Mobile Pervasive Augmented Reality Systems - MPARS

The Role of User Preferences in Perceived Quality of Experience in Outdoor Applications

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This work addresses reasons and aspects required to boost the acceptance and use of mobile pervasive augmented reality systems - MPARS - for outdoor applications and the need to develop context-aware close-to-real-time feedback mechanisms that take into consideration a continuous measurement of Quality of Experience. For this purpose, we delve into how user preferences can be integrated in context-aware feedback systems, proposing a Quality of Experience theoretical model derived from an analysis on technology adoption models and user preferences. The how and why such model can be integrated into future solutions is also addressed.

Additional Key Words and Phrases: Mobile Pervasive Augmented Reality Systems, Mobile Applications, Perceived Quality of Experience, Technology Acceptance Models.

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1 INTRODUCTION

Augmented Reality (AR) is today one of the most popular computer science areas, being the derived technology applied into a diversified set of realms, such as gaming, health, commerce, sports, tourism [38]. Moreover, today the end-user carries around multiple personal devices with strong sensing capabilities. Portability and the capacity to provide feedback and information to users almost in an "always on" fashion are aspects that keep on strengthening the applicability of the most varied mobile technology in our daily lives.

While AR has been around for over forty years, studied extensively over the last few decades [11], *Mobile Augmented Reality Systems (MARS)* are still in their infancy. Unlike a laptop or desktop, a truly MARS should fit in one's pocket; should be portable, and support both mobility and intermittent connectivity [9]. This can be seen as a new phase in the evolution of MARS, which we coin as *Mobile, Pervasive Augmented Reality Systems (MPARS)*. Such systems face new challenges, for instance: devices are mobile and often energy constrained; Internet access is intermittent; GPS may not always work (e.g., indoors); data classification may benefit from being performed closer to the user,

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e.g., to reduce latency. Moreover, new interfaces for MPARS must be more intuitive, context-aware, and adaptative [32].

Therefore, even though AR has a consolidated growth, the new Internet reality requires significant adaptations for AR systems to become widely accepted [29]. At the same time, MPARS can benefit from new features introduced by mobile, pervasive devices with the possibility to exploit a multitude of available sensors, and have maximum flexibility [26]. With the data captured by such sensors, MPARS middleware can integrate a fine-grained contextual-awareness and result in tools that are more useful to the end-user. This aspect can improve the perceived user *Quality of Experience (QoE)* and thus contribute to a wider deployment of AR in new realms. Moreover, AR usability and user experience issues still need to be improved [11].

Small data captured by sensors in personal mobile devices bring in new challenges as well, as such data comes from individual sources and is specific to an individual. Therefore, in what concerns data cleaning, validation, and classification, today the data captured via personal mobile devices is treated and classified on the cloud, in remote servers. These machines can easily support the execution of intensive computational aspects, such as the classification of specific activities [8].

A trade-off of cloud-based data analytics is the delay, an aspect which jeopardizes the adoption of MAR, as well as MPARS especially in outdoor environments, given that in such context the user is expected to want close-to-real-time feedback. How to assist in reducing latency [37] and in better-distributing network functions to support data classification and transmission is one of the key aspects being researched in the context of mobile edge computing [12] with respect to QoE [6].

Another highly relevant aspect to work in regards to better support MPARS in outdoor activities is to make it people-centric, in regards to feedback modelling [30], avoiding as far as possible information overload [25]. The focus of this paper falls into this latter category. The paper contributes an investigation of user preference drivers for AR mobile middleware and proposes a new model which integrates technical dimensions and human dimensions for the technology acceptance. By *user preference* it is meant the explicit interest of users on specific features e.g., from a survey. The investigation developed concerning user preferences has been derived from a survey that involved 114 persons in 2018.

The rest of the paper is organized as follows. Still in this section, the paper addresses the proposed research questions. Section 2 goes over related work. Section 3 debates on the challenges that current technology adoption models have in these new environments. Section 4 shows the relevant user preference indicators to building future MPARS. Section 5 describes our model, including the user driver preferences findings. Section 6 concludes the document and provides guidelines for future work.

1.1 Research Questions

In this work a first aspect tackled was to understand whether or not the assumptions of current *Technology Adoption Models (TAM)* could be applied to derive a QoE model suitable for the MPARS environments, in particular when considering outdoor activities. The questions to be answered are:

- Can the main assumptions of today's Technology Adoption Models be relied upon to derive QoE?
- In terms of user preferences, are MPARS relevant in the context of activities that require close-to-real-time feedback derived from both technical and human dimensions, such as tourism, sports, games, and leisure?
- How relevant are different small data categories, such as location, temperature, movement, social interaction, from a QoE perspective?

- How should user-preference variables be weighted to have a better sense of continuous QoE, and which adaptations should be considered in future work, to improve AR technology acceptance in outdoor environments?

2 RELATED WORK

This section begins by indicating the relevant surveys on current Mobile Augmented Reality Systems and the introduction of the rationale that supports the need to take advantage of the sensors available in today's smart mobile systems (e.g., smartphones, smart glasses) that helps justifying our decision of adding the word *Pervasive* into *MARS*. It also includes a summary of important works on technology acceptance models, the problem of information overload, and user preference indicators aiming to understand how to improve the process of adoption of AR technology, and contributing to a better *User Experience* in outdoor environments.

2.1 Mobile AR Systems

Mobile AR systems (MARS) architectural design is first debated by Höllerer et al. [14]. The authors provide a first functional framework for MARS, including: registration; wearable input and interaction; data transmission based on wireless networking, discusses its challenges, and potential applications.

Papagiannakis et al. [23] survey mobile and wireless technologies for the support of MARS, describing key existing components and potential software architectures. Albeit this work looks into MARS, the possibility to exploit pervasive and participatory sensing to further enrichment of the systems are aspects which were not foreseen in this work.

2.2 Technology Adoption Models

In what concerns technology adoption models, diverse designs have been proposed. Davis et al. (1989) are the first authors to propose a TAM intended to model technology acceptance by end-users [10]. Their model gathers useful information for assessing the relative likelihood of success of new systems at an early development stage and is based on the principle of the user's motivation. An extension of this work, TAM2, integrates features to explain the *perceived usefulness* and *usage intentions* in terms of social influence and cognitive instrumental processes. This model aims at understanding how the effects of these determinants change with an increase in the user's experience over time [28].

