavior
(Ajzen, 1991)

Starting from those earliest theories, Davis (1986) developed this new version to better explain technology usage behavior and to identify the factors that lead to user's acceptance or rejection of specific technology by combining technological aspects with organizational behavior (Davis, Bagozzi, & Warshaw, 1989; Davis, 1989). This model (Figure 2) assumes that an individual's technology acceptance is determined by two major variables: perceived usefulness and perceived ease of use (Marangunić & Granić, 2015).

As Davis (1986) mentioned, employees tend to use or not use a new technology or a new IT application to the extent they believe it will help them perform their job better. Moreover, even if potential users believe that a given technology is useful, they may, at the same time, believe that the system is too hard to use and that the performance benefits of usage are outweighed by the effort of using that specific technology. It refers to the effort a person estimates it would take to use technology and is closely related to competence beliefs (Scherer, Siddiq, & Teo, 2015).

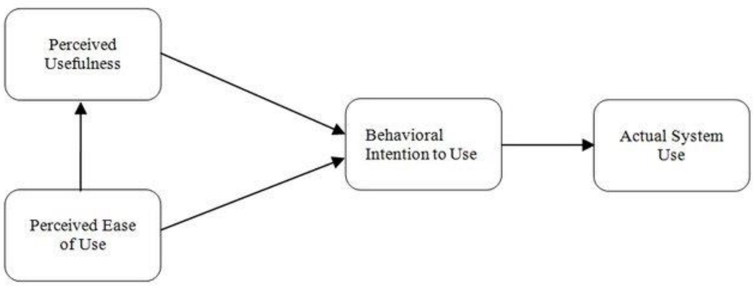

Figure 2. The earliest technology acceptance model
(Davis, 1989)

The importance of perceived ease of use is supported by Bandura's (1982) extensive research on self-efficacy, defined as "judgments of how well one can execute courses of action required to deal with prospective situations" (p. 122). Therefore, in this context, self-efficacy is similar to perceived ease of use as defined above.

Hence, perceived usefulness and perceived ease of use are indicated as fundamental and distinct constructs that are influential in decisions to use new technology. Although certainly not the only variables of interest in explaining user behavior (Cheney, Mann, & Amoroso, 1986; Davis, Bagozzi, & Warshaw, 1989; Swanson, 1988), they do appear likely to play a central role.

Shroff, Deneen, and Ng (2011) described that by manipulating these two variables, technology systems developers can have better control over users' beliefs about a specific system and so can better predict their behavioral intention and actual usage of the system. Attitude towards using new technology or system has been classified as a determinant that guides future behavior or as a cause of intention that eventually leads to a certain behavior (Alomary & Woollard, 2015). In TAM, attitude towards using a system refers to the evaluative effect of positive or negative feelings of individuals in performing certain behaviors (Shroff et al., 2011).

Although researchers and practitioners very well received it, some argue that the TAM does not take into consideration possible obstacles that would prevent the individual from adopting a particular technology (Taylor & Todd, 2001). Bogozzi (2007) has stated that the TAM is too simple and leaves out important variables (Bogozzi, 2007).

Thus, Mugo and colleagues (2017) stated that both perceived ease of use and perceived usefulness are influenced by two categories of variables: internal and external variables. Internal variables consist of factors such as the attitude of the user, their pedagogical beliefs towards, and level of competency, whereas external variables include those external barriers faced by users during utilization. Such factors include organizational barriers, technological barriers, and social barriers.

Other authors (Abdullah & Ward, 2016; Schepers & Wetzels, 2007) pointed that those two important variables (perceived usefulness and perceived ease of use) are often accompanied by external variables explaining variation in perceived usefulness and ease of use: subjective norms (SN), self-efficacy (CSE), and facilitating conditions (FC).

The final version of the Technology Acceptance Model was formed by Venkatesh and Davis (1996) as shown in Figure 3 both perceived usefulness and perceived ease of use were found to have a direct influence on behavior intention (Lai, 2017).

