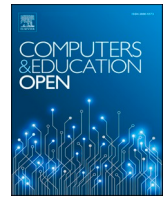


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Disentangling the influence of mobile learning usability and its determinants–PLS-SEM and importance-performance investigation

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ABSTRACT

Today, numerous mobile learning applications are used to enable learning during the working process or on-the-go. However, few insights that are available regarding mobile application usability (MAU) and its determinants in the context of mobile learning. More specifically, there is a critical need to disentangle the determinants of MAU and their overall impact on MAU while also acknowledging the possible motivational consequences. Therefore, we developed a theoretical model of MAU, its determinants, and its consequences. By utilizing a free simulation experiment, we investigated the role of MAU in the domain of mobile learning. We used structural equation modeling to analyze the theoretical model. The results show a significant influence of MAU on mobile learning compatibility, performance expectancy, and self-efficacy. The results also indicate that compatibility acts as a partial mediator of usability on performance expectancy. Finally, we conducted an importance-performance analysis that reveals key usability insights: UI output, the most critical factor, underperforms, highlighting a major improvement area. UI structure and application design also need enhancement. In contrast, UI input and application utility perform well despite lower importance, with UI graphics showing adequate performance despite being least crucial. The present paper contributes to the discussion concerning MAU and its impact on mobile learning, while delivering formative insights of MAU for mobile learning applications.

1. Introduction

When learning with in IT proliferates to rich physical environments [1,2], as, e.g., on-the-job learning using augmented reality technology, learning providers oftentimes draw on mobile learning applications [3,4]. Mobile learning can be characterized “[...] as the processes (personal and public) of coming to know through exploration and conversation across multiple contexts, amongst people and interactive technologies” ([5], p. 237). With the ubiquity of mobile devices, learners can conveniently access training materials and interactive learning modules while being on the move or during downtime [6,7]. This empowers learners to engage in continuous skill development and apply knowledge in real-life scenarios [8].

However, being instructed by the mobile device and in full control of their learning processes, learners are in danger of getting frustrated and losing track of their learning progress and activities [9]. Moreover, without any progress reports, tutorials or hints, mobile learning usage might lead to overstrained learners with poor learning outcomes.

Especially when studying real-world issues in indoor environments, e.g., learning at the workplace [10,11], or outdoor environments [12] with minimal support, learners have to deal with multiple pieces of information, including physical objects in their surroundings as well as information on the mobile device [4]. Being confronted with these challenges, mobile learning providers have to make sure that the mobile learning design enables learners to concentrate on their learning activities and to build applications that are easy to use [13,14].

Against this backdrop, research suggest taking usability into account to design more effective information systems (IS) as in our case mobile learning applications that are easy to use [13,15,16]. To ensure the success of mobile learning, a high degree of usability ensures that individuals use the provided learning methods and structures effectively [17,18] and positively impact learning outcomes [19]. However, mobile learning applications present providers with new usability challenges that we aim to tackle by relying on acknowledged research regarding the usability of mobile devices such as smartphones and mobile applications [20] and applying these insights on the research field of usability in the

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domain of mobile learning to complement prior studies especially on heuristic mobile learning usability evaluation [21–23]. In contrast to holistic but device-agnostic usability evaluations such as the system usability scale (SUS; [24,25]), it is important to consider the specifics of mobile applications for usability evaluation [20].

Despite mobile application usability (MAU) being an important concept in literature [20] as well as in the field of Human Computer Interaction (HCI; [15]), very little research has been conducted on the perceptions of usability in the context of mobile learning [13]. In this regard, e.g., Kumar and Mohite [17] identified no >23 research papers in the last 13 years focusing on usability in the domain of mobile learning and also the recent review of Lee [13] indicated this need to investigate MAU. Hence, our study aims as a central contribution to disentangle the determinants of MAU as well as to investigate the relationship between perceived MAU and the perception-based outcomes of mobile learning in a systematic and empirical manner.

In this regard, we develop in this paper a theoretical model to investigate how MAU relates to the outcomes of mobile learning applications. This paper answers the call to isolate the effects of specific usability determinants regarding mobile learning applications by proposing a free simulation experiment. We base our paper on the following overarching research question: *How does MAU impact the outcomes of mobile learning?* To answer the research question, we take an empirical approach to evaluate MAU, its determinants, and (motivational) outcomes in the domain of mobile learning. We provide with our findings from a free simulation experiment, a prediction-oriented structural equation modeling (SEM) approach, as well as an Importance-Performance Matrix Analysis (IPMA) evidence-based mobile learning design implications for HCI research and practice. By this means, we propose with our simulation experiment and SEM-based IPMA a method tandem that corresponds to the goal of this paper and the call of the research question to a) disentangle the determinants of MAU and b) provide an impact perspective of MAU determinants that could inform the design of usable mobile learning applications.

The remainder of this paper is structured as follows: We first outline the theoretical background and our hypotheses. Next, we present our research method and results. Then, we discuss the implications and limitations of our findings as well as possible future research. The paper closes with a brief conclusion.

2. Theoretical background and hypotheses development

2.1. Mobile learning and challenges for learning processes

Mobile learning can be seen from various perspectives and can be described by various terms such as “[...] wireless, ubiquitous, seamless, nomadic or pervasive learning/education, as well as mobile computer-supported collaborative learning, and mobile e-learning” ([9], p. 308). Following the definition provided in the introduction, we consider mobile learning as a subset of learning with educational technologies [26], which is defined as “[...] an environment in which the learner’s interactions with learning materials (readings, assignments, exercises, etc.), peers, and/or instructors are mediated through advanced information technologies” ([27], p. 2). However, mobile learning has some distinctive characteristics that are important to consider.

A key and differentiating element of mobile learning is that it is taking place when the learner is not at a fixed or predetermined location [28,29]. Mobile learning allows for spontaneous, ubiquitous, and pervasive learning [30], thus, offering novel ways for interaction with learning material [31]. The learner has access to knowledge and information anywhere and anytime via wireless, portable, handheld, and mobile devices [32]. Flexibility and mobility enable real-time interaction with learning materials, experts, and peers [28]. In real-life settings, mobile learning combines attributes of learning and mobility, but – with wireless technology as a constant companion in a connected society – mobile learning can also become a habit, as with smartphone usage

[33].

Studies concerning mobile learning have increased in number since the advancement of mobile and wireless communication technologies [13,14,34], revealing both its benefits and its challenges. The advantage of mobile learning is that learners can be situated in a real-world scenario associated with the learning content, with no limitation by space or time [12,35]. However, the information-rich, real-world learning scenarios provided by the mobile learning application as well as the learning environment can overwhelm or overload learners [36,34]. The challenges of mobile learning include the prevalence of multiple media, integrating physical objects into users’ surroundings, depicting information regarding physical objects in parallel on a mobile device [4] as well as new learning scenarios. One way to tackle these challenges of mobile learning is through a high degree of usability.

2.2. Mobile application usability and its consequences

To overcome the aforementioned challenges of mobile learning, we here refer to the importance of *mobile application usability* (MAU) that refers to the extent to which the installed software is user friendly, whereas mobile device usability refers to the usability of the installed operating system [20]. Since this research paper focuses on usability regarding mobile learning, we do not address the latter case. Usability is an important criterion for evaluating the quality of IS in general [37] and for mobile applications in specific [38,39]. However, it can also be a limitation that affects the success of a mobile application; people may refuse to use mobile applications with poor usability, especially when application use is voluntary. Thus, we refer to three MAU consequences in this study that are connected to motivation relevant for mobile learning, i.e., performance expectancy, self-efficacy, and compatibility (cf. also [40]).

Within mobile learning usability, the contexts of use and the user are of particular importance in improving an application’s usability [41,42]. Besides planning the particular learning goals for a mobile learning application, Malliou et al. [42] call attention to the user, which should be taken into account in the design process. In this regard, it is easy to understand that a mobile learning application that is used in the workplace should focus strongly on small learning units that are delivered when the knowledge in the work process is needed and should work straight away after switching the device on. The opposite – complex learning content and/or lengthy boot-up time – does not serve the user well and may distract the user, which is also true when the mobile learning application is intended to be used in spare time. Application design traits such as small screen display, low resolution, and poor network connectivity are some possible general mobile device constraints, no matter where and from whom a mobile learning application is used [18,41,42]. In this context, Appendix A reviews selected empirical findings related to MAU that range from general usability perceptions (e.g., [43]), differences in user group perceptions (e.g., [44]), to presentation formats (e.g., [45]). Although these general aspects are also critical, a more distinct view on MAU in mobile learning is missing up until. However, a more in-depth understanding of MAU and its representing determinants could contribute to a better user experience when considering the case of mobile learning.