A follow-up of this work is the *Theory of Reasoned Action (TRA)*, a study to better understand why people accept or reject computers [4]. TRA has been adapted for use in many fields and is widely used in academia and business today. This theory explains how external variables influence internal beliefs, attitudes, purchase intentions and actual use of technology [4]. According to TRA, people behave according to context and according to the available time space [4]. That is, the user has to realize (1) the utility and (2) the ease of use of an AR technology, and this perception involves prior education (e.g., prior training or acquired experience using AR).

Venkatesh et al. propose the *Unified Theory of Acceptance and Use of Technology (UTAUT)* [34]. UTAUT shows four core determinants of intention and usage, and up to four moderators of key relationships. Four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, have been theorized in the formulation of UTAUT with the aim of determining user acceptance and usage behavior for technology [28]. A follow-up of UTAUT, UTAUT2 is provided by the same authors, incorporating three additional variables for consumer context. The new variables are: hedonistic motivation (i.e., utilitarian or enjoyable), price value and habit under individual differences - namely, age, gender and experience [28] [34].

2.3 Interaction with AR Systems

Research developed by Furht shows that the interaction with AR systems implemented in mobile applications needs to be subtle, discreet and gentle, so as not to disturb the end-user, if such systems are under a high workload and the disruption is not a priority [13]. A system that is subtle, discreet and moderate has a higher probability of acceptance.

Hence, in this context and taking into consideration that MPARS can be further enriched via context derived from smart data, *pervasive sensing* is an approach that needs to be considered in the development of MPARS. This is, for instance, the case of "GymSkill" a personal trainer for ubiquitous monitoring and assessment of physical activity [22]. This system identifies interesting portions of the recorded sensor data and provides suggestions for improving the individual performance. Data is provided via sensors of mobile systems, such as smartphones, with a growing set of cheap powerful embedded sensors [20].

Rauschnabel et al. perform an investigation of technology acceptance drivers for smart glasses based on the specific case of the Google glasses technology. They provide a first glance into the mechanisms that assist technology adoption modelling of smart glasses [27]. Our work follows a similar approach, expanding for the case of AR in the context of outdoor environments.

An AR survey conducted by Wang et al. addresses the integration of networking, caching and computing for efficient use of resources required on mobile systems [35]. The authors discuss performance metrics to compare different architectures, management systems, resource allocation algorithms, customization flexibility, interfaces, energy saving, envisioning mobile environment challenges, such as latency, bandwidth, interfaces, and mobility management.

Kim et al. discuss concepts to applications and highlight the needs for technological efficiency [16]. The authors describe issues that are relevant to the development of fundamental technologies and applications. The use of smartphones or tablets to access AR content is arguably the most common method today, mostly due to ubiquity and widespread availability of the respective operating systems. While information ubiquity tends to grow with the most recent advances of mobile systems and technology, ubiquitous use of AR glasses is still in the rise.

Billinghurst et al. investigate some action fields of AR technology, such as tracking and display, development tools, input and interaction, and social acceptance [5]. For instance, mobile devices present new opportunities for hybrid tracking, as they include not only cameras but other relevant sensors for tracking, such as accelerometer and gyroscope, GPS, as well as wireless interfaces, which can be combined to provide a highly accurate estimation of tracking.

2.4 Information Overload and Information Presentation

In our opinion, one aspect that is often overlooked and that has significant impact for MPARS adoption is *Information Overload* [21] [25]. This aspect can be improved by considering *contextual-awareness* as a necessary input filter to better adjust feedback provided to the user via a MPARS solution. This opinion is in line with the study of Sawyer et al. where they assess the distraction potential of "texting" with Google Glass, which is a mobile wearable platform capable of receiving and sending messages [30]. They asked drivers in a simulator to drive and use either Google Glass or a smartphone-based messaging interface, then interrupted them with an emergency brake event. Both the response event and subsequent recovery were analyzed. Messages while driving with AR smart systems harm the attention of drivers and cause a cognitive distraction in tasks in the context of driving.

Kitamura et al. study the distribution of attention to frontal space in AR with two experiments to compare binocular and monocular observation when an AR image was presented. The results indicated that the useful field of view became wider in the monocular observation [17]. Their study is reinforced in [18] where they compare the binocular AR presentation and monocular AR presentation in a situation where continuous viewings of AR images were required. During the monocular presentation, more changes in the peripheral field of vision are detected. Thus, observers might be able to acquire more information during monocular AR presentation. Therefore, in our opinion, the monocular feature has advantages in adapting the MPARS to adjust the information provided to the user.

3 MARS TECHNOLOGY CHARACTERISTICS

Preventing information overload requires that aspects derived from technology acceptance models are taken into consideration. As a first step towards a better design of MPARS, Figure 1 illustrates an adaptation of Davis' TAM for the study of acceptance of AR technology.

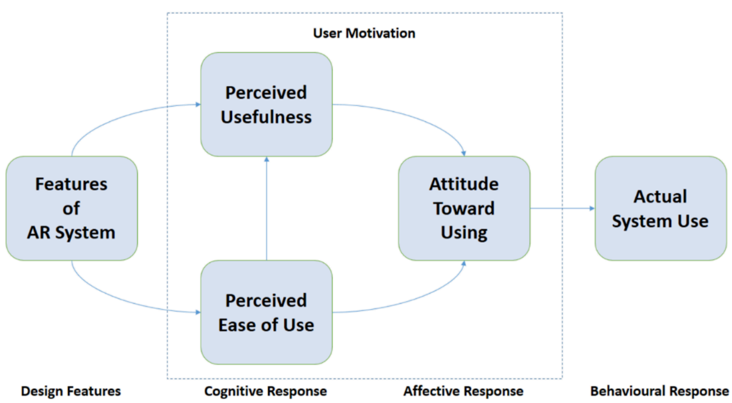

Fig. 1. Adaptation of Davis' model, TAM [10], for MPARS.