However, despite those critics, it has also been recognized by others as a powerful, valid, and highly reliable predictive model that can be used in several contexts (Legris, Ingham, & Collerette, 2003; Sharma & Chandel, 2013). Moreover, it constitutes an important theoretical contribution towards understanding technology usage and acceptance behaviors (Chen, Li, & Li, 2011). Other scholars (Lucas & Spitler, 1999; Venkatesh & Davis, 2000) considered TAM a parsimonious and powerful theory that help researchers and practitioners to distinguish why a particular technology or system may be acceptable or unacceptable and take up suitable measures by explanation besides providing prediction (Lee, Kozar, & Larsen, 2003).

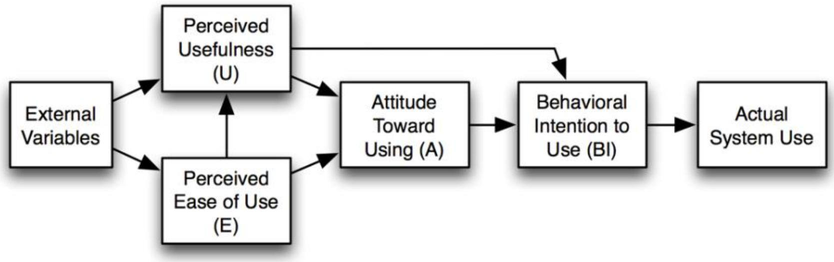

Figure 3. Final version of Technology Acceptance Model (TAM)
(Venkatesh & Davis, 1996)

Even though TAM has been tested widely with different samples in different situations and proved to be a valid and reliable model explaining information system acceptance and use (Mathieson, 1991; Davis & Venkatesh, 1996), many extensions to the TAM have been proposed and tested (Venkatesh & Davis, 2000; Henderson & Divett, 2003; Lu, Yu, Liu, & Yao, 2003; Lai & Zainal, 2015; Lai, 2016).

Hornbæk and Hertzum (2017) have mentioned that a variety of moderators of the adoption and use of technology were identified in addition to the perceived usefulness and perceived ease of use. One of these constructs is perceived enjoyment (Liao et al., 2008; van der Heijden, 2003), which adds experiential and hedonic aspects to TAM. Other external variables that were introduced into TAM as suggested by Davis (1989) are system quality (Igbaria, Guimaraes, & Davis, 1995), training (Igbaria, Iivari, & Maragahh, 1995), compatibility, computer anxiety, self-efficacy, enjoyment, computing support, and experience (Chau, 1996).

During the last decade, the growth of wearable products such as smartwatches, display glasses, smart tattoos, wrist-bands, and headbands has been increasing and propagated rapidly to mainstream usage, due to their capability for both leisure or fitness and medical data tracking (Celik, Salama, & Eltawil, 2020; Nam & Lee, 2020). The review of the literature revealed that wearable technology has spread through a large array of areas including medical, healthcare, fitness, and fashion industries (Dunne, 2010; Gepperth, 2012; Perry et al., 2017). Sharma and Biros (2019) defined wearables as "a subset of IoT that includes 'things 'that can be incorporated into clothing or worn on the body as accessories" (p. 35).

According to Seneviratne and colleagues (2017) "wearables can sense, collect, and upload physiological data in a 24x7 manner, providing opportunities to improve quality of life in a way not easily achievable with smartphones alone. Wearables can also help users perform many other useful micro-tasks, such as checking incoming text messages and viewing urgent information, much more conveniently and naturally than possible with a smartphone, which is often carried in pockets or bags" (Seneviratne *et al.*, 2017, p. 2573). Moreover, in the last few years, wearables have become so technologically advanced that they have become capable of monitoring heart rate, calories burned, steps walked, blood pressure, time spent exercising, quality of sleep, and the electrical activity of the heartbeat (Swan, 2013).