To acquire a better understanding of MAU, we draw on a multi-dimensional MAU approach. Hoehle and Venkatesh [20] identified for this purpose six constructs representing MAU. These determinants of MAU include the application design, application utility, user interface (UI) graphics, UI structure, UI input, and UI output. The definition for each construct is outlined in Table 1 below.

Referring to the first construct of MAU determinants, a good *mobile application design*, refers to a short reaction time (both when starting and using the application) as well as an effective presentation of information [46]. Especially the latter is important for mobile learning when considering the presentation of learning material and how this presentation influences learning processes.

Table 1

Construct definitions for MAU determinants. Based on Hoehle and Venkatesh [20].

Construct Name	Construct Definition
Application design	The degree to which a user perceives that the mobile application is generally designed well.
Application utility	The degree to which a user perceives that the mobile application generally serves its purpose well.
UI Graphics	The degree to which a user perceives that the mobile application's UI graphics are effectively designed.
UI structure	The degree to which a user perceives that the mobile application is structured effectively.
UI input	The degree to which a user perceives that the mobile application allows users to input data easily.
UI output	The degree to which a user perceives that the mobile application presents content effectively.

Good *application utility* means that the user should get what they expected by using the application. An application's utility can be increased through the integration of elements that reduce a user's cognitive effort to use a mobile application [47]. In this regard, the user should be given the opportunity to search for information [46], thus, a good navigation can increase the mobile application's utility. In contrast, displaying redundant or unnecessary information and screens distract a user from relevant content [48]. This is especially prevalent in mobile learning, when considering cognitive load, which is basically concerned with effects of limited cognitive capacities of learners on the acquisition of learning content [49]. Especially when redundancy effects, induced by the need to pay attention to various information sources at once, as well as split-attention effects, induced by the need of learners to process learning content from multiple sources come into place, mobile usability issues may arise [4].

Concerning the construct *UI graphics*, the integration of realistic icons and images that are aesthetically integrated can improve a user's perception of UI [48,50]. For example, calendar and address book icons are oftentimes realistic illustrations that indicate the function behind the software [20]. In case of mobile learning, better UI graphics may engage the exploitation of features relevant for learning.

A logical content structure (arrangement) as well as an expected path structure are crucial to build an effective *UI structure* of a mobile application [48,51]. The information structure should be structured from the top to the bottom (hierarchically) of a page as Hoehle et al. [46] and Adipat et al. [51] suggest, since people are most likely to initially search for information at the top of the displayed content without scrolling down, e.g., considering the learning process of users upfront when considering the navigation structure.

Referring to *UI input*, forms should be large enough to make the operation as easy as possible for the user. The size of the fingertips can be used as a reference for the adjustment of buttons and forms [20]. In addition, forms should be understandable, intuitive, and easy to use, allowing users to quickly understand and apply the mobile application [46], especially when taking into account that some mobile learning applications can be used on the job [9,52].

The construct *UI output* refers to effectively provided content, where the content should be presented briefly, concisely, in common language, and avoiding technical jargon [46,48], thus, also avoiding cognitive load that may inhibit learning [53].

Using the above-mentioned determinants, MAU can meet the needs of mobile learning users and influence how compatible they perceive the application to be. The term *compatibility* describes the "[...] degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" ([54], p. 238). Individuals with a high perceived compatibility concerning a new IT artifact are more certain about adopting the application [55]. A new artifact that gives the user a sense of familiarity is likely to be compatible with them; it meets the user's socio-cultural values, needs, and ideas

[54]. Regarding the adoption of mobile learning applications, users' compatibility with the application is essential, as it is important that the way in which knowledge is imparted by the mobile learning application coincides with the values of the learners. On the one hand, learners who are used to learning in self-regulated ways should be enabled to do so by the mobile learning application, e.g., by a logical content structure and search navigation that works without technical terminology [56]. On the other hand, learners who are used to being guided through the learning process should have the opportunity to request instructions, e.g., by the provision of help buttons. Since good mobile learning usability should contain these configurations and thus support the user's sense of being familiar with the new mobile learning application, we derive the following hypothesis:

H1. MAU has a positive impact on compatibility.

When a learner has the sense of being familiar with a new mobile learning application because it supports the learner's needs, the learner will more likely classify the mobile application to be helpful for his or her demands and will have enhanced expectations towards the mobile learning application. Literature refers to this as *performance expectancy* and defines it as the "[...] degree to which an individual believes that using the system will help him or her to attain gains in job performance" ([57], p. 447).¹ We expect that someone who has a sense of being compatible with a mobile learning application will more likely believe that using the application will help him or her to attain goals, compared to someone who uses an application he or she is not compatible with, since it fits the user's needs and values. Thus, we also expect that performance expectancy is mediated through compatibility. We hypothesize:

H2. Compatibility has a positive impact on performance expectancy.

However, someone who uses a mobile learning application the first time and hasn't experienced any comparable learning application before will find their way better and faster using the application if it reflects usability criteria that are generally accepted and proven to be helpful. Thus, a short orientation time and effective usage are results of a good usability. Subsequently, the user will expect to perform better when using a mobile learning application with a high usability, since the experienced impression of simplicity using the application will be mapped to the expectancy regarding the performance. Therefore, we hypothesize:

H3. MAU has a positive impact on performance expectancy.

Moreover, MAU may also have a positive influence on an individual's meta-cognition. *Self-efficacy* was originally coined by Bandura [58]. Referring to Bandura [58], Zimmerman [[59], p. 83] defines self-efficacy as the "[...] personal judgments of one's capabilities to organize and execute courses of action to attain designated goals [...]". Or to put it differently, self-efficacy indicates one's expectations regarding how well he or she will perform a specified task [60]. When considering educational technology, research oftentimes focuses on computer self-efficacy [61–63]. However, we focus on the general level of self-efficacy that is of great importance as self-efficacy influences one's set goals [64]. People with a high self-efficacy set themselves higher goals and often engage harder, show a higher commitment, to reach the goals [64,65]. The mobile learning application should give the user the sense that it helps to reach a designated learning goal. If the usability of the mobile learning application makes things more difficult for the user, it will be more likely that reaching the goals will recede into the distance and the learner's judgment of their capability to reach the goal will shrink. Vice versa, a mobile application that supports reaching learning goals by intuitive handling and interface will give the user the

¹ In our case, the believe to attain gains in job performance refers to learning something with the mobile application.

feeling that organizing and executing the courses of action will be just as easy as using the mobile learning application. Thus, we derive the following hypothesis:

H4. *MAU has a positive impact on the self-efficacy.*

Besides the direct influences of MAU on compatibility and performance expectancy as well as the influence of compatibility on performance expectancy that we considered in our study, we also expect that compatibility is a crucial construct when considering the influence of MAU on performance expectancy. Instead of MAU directly influencing performance expectancy, users of mobile learning application might relate their perception of the application's usability with their existing values and needs, e.g., an integrated progress bar might increase a mobile learning application's usability, however, someone who has little patience when using such applications will more likely feel a sense of being compatible with the application when elements that provide direction are included. Thus, users might relate mobile application usability with their own expectance to obtain gains in job performance, whereas the degree of the influence depends on the perceived compatibility with the mobile learning application. Therefore, we hypothesize:

H5. *Compatibility mediates the influence of mobile application usability on performance expectancy.*

In summary, Fig. 1 depicts our research model of MAU, its determinants, its consequences, and the five related hypotheses.

3. Research method

For an overview of the research method, Table 2 provides an initial step-by-step overview on how this study answers the proposed research question.

3.1. Procedures

To test the theoretical model and to determine the impact of MAU on its outcomes, a free simulation experiment was conducted. In contrast to experiments that rely on a treatment to manipulate one or more

Table 2
Research overview.

