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REVIEW

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User needs over time: the market and technology maturity model (MTMM)

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Abstract

This paper conceptualizes how consumers perceive innovations at different stages of technology maturity. The market and technology maturity model (MTMM) combines the constructs of acceptability, acceptance, and adoption with the widely used technology readiness level (TRL). The MTMM proposes that different aspects impact users' attitudes and behavior at different stages of technology maturity. To demonstrate the effect of technology maturity on the acceptance factors, a review was conducted based on previous studies on the acceptance of new technologies at various stages of technological maturity. The findings demonstrate that *performance expectancy* remains stable across the TRL stages, but *effort expectancy* tends to gain importance only after TRL 7. This indicates that consumers do not consider *effort* when the technology is still in early development. The results show that the importance of technology acceptance constructs differs across the stages of technology maturity. A limitation of this study is that only the most commonly used factors influencing acceptance have been considered. Future meta-studies should confirm the hypothesis with other factors such as social influence and hedonic motivation.

Keywords: Acceptability, Acceptance, Adoption, Technology

Introduction

Understanding consumer needs is a success driver for new products (Cooper, 2019). When their needs are not considered sufficiently, most consumers reject innovations (Otto & Wood, 2001; Pahl et al., 2007). At different stages of technology development, possibilities for collecting consumer feedback differ significantly. In its early stages of technological maturity, a product can often only be presented as a rough concept to consumers. In contrast, technologies in later stages of maturity can be presented to consumers as real products. According to Trope et al. (2007), people's thoughts and behavior can change depending on how abstract or concrete they perceive an object. Therefore, the temporality of the interaction between a user and a new technology must be considered (Alexandre et al., 2018; Distler et al., 2018). The concepts of acceptability, acceptance (Barcenilla & Bastien, 2009; Lee et al., 2003), and adoption (Rogers, 1962) all describe customers' attitudes towards various technologies. When looking at their detailed descriptions, it can be noted that they address different stages of technology maturity. Acceptability describes the prospective judgment towards a new technology when the subject has not yet experienced it (Regan et al., 2014), whereas acceptance refers to the judgment, attitude, and behavioral reactions towards a new technology or tool after the first experience or use (Distler et al., 2018; Venkatesh et al., 2012). Regarding the temporality of the interaction with a new technology, the adoption stage occurs after the acceptability and acceptance stages, when users establish a repeated or continuous use of the new technology (Rogers, 1962).

In current literature, however, acceptability, acceptance, and adoption are not treated as distinct constructs. The predominant models used to explain the attitude and behavioral reactions to a new technology mainly focus on acceptance but are also widely applied in the context of acceptability and adoption (e.g., Rohlik & Stasch, 2019 or Han, 2019). The most widely used model is Davis' (1985) technology acceptance model (TAM), which was subsequently developed further into TAM 2 (Davis, 1989) and TAM 3 (Venkatesh & Bala, 2008). In recent years, the UTAUT 2 (Venkatesh et al., 2012) has gained popularity (Tamilmani et al., 2020) and is now often taken as the standard approach to explaining the intention to use new technology. While this model introduced a variety of factors that potentially influence human reactions to a new technology, it does not consider the temporality of the interaction.

Current literature has identified a gap in research addressing this issue. Rohlik and Stasch (2019) state that research on comparing the level of technology maturity from a consumer perspective could be promising. According to Martin et al. (2016), research on technology evaluation changes by users over time is limited. Adell and Varhelyi (2008) also state that there can be different results on different levels of technology maturity. If these differences in results are not considered, the wrong focus can be set in product development.

To fill this gap, this paper investigates the attitude towards technology at different stages of maturity. This review was conducted on studies employing TAM or UTAUT and its successors on technologies at different stages of technology maturity. To ensure consistency, the authors only focused on factors that are included in all models, which are *performance expectancy* and *effort expectancy*. These factors are called *perceived usefulness* and *perceived ease of use* in the TAM models and focus on users' perceptions of the usefulness of the performance of a new technology and the perceived effort needed to learn how to use the new technology. Furthermore, the authors identified four recent studies for each technology. The selection criterion for each study was that it included the two constructs in a regression-based approach with a direct path to attitude or intention to use the technology. This initially highlights how consumer needs differ at different stages of technology maturity. We propose that *performance expectancy* is important throughout all stages of TRL, but *effort expectancy* only gains importance in the later stages of technology maturity. Therefore, the current model is the first that combines the maturity of a technology with the consumer needs perspective. From a theoretical standpoint, this model provides new insights, since it attempts to integrate the temporality of technological development into the models that explain the acceptance behavior of potential users. For practitioners, this article offers a guideline on how to better understand consumer feedback at different stages of the development of new technology.