Following Wright and Keith's (2014) conceptualization, wearable technology and wearable devices are phrases that describe electronics that are integrated into clothing and other accessories that can be worn comfortably on the body. Although these technologies are mainly encountered in fashion and entertainment areas, they have the largest impact in the areas of health, medicine, and fitness (Wright & Keith, 2014). Wearables constantly provide users with information regarding their habits, activity levels, and different physiological data (Motti & Caine, 2014). According to the same authors, the wearables pervasiveness, small size, and autonomy enlarge the potential of these devices to be employed in different activities and scenarios (Motti & Caine, 2014).

We have chosen the TAM because this model has been extensively studied and utilized by many researchers in studying the adoption of different types of technologies such as mobile phones (Joo & Sang, 2013; Kim & Sundar, 2014), ICT (Edmunds et al., 2012) and smartwatch (Kim & Shin, 2015). Therefore, this study aims to adopt this model as the theoretical framework for investigating the user acceptance of wearable technology among students. Following the original model, we propose that (Figure 4):
H1. PU will be positively correlated with ASU
H2. PEU will be positively correlated with ASU
H3. PU will be positively correlated with Utility
H4. PEU will be positively correlated with Utility
H5. PU will be negatively correlated with Dystopia
H6. PEU will be negatively correlated with Dystopia

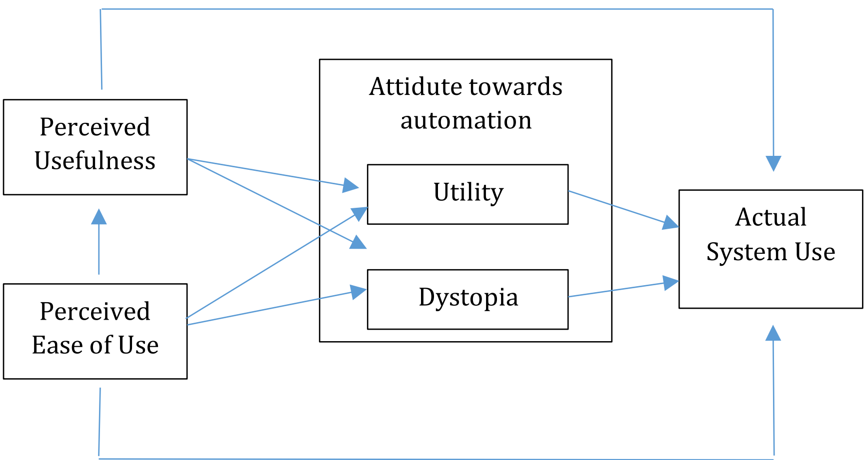

Figure 4. Conceptual framework

Methods

The sample consisted of 261 students (48 males, 213 females). The age range of the participants was from 18 to 29 years (M=21,73, SD=3,70). For data collection, a purposive convenience sampling technique was used. A self-reported data collection technique was employed. Before completion, the purpose of the study was briefly explained to the participants and informed consent was obtained. All participants were ensured about the confidentiality of the data and that it would be only used for research purposes. They were invited to fill in a set of questionnaires compiling the following measures: ATAS - Attitude Towards Automation Scale (Humphrey, 2018) and Technology Acceptance Model (Davis, 1989).

a) ATAS - Attitude Towards Automation Scale (Humphrey, 2018). The questionnaire consists of 30 items, distributed on 4 scales: Utility, Dystopia, Social utility and Social impact. Ratings were completed on a five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree). The analysis of Cronbach alpha coefficients showed good internal consistency coefficients for all ATAS scale: 0.807 for Utility, 0.754 for Dystopia, 0.502 for Social utility, and 0.527 for Social impact. Due to the low reliability of Social utility, and Social impact scales we have decided to further use only the scales with good internal consistency.

b) Technology Acceptance Model (Davis, 1989), consists of 12 items, covering two dimensions: perceived usefulness and perceived ease of use. The answers are distributed on a seven-options Likert scale from 1 (Extremely unlikely) to 7 (Extremely likely). The internal consistency coefficient (Cronbach's Alpha) of those scales was 0.789 for perceived ease of use and 0.753 for perceived usefulness.

Results

After collection, the data were analyzed using SPSS 26.0 version software. The analysis of Skewness and Kurtosis coefficients showed a normal distribution of data, therefore, to test the proposed hypotheses, the Pearson correlation was used.