Research Step	Purpose
(1) Free Simulation Experiment	Participants interact with the app freely to form perceptions about the IT artifact, performing tasks that teach automotive component identification and problem analysis in a vocational training context. Collect data on user perceptions and experiences, informing the structural model evaluation.
(2) Survey	To analyze the structural relationships between constructs using the Partial Least Squares (PLS) approach. This step evaluates how different determinants (like application design and utility) influence the outcomes associated with MAU.
(3) PLS Model Evaluation	Identify key areas for improvement and strengths in the mobile learning application based on how important users perceive usability determinants and how they rate their performance.
(4) Importance-Performance Matrix	

independent variables of interest, a *free simulation experiment* [66,67] encompasses specific tasks that are pre-defined by the experimenter and should be completed by the study participant. Nonetheless, participants are able to explore the system and thereby form meaningful perceptions concerning the IT artifact under investigation [68]. In our free experiment, we used a fully functional prototype of a mobile learning application. The purpose of our mobile learning application was to increase the user's ability to identify automotive components and to analyze the causes of car problems. The mobile learning application MoKe, which stands for the German term 'Mobile Kompetenzentwicklung' (translated as 'Mobile Competency Development' in English), was developed as part of a larger design research project [69]. It has been implemented in corporate and vocational school settings, specifically in the context of vocational training for motor mechanics [69]. Fig. 2 shows screenshots of the mobile applications.

The mobile learning application comprises two tasks. The first task aims to teach basics on automotive components, the second task teaches the identification of error causes for various car damages.

The top row shows screenshots of the application menu that enables to choose between two main learning modes. The middle row is offering

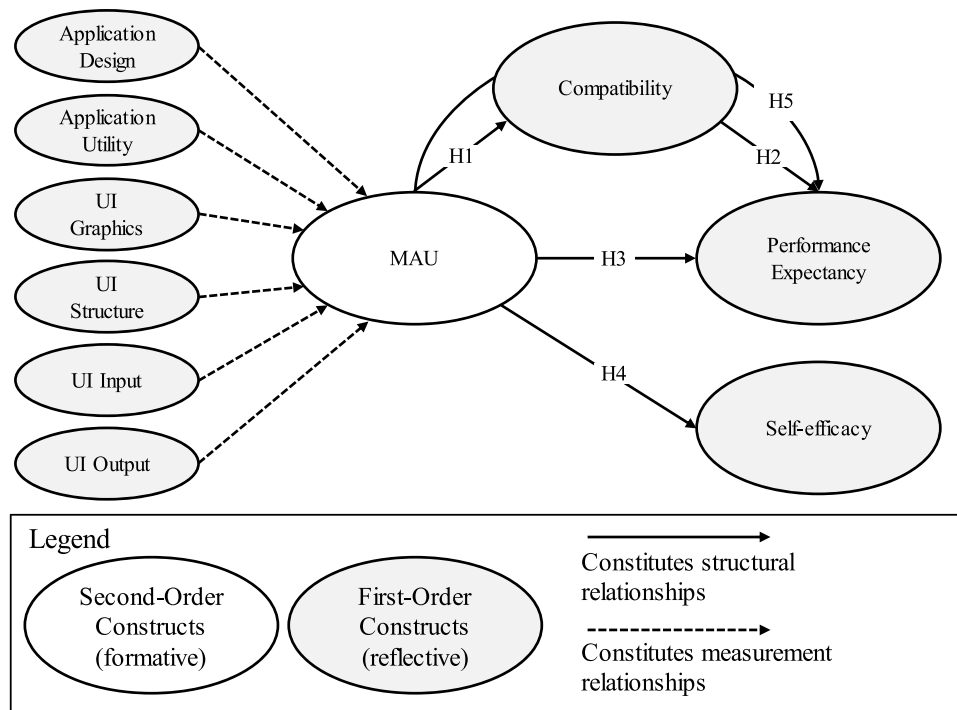


Fig. 1. Theoretical model.



Fig. 2. Screenshots of the mobile learning prototype used in the experiment.

basic information about automotive components. The first task in the middle row consists of the following steps: in the beginning, participants are asked to identify a specific automotive component on a car image after the participant has been given the name of the car part. After

choosing the right component by clicking on the respective part on the car simulation, the mobile learning application provides learning content regarding the component. Afterwards, a multiple-choice question as a learning success control as well as a help button for a request of

solution hints and further explanations are displayed. A solution for the multiple-choice question appears after input confirmation (screenshot five and six from the left).

The bottom row shows screenshots of the application regarding the analysis of causes of various car problems. The task starts with an error description and requires the participants to reflect on the problem. After an introductory question that refers to plausible causes, participants have to try to solve the problem by selecting automotive components that must be considered as a possible error cause. The task ends with an in-depth question regarding the procedure for a specific problem analysis and correction. Solutions are marked after input confirmation.

In greater detail, the experiment proceeded as follows. A brief description of the mobile learning application and its features was given to the participants. In addition, all participants were asked to put themselves in the position of a vocational student who could use the displayed mobile learning application both during school lessons and outside regular classes for advanced training. Then, the participants were asked to complete the two tasks provided by the mobile learning application. During the usage, the participants were able to navigate freely within the app using the drop-down menu and the "Home" and "Back" buttons, which allow intuitive and easy-to-understand handling. To ensure that the participants tested the app, three control questions were included in the online questionnaire (displayed after the app testing) and checked for correctness. While the first and second questions verified acquired knowledge regarding the automotive components, the third question referred to an analysis of a problem cause. After answering all control questions correctly, participants were asked to complete the questionnaire.

3.2. Instrument development

All indicators were applied from literature before being adapted to the context of the investigation object. Table 3 presents the instrument overview of the final analysis for determining the respective constructs, their construct types, as well as the related literature sources for the indicators. The original items can be found in the literature sources indicated below and were adapted to the context of this study, i.e., mobile learning. We especially draw upon the MAU instrument developed by Hoehle and Venkatesh [20] that underwent a rigorous scale development process and is, in consequence, a suitable instrument for the underlying study. The complete survey instrument as adapted for this study is depicted in Appendix B.

We measured all latent variables with reflective indicators. The indicators were therefore pre-evaluated regarding their correct specification according to the guidelines of Jarvis, MacKenzie, and Podsakoff [73]. To evaluate the items, a 7-point Likert scale was used ranging from 1 ("strongly disagree") on the left to 7 ("strongly agree") on the right, with 4 as a neutral point. In addition, while answering the survey, the participants could select "N/A" if the statement was not applicable to prevent a tendency toward neutral responses. To deal with missing values in the data set, we followed the advice of Hair, Hult, Ringle, and Sarstedt [74] and used the mean replacement approach to impute the missing values.

Table 3
Measurement of constructs.

Construct	Construct Type	Sub-construct	Sub-construct Type	Items	Literature Source
MAU	Formative	Application Design	Reflective	4	Hoehle and Venkatesh [20]
		Application Utility	Reflective	4	
		UI Graphics	Reflective	4	
		UI Structure	Reflective	4	
		UI Input	Reflective	4	
		UI Output	Reflective	4	
Compatibility	Reflective	–	–	3	Agarwal and Prasad [70]; Cheng [71] Venkatesh et al. [57] Compeau and Higgins [72]
Performance Expectancy	Reflective	–	–	3	
Self-efficacy	Reflective	–	–	2	

3.3. Data collection and modelling methods

All participants performed the experiment voluntarily and were recruited on online platforms. As an incentive to participate in our free online experiments, we raffled vouchers for a well-known e-commerce shop among all participants.

In total, 118 participants interacted with the provided mobile learning prototype, solved the pre-assigned tasks correctly, and completed the questionnaire. However, we took the guideline of Hair et al. [74] into account and removed data sets with >15 % missing values. We also removed the data sets of respondents who answered reverse-coded attention check questions "wrong", completed the online experiment in an unusually short time, or answered all questions with extreme answers (e.g., 1 or 7). The adjusted and final sample consisted of 103 data sets, represented by 49 females and 52 males (2 individuals did not reveal their gender), with an average age of 28.8 years, and with 80.6 % having a higher educational level.

We also considered common method variance (CMV) caused by the measurement method, rather than the construct measures [75,76]. To control these biases, we made several procedural remedies. In order to ensure a psychological separation of measurement, we did not reveal the purpose of the survey and provided a cover story [75]. Additionally, we guaranteed the anonymity of the participants. In order to control effects such as socially desirable responses [77], we assured participants that there were no wrong answers and requested them to answer the questions as honestly as possible [75]. Afterwards, we conducted the Harman's Single Factor Test [75]. We performed an exploratory factor analysis with all model indicators and examined the unrotated factor solution. Since more than one factor emerged and the first factor does not account for the majority of covariance among the measures, common method variances should not be a major problem within this study [75].