The remaining sections are organized as follows: "Distinction between acceptability, acceptance, and adoption" section discusses how acceptability, acceptance, and adoption can be clearly distinguished; "The market and technology maturity model" section introduces the conceptual model; "Methods" section discusses the research methodology, including the research design of the review, selection criteria, sources of data, and study analysis. The results are presented in "Results" and "General discussion" sections contains the discussion and conclusion.

Distinction between acceptability, acceptance, and adoption

Previous research reveals that acceptability, acceptance, and adoption can be distinguished based on the temporality of the interaction between the user and the new technology (Alexandre et al., 2018). The representation of a new technology is not entirely defined in advance (acceptability) but is also generated during its actual use (acceptance), as acceptance requires real activity from the user (Alexandre et al., 2018; Distler et al., 2018) and is achieved after continuous usage (adoption) of the new technology (Rogers, 1962). The issue of these constructs has been addressed in many approaches using different key criteria or concepts that sometimes overlap (Adell & Varhelyi, 2008; Distler et al., 2018). We define the concepts of acceptability, acceptance, and adoption individually.

In general, attitudes are determined by people's beliefs about the consequences of the object at state. The outcome of an object can be judged to be favorable, neutral, or unfavorable, referring to the valence of the belief. Beliefs can change over time due to experiences or context changes and thus result in an attitude change (Ajzen, 1991). Acceptability is an attitude construct (Regan et al., 2014) that predicts the intention to use the new technology and can be defined as the prospective judgment towards a new technology (Schade & Schlag, 2003) or judgment of measures to be introduced in the future. Thereby, acceptability is an a priori phenomenon in the time scale of confrontation with a technology (Alexandre et al., 2018) and refers to a point in time when the subject has no experience with the new technology. Acceptability is related to the question of whether the system is good enough to satisfy all the needs and requirements of the users and other potential stakeholders (Vlassenroot et al., 2010). Hence, acceptability is defined as an explicit willingness to use a new technology and represents the (positive) mental representation that a user has before using a new technology (Alexandre et al., 2018).

Acceptance consists of attitudes and behavioral reactions after introducing a new technology (Regan et al., 2014). As a posteriori evaluation (Alexandre et al., 2018), acceptance refers to the judgment, attitude, and behavioral reactions towards a new technology after the first usage (Alexandre et al., 2018; Distler et al., 2018). Due to a change in beliefs, those attitudes can also change over time (Ajzen, 1991). Such an attitude change in favor of the new technology is to be expected. Several studies have found an attitude change after showing a proof of concept of the new technology with a fully functional prototype (Schuitema et al., 2010) or after product implementation. Experiences and context seem to change when real prototypes are available for testing in a realistic environment (NASA, 2012).

Adoption begins when continuous usage of the new technology is established (NASA, 2012; Rogers, 1962). It occurs after the stages of acceptability and acceptance regarding the temporality of interaction between the user and the new technology. The diffusion of innovations theory was developed by Rogers (1962). It describes the relative speed with which members of a social system adopt an innovation. For most new technologies, total adoption by users follows a bell curve that features exponential growth in the number of adopters in the different phases of adoption. Due to individual attitudes and social interactions, users decide independently when to adopt a new technology, and as a result, different adoption times arise. On the bell curve, 68% of adoptions are one standard deviation of the mean adoption time, labeled as the early and late majority phases. 13.5% of adoptions before the majority phase can be referred to as the early adoption phase, and those in the 2.5% band can be referred to as the innovation phase. Regarding the adoption, the innovators instantly adopt the new technology, whereas the early adoption phase is characterized by a quick adoption of the new technology. The majority waits until the new technology is widely adopted and reliable. In the laggard phase, represented by 16% at the end of the bell curve, adopting the new technology occurs quite late as laggards are cautious regarding any innovation (Rogers, 1962).