H1. Perceived Usefulness will be positively correlated with Actual System Use
H2. Perceived Ease of Use will be positively correlated with Actual System Use

To test these hypotheses, the Pearson intercorrelation coefficients were calculated, both between the PEU and ASU and PU and ASU. The results presented in Table1 highlight the existence of significant positive relationships, both between PEU and PU ($r=.502^{**}$, $p<.01$) and between PEU and ASU ($r=.279^{**}$, $p<.01$), and PU and ASU ($r=.386^{**}$, $p<.01$), both hypotheses being confirmed by the obtained results.

Table 1. Bivariate correlations between TAM and Actual system usage

		Perceived Ease of Use	Perceived Usefulness	Actual system usage
Perceived Ease of Use	Pearson Correl.	1	.502**	.279**
	Sig. (2-tailed)		.000	.000
	N	261	261	261
Perceived Usefulness	Pearson Correl.	.502**	1	.386**
	Sig. (2-tailed)	.000		.000
	N	261	261	261

Perceived usefulness describes a user's subjective beliefs that using a specific system would enhance his or her performance (Davis, 1989). Perceived usefulness has been acknowledged as one of the most important drivers in predicting and explaining users' intention in accepting a specific technology (Dutot et al., 2019; Kalantari, 2017). The importance of perceived usefulness in acceptance and adoption of different technologies has been confirmed in various contexts, such as in internet banking (Lee et al., 2016), smartphones (Agrebi & Jallais, 2015), and wearable technology (Talukder et al., 2019).

Similarly, perceived ease of use, the way individuals perceived wearables technology as being easy to operate, represent an important factor in the actual adoption of that specific wearable technology. Results from previous empirical research indicate that the perceived ease of use of specific technology (e-book readers) has a strong, positive influence on perceived usefulness. This means that those who thought that technology would be simple to use also thought that would technology be useful (Antón, Camarero, & Rodríguez, 2013), mirroring the results obtained in the current study (PEU and PE correlation $r=.502$, $p<.01$).

Regarding the relationships between TAM (PEU and PU) and ATAS (Utility and Dystopia), the results presented in table 2 confirmed our previously stated hypotheses (3 to 6).

H3. Perceived Usefulness will be positively correlated with Utility
H4. Perceived Ease of Use will be positively correlated with Utility
H5. Perceived Usefulness will be negatively correlated with Dystopia
H6. Perceived Ease of Use will be negatively correlated with Dystopia

Table 2. Bivariate correlations between TAM and ATAS scales

		Utility	Dystopia
Perceived Ease of Use	Pearson Correl.	.238**	-.261**
	Sig. (2-tailed)	.000	.000
	N	261	261
Perceived Usefulness	Pearson Correl.	.347**	-.266**
	Sig. (2-tailed)	.000	.000
	N	261	261

The ATAS scale takes into account two dimensions, a vision for our future and the impact automation has on humans in terms of its utility. It draws from the initial theory of technology acceptance (Davis, 1986, 1989) where a new, ideological feature is added, namely, the author builds on a pre-existing condition of humans' views about their future on Earth - which can be a Dystopic or a Utopic one. In the Dystopic future, AI and automation take over and work against humans, while in the Utopic future AI and automation work for the benefit of humankind. Therefore, we were expected to observe positive correlations with the Utopic (utility) dimension and negative correlations with the Dystopic dimension.

The results presented in Table 2 show positive correlations between PEU and Utility ($r=.238^{**}$, $p<.01$) and between PU and Utility ($r=.374^{**}$, $p<.01$), and negative ones PEU and Dystopia (r=-.261**, p<.01) and between PU and Dystopia (r=-.266**, p<.01), confirming the hypotheses.

A synthesis of the results is presented in Figure 5.