We applied the variance-based partial least squares (PLS) approach to evaluate the structural equation model of this paper [78,79]. We chose this "causal-predictive" approach ([80], p. 270) since it is more applicable to evaluate the influence of specific determinants on target constructs and make out of sample predictions [81,82]. Thus, the PLS approach aligns more closely with the goal to provide a theoretical contribution for explanation and prediction [83], i.e., in our case to investigate the influence of MAU on its outcomes (see also in the next section the results concerning the predictive power of the model). As our model includes MAU as a hierarchical latent variable, a type II second-order factor model was applied [73,84]. We followed the suggestions of Ringle et al. [84] and Becker, Klein, and Wetzels [85] to use the repeated indicator approach (Mode A for repeated indicators), instead of the two-step approach [79,86]. To obtain unbiased results, the number of indicators for every first-order construct is equal as shown in the results section [87,84]. SmartPLS 3.2.8 was used as the analysis tool [88].

Further, we analyzed in the end the data with an Importance-Performance Matrix Analysis (IPMA; e.g., [74,89]) By following the procedures of Hair et al. [74] and the steps outlined by Ringle and Sarstedt [90]. The IPMA results produce more conclusive insights

concerning the importance of each MAU determinants, while also taking the current performance evaluation of the constructs of interest into account. In specific, we followed the following steps. (1) We computed in the first step the performance value by rescaling the dataset to a 0–100 index. Through computation of the model, we obtained latent variables scores on a 0–100 index, indicating the performance of each construct. (2) We obtained the total effects of each variable on the dependent variable MAU. The total effect explains the importance of each MAU determinant. (3) After obtaining all values, we created the IPMA by plotting each MAU determinant with its performance on the y-axis and the importance on the x-axis. Therefore, from this procedure, we deduce additional implications especially for design research, highlighting on which MAU determinant focus is important.

3.4. Control variable

In line with previous research on digital learning [91], we also assessed personal innovativeness in the domain of IT defined as “the willingness of an individual to try out any new information technology” ([70], p. 206) as a control variable in the present study. Since personal innovativeness in the domain of IT may influence the perceptions of IT in general, we control for its influence on performance expectancy, because individuals who are more willing to try out technology may more easily recognize the potential of a technology and, thus, expect more performance. We measured it with the instrument of Agarwal and Prasad [70].

4. Results

The evaluation of the model followed a two-step process: first, the evaluation of the outer model; and second, the evaluation of the inner model [92–94].

4.1. Evaluation of outer model

In the evaluation of the outer model, we focused on the measurement models in order to reveal the reliability and validity of criteria that are associated with latent variables. The evaluation of the inner model and the structural relationships followed in the second step, since this evaluation only makes sense if the outer model evaluation shows evidence of sufficient reliability and validity [94]. In accordance with research regarding hierarchical latent variable models with repeated indicators, the outer model evaluation included solely the first-order constructs [85]. The quality criteria of the outer model are reported in Table 4.

We assessed the indicator reliability by using the standardized loadings. Except for one (MAU_AU4), all indicators loaded above the value threshold of ≥ 0.70 [95]. We decided to keep the indicator for three reasons. First, the indicator loading value of 0.692 is just slightly under the threshold. Second, the composite reliability value of the construct suggests a high internal consistency, therefore pointing out that the indicator does not impact the internal consistency. Third and most importantly, we decided to keep all indicators of the second-order constructs of MAU to avoid biased results caused by an unequal number of indicators across the second-order constructs when using the repeated indicator approach [84]. We evaluated the internal consistency reliability by using the composite reliability [92,93]. Values above 0.70 indicated an acceptable composite reliability [96]. We assessed the convergent validity by using the average variance extracted (AVE). Values of Average Variance Extracted (AVE) were all above 0.50 and acceptable [96].

Afterwards, we assessed the discriminant validity by using the Fornell-Larcker criterion [97]. As Table 4 shows, this criterion is fulfilled because the square root value of each latent variable’s AVE was higher than that latent variable’s correlation with any other latent variable. In addition, we assessed the heterotrait-monotrait ratio (HTMT) and the

Table 4
Overview of quality and criteria of the first-order constructs.

Construct	Indicators	Loadings	AVE	Composite Reliability	RMSE _{PLS-SEM}	$Q^2_{\text{Predict PLS-SEM}}$	RMSE _{LM}	PLS-SEM – LM RMSE
Application Design	MAU_AD1 MAU_AD2 MAU_AD3 MAU_AD4	0.910 0.940 0.936 0.934	0.865	0.962	Not applicable for exogenous constructs.			
Application Utility	MAU_AU1 MAU_AU2 MAU_AU3 MAU_AU4	0.785 0.795 0.879 0.692	0.625	0.869				
UI Graphics	MAU_UG1 MAU_UG2 MAU_UG3 MAU_UG4	0.864 0.896 0.842 0.901	0.768	0.930				
UI Structure	MAU_UIS1 MAU_UIS2 MAU_UIS3 MAU_UIS4	0.917 0.960 0.941 0.911	0.869	0.964				
UI Input	MAU_UII1 MAU_UII2 MAU_UII3 MAU_UII4	0.795 0.935 0.959 0.897	0.808	0.944				
UI Output	MAU_UIO1 MAU_UIO2 MAU_UIO3 MAU_UIO4	0.953 0.966 0.965 0.958	0.923	0.979				
Performance Expectancy	PE1 PE2 PE3	0.911 0.914 0.922	0.838	0.940	1.087 1.284 1.439	0.347 0.270 0.223	1.094 1.407 1.492	–0,007 –0,123 –0,053
Compatibility	COMP1 COMP2 COMP3	0.890 0.967 0.938	0.869	0.952	1.100 1.440 1.565	0.250 0.226 0.151	1.136 1.498 1.697	–0,036 –0,058 –0,132
Self-efficacy	SE1 SE2	0.868 0.888	0.771	0.871	1.224 1.212	0.013 0.032	1.562 1.468	–0,338 –0,256

heterotrait-monotrait inference criteria (HTMT_{inference}; [98]). The analysis in Table 5 shows that the conservative HTMT₈₅ measure (indicated through all HTMT measures under 0.85) is established. Also, the HTMT_{inference} values are all significantly below the threshold of 1.² Finally, the results of the cross-loadings shown in Appendix C indicate that all indicators load the highest on their own construct [78].

4.2. Evaluation of inner model and hypotheses

Since the outer model evaluation showed sufficient reliability and validity, we proceeded to the evaluation of the inner model, which included the path coefficients, explained variances, and significance levels. The evaluation also encompassed an assessment of the effect sizes and predictive relevance [84]. The complete results of the structural model are depicted Fig. 3.

As depicted in Fig. 3, the results of the structural model show that all relationships in the structural equation model are significant at least at a level of $p < 0.05$ (5.000 bootstrap samples were drawn). Thus, all hypotheses are confirmed.

Concerning the path coefficients of the first-order constructs that determine MAU, UI Output ($\beta = 0.284$) has the highest influence, followed by UI Structure ($\beta = 0.244$), Application Design ($\beta = 0.205$), Application Utility ($\beta = 0.178$), UI Input ($\beta = 0.163$), and finally UI Graphics ($\beta = 0.146$). According to the value of the path coefficients, MAU has the highest effect on compatibility ($\beta = 0.510$), followed by its effect on performance expectancy ($\beta = 0.348$), and self-efficacy ($\beta = 0.275$); therefore, we confirm hypotheses H1, H3 and H4. In addition, compatibility has a strong significant influence on performance expectancy ($\beta = 0.519$), confirming H2. Moreover, we were also able to confirm H5 observing a significant influence ($\beta = 0.265$) of compatibility mediating the influence of MAU on performance expectancy. Our analysis revealed that compatibility is partially and complementarily mediating the influence of MAU on performance expectancy [74,99], as indicated through bootstrap of the sampling distribution of the indirect effects [100,101] ($p < 0.001$). Partial mediation is estimated by the variance accounted for (VAF) ratio of the indirect-to-total effect, which is 43 % in our case and therefore above the 20 % threshold for partial mediation and under the 80 % threshold for full mediation [99], as well as the fact that the relationship between MAU and performance expectancy is significant. Finally, we determined the complementarity of the mediation through the positive sign of the product of the indirect and direct effect.

The explained variance of the endogenous construct self-efficacy is considered as weak ($R^2 < 0.25$), while the explained variance of performance expectancy and compatibility can be considered as moderate [74]. Since we modeled MAU through the repeated indicator approach, all of its variance is explained through the indicators of its subconstructs and, therefore, R^2 is naturally 1.00 [84].