As shown in Figure 1, the proposed adaptation is based on the fact that the AR user's attitude is a function of two major beliefs: *perceived usefulness* and *perceived ease of use*. Perceived ease of use has a causal effect on perceived usefulness. The design of AR features directly influences perceived usefulness and perceived ease of use [10].

In the recent past, research teams, such as the MIT Media Lab, have been consistently trying to reduce the amount of unwanted visible devices or attempting to arrange them in different ways in terms of technology design [13]. Similarly, MPARS solutions need to be light, subtle and discreet. For sensing, they need to consider opportunistic sensing, in order to be less intrusive. Non-intrusiveness relates also with the capability to be parsimonious in terms of sound, battery, as well as of Internet use [7] [31].

The influence of information overload in relation to technology adoption variables has been analyzed by Pascoal et al. [25]. One of the findings concerns the fact that when information overload becomes higher, the systems have fewer appropriate features, have a lesser ease of use and thus provide fewer benefits for the end-user. The outcome is a lower social acceptance of the technology [25].

While there are several MARS on the market that are increasingly part of our lives today, smart glasses are one of the most relevant examples. Smart glasses can be classified into different sets within the family of mixed reality technology [13]. To provide a detailed comparison, the following

Table 1. Comparative table of MARS smart glasses' characteristics.

MARS	Sensors	Features (Weight/Vision)	Battery Lifetime (Hours)	Network Interface	Release Date (Year)
Alpha Glass AR Glasses©	Accelerometer, Compass, Gyroscope	80g Monocular	6	Bluetooth, Wi-Fi	2017
Atheer Air©	Accelerometer, Compass, Gyroscope, Ambient light, Proximity capacity touch, GPS	75g Monocular	8 + Extensible battery	Bluetooth, Wi-Fi	2016
Epson Moverio BT-300®©	Accelerometer, Compass, GPS, Ambient light, Proximity capacity touch	Headset 69g Controller 129g Binocular	6	Bluetooth, Wi-Fi	2017
GlassUP©	Accelerometer, Compass, Ambient light + provided via connected device	65g Monocular	24	Bluetooth, Wi-Fi	2013
LaForge Icis©	By phone	50g Monocular	18	Bluetooth, Wi-Fi, NFC	2014
Laster SeeThru©	Accelerometer, Compass, Gyroscope, GPS tracking, Head tracking	55g Monocular	6-8	Bluetooth	2014
Mad Gaze Ares©	Accelerometer, Gyroscope, Proximity sensor, GPS	400g Monocular	5	Bluetooth, Wi-Fi	2016
Meta Pro Space©	Accelerometer, Compass, Gyroscope	500g Binocular	4	Bluetooth, Wi-Fi	2014
Microsoft HoloLens©	IMU, Environment understanding depth camera, HD video camera, Mixed reality capture, Microphones, Ambient Light	579g Binocular	2-3	Bluetooth, Wi-Fi	2016
ODG R-9©	Multiple integrated IMU Accelerometer, Gyroscope, Magnetometer, Altitude and Humidity sensor, Ambient Light Sensor, GPS	184g Binocular	8	Bluetooth, Wi-Fi	2017
Optinvent ORA-2©	Accelerometer, Compass, Gyroscope, GPS	90g Monocular	5	Bluetooth, Wi-Fi	2014
Sony SmartEyeglass©	Accelerometer, Compass, Gyroscope, Brightness sensor, Microphone noise suppression	77g Binocular	1,5	Bluetooth, Wi-Fi	2015
Vuzix M300©	Accelerometer, Compass, Gyroscope, Proximity inward facing, Proximity/ALS outward facing	50g Monocular	2 12 (external battery choice)	Bluetooth, Wi-Fi	2017
Tobii Pro Glasses 2©	Accelerometer, Gyroscope, Parallax compensation Tracking technique Corneal reflection, Dark pupil tracking	45g 312g (recording unit) Binocular	10	Bluetooth, Wi-Fi	2018

NFC - Near-field communication; IMU - Inertial measurement unit

Table 1 describes examples of existing smart glasses systems. The table's columns consist of: *sensors*, standing for the type of sensors each solution encompasses; *features*, standing for aspects, such as weight and type of vision supported; *battery lifetime*; *network interface*, standing for the type of connectivity support (Wi-Fi, Bluetooth, 3G/4G), and the release date. It is possible to see that most solutions exhibit similar capabilities in terms of sensors, as well as for battery lifetime. Regarding the sensors, solutions consider the usual set of gyroscope, accelerometer, GPS and compass. A few solutions, such as ODG R-9, integrate other sensors, like a humidity sensor.

The weight of the devices is a feature that is relevant from a portability and comfort perspective. Note that most of the examples are considered to be light. In terms of connectivity and controls, most solutions available support Wi-Fi and Bluetooth (short-range wireless). We did not find a solution supporting 3G/4G directly and the reason is possibly due to battery consumption.

In the systems analyzed, there seems to occur some proportionality between the weight and battery life [24], in the sense that, when weight increases, the autonomy of the battery is shorter (Table 1). In what concerns outdoor environmental conditions, the AR display must work across a wide variety of lighting conditions, from bright sunlight to a moonless night [3]. This means, for instance, that Microsoft© HoloLens is not adequate for outdoor using due to three main indicators: (1) weight, (2) battery life, and (3) the sun reflex on the smart glasses. However, HoloLens© are suitable for controlled indoor environments, where there are uniform light conditions and ease of battery supply. In comparison, other MARS on market, such as Asus©, Hewlett Packard© and Acer© working with mixed and augmented reality with a similar but lower-cost design in relation with the Microsoft's HoloLens©. The Tobii Pro© smart glasses 2 are adapted for eye tracking to anticipate behavioral intentions of end-users.

In terms of connectivity, it is relevant to state that wireless and cellular technology is evolving to integrate by design aspects, such as mobility management and end-to-end security, in addition to bringing significant improvements on data acquisition rates. Nevertheless, none of the available tools directly support cellular communications [35]. To provide richer interactivity in AR applications, there has been a significant effort to combine various inputs. Among different combinations, speech and gesture recognition data is one of the most widely and actively researched combinations. This is due to the fact that input modalities that are complementary with speech, being good for quantitative input, are ideal for qualitative input [5].