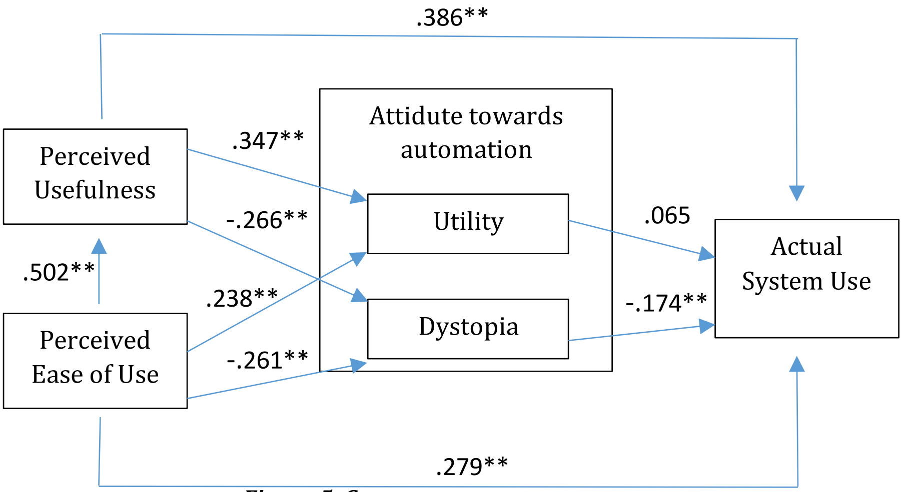

Figure 5. Correlations summary

Conclusions

Current findings are supported by previous studies that highlighted positive correlations between PEU, PU, and behavioral intention or actual system usage (Davis, 1986, 1989). Similar to office software (Davis, et al., 1989), e-commerce (Hubert, et al., 2017), online financial services (Featherman & Pavlou, 2003), or smart home systems (Hubert, et al., 2018), the results demonstrate that PU is also a strong predictor of usage intention in the context of wearables technologies. One of the most well-known meta-analyses conducted by King and He (2006) also confirmed the importance of perceived benefits in technology acceptance.

Despite the valuable findings of this study, it is not without limitations. One of the main weaknesses of this study was the use of a cross-sectional design, which does not allow for an assessment of the cause-effect relation. Also, another limitation, common to many studies, is related to the fact the questionnaires were self-reported, and the tendency is to investigate and report attitudes, rather than behaviors (Hughes, et al., 2018). Another issue to be considered when evaluating the results is the small sample, which makes the results difficult to generalize, and that most respondents of this study were young (18-29 years old). It has been known that younger individuals are the primary users of wearable devices, therefore older consumers who might be not so familiar with those technologies should be considered for future studies.

The reality is that the interest in wearables is growing fast, during the last few years, a large variety of wearables has been offered to the market (Seneviratne, et al., 2017). A forecast of the wearable industry shows that it will most likely experience important changes within the next few years, wearables being more and more present in mainstream usage. Already many users share their data with others or with different social media platforms to compare results and provide instant feedback (e.g. notifying about how many steps one has taken) or to compete for step/fitness supremacy. Those devices collect and store highly personal data, arguably more intimate than any other type of user information (e.g. heart rate, location), and so privacy and confidentiality risks abound. There are many unresolved questions about who has authority to use data collected by wearable devices, and in what way (Lee, et al., 2020). Future studies should focus not only on factors related to technology adoption but also on the more and more important issue of security of both data and devices. Just imagine what could happen if someone will be able to hack into our heart pacemaker or access sensitive medical data.

References

Abdullah, F., & Ward, R. (2016). Developing a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computers in Human Behavior, 56*, 238 - 256. https://doi.org/10.1016/j.chb.2015.11.036

Agrebi, S., & Jallais, J. (2015). Explain the intention to use smartphones for mobile shopping, *Journal of Retailing and Consumer Services, 22*(C), 16–23. https://doi.org/10.1016/j.jretconser.2014.09.003

Ajzen, I. (1985). *From intentions to actions: A theory of planned behavior.* Springer.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control and the theory of planned behavior. *Journal of Applied Social Psychology, 32*(4), 1–20.