In a next step, we measured the effect size f^2 for the impact of compatibility and MAU on performance expectancy. The effect size f^2 constitutes the influence of exogenous constructs on an endogenous construct by considering the changes in the coefficient of determination, R^2 [102]. Values above 0.02, 0.15, and 0.35 indicate a low, moderate, or high effect on the structural level [94]. Our results therefore indicate that the effect of MAU ($f^2=0.209$) constitutes a moderate effect, while the effect of compatibility ($f^2=0.485$) can be considered as high.

In a last step, we evaluated the predictive relevance as a conclusive assessment of the structural model [78] as well the predictive power of our model to make assumptions concerning the accuracy of the model to predict outcome values of new cases [103]. First, we assessed the predictive relevance by using the blindfolding procedure proposed by Stone [104] and Geisser [105], which omits one part of the data in a systematic

way and uses the resulting estimates to predict the omitted part [92]. We chose $d = 7$ as omission distance, which is not a multiple integer of the analyzed cases ($N = 103$) [93]. We assessed Q^2 as the cross-validated redundancy measure to estimate the structural model and measurement models for the data prediction [92]. The blindfolding procedure is applied to endogenous reflective constructs, and if the value of Q^2 is larger than zero for a particular construct, its explanatory variables have a predictive relevance [94]. This is the case for all endogenous constructs of the model. The relative impact of the predictive relevance can be evaluated by the measure q^2 : values above 0.02, 0.15, and 0.35 indicate a small, medium, and large predictive relevance of constructs, explaining the endogenous construct that is evaluated [94]. Our results show that MAU ($q^2 = 0.164$) has a medium predictive relevance on performance expectancy, while compatibility ($q^2 = 0.339$) has a medium but almost large relative predictive relevance for performance expectancy. Second, we assessed the predictive power with the PLSpredict approach [103] in line with the guidelines of Shmueli et al. [82] (10 folds, one repetition to mimic performance how the PLS model will be eventually used to predict a new observation). With this approach, we can focus our analysis of the predictive power on the endogenous constructs of the model. As the analysis shows, all endogenous constructs' indicators have $Q^2_{predict}$ values above 0 (see Table 3), indicating in a first step that the most naïve benchmark with training sample's indicator means is outperformed. In a second step, we analyze the prediction errors in greater detail. For this purpose, we compare the root mean squared error (RMSE) with the values of the linear regression model (LM) since the visual inspection of the prediction errors of the model indicators suggests that the distribution is not highly non-symmetric. The analysis in Table 3 shows that the PLS analysis produces lower prediction errors for all indicators, indicated through the negative values ($RMSE_{PLS-SEM} - RMSE_{LM}$). Thus, we conclude that the model has a high predictive power. Concerning our control variable, we conclude that personal innovativeness in the domain of IT did not have a significant influence on performance expectancy ($p > 0.05$).

4.3. Importance-Performance matrix analysis of mau determinants

Fig. 4 depicts the IPMA for the first-order constructs of MAU while considering the second-order MAU construct as a dependent variable.

As the IPMA matrix shows, UI output has the greatest importance but has a rather low performance in comparison to the other factors. UI structure as the second most important factor has a medium performance. Application design is the third most important factor but with the lowest performance. For the UI input and application utility, importance is relatively low, but performance scores are rather high. UI graphics have least importance but with medium performance. We will discuss the implications of all these analyses in the next section.

5. Discussion and implications

5.1. Discussion of findings

Although MAU is recognized as crucial in literature related to Human Computer Interaction [15,20], research on its perception in mobile learning is limited. Recent reviews [13,17], have underscored the need for further investigation. Our study fills this gap by systematically exploring the relationship between perceived MAU, its determinants, and outcomes for the educational context in mobile learning.

For this purpose, we developed a theoretical model that we evaluated with a free simulation experiment in order to obtain perceptions of potential mobile learning users concerning MAU and its consequences. Further, we relied on advanced PLS-SEM modeling with the IPMA method to obtain detailed and actionable insights as a contribution for the HCI community and practitioners concerned with designing mobile learning artifacts. To restate our research question, *how does MAU impact the outcomes of mobile learning?*

² For the sake of brevity, we refrained from additionally depicting the HTMT_{inference} statistics.

Table 5
Assessment of discriminant validity.

Construct	1	2	3	4	5	6	7	8	9
1. Application Design	0.930								
2. Application Utility	0.561 (0.631)	0.790							
3. UI Graphics	0.765 (0.813)	0.441 (0.501)	0.876						
4. UI Structure	0.652 (0.686)	0.636 (0.704)	0.629 (0.668)	0.932					
5. UI Input	0.374 (0.386)	0.435 (0.485)	0.338 (0.366)	0.533 (0.563)	0.899				
6. UI Output	0.641 (0.667)	0.661 (0.736)	0.613 (0.641)	0.804 (0.837)	0.544 (0.566)	0.960			
7. Performance Expectancy	0.416 (0.444)	0.680 (0.792)	0.257 (0.272)	0.548 (0.587)	0.321 (0.328)	0.641 (0.679)	0.915		
8. Compatibility	0.317 (0.336)	0.573 (0.652)	0.169 (0.183)	0.439 (0.466)	0.339 (0.356)	0.546 (0.576)	0.696 (0.754)	0.932	
9. Self-efficacy	0.152 (0.188)	0.210 (0.262)	0.150 (0.189)	0.234 (0.287)	0.299 (0.377)	0.279 (0.336)	0.248 (0.303)	0.075 (0.101)	0.878

* Diagonal elements in bold are square roots of the AVE and all off-diagonal elements are correlations of the latent first-order constructs. Values in parentheses show the HTMT criterion, whereby 0.85 represents a conservative threshold. Therefore, the values show that the conservative HTMT₈₅ criterion is fully satisfactory and confirming discriminant validity.

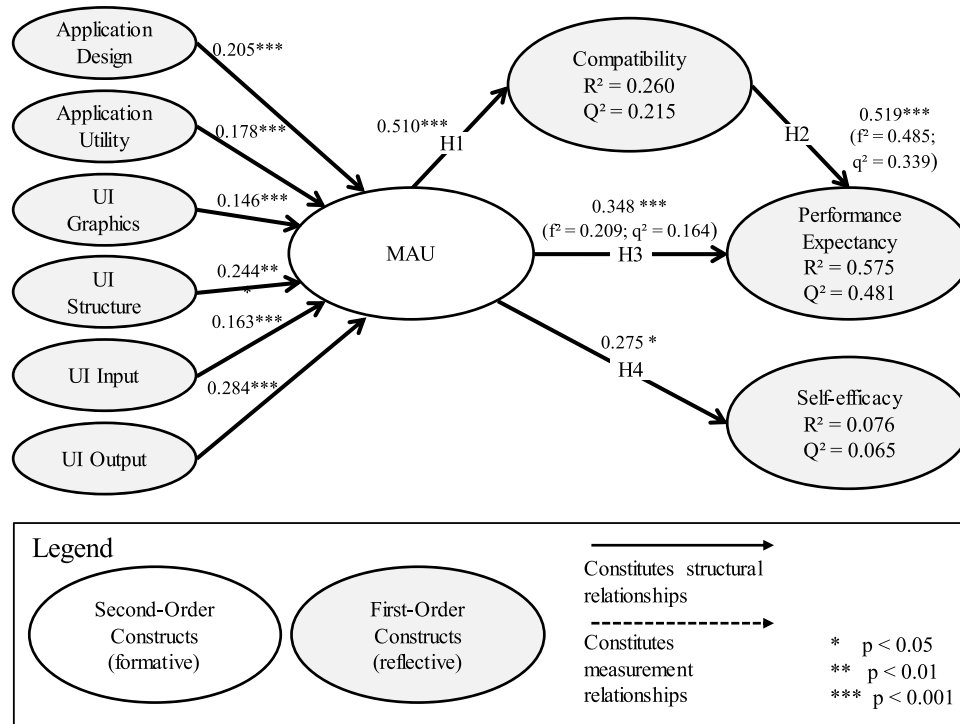


Fig. 3. Results of the theoretical model.

Our results provide several significant empirical insights concerning the overall model. We reveal the significant influence of MAU on self-efficacy, compatibility, as well as performance expectancy. Concerning the influence of MAU on performance expectancy, we also show that the effect of MAU is partially mediated through compatibility, thus highlighting that MAU both directly and indirectly influences performance expectation perceptions. Since most mobile learning applications are used on a voluntary basis, performance expectancy is an important criterion for the mobile learning application to be used at all [106]. In this regard, the usability of mobile learning applications should help users to orient themselves in the learning process. For example, performance metrics or error rates can help users to appreciate their learning progress. Moreover, usability for mobile learning could draw on approaches in the field of educational science and define educational

objectives the user will reach after using the mobile learning application or performing a certain task [107,108].