4 BUILDING FUTURE MPARS

The previous sections introduced the need to identify and discuss indicators for user preferences to build future MPARS middleware, issues that are being addressed in the following sections.

4.1 User Preference Indicators

In order to improve and devise MPARS functional features, and having in mind the need to prevent information overload, a public survey has been delivered via Survio[1] from November 26, 2017, until March 2, 2018. The questionnaire was answered by 114 people after it was shared via academic communities, Online Social Networks[2] and E-mail. This questionnaire integrates 10 questions and, besides demographic and gender diversity information, a yes/no/maybe question is asked to assert if the respondent has previous acquaintance with AR technology.

The remaining questions aimed to gather user preference drivers. For that, a 5-degree Likert scale was employed. In addition to the referred demographic, age and gender and prior acquaintance of AR systems, the questionnaire addresses the importance of social influence and price, the degree of preference towards dedicated systems and preference towards autonomous AR systems. The questionnaire also asks the user preference towards a specific activity (e.g., sport, tourism, leisure, game) and the user's preferences towards different sets of smart data: location, weather, biometry and social interaction.

The population sample forms an heterogeneous group, including 56% males and 44% females, with a range of ages between 15 years and 69 years and the average age is 38 years. This population has been anonymously formed via publicizing the online survey on both involved academic entities (ISCTE-IUL and University Lusófona), or international mailing-lists, such as the ACM TCCC-Announce mailing-list. The channels of both entities (E-mail and Online social Network) reach students, academics, but also other samples of population. The ACM TCCC-Announce mailing-lists reaches worldwide research and academic entities. Thus, due care must be taken with possible generalizations of the results. However, it serves our purpose of illustrating how to integrate user preferences into the theoretical framework to built future *MPARS*.

[1] https://www.survio.com/survey/d/S9A7J3I7Q8M9L4G3A
[2] Such as: www.facebook.com and www.linkedin.com

The first question aims to establish previous acquaintance with AR. It was found that 59% have never experienced, tried or worked with an AR technology and 9% are not sure whether they have experienced it or not. We believe that this occurs due to some confusion concerning notions of augmented reality vs. virtual reality [2] [25]. In short, only 32% have really used AR.

Note that the next figures (Figures 2 to 5) present answer percentages, where the negative answers (nothing important at all and not important) and positive answers (important and very important) were grouped together for sake of legibility.

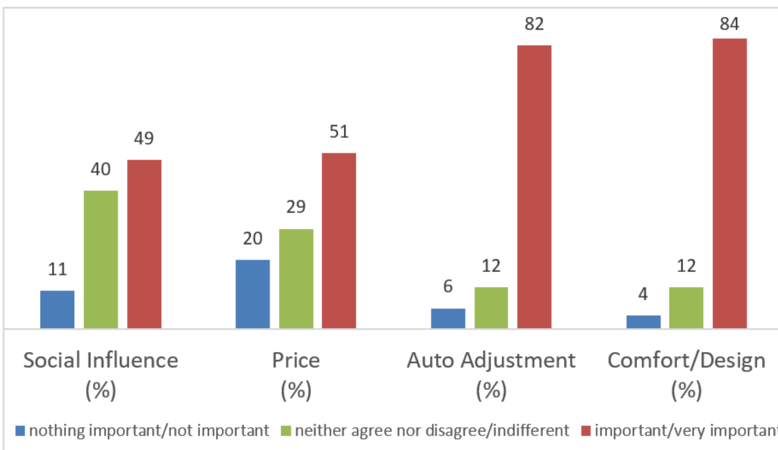

Fig. 2. Importance drivers: Social Influence, Price, Auto Adjustment and Comfort/Design are all preferred - more in Comfort/Design and Auto-Adjustment.

Figure 2 shows the results obtained about the main drivers for using an AR technology, namely social influence, price, auto-adjustment, and comfort/design. It was found that 84% (i.e., 96 participants) look into the comfort/design that the technology brings. Other important driver is the fact that the system automatically adjusts its configuration (features and information) according to the activity (93 participants). Note this also implies higher comfort when compared with a system that calls for manual adjustment. Regarding recommendations, only 11% stated that they would not buy an AR system even if their friends or family had this technology, an aspect which corroborates the importance of social influence. Price is a significant feature: 51% (i.e., 58 participants) will only buy an AR system if it is cheap.

Figure 3 illustrates the preference levels for MPARS in terms of the proposed outdoor activities (such as sport, tourism, leisure, and game). Users consider that MPARS solutions are more important for touristic activities, closely followed by sports and leisure, with game activity as the one that matters the least. These answers are quite interesting since AR is commonly associated with games and leisure applications.

Figure 4 concerns how users perceive the importance of smart data. There is a clear preference for location data (88%, i.e., 100 participants). Nevertheless, weather and biometric data have raised significant preference levels. Social data was less relevant, that is, users seem to consider that social interaction data is less necessary in an AR system, even though the total amount of users considering this as relevant amounts to 54% (i.e., 61 participants). It should be highlighted that 35% of the respondents were indifferent to this feature, which can be an indicator that this is a feature which the users do not understand well yet, thus they do not think it to be important or they don't care. We believe that this occurs possibly due to the lack of understanding on what social

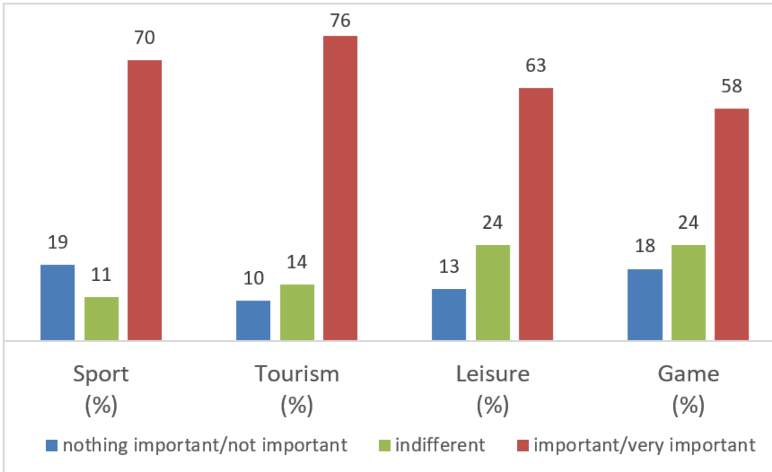

Fig. 3. Preferred activities: Sport, Tourism, Leisure, and Game Activities are all preferred - more in Tourism and Sport.

information is and may also be due to the fear of lack of privacy. Note that, among the participants that had never experienced AR, 33 stated that they preferred geographic information, 26 preferred biometric data, 25 preferred climatic information and only 15 preferred social information.