The market and technology maturity model

For structuring the development of innovations from a technological perspective, NASA's (2012) technology readiness levels (TRL) present one of the most widely used concepts. For example, there is an EU-wide mandate to link research to the TRL across all publicly funded programs (Héder, 2017). The different TRLs can be directly linked with users' perspectives of acceptability and acceptance. From the perspective of existing technology, Rogers' diffusion of innovation covers different periods of adopting a new technology (Rogers, 1962). By combining NASA's TRL with Rogers' diffusion of innovation, we present a new conceptual model: the Market and Technology Maturity Model (MTMM). The model provides a more holistic view of technology maturity from a consumer and technological perspective beginning with TRL 1–4 (acceptability stage) to TRL 5–8 (acceptance stage) and TRL 9 (adoption stage). The linkage and combination of those models with acceptability, acceptance, and adoption are illustrated in Fig. 1.

The NASA TRL assesses the maturity level of a new technology as each technology is evaluated against the respective parameters of each maturity level. Acceptability covers TRL 1 to TRL 4. TRL 1 indicates scientific research that is translated into future research and development. TRL 2 represents speculative technology, as there is no proof of concept of this new technology. When active research and design start, a technology is elevated to TRL 3. Analytical and laboratory studies are required to prove that the new technology is viable and ready to proceed, and proof of concept models are constructed. Once the proof of concept technology is ready, the technology advances to TRL 4, and multiple components are tested. In TRL 5, the technology must undergo more rigorous testing in environments that are close to realistic (NASA, 2012). Therefore, there is a transition of acceptability and acceptance between the TRL 4 and TRL 5 phases as the technology becomes a more tangible product that potential users can increasingly experience. Once the testing of TRL 5 is complete, a new technology may advance to TRL 6. At TRL 6, a technology has a fully functional prototype or representational model. TRL 7 technology requires that the prototype is demonstrated in a real environment. At TRL 8, new technology has been tested and is ready for implementation into an existing technology or technology system. Once a technology is successful, it reaches TRL 9.

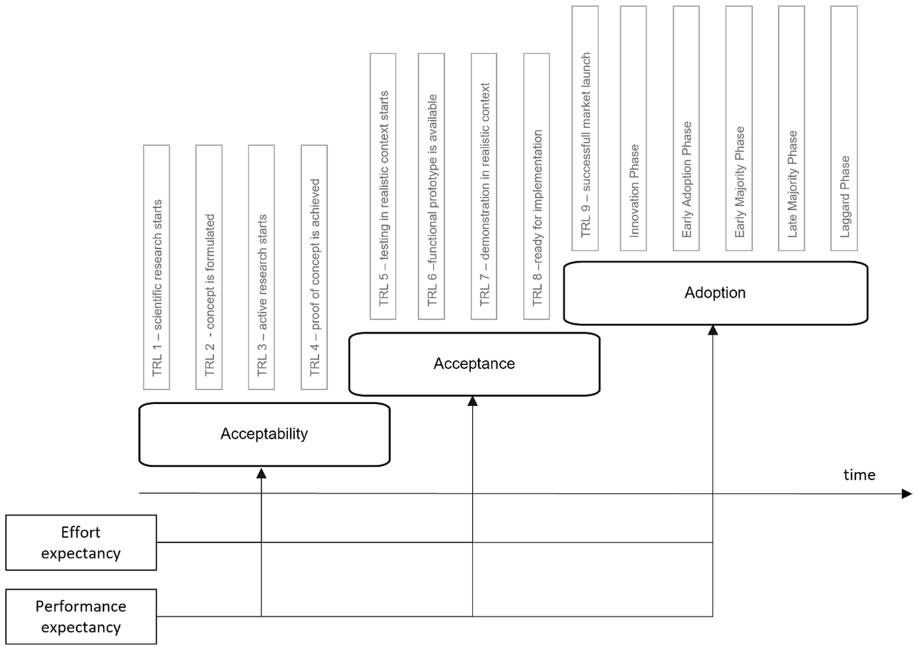

Fig. 1 Combination of the NASA Technology Readiness Level (TRL), TAM, UTAUT, and Rogers' diffusion of innovation to investigate the level of acceptability, acceptance, and adoption of a new technology: market and technology maturity model (MTMM)

It is ready to be launched in the market at this stage, and potential adoption can occur. The TRL 9 and innovation phases overlap as innovators, as defined by Rogers (1962), are likely to adopt the new technology before it is proven or widely available. Therefore, during or after TRL 9, the adoption phase begins as continuous usage of the new technology can be established in society. This is at the end of the temporality of interaction between the user and the new technology. Individuals receive information through their personal networks, which enables them to decide whether to adopt the technology and thus leads to different times of adoption. It is important to note that the model does not imply linearity, as the technology maturity phases sometimes overlap with the phases of acceptability, acceptance, and adoption. Moreover, a new technology can revert to earlier stages if, for example, the proof of concept fails and further research is required to reach the next technology maturity level.