Furthermore, our results reveal that MAU has a significant influence on self-efficacy. MAU supports a user's ability to judge their capabilities to solve a task or to attain a certain goal. By defining the goals e.g., following Bloom's taxonomy [107,108] as well as outlining the required individual skills and capabilities to attain the goals, the mobile learning application can help someone to judge if they are up to the task.

As our goal was to disentangle the influence of MAU determinants, we utilized the instrument provided by Hoehle and Venkatesh [20] to measure MAU and embed this instrument in a new context, i.e., mobile learning. Since we modeled MAU as a reflective-formative (type II) hierarchical latent variable, our results also show the influence of the specific first-order constructs on MAU. In addition, we used an IPMA

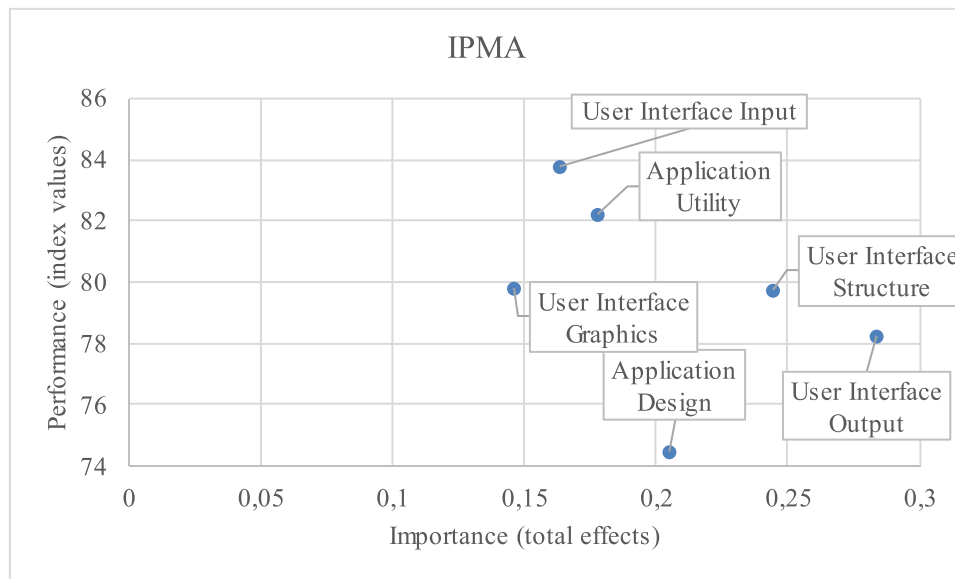


Fig. 4. Results of the IPMA.

approach to investigate the performance of each first-order construct on the higher-order MAU construct. Our results show that – in comparison to the other MAU determinants – UI output, UI structure, and application design have a higher influence on MAU but a rather low performance and thus, should be in focus to design better mobile learning applications with greater usability. Furthermore, we showed the feasibility of the construct provided by Hoehle and Venkatesh [20] within the context of mobile learning.

5.2. Implications

Taking a closer look at our results, our findings have the following design implications:

- (1) Our results indicate a high influence of MAU on compatibility. Against this backdrop, design decisions should be made based on user requirements and user demands to properly address the adopters' needs and values [109]. To best integrate the users' wishes and needs, as part of compatibility, extant literature refers to the concept of user-centered design, which involves the user early in the development process in which prototypes are iteratively built, refined, and tested [110]. If it is not feasible to involve the user in the mobile learning development process, design guidelines for building mobile applications as provided by Apple or Google can be followed to design mobile learning application that are "[...] consistent with existing values, past experiences, and needs of potential adopters" ([54], p. 240). However, since these design guidelines are not built for mobile learning applications, the developer should pay additional attention to the three constructs of *UI structure*, *UI output* and the *application design*, as the IPMA revealed.
- (2) Although, many mobile applications do not need a detailed navigation structure, the navigation and *UI structure* in the context of mobile learning not solely serves the purpose to help to orient oneself in the application, but to also enable learners to set themselves goals and learning milestones. Furthermore, tasks that build on one another and level of difficulty must be indicated to allow for an effective mobile learning usage. In this regard, also the provision of details on the tasks like time, difficulty and type, can help the learners to reduce extraneous load and thus, to better engage cognitively in the mobile learning process, which is crucial for the success of mobile learning [111].

- (3) Moreover, the usage of common language and a thoughtful integration of content related to the *UI output* can also reduce cognitive load and make the application more attractive for potential learners, which increases their subjective willingness to use the mobile learning application – another success factor for mobile learning success [111]. In this regard, the application should just provide as much as information as needed.
- (4) Mobile learning applications and their *application design* should be in no way inferior to mobile application regarding their system performance and reaction time. Being distracted by the mobile learning application's performance, learners may not concentrate on the learning content.

When looking at the outcomes of MAU, the influence of MAU on self-efficacy, compatibility, and performance expectancy, as highlighted in the study, provides clear design implications for mobile learning applications.

- (1) Enhancing compatibility can facilitate the indirect effects of MAU on performance expectancy. This implies that the design of mobile learning apps should prioritize seamless integration with existing user work processes and compatibility with learning environments [112].
- (2) The direct impact of MAU on performance expectancy suggests that clear and measurable performance metrics should be integrated within the app. These metrics could include tracking error rates or providing progress indicators through the UI, which can help users recognize and appreciate their learning advancements [113].
- (3) The influence of MAU on self-efficacy highlights the need for mobile learning applications to support users in understanding their capabilities relative to set learning objectives. Designers should consider incorporating structured goal-setting features in their UI based on educational frameworks like Bloom's Taxonomy. Such features should articulate what users should expect to learn and achieve, thus enhancing users' confidence in their ability to meet those objectives.

As a theoretical as well as a practical contribution, we offer ways to build better mobile learning applications on the basis of our model as well as the IPMA implications for design science research. We specifically focus on the MAU determinants with higher importance but lower

performance, since these determinants show the need for action and room for improvement. Studying real world problems with a mobile device that provides minimal support might result in users' orientation loss and poor learning outcomes [36]. Providing additional help or instructions to guide the learner when starting mobile learning training – e.g., by procedural scaffolds as a relevant concept from educational research (e.g., [114]) – could improve usability. By highlighting relevant challenges in mobile learning environments, such procedural scaffolds could facilitate initial orientation and navigation in mobile learning application [115] and, thus, engage mobile usability. Moreover, being used to commercial applications with great performance and design, users of mobile learning applications are not willing to be disadvantaged.

6. Limitations and future research

We acknowledge three limitations to this study, which in turn present opportunities for future research. First, there are some threats to the internal and external validity of the empirical study, concerning the unambiguity and generalizability of the results [116,117]. Characteristics of the convenience sample could threaten the internal validity [116]. As it is a non-probability sampling, its internal validity is threatened by its inhomogeneity. Moreover, we have to consider self-selection effects of the sample because the participation was on a voluntary basis. Therefore, future research might evaluate the model with more homogenous samples to avoid such effects. For instance, when considering samples with elderly users that want to make use of mobile apps for lifelong learning, usability results may differ from this sample. Future studies should in particular compare IPMA results concerning MAU and contrast our findings with additional insights. Additional threats to the external validity could occur from the use of a web-based prototype of the application.

Second, another risk regarding the external validity of our study relates to the application of a web-based mobile learning application prototype. The used prototype included all typical functions of a mobile learning application and provided a good usability. Notwithstanding, even if the participants were able to use the web-based prototype as naturally as possible, the prototype is no substitute for a mobile learning application that is used in the reality of working processes. However, we took this limitation into account to control for the already mentioned effects such as different phones or different screen resolutions. In addition, prior research suggests that there are in our case negligible differences when conducting empirical studies either on mobile devices or a desktop computer [118]. Still, future research should assess the model through the application of field experiments to account for environmental aspects (see also [119] for learning effects in rich physical environments). In addition, we also acknowledge in this regard that the ultimate target group of the proposed application is concerned with the area of vocational training and education [120], while the data collection was not focused on this target group of users. Thus, we have to take certain limitations into account, when considering MAU consequences that relate to the motivational aspects when using the provided mobile learning application. With a different user group, results might differ, although our results from the PLSpredict approach [103] suggest the prediction performance of the model, also for other respondents (out of sample predictions, see also [81,82]).