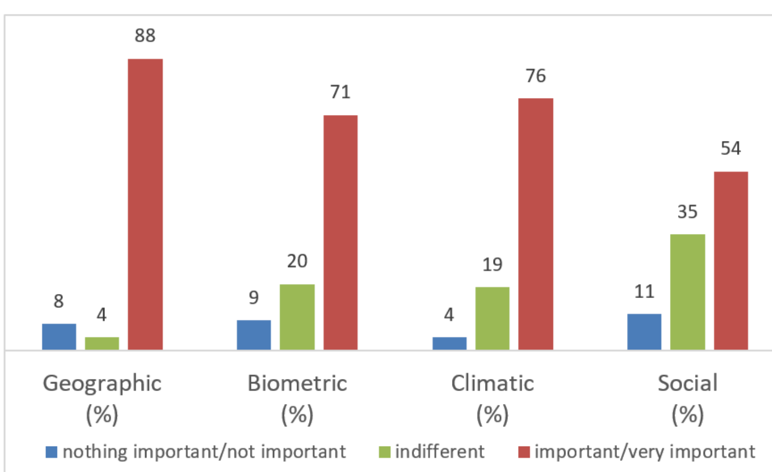

Fig. 4. Geographic, Biometric, Climatic and Social Information are all preferred - more in geographic information.

Figure 5 provides results concerning user preference drivers towards dedicated MPARS, where 82% (i.e., 94 participants) preferred an AR system that can be used via a smartphone, followed by smartwatch and bracelet. The least preferred option is the belt connection.

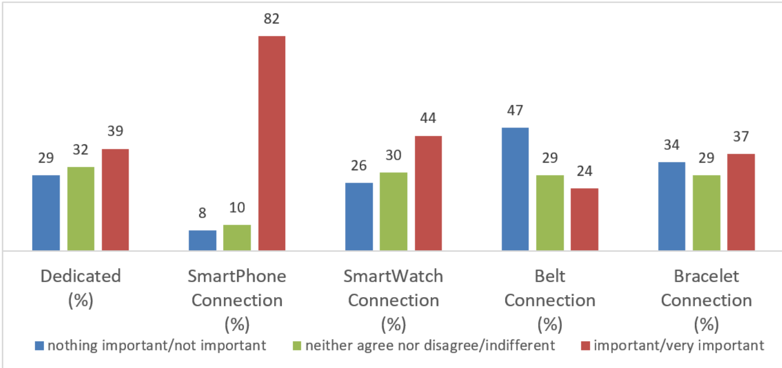

Fig. 5. AR system device preference - more in smartphone connection.

4.2 Discussion

The previous survey provides interesting insights concerning user-preference drivers that should be taken into account in the future design of MPARS solutions, in particular for solutions that are expected to be used in outdoor environments. The aim is to assist in reducing information overload. The survey shows that the majority of participants (93 or 82%) prefer an auto adjustment. Therefore, being able to adequately understand context while on the move is one of the aspects that should be emphasized to accommodate appropriate feedback information.

The survey showed that the majority of users feel that outdoor activities, such as sports and tourism are environments where MPARS are useful. It is also acceptable for end-users to be fed with a specific volume of information either from biometric, climatic, geographical or social data (interaction indicators, for instance).

Touristic activities, either for recreation, or for educational purposes are the most preferred activities, as 76% of participants choose tourism. A *"smart tourist system"* can indeed benefit from AR, especially if it offers a multimodal interface, taking advantage of both speech and gesture interaction, and providing close-to-real-time assistance to the tourist. The software will need to support natural language processing, speech recognition, machine translation and handwriting recognition [36]. The preference for tourism activities is reinforced by the 99 participants who preferred to have regular feedback on geo-location.While for touristic activities users preferring to have regular feedback on geo-location corresponds to 82% of the population sample.

The second most relevant activity is sport, with 70% of participants viewing it as also important. For instance, tracking one's personal training, its quality and success to give feedback, as well as to engage and motivate regular exercising [19]. Or a mobile sensing system for cyclist experience, leveraging opportunistic sensor networking principles and techniques. Although games were the least favourite activity, it is important to remark that today we begin to find mobile applications, like Pokémon Go©, that use games to motivate physical activity, both trying to promote healthier habit. Nevertheless, the potential long-term effects of these mobile applications are still to be studied [1].

Another additional aspect to consider when developing future MPARS is the consideration of aspects of the user's behavior, that is, specific habits and interaction habits, via non-intrusive sensing. Having MPARS fed by information about specific daily habits (e.g., sleep) allows to induce system changes (e.g., shutdown a few sensors to reduce energy consumption) or provide feedback in close-to-real-time to the user [33]. This implies that MPARS need to support a somewhat continuous level of activity recognition [15].

Guidelines derived from the previous findings and discussion provide us with some MPARS requirements in the context of outdoor environments. As such, a MPARS application should:

- be portable and easily adaptable to variable contexts [9] [32];
- be able to be integrated into energy-constrained devices [33] [35];
- work even in case of intermittent connectivity [9];
- integrate smart data to enrich feedback to the user [22];
- prevent information overload, in order to optimize resources and to improve acceptance [25] [30];
- adapt the information to the current context [15] [24].

5 IMPROVING QOE IN MPARS VIA PREVENTION OF INFORMATION OVERLOAD

Preventing information overload improve the QoE, so we propose incorporate the user preference drivers in a model.