The MMTM also proposes that different aspects influence user attitudes and behavior at different stages of technology maturity. In line with the assumptions of construal level theory (Trope et al., 2007), it is assumed that in the early stages of technology maturity, concrete aspects are more important in a user's evaluation of the product than abstract aspects. To illustrate this, we focus on two constructs that previous research has identified as crucial in users' evaluation of products and services. Performance expectancy is the extent to which a technology benefits the user, while effort expectancy is how difficult or easy it is to use a technology (Venkatesh et al., 2012). The model suggests that the more concrete effort expectancy is only of interest to users at later stages when the product is functional and can be realistically tested or demonstrated. Therefore, effort expectancy should not be of interest in the early stages of acceptability. Performance expectancy, on the other hand, as a more global construct, should be important in the early stages. However, its importance will decrease in the later stages as more concrete factors, such as effort expectancy, come into play in users' evaluations. This illustration demonstrates the potential benefits of incorporating a temporal dimension into user acceptance models to better understand when certain constructs play a role and can be reliably evaluated.

Methods

To compare the MMTM's assumptions with previous research, we reviewed previous studies on the acceptance of new technologies at various stages of technological maturity. Studies on accepting new technologies vary widely regarding applied methodologies and theoretical models. It was checked for which technologies the with target constructs were significant depending on their TRL. This was done, so that a hypothesis could be derived from the model.

Selecting key variables

To ensure comparability of the results, the authors compared applied theoretical models and underlying factors across different studies on technology acceptance. *Performance expectancy* and *effort expectancy* appear in many widely used technology acceptance models. As explained above, they also differ in how abstract or concrete users construe them. They should show differential impact patterns over the different phases of technology maturity. More specifically, performance expectancy should be important throughout all the TRL stages. *Effort expectancy*, however, should gain importance only in the later stages of technology maturity. Thus, this study employed these two factors as key variables for comparison.

Selection criteria

Studies employing performance and effort expectancy on technologies at different stages of technology maturity were analyzed to derive a hypothesis from the MMTM. To ensure the most inclusive set of relevant studies, Google Scholar was used as a search engine for this review. The keywords were the name of the technology and acceptance (e.g., air taxi acceptance). Technologies for which the TRL could be derived from the literature were chosen. Articles from journals and final theses were considered. To ensure consistency, the authors only included technologies with at least four recent studies from 2014 to 2022. A further selection criterion was that the studies included the two constructs in a regression-based approach with a direct path to attitude or intention to use. Only the results for the main sample were considered, as not all studies were divided into subsamples.

Results

Application of the model—technologies at TRL 3

Smart clothing in 2018 and air taxis in 2020 were technologies at the TRL 3 stage (Lacueva-Pérez et al., 2018; Werner & Albert, 2020). There is a tendency for *performance expectancy* to be important at TRL 3. Four studies on air taxis report the significant influence of *performance expectancy* (Al Haddad et al., 2020; Astfalk et al., 2021; Fu et al., 2019; Rohlik & Stasch, 2019). Similarly, four studies on smart clothing report the significant influence of *performance expectancy* (Han, 2019; Hwang, 2014; Hwang et al., 2016; Turhan, 2012). The *effort expectancy* factor was found to be not important at TRL 3. For air taxis, one study reports a significant influence (Astfalk et al., 2021), and three studies report a non-significant influence of the construct (Al Haddad et al., 2020; Fu et al., 2019; Rohlik & Stasch, 2019). For smart clothing, low importance of effort expectancy can be observed. One study reports a significant influence (Turhan, 2012), and three studies report a non-significant influence (Han, 2019; Hwang, 2014; Hwang et al., 2016).

Application of the model—technologies at TRL 7

In 2018 augmented reality display technologies and in 2020, autonomous cars were at the TRL 7 stage (Lacueva-Pérez et al., 2018; Werner & Albert, 2020). For *performance expectancy,* a tendency that the factor is important at TRL 7 can be observed. Three studies on autonomous cars report a significant influence for performance expectancy (Nastjuk et al. 2020); (Park et al., 2020; Yuen et al., 2021), but one study reports a non-significant influence (Chan & Lee, 2021). For augmented reality display technologies, four studies report a significant influence for performance expectancy (Alsharhan et al., 2022; Jang et al., 2021; Papakostas et al., 2021; Shen et al., 2022). Regarding *effort expectancy,* there is a tendency that the factor is important at TRL 7. Three studies on autonomous cars show a significant influence for *effort expectancy* (Nastjuk et al. 2020); (Park et al., 2020; Yuen et al., 2021) and one study has a non-significant influence (Chan & Lee, 2021). For augmented reality display technologies, three studies show *effort expectancy* has a significant influence (Alsharhan et al., 2022; Jang et al., 2021; Papakostas et al., 2021), and one study shows a non-significant influence (Shen et al., 2022).