Third, since the same measurement instrument was used with all participants of the study to assess the dependent and independent latent variables, common method variance could be a problem of this study. Therefore, procedural remedies were taken to avoid biases ex-ante, as described in the section regarding the data collection. In addition, Harmann's Single Factor test was conducted ex-post, and provided

evidence that common method variances should not be a major problem in this study. However, this test also has, as other tests (e.g., [121]), its limitations [75], and thus biases cannot be absolutely excluded. Therefore, future research should also examine objective outcomes of mobile learning such as cognitive knowledge acquisition or actual use behavior instead of for example self-efficacy as a meta-cognitive learning outcome or performance expectancy.

7. Conclusion

MAU is a critical factor in positively shaping the outcomes of mobile learning. To evaluate the influence of MAU, we conducted an empirical study in the domain of mobile learning. We implemented a prototype of a mobile learning application, gathered our data in a free simulation experiment, and analyzed the data and our proposed model in a PLS-SEM approach. With a formative modeling of the MAU determinants in a second-order model, it was possible to evaluate the impact of each MAU determinant. Moreover, the IPMA informed us about the performance of each determinant. The IPMA highlights that while UI output is most important, its performance is low, indicating a crucial need for improvement. UI structure and application design also require attention in mobile learning due to their significant importance yet suboptimal performance. In contrast, UI input and application utility, though less critical, show strong performance, demonstrating areas of strength. UI graphics, although least important, perform adequately. These findings suggest targeted areas for enhancing usability in mobile learning applications. Thus, our study highlights that MAU is a crucial construct for mobile learning applications whose design should concentrate on UI output and structure as well as application design in general to address issues like cognitive load. Our results also show the influence of MAU on compatibility, self-efficacy, and performance expectancy. Furthermore, our results reveal that compatibility acts as a partial mediator for MAU on performance expectancy.

Indeed, the discussion about usability for mobile application is ongoing, and our results are one of the first attempts to investigate this important phenomenon in mobile learning. Nevertheless, in this study, we can already offer theoretical and practical starting points for how MAU can be enhanced during the design process. Thus, HCI research in educational contexts could take our results as a starting point and further investigate how mobile learning and usability are intertwined, e.g., by considering cognitive aspects such as cognitive load explicitly or integrating our results into rigorous design science approaches [122].

CRedit authorship contribution statement

Andreas Janson: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Sissy-Josefina Ernst:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.caeo.2024.100230](https://doi.org/10.1016/j.caeo.2024.100230).

Appendix

Appendix A

Review of Selected Empirical Literature on Mobile Usability

Full Citation	Study Context	Methodology	Independent Variables	Dependent Variable Moderating Variable	Relevant Findings
Aryana, B., & Clemmensen, T. [44]. Mobile Usability: Experiences From Iran and Turkey. <i>International Journal of Human-Computer Interaction</i> , 29(4), 220–242. doi:10.1080/10.447.318.2013.765760 *	Mobile Usability; Smartphone Usage and Adoption	Focus group study	SMS and networking task, Music task, Contacts and hierarchy test	Usability-Related Errors (Theme-related and non-Theme-related errors)	While social networking via use of an SMS service was favored by Iranian users, Turkish users were inclined to apply hierarchies to their own daily personal contacts. The source of these problems is most likely due to a combination of certain contextual characteristics that are endemic to both Iran and Turkey, and not just to ethnic, religious or cultural issues.
Duh, H. B.-L., Tan, G. C. B., & Chen, V. H.-h. [43]. Usability evaluation for mobile device: A Comparison of Laboratory and Field Tests. In M. Nieminen & M. R��ykk��e (Eds.), <i>Proceedings of the 8th conference on Human-computer interaction with mobile devices and services - MobileHCI '06</i> . New York, New York, USA: ACM Press.	Evaluation of the effectiveness of laboratory usability test; Comparison between real life and laboratory situations	T-Test; Categorization of usability problems	Mobile phone usability tests in laboratory and field test	Usability Problems	The laboratory usability test was insufficient in detecting usability problems of mobile devices in their actual usage context. The behavior of the participants when performing the usability tests in the laboratory was different from their behavior in the actual situation of cell phone use. Some usability problems and behaviors only occurred in the field.
Gu, X., Gu, F., & Laffey, J. M. [2]. Designing a mobile system for lifelong learning on the move. <i>Journal of Computer Assisted Learning</i> , 27 (3), 204–215. doi:10.1111/j.1365-2729.2010.00391.x *	Design of a life-long learning system for mobile devices	walkthrough protocol; follow-up focus group meeting	Two systems were rated (Expo English and a Six-Step Change Tire System)	Heuristic Evaluations	Both practical and micro-principles have been accepted by users as methods for integrating learning activities into their daily lives. Audio was preferred, especially for language learning. Concerns about technical usability, which are consistent with previous web experiences, were identified. Usage mechanisms should be consistent with conventional usability standards when designing usage mechanisms of learning products. Attractive and appropriate media design should be implemented.
Hoehle, H., & Venkatesh, V. [46]. Mobile Application Usability: Conceptualization and Instrument Development. <i>MIS Quarterly</i> , 39(2), 435–472	Mobile application usability conceptualization and survey instrument construction	Benchmarking between the new conceptualization and previous instruments.	Mobile application usability	Continued intention to use, mobile application loyalty	The adaption of the apple user experience guidelines led to more explained variance than the adaption of the

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Full Citation	Study Context	Methodology	Independent Variables	Dependent Variable <i>Moderating Variable</i>	Relevant Findings
Hoehle, H., Zhang, X., & Venkatesh, V. [46]. An espoused cultural perspective to understand continued intention to use mobile applications: A four-country study of mobile social media application usability. <i>European Journal of Information Systems</i> , 24(3), 337–359. doi:10.1057/ejis.2014.43 *	Cultural perspective to understand continued intention to use mobile applications, development of a model that is integrating cultural values at the individuals' model	Online survey; partial least squares (PLS) structural equation model; and a slope differences <i>t</i> -test	Mobile application usability; espoused national cultural values	Continued intention to use	Microsoft's usability guidelines. The developed model including espoused cultural values as contingency factors could explain more variance compared to a model main effects-only model and a model using country dummy variable. Thus, one can say, espoused cultural values should be regarded when examining the relationship between mobile application usability and individuals' continued intention to use mobile social media applications. Mobile application interfaces should therefore be adapted to the respective culture.
Kortum, P., & Sorber, M. (2015). Measuring the Usability of Mobile Applications for Phones and Tablets. <i>International Journal of Human-Computer Interaction</i> , 31(8), 518–529. doi:10.1080/10.447,318.2015.1064658 *	Mobile applications for phones tested on tablets	Factor Analysis; Alpha Reliability	iPhone, Android, iPad, Android Tablet; Top 10 Apps on each platform and user-selected Apps	System Usability Scale (SUS)-Ratings	Even though the top 10 used apps were rated, the average SUS rating was 77.7. Which means the apps are usable but not perfectly usable, the range between the ratings were also with a 20-point spread, so some apps, even if they are in the top 10 do not guarantee usability. The user selected apps somehow did not receive high ratings, the author argue that the utility and high availability of the apps led to the continued use of these apps.
Mohtar, S., Jomhari, N., Omar, N. A., Mustafa, M. B. P., & Yusoff, Z. M. [123]. The usability evaluation on mobile learning apps with gamification for middle-aged women. <i>Education and Information Technologies</i> , 28(1), 1189–1210	Mobile learning and gamification for middle-aged women	Preliminary study using pre and post-tests	Use of a gamification application (Number of taps, number of attempts, quiz score)	Effectiveness, efficiency, and satisfaction of the mobile app	Gamification can motivate learning among middle-aged women. The proposed mobile app was effective as users successfully utilized all modules and quizzes.
Zander, S., Montag, M., Wetzel, S., & Bertel, S. [45]. A gender issue?: How touch-based interactions with dynamic spatial objects support performance and motivation of secondary school students. <i>Computers & Education</i> , 143, 103,677. doi:10.1016/j.compedu.2019.103677 *	Touch-based interactions with dynamic spatial objects	Mixed within-between subject design; paired <i>t</i> -test; MANOVA	Presentation format (static vs. dynamic) and gender (female vs. male)	Success rate, mental effort, intrinsic motivation, and frustration	Both genders success rates increased, and mental effort decreased in the dynamic condition, only female students experienced beneficial effects for intrinsic motivation and frustration. For the dynamic tasks: it appears that females draw greater benefit of more exploratory ways of solving spatial tasks and male students at more goal-oriented approaches.
Zhang, T., Rau, P.-L. P., & Salvendy, G. (2010). Exploring critical usability factors for handsets. <i>Behaviour & Information Technology</i> , 29(1), 45–55. doi:10.1080/01,449,290,802,666,747 *	Critical factors that predict the perceived usability of handsets	Exploratory factor analysis, Multiple linear regression analysis	Multiple linear regression: design feature	Multiple linear regression: usability factor	Nine factors were identified as critical factors from the exploratory factor analysis, including satisfaction, controllability,