5.1 Proposed User-Preference Based Model

To prevent information overload, a first step is to adequately incorporate the user preference drivers last discussed into an AR technology adoption model. The input variables were adopted from related work [24] [28] and their weights have been derived from the questionnaire results. These variables are: *expectancy*, *social influence*, experience (*training* & *habit*), *price*, social suitability (*comfort* & *design*), auto adjustment (*custom settings* & *adjustable system*), *information overload*, and user characteristics (*age* & *gender*). The proposed relative weights (see Table 2) were calculated based on the positive results of the questionnaire, i.e., based on answers in the form of "agree" and "completely agree" or "important" and "very important", using W - the weight of the average X of the number of positive answers:

$$W = \frac{\sum X}{n}, \tag{1}$$

where n is the number of directly related variables described in each row of Table 2.

Based on the calculated weights (Table 2), both Information Overload and Experience have the strongest influence on the adoption of AR technology (83 and 74 respectively). Auto Adjustment and Price preferences come next (71 and 68), and Social Suitability is also a highly rated preference (63). Expectancy (62), Social influence (58), and User Characteristics (57) are the least relevant preferences, from the user perspective.

Our survey on user preferences enables the construction of such a model for the contextual-aware feedback system, illustrated by Figure 6, where the different input variables concern different user characteristics and preferences. The expected output is a weighted index (%) of technology acceptance.

5.2 Integration of our Model in Future MPARS

The model just proposed (Figure 6) tightly incorporates the findings of the questionnaire. However, in order to integrate these findings in a more generalist way, Figure 7 provides a higher-level perspective of a model for a future MPARS since the adoption of MPARS with QoE is heavily influenced by both the technical and the human dimensions. Thus, the general model in Figure 7 presents four main groups of characteristics that influence the level of technology acceptance and thus the satisfaction rate of the user, which is the QoE measurement, i.e., the degree of satisfaction or dissatisfaction with the application provided by the MPARS. The goal of this measure is helping to understand what may be wrong with and how to improve them.

The upper block on the left-hand side of Figure 7 integrates *internal device context*, i.e., the technical dimension (system features, capabilities, and quality). Technical capabilities are expected to influence the user's motivation (upper block on the right-hand side) to use a MPARS over

Table 2. Composition of variables in our model.

Variable	Features	Answers	Average	%
Expectancy	Social Influence	56	62	71
	Price	58		
	Training & Habit	37		
	Comfort & Design	96		
Social Suitability	Expectancy	62*	63	72
	Price	58		
	Training & Habit	37		
	Comfort & Design	96		
Information Overload	Experience	72	83	95
	Custom Settings & Adjustable System	93		
Experience	Expectancy	62*	74	84
	Training & Habit	37		
	Comfort & Design	96		
	Custom Settings & Adjustable System	93		
	Information Overload	83*		
Auto Adjustment	Custom Settings & Adjustable System	93	71	81
	Training & Habit	37		
	Information Overload	83*		
User Characteristics	Social Influence	56	57	65
	Price	58		
Social Influence	Social influence	56	58	66
	Expectancy	62*		
	Age & Gender	57*		
Price	Price	58	68	78
	Expectancy	62*		
	Comfort & Design	96		
	Age & Gender	57*		

*from Average

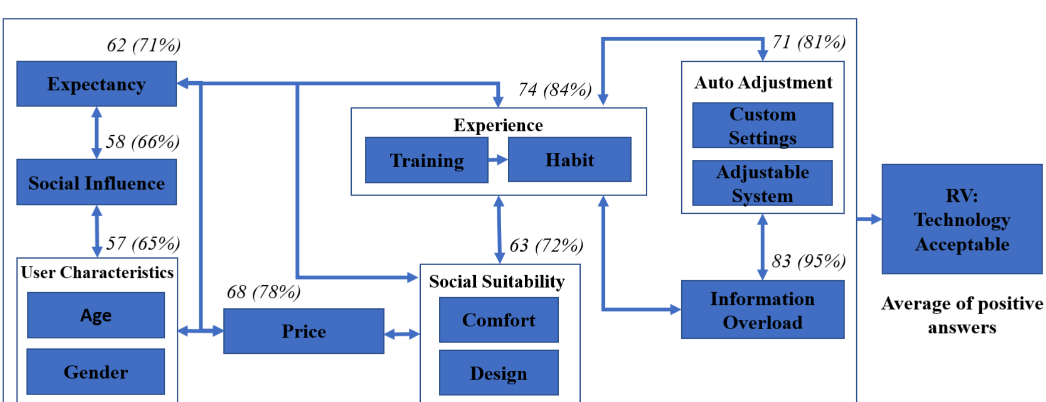

Fig. 6. User-preference Based Model for Technology Acceptance & result variable of technology acceptance.

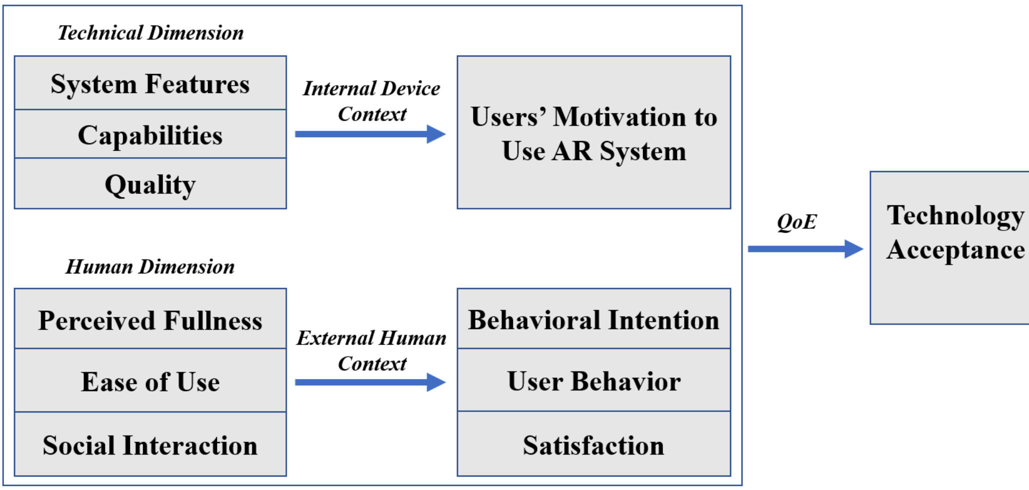

Fig. 7. Integration of the user-preference model in MPARS.

time and space. The lower block on the left-hand side corresponds to *external human context*, which is derived from perceived fullness, ease of use and social interaction. This block integrates human dimension that impact behavioral related aspects: behavioral intention, user behavior and satisfaction. Behavioral intention has been defined as an individual's subjective probability to perform a specified behavior [10], user behavior is their actual behavior, and satisfaction is a feeling of appreciation, or a wish fulfilled. The resulting variable is QoE, contributing to the technology acceptance, which can then be fed into the feedback system to assist in a better adjustment in close-to-real-time.