Alomary, A., & Woollard, J. (2015). How is technology accepted by users? A review of technology acceptance models and theories. In *Proceedings of the 5th International Conference on 4E, United Kingdom.*

Antón, C., Camarero, C., & Rodríguez, J. (2013). Usefulness, enjoyment, and self-image congruence: The adoption of e-book readers. *Psychology and Marketing, 30*(4), 372-384. https://doi.org/10.1002/mar.20612

Bandura, A. (1982). Self-Efficacy Mechanism in Human Agency. *American Psychologist, 37*(2), 122-147.

Bogozzi, R.P. (2007). The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift. *Journal of the Association for Information Systems, 8*(4), 244–254.

Celik, A., Salama, K. N., & Eltawil, A. (2020). The Internet of Bodies: A Systematic Survey on Propagation Characterization and Channel Modeling. *IEEE Internet of Things Journal,* https://doi.org/10.36227/techrxiv.12912752

Chau, P.Y.K. (1996). An Empirical Assessment of a Modified Technology Acceptance Model. *Journal of Management Information Systems, 13*(2), 185-204.

Chen, S.C., Li, S.H., & Li, C.Y. (2011). Recent related research in technology acceptance model: A literature review. *Australian Journal of Business and Management Research, 1*(9), 124-127.

Cheney, P.H., Mann, R.I., & Amoroso, D.L. (1986). Organizational Factors Affecting the Success of End-User Computing. *Journal of Management Information Systems, 3*(1), 65-80.

Chuttur, M. Y. (2009). Overview of the technology acceptance model: Origins, developments and future directions. *Working Papers on Information Systems*, *9*(37), 9-37.

Davis, F. D. (1986). *Technology Acceptance Model for Empirically Testing New End-user Information Systems Theory and Results*. Unpublished Doctoral Dissertation, MIT.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.
Davis, F. D., Bagozzi, R., & Warshaw, P. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, *35*(8), 982-1003.
Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: Three experiments. *International Journal of Human-Computer Studies*, *45*(1), 19–45.
Dunne, L. (2010). Smart clothing in practice: Key design barriers to commercialization. *The Journal of Design, Creative Process & the Fashion Industry*, *2*(1), 41–65. https://doi.org/10.2752/175693810X12640026716393
Dutot, V., Bhatiasevi, V., & Bellallahom, N. (2019). Applying the technology acceptance model in a three-countries study of smartwatch adoption. *The Journal of High Technology Management Research, 30*(1), 1–14. https://doi.org/10.1016/j.hitech.2019.02.001
Edmunds, R., Thorpe, M., & Conole, G. (2012). Student attitudes towards and use of ICT in course study, work and social activity: a technology acceptance model approach. *British Journal of Educational Technology, 43*(1), 71–78.
Featherman, M.S., & Pavlou, P.A. (2003). Predicting e-services adoption: a perceived risk facets perspective, *International Journal of Human-Computer Studies, 59*(4), 451-474.
Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research. Addison-Wesley.
Gepperth, J. (2012). Smart Things: Wearables & Clothing. In M. Karnz, E. Steinbach, S. Diewald, A. Moller, & L. Roalter (Eds.), *Advance in media technology* (pp. 41–48). Distributed Multimodal Information Processing Group: Munich, Germany.
Henderson, R., & Divett, M. J. (2003). Perceived usefulness, ease of use and electronic supermarket use. *International Journal of Human-Computer Studies*, *59*(3), 383-395.
Hornbæk, K., & Hertzum, M. (2017). Technology Acceptance and User Experience: A Review of the Experiential Component in HCI. *A C M Transactions on Computer - Human Interaction*, *24*(5), 33.
Hubert, M., Blut, M., Brock, C., Backhaus, C., & Eberhardt, T. (2017). Acceptance of smartphone-based mobile shopping: mobile benefits, customer characteristics, perceived risk and the impact of application context. *Psychology and Marketing, 34*(2), 175-194. https://doi.org/10.1002/mar.20982
Hubert, M., Blut, M., Brock, C., Zhang, R.W., Koch, V., & Riedl, R. (2019). The influence of acceptance and adoption drivers on smart home usage. European Journal of Marketing, 53(6), 1073-1098. https://doi.org/10.1108/EJM-12-2016-0794
Hughes, D. J., Lee, A., Tian, A. W., Newman, A., & Legood, A. (2018). Leadership, creativity, and innovation: A critical review and practical recommendations. *Leadership Quarterly, 29*(5), 549-569. https://doi.org/10.1016/j.leaqua.2018.03.001
Humphrey, C. (2018). Personality and Technology: Development of the Attitudes Towards Automation Scale (ATAS) (Kindle Locations 1746-1747). Kindle Edition.
Igbaria, M., Guimaraes, T., & Davis, G.B. (1995). Testing the Determinants of Microcomputer Usage Via a Structural Equation Model. *Journal of Management Information Systems, 11*(4), 87-114.
Igbaria, M., Iivari, J., & Maragahh, H. (1995). Why do Individuals Use Computer Technology? A Finnish Case Study. *Information & Management, 29*(5), 227-238.
Joo, J., & Sang, Y. (2013). Exploring Koreans' smartphone usage: an integrated model of the technology acceptance model and uses and gratifications theory. *Computers in Human Behavior, 29*(6), 2512–2518. https://doi.org/10.1016/j.chb.2013.06.002
Kalantari, M. (2017). Consumers' adoption of wearable technologies: Literature review, synthesis, and future research agenda. *International Journal of Technology Marketing, 12*(3), 274-307. https://doi.org/10.1504/IJTMKT.2017.089665
Kim, K. J., & Shin, D. H. (2015). An acceptance model for smart watches: Implications for the adoption of future wearable technology. *Internet Research, 25*(4), 527–541.
Kim, K. J., & Sundar, S. S. (2014). Does screen size matter for smartphones? Utilitarian and