Application of the model—technologies at TRL 9

In 2018 smart mobile devices and in 2020, electric cars were at the TRL 9 stage (Lacueva-Pérez et al., 2018; Werner & Albert, 2020). Regarding performance expectancy, there is a tendency for the factor to be important at TRL 9. Three studies report that performance expectancy has a significant influence for electric cars (Müller, 2019; Park et al., 2018; Tu & Yang, 2019), and one study found a non-significant influence (Haustein & Jensen, 2018). For smart mobile devices, four studies report a significant influence for performance expectancy (Botero et al., 2018; Gómez-Ramirez et al., 2019; Hao et al., 2017; Liu & Guo, 2017). For effort expectancy, there is a tendency for the factor to be important at TRL 9. Four studies report the significance of effort expectancy for electric cars (Haustein & Jensen, 2018; Müller, 2019; Park et al., 2018; Tu & Yang, 2019). For smart mobile devices, three studies report a significant influence for effort expectancy (Gómez-Ramirez et al., 2019; Hao et al., 2017; Liu & Guo, 2017), and one study reports a non-significant influence (Botero et al., 2018).

The analysis results for the importance of the two constructs, *performance expectancy* and *effort expectancy,* are visualized in Fig. 2. The "+" indicates where the respective construct was used and found significant in most analyzed studies. The "*x*" indicates where the respective construct was used but was not significant in most analyzed studies.

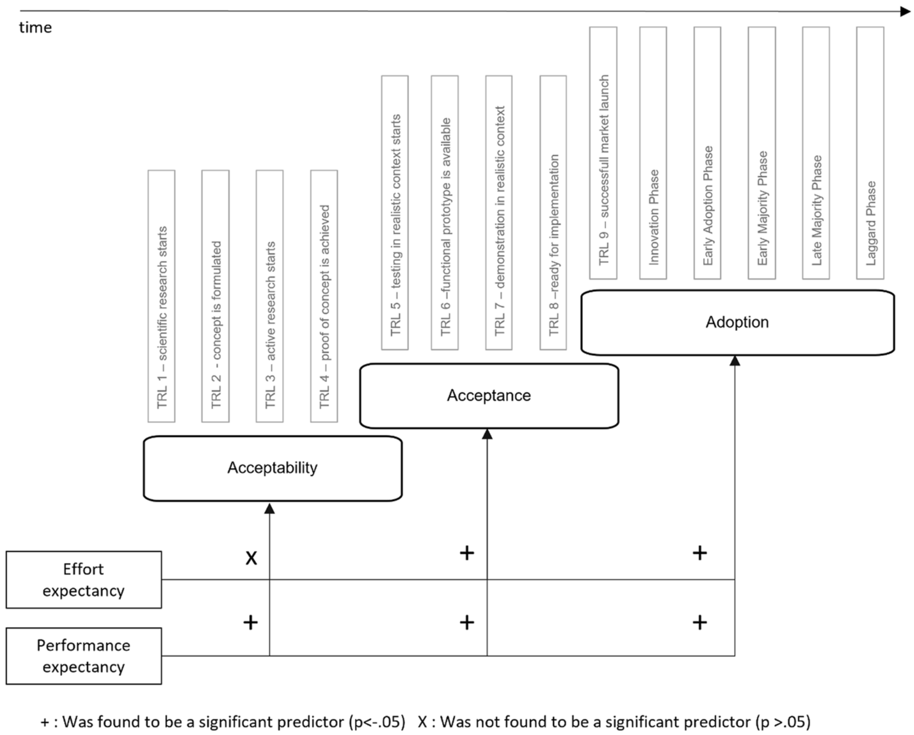

Fig. 2 Visualization of the analysis of the importance of the two constructs, performance expectancy and effort expectancy. The points indicate where the respective construct was used, and the triangles indicate where the respective construct was significant according to the analysis

The analysis shows that both *performance expectancy* and *effort expectancy* appear to be valid explanations for the acceptance and adoption of a new technology. For technologies in the early stages of maturity, however, *effort expectancy* is consistently not a significant predictor.