6 CONCLUSIONS AND FUTURE WORK

This paper debates the evolution from mobile augmented reality systems (MARS) to mobile pervasive augmented reality systems (MPARS), addressing adoption issues and presents the requirements to build technologically accepted future MPARS application that incorporate Quality of Experience, in particular concerning their applicability in the context of outdoor activities.

To increase the acceptance of MPARS and, as a consequence, to improve the QoE of MPARS, a new QoE theoretical model is proposed, aiming user motivation and satisfaction by internal and external context (technical and human dimensions). The model has been derived from prior technology adoption models and from a set of weighted variables for user preferences, such as expectancy, social suitability, information overload, experience (training, habit), auto adjustment (custom settings, adjustable system), user characteristics (age, gender), social influence (comfort, design), and price, whose weights are calculated from the results of a public questionnaire on AR system aspects specifically focused in outdoor activities. The model is expected to be a step towards the creation of MPARS applications with of close-to-real-time feedback of smart information adjusted to the surrounding context, to the support device and the user's (social) context on the go.

Future work needs to study a set of auto-adjustable features derived from context(activity, information, resources), which involves a new process of activity recognition and a new model of energy efficiency, as well as derived from user preferences, for which the proposed model is a cornerstone. By building smarter systems adjusted to user preferences it is possible to improve technology acceptance making it people-centric.

REFERENCES

[1] Tim Althoff, Ryen W White, and Eric Horvitz. 2016. Influence of Pokémon Go on physical activity: study and implications. *Journal of medical Internet research* 18, 12 (2016).

[2] Ronald T Azuma. 1999. The challenge of making augmented reality work outdoors. *Mixed reality: Merging real and virtual worlds* (1999), 379–390.

[3] Ronald T Azuma. 2016. The most important challenge facing augmented reality. *PRESENCE: Teleoperators and Virtual Environments* 25, 3 (2016), 234–238.

[4] Richard P Bagozzi, Paul R Warshaw, et al. 1989. User acceptance of computer technology: a comparison of two theoretical models. *Management Science* 35, 8 (1989), 982–1003.

[5] Mark Billinghurst, Adrian Clark, Gun Lee, et al. 2015. A survey of augmented reality. *Foundations and Trends® in Human–Computer Interaction* 8, 2-3 (2015), 73–272.

[6] Tristan Braud, Farshid Hassani Bijarbooneh, Dimitris Chatzopoulos, and Pan Hui. 2017. Future networking challenges: The case of mobile augmented reality. In *2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS)*. IEEE, 1796–1807.

[7] Julie Carmigniani, Borko Furht, Marco Anisetti, Paolo Ceravolo, Ernesto Damiani, and Misa Ivkovic. 2011. Augmented reality technologies, systems and applications. *Multimedia tools and applications* 51, 1 (2011), 341–377.

[8] Dimitris Chatzopoulos, Carlos Bermejo, Zhanpeng Huang, and Pan Hui. 2017. Mobile Augmented Reality Survey: From Where We Are to Where We Go. *IEEE Access* (2017).

[9] Alan B Craig. 2013. *Understanding augmented reality: Concepts and applications*. Newnes.

[10] Fred D Davis. 1985. *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Ph.D. Dissertation. Massachusetts Institute of Technology.

[11] Arindam Dey, Mark Billinghurst, Robert W Lindeman, and J Swan. 2018. A systematic review of 10 years of augmented reality usability studies: 2005 to 2014. *Frontiers in Robotics and AI* 5 (2018), 37.

[12] Paula Fraga-Lamas, Tiago M Fernández-Caramés, Óscar Blanco-Novoa, and Miguel A Vilar-Montesinos. 2018. A review on industrial augmented reality systems for the industry 4.0 shipyard. *IEEE Access* 6 (2018), 13358–13375.

[13] Borko Furht. 2011. *Handbook of augmented reality*. Springer Science & Business Media.

[14] Tobias Höllerer. 2004. *User interfaces for mobile augmented reality systems*. Ph.D. Dissertation. Columbia University New York, NY.

[15] Ozlem Durmaz Incel, Mustafa Kose, and Cem Ersoy. 2013. A review and taxonomy of activity recognition on mobile phones. *BioNanoScience* 3, 2 (2013), 145–171.

[16] Soo Kyun Kim, Shin-Jin Kang, Yoo-Joo Choi, Min-Hyung Choi, and Min Hong. 2017. Augmented-Reality Survey: from Concept to Application. *KSII Transactions on Internet & Information Systems* 11, 2 (2017).

[17] Akihiko Kitamura, Hiroshi Naito, Takahiko Kimura, Kazumitsu Shinohara, Takashi Sasaki, and Haruhiko Okumura. 2014. Distribution of Attention in Augmented Reality: Comparison between Binocular and Monocular Presentation. *IEICE Transactions on Electronics* 97, 11 (2014), 1081–1088.

[18] Akihiko Kitamura, Hiroshi Naito, Takahiko Kimura, Kazumitsu Shinohara, Takashi Sasaki, and Haruhiko Okumura. 2015. Comparison between Binocular and Monocular Augmented Reality Presentation in a Tracing Task. *Journal of the Institute of Image Information and Television* 69, 10 (2015), J292–J297.

[19] Matthias Kranz, Andreas MöLler, Nils Hammerla, Stefan Diewald, Thomas PlöTz, Patrick Olivier, and Luis Roalter. 2013. The mobile fitness coach: Towards individualized skill assessment using personalized mobile devices. *Pervasive and Mobile Computing* 9, 2 (2013), 203–215.

[20] Nicholas D Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, and Andrew T Campbell. 2010. A survey of mobile phone sensing. *IEEE Communications magazine* 48, 9 (2010).