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Full Citation	Study Context	Methodology	Independent Variables	Dependent Variable <i>Moderating Variable</i>	Relevant Findings
					effectiveness, frustration, customizability, navigation, attractiveness, helpfulness and consistency. Functional relationships between usability factors and design factors were examined as well. Fashion, capability and battery duration were considered to be the most significant predictors for the satisfaction factor. Regarding the subscale of customizability, the feature of a shortcut menu was the most significant predictor. Body color and ringtone were identified as most significant predictors for attractiveness. The user interface layout and menu structure appeared in almost all regression models.

Appendix B

Measurement Instruments

Code	Item Used	Source
Application Design		
MAU_AD1	Overall, I think the MoKe is designed well.	Adapted from Hoehle and Venkatesh [20]
MAU_AD2	In general, I believe that MoKe has a great design.	
MAU_AD3	Generally speaking, MoKe process) is well designed.	
MAU_AD4	I am very satisfied with the overall design of MoKe.	
Application Utility		
MAU_AU1	To me, MoKe is very functional.	Adapted from Hoehle and Venkatesh [20]
MAU_AU2	Overall, I think that MoKe is useful.	
MAU_AU3	Generally speaking, MoKe serves its purpose well.	
MAU_AU4	In general, MoKe is of value to me.	
User Interface Graphics		
MAU_UIG1	Overall, I think that the graphics displayed on MoKe are designed effectively.	Adapted from Hoehle and Venkatesh [20]
MAU_UIG2	In general, the interface graphics of MoKe are designed well.	
MAU_UIG3	Generally speaking, I like the graphics displayed on the interface of MoKe.	
MAU_UIG4	Overall, MoKe has very good user interface graphics.	
User Interface Input		
MAU_UII1	In general, MoKe allows me to input data easily.	Adapted from Hoehle and Venkatesh [20]
MAU_UII2	Overall, the user input mechanisms are designed effectively on MoKe.	
MAU_UII3	I am very satisfied with the input mechanisms of tMoKe.	
MAU_UII4	Generally speaking, it is easy to type in data into MoKe.	
User Interface Output		
MAU_UIO1	In general, the content of MoKe is presented effectively.	Adapted from Hoehle and Venkatesh [20]
MAU_UIO2	Overall, I believe that MoKe presents content very well.	
MAU_UIO3	Overall, I think that MoKe presents content effectively.	
MAU_UIO4	I am very satisfied with the way that MoKe presents content.	
User Interface Structure		
MAU_UIS1	Overall, I think MoKe structures information effectively.	Adapted from Hoehle and Venkatesh [20]
MAU_UIS2	In general, MoKe is structured very well.	
MAU_UIS3	I am very satisfied with the way MoKe is structured.	
MAU_UIS4	Generally speaking, MoKe is structured nicely.	
Performance Expectancy		
PE1	I would find MoKe useful for my learning purpose.	Adapted from Venkatesh et al. [57]
PE2	Using MoKe enables me to accomplish tasks more.	
PE3	Using MoKe increases my productivity.	
Self-Efficacy		

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Code	Item Used	Source
SE1	I could complete the job using MoKe if there was no one around to tell me what to do as I go.	Adapted from Compeau and Higgins [72]
SE2	I could complete the job using MoKe if I had just the built-in help facility for assistance.	
Compatibility		Agarwal and Prasad [70] adapted according to Cheng [71]
COMP1	Using MoKe is compatible with most aspects of my learning.	
COMP2	Using MoKe fits well with the way I like to learn.	
COMP3	Using MoKe fits my learning style.	

Appendix C

Cross Loadings

	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)
MAU_AD1	0.910	0.498	0.683	0.578	0.289	0.578	0.380	0.278	0.248
MAU_AD2	0.940	0.550	0.698	0.651	0.362	0.617	0.436	0.340	0.079
MAU_AD3	0.936	0.487	0.719	0.567	0.314	0.593	0.345	0.258	0.117
MAU_AD4	0.934	0.547	0.743	0.627	0.421	0.596	0.385	0.300	0.129
MAU_AU1	0.565	0.785	0.420	0.630	0.431	0.556	0.547	0.507	0.226
MAU_AU2	0.395	0.795	0.297	0.476	0.260	0.468	0.492	0.459	0.062
MAU_AU3	0.441	0.879	0.381	0.560	0.372	0.632	0.610	0.498	0.255
MAU_AU4	0.3377	0.6917	0.2665	0.2754	0.2823	0.3926	0.4913	0.3121	0.0741
MAU_UIG1	0.5385	0.3322	0.8636	0.42	0.3099	0.3979	0.1174	0.1547	0.1418
MAU_UIG2	0.7008	0.3664	0.8963	0.5358	0.2506	0.5394	0.1729	0.0686	0.0663
MAU_UIG3	0.5919	0.356	0.8424	0.5273	0.2636	0.4921	0.2488	0.1904	0.1997
MAU_UIG4	0.8025	0.4668	0.9006	0.6794	0.3531	0.6723	0.3272	0.178	0.1245
MAU_UIS1	0.5929	0.6017	0.5719	0.9165	0.4953	0.7706	0.5432	0.4244	0.2449
MAU_UIS2	0.6075	0.6166	0.5735	0.96	0.5103	0.7575	0.5557	0.4164	0.1931
MAU_UIS3	0.6443	0.6494	0.5732	0.9414	0.5542	0.7343	0.5323	0.4706	0.1678
MAU_UIS4	0.5862	0.4993	0.6308	0.9106	0.4236	0.7368	0.4057	0.3209	0.2701
MAU_UII1	0.194	0.2231	0.2739	0.3982	0.7954	0.3575	0.1059	0.1634	0.2961
MAU_UII2	0.3959	0.4429	0.3246	0.5051	0.9351	0.541	0.3192	0.3534	0.2903
MAU_UII3	0.4286	0.4511	0.3623	0.5616	0.9592	0.5628	0.3645	0.3815	0.2582
MAU_UII4	0.2798	0.4056	0.2436	0.4293	0.8969	0.4606	0.3156	0.2798	0.2428
MAU_UIO1	0.5414	0.6359	0.5501	0.7942	0.4969	0.9531	0.6048	0.5186	0.2498
MAU_UIO2	0.6585	0.6182	0.6178	0.7594	0.5088	0.9658	0.6287	0.4983	0.2349
MAU_UIO3	0.6083	0.6726	0.5596	0.7557	0.5776	0.9654	0.6264	0.5366	0.2902
MAU_UIO4	0.6529	0.612	0.6263	0.7807	0.5055	0.9576	0.6006	0.5445	0.2957
PE1	0.4503	0.6773	0.2554	0.5241	0.4191	0.6411	0.9105	0.7117	0.3152
PE2	0.3718	0.5743	0.2437	0.4939	0.248	0.5812	0.9139	0.5513	0.1902
PE3	0.308	0.6044	0.2026	0.4812	0.1884	0.5265	0.9221	0.6313	0.1567
COMP1	0.380	0.584	0.218	0.450	0.264	0.527	0.619	0.890	−0.006
COMP2	0.301	0.555	0.169	0.423	0.348	0.514	0.687	0.967	0.111
COMP3	0.200	0.457	0.081	0.351	0.337	0.485	0.638	0.938	0.105
SE1	0.123	0.203	0.098	0.190	0.279	0.228	0.239	0.081	0.868
SE2	0.144	0.167	0.162	0.219	0.248	0.260	0.197	0.053	0.888

(A) Application Design; (B) Application Utility; (C) UI Graphics; (D) UI Structure; (E) UI Input; (F) UI Output; (G) Performance Expectancy; (H) Compatibility; (I) Self Efficacy.

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