General discussion

This paper introduces the market and technology maturity model (MTMM) as a new approach to understanding consumer acceptance of new technologies. This model is the first to combine the maturity of a technology with the consumer perspective. The results indicate that the factors that lead to either acceptance or rejection of a new technology change over time as the technology becomes more mature.

For theory, this model provides new insights, since it is the first attempt to include the temporality of technological development into the models that explain the acceptance behavior of potential users. Interestingly, *performance expectancy* tends to remain stable across the different TRLs, while *effort expectancy* becomes more important after TRL 7. The tendency of effort expectancy to become more important at later stages of technology maturity aligns with results from construal level theory. Trope et al. (2007) developed construal level theory, which describes the influence of psychological distance on people's behavior and thoughts. A low construal level is associated with a concrete conception of objects, and a high construal level with an abstract conception. Ho et al. (2020)

demonstrated that effort expectancy was more strongly related to the intention to use an e-learning system in consumers with a low construal level than a high construal level. A direct product experience (TRL 7–9) can be associated with lower abstraction and, thus, a lower construal level. No experience can be associated with higher abstraction and, thus, a higher construal level (Kardes et al., 2006; Kim & Song, 2019). The results provide the first insight into the hypothesis that the importance of technology acceptance constructs differs in technologies with different stages of technology maturity.

Practically, this article offers a guideline on how to better understand consumer feedback at different stages of developing a new technology. In the early stages of development, consumers have minimal concerns about the potential efforts required to learn the new technology. However, as the technology matures, the impact of this factor increases. Therefore, companies developing new technologies might underestimate the barrier to usage derived from the perceived efforts of users in the early stages of development.

Limitations and recommendations for future research

One limitation of this article is the limited number and the recency of the studies analyzed. Furthermore, only results for two constructs from technology acceptance models have been included. This is due to the limited number of studies with comparable research models for technologies at the early stages of development, such as air taxis. Future studies should confirm the results in a full meta-analytic review design. In addition, the importance of other technology acceptance constructs should be examined in future studies. For example, hedonic motivation could be more important in the earlier stages as the novelty of an innovation that excites people could diminish when the technology moves to later stages of maturity (Venkatesh et al., 2012). Furthermore, social influence could be more important at later stages as not many people in the closer environment of potential users know of innovations when they first enter the market and thus will not articulate an opinion to them at the early stages of technology maturity. When the technology enters the market and more people adopt it, they form an opinion and communicate it to potential users. Technologies from sectors other than mobility and consumer electronics could deliver promising results.

Conclusion

The market and technology maturity model (MTMM) provides a new perspective for studying user acceptance of new technologies. This paper demonstrates that the factors leading to either acceptance or rejection of a new technology change considerably as a technology becomes more mature. Thus, including the temporality of innovation becomes imperative for understanding technology acceptance. For research, integrating technology maturity in current acceptance models will provide new insights into consumer decision-making. For the industry, the findings offer a cautionary tale on measuring consumer perception in the early stages of technological development. Continued user feedback is important as the user perspective may change in the next development steps. In sum, the MTMM is a basis for a better understanding of the temporality of the user perspective.

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JS, SA, PP, PM: conceptualization, methodology and data curation. JS, SA: writing (original draft preparation), visualization and investigation. PP, PM: writing (reviewing and editing). All authors read and approved the final manuscript.

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Availability of data and materials
Not applicable.

Declarations

Competing interests
The authors declare that they have no competing interests.

Glossary

Acceptability	Acceptability is an a priori phenomenon in the time scale of confrontation with a technology and predicts the intention to use the new technology as the prospective judgment. Acceptability refers to when an individual has no experience with the new technology.
Acceptance	Acceptance is a posteriori evaluation and consists of attitudes and behavioral reactions after the introduction of a new technology. Acceptance refers to the judgment, attitude, and behavioral reactions towards a new technology after the first usage.
Adoption	Adoption is the relative speed with which members of a social system adopt an innovation, follows a Bell curve, and occurs after the stages of acceptability and acceptance regarding the temporality of interaction between the user and the new technology.
Market and Technology Maturity Model	The Market and Technology Maturity Model (MTMM) provides a holistic view of technology maturity from a consumer and a technological perspective with a linkage and combination of acceptability, acceptance, and adoption.

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