hedonic effects of screen size on smartphone adoption. *Cyberpsychology Behavior and Social Networking, 17*(7), 466–473. https://doi.org/10.1089/cyber.2013.0492
King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740–755. https://doi.org/10.1016/j.im.2006.10.007
Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management*, *14*(1), 21-38.
Lai, P. C. (2016). Design and Security impact on consumers' intention to use single platform E-payment. *Interdisciplinary Information Sciences*, *22*(1), 111-122.
Lai, P. C., & Zainal, A. A. (2015). Perceived Risk As An Extension To TAM Model: Consumers' Intention To Use A Single Platform E-Payment. *Australian Journal of Basic and Applied Sciences*, *9*(2), 323-331.
Lee, M., Bodreaux, B., Chaturvedi, R., Romanosky, S., & Downing, B. (2020). *The Internet of Bodies. Opportunities, Risks and Governance*, Rand Corporation.
Lee, J., Kim, D., Ryoo, H. Y., & Shin, B.S. (2016). Sustainable wearables: Wearable technology for enhancing the quality of human life. *Sustainability*, *8*(5), 466. https://doi.org/10.3390/su8050466
Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The Technology Acceptance Model: Past, Present, and Future. *Communications of The Association for Information Systems*, *12*(50), 752-780.
Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191– 204.
Liao, C. H., Tsou, C. W., & Shu, Y. C. (2008). The roles of perceived enjoyment and price perception in determining acceptance of multimedia-on-demand. *International Journal of Business and Information, 3*(1), 27–52.
Lu, J., Yu, C. S., Liu, C., & Yao, J. (2003). Technology acceptance model for wireless internet. *Journal of Internet Research*, *13*(2), 206-222. https://doi.org/10.1108/10662240310478222
Lucas, H. C., & Spitler, V. K. (1999). Technology Use and Performance: A Field Study of Broker Workstations. *Decision Sciences, 30*(2), 291-311.
Malmivaara, M. (2009). The emergence of wearable computing. In McCann, J. & Bryson, D. (Eds.), *Smart Clothes and Wearable Technology*, (pp. 3-24). Woodhead Publishing.
Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society, 14(*1), 81–95.
Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. *Information Systems Research*, *2*(3), 173-191.
Motti, V. G., & Caine, K. (2014). Human factors considerations in the design of wearable devices. In *Proceedings of the Human Factors and Ergonomics Society 58th Annual Meeting* (pp. 1820–1824). Human Factors and Ergonomics Society.
Mugo, D., Njagi, K., Chemwei, B., & Motanya, J. (2017). The Technology Acceptance Model (TAM) and its Application to the Utilization of Mobile Learning Technologies. *Journal of Advances in Mathematics and Computer Science*. *20*(4), 1-8.
Nam, C., & Lee, Y. A. (2020). Validation of the wearable acceptability range scale for smart apparel. *Fashion and Textiles,* 7**,** 13. https://doi.org/10.1186/s40691-019-0203-3
Perry, A., Malinin, L., Sanders, E., Li, Y., & Leigh, K. (2017). Explore consumer needs and design purposes of smart clothing from designers' perspectives. International *Journal of Fashion Design, Technology and Education, 10*(3), 372–380. https://doi.org/10.1080/17543266.2016.1278465
Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management, 44*(1), 90–103. https://doi.org/10.1016/j.im.2006.10.007
Scherer, R., Siddiq, F., & Teo, T. (2015). Becoming more specific: Measuring and modeling teachers' perceived usefulness of ICT in the context of teaching and learning. *Computers*