[21] Rui Pedro Figueiredo Marques and Joao Carlos Lopes Batista. 2017. *Information and Communication Overload in the Digital Age*. IGI Global.

[22] Andreas Möller, Luis Roalter, Stefan Diewald, Johannes Scherr, Matthias Kranz, Nils Hammerla, Patrick Olivier, and Thomas Plötz. 2012. Gymskill: A personal trainer for physical exercises. In *Pervasive Computing and Communications (PerCom), 2012 IEEE International Conference on*. IEEE, 213–220.

[23] George Papagiannakis, Gurminder Singh, and Nadia Magnenat-Thalmann. 2008. A survey of mobile and wireless technologies for augmented reality systems. *Computer Animation and Virtual Worlds* 19, 1 (2008), 3–22.

[24] Rui Pascoal, Bráulio Alturas, Ana de Almeida, and Rute Sofia. 2018. A survey of augmented reality: Making technology acceptable in outdoor environments. In *2018 13th Iberian Conference on Information Systems and Technologies (CISTI)*. IEEE.

[25] Rui Miguel Pascoal and Sérgio Luís Guerreiro. 2017. Information Overload in Augmented Reality: The Outdoor Sports Environments. In *Information and Communication Overload in the Digital Age*. IGI Global, 271–301.

[26] Achille Peternier, Xavier Righetti, Mathieu Hopmann, Daniel Thalmann, Matteo Repettoy, George Papagiannakis, Pierre Davy, Mingyu Lim, Nadia Magnenat-Thalmann, Paolo Barsocchi, et al. 2007. Chloe@ University: an indoor,

mobile mixed reality guidance system. In *Proceedings of the 2007 ACM symposium on Virtual reality software and technology*. ACM, 227–228.
[27] Philipp A Rauschnabel and Young K Ro. 2016. Augmented reality smart glasses: An investigation of technology acceptance drivers. *International Journal of Technology Marketing* 11, 2 (2016), 123–148.
[28] GDMN Samaradiwakara and CG Gunawardena. 2014. Comparison of existing technology acceptance theories and models to suggest a well improved theory/model. *International Technical Sciences Journal* 21 (2014).
[29] Mahadev Satyanarayanan, Paramvir Bahl, Ramón Caceres, and Nigel Davies. 2009. The case for vm-based cloudlets in mobile computing. *IEEE pervasive Computing* 8, 4 (2009).
[30] Ben D Sawyer, Victor S Finomore, Andres A Calvo, and Peter A Hancock. 2014. Google Glass: A driver distraction cause or cure? *Human factors* 56, 7 (2014), 1307–1321.
[31] Rute C Sofia, Saeik Firdose, Luis Amaral Lopes, Waldir Moreira, and Paulo Mendes. 2016. NSense: A People-centric, non-intrusive Opportunistic Sensing Tool for Contextualizing Social Interaction. (2016).
[32] Bruce Thomas. 2003. Challenges of making outdoor augmented reality games playable. In *2nd CREST Workshop on Advanced Computing and Communicating Techniques for Wearable Information Playing*.
[33] Luca Vacchetti, Vincent Lepetit, Michal Ponder, George Papagiannakis, Pascal Fua, Daniel Thalmann, and Nadia Magnenat Thalmann. 2004. A Stable Real-time AR Framework for training and planning in Industrial Environments. In *Virtual and Augmented Reality Applications in Manufacturing*. Springer, 129–145.
[34] Viswanath Venkatesh, James YL Thong, and Xin Xu. 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. (2012).
[35] Chenmeng Wang, Ying He, F Richard Yu, Qianbin Chen, and Lun Tang. 2017. Integration of networking, caching and computing in wireless systems: A survey, some research issues and challenges. *IEEE Communications Surveys & Tutorials* (2017).
[36] Jie Yang, Weiyi Yang, Matthias Denecke, and Alex Waibel. 1999. Smart sight: a tourist assistant system. In *Wearable Computers, 1999. Digest of Papers. The Third International Symposium on*. IEEE, 73–78.
[37] Wenxiao Zhang, Bo Han, and Pan Hui. 2017. On the networking challenges of mobile augmented reality. In *Proceedings of the Workshop on Virtual Reality and Augmented Reality Network*. ACM, 24–29.
[38] Feng Zhou, Henry Been-Lirn Duh, and Mark Billinghurst. 2008. Trends in augmented reality tracking, interaction and display: A review of ten years of ISMAR. In *Proceedings of the 7th IEEE/ACM International Symposium on Mixed and Augmented Reality*. IEEE Computer Society, 193–202.

APPENDIX

A RESEARCH METHOD

This work addresses design and adoption issues for Mobile Pervasive Augmented Reality Systems (MPARS), following the research lines:

- Providing a historical context on augmented reality systems, and use that context to highlight some of the unique characteristics of mobile pervasive AR, namely limitations on connectivity, adaptability, lighting issues, information overload issues, etc.
- The debate of the evolution from Mobile Augmented Reality Systems (MARS) to Mobile Pervasive Augmented Reality Systems (MPARS) and presents the requirements to build technologically accepted future MPARS that incorporate Quality of Experience (QoE), concerning their applicability in the context of outdoor activities.
- The describe of characteristics of MPARS technology, citing examples of COTS systems which have had varying degrees of acceptance and have differing performance.
- Four research questions, covering quality of experience, user preferences, data categories, and improvements to AR systems.
- A survey of conceptual models describing acceptance of technology more generally, some of which are specific to mobile AR.
- The general approach using a literature survey to identify gaps in existing knowledge, conducting a user questionnaire to get data to inform the development of a model, and proposing the model that results from those data.

- Collecting data describing users' attitudes about MPARS, the results of which are used to motivate a new conceptual model for describing the quality of experience of MPARS.
- Incorporating the identified user preference drivers into an AR technology adoption model.

2 WORK OVERVIEW

The overview of the work is:

(1) Introduction of the concept.
(2) Research questions.
(3) Related work.
(4) Debates on the challenges that current technology adoption models have in outdoor environments.
(5) Relevant user preference indicators to building future MPARS applications.
(6) Description of a new model, including the user driver preferences findings.
(7) Conclusions of the document and guidelines for future work.