& Education, 88, 202-214. https://doi.org/10.1016/j.compedu.2015.05.005
Seneviratne, S., Hu, Y., Nguyen, T., Lan, G., Khalifa, S., Thilakarathna, K., Hassan, M., & Seneviratne, A. P. (2017). A Survey of Wearable Devices and Challenges. IEEE Communications Surveys & Tutorials, 19, 2573-2620.
Sharma, S., & Chandel, J. (2013). Technology Acceptance Model for the Use of Learning Through websites Among Students in Oman. *International Arab Journal of e-Technology, 3*(1), 44-49.
Sharma, M., & Biros, D. (2019). Building Trust in Wearables for Health Behavior, *Journal of the Midwest Association for Information Systems (JMWAIS)*, *2019*(2), Article 3. https://doi.org/10.17705/3jmwa.000051
Shroff, R. H., Deneen, C. C., & Ng, E. M. W. (2011). Analysis of the technology acceptance model in examining students' behavioural intention to use an e-portfolio system. *Australasian Journal of Educational Technology*, *27*(4), 600–618. https://doi.org/10.14742/ajet.940
Swan, M. (2013). The Quantified Self: Fundamental Disruption in Big Data Science and Biological Discovery, *Big data, 1*(2), 85-99. https://doi.org/10.1089/big.2012.0002
Swanson, E. B. (1988). *Information System Implementation: Bridging the Gap Between Design and Utilization*, Richard Irwin.
Taiwo, A., & Downe, A. (2013). The Theory of User Acceptance and Use of Technology (UTAUT): A Meta-Analytic Review of Empirical Findings. *Journal of Theoretical and Applied Information Technology, 49*(1), 48–58. https://doi.org/10.12691/ajis-3-2-3
Talukder, M. S., Chiong, R., Bao, Y., & Hayat Malik, B. (2019). Acceptance and use predictors of fitness wearable technology and intention to recommend: An empirical study. *Industrial Management & Data Systems, 119*(1), 170–188. https://doi.org/10.1108/IMDS-01-2018-0009
Taylor, S., & Todd, P. (2001). Understanding Information Technology Usage: A Test of Competing Models. *Information Research, 6*(2), 144–176.
van der Heijden, H. (2003). Factors influencing the usage of websites: The case of a generic portal in the Netherlands. *Information and Management, 40*(6), 541–549.
Venkatesh, V., & Davis, F.D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926
Wright, R., & Keith, L. (2014). Wearable Technology: If the Tech Fits, Wear It, *Journal of Electronic Resources in Medical Libraries, 11*(4), 204-216. https://doi.org/10.1080/15424065.2014.969051
Zhang, K. (2018). Theory of Planned Behavior origins, Development and Future Direction. *International Journal of Humanities and Social Science Invention, 7*(5), 76-83.