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ORIGINAL ARTICLE

Understanding augmented reality adoption trade-offs in production environments from the perspective of future employees: A choice-based conjoint study

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Abstract

The implementation of augmented reality (AR) systems in production environments is associated with a variety of advantages, such as productivity gains, lower costs and reduced operating times. Despite these potential benefits, the lack of user acceptance due to issues such as privacy concerns constitutes a barrier to diffusion in workplace environments. In order to better understand the issues surrounding AR acceptance, we employed a conjoint study to empirically examine the trade-offs that future employees perceive when being involved in adopting such systems. Using a hierarchical Bayes estimation, we discover that functional benefits such as productivity gains and safety enhancement are the main adoption drivers. In contrast, future employees indeed perceive monitoring through head-worn AR devices as negative. However, a complementary cluster analysis indicates that not all respondents share a negative view of monitoring, and one third are likely to share their performance data with employers. We identify three groups with significantly different utility patterns. Furthermore, we monetize the value of privacy to determine compensation payments. The results may help employers, decision-makers, software solution providers as well as researchers in the information systems domain to better understand the factors surrounding acceptance of AR assistance systems. To the best of our knowledge, we are the first to address this issue using conjoint analysis.

Keywords Augmented Reality · Adoption Trade-Offs · Choice-Based Conjoint Analysis · Privacy

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1 Introduction

Augmented reality (AR) systems are expected to become ubiquitous in modern production environments (Kagermann et al. 2013; Rüßmann et al. 2015). They are an essential component of Industry 4.0, providing context-sensitive information to employees to support knowledge-intensive tasks such as maintenance, assembly and picking processes (Liao et al. 2017; Masood and Egger 2019; Metzger et al. 2017). Such systems can reduce operating time, improve production flexibility, increase product quality, lower cost and enhance user safety (Bosch et al. 2017; Henderson and Feiner 2011; de Souza Cardoso et al. 2020). Given these advantages, an increasing number of industrial companies have experimented with AR technologies in recent years (Staufen AG 2019). For example, the internationally renowned automotive manufacturer Volkswagen implemented an AR-based user assistance system to increase productivity and ensure process safety (Volkswagen AG 2015).

Despite the manifold benefits of AR systems, the vast majority of implementations still constitute pilot projects (Oesterreich and Teuteberg 2018; Palmarini et al. 2018; Staufen AG 2019). To better understand the issues impeding large-scale implementations of AR, several studies have identified technological, organizational and environmental barriers to adoption (e.g. Syberfeldt et al. 2016; de Souza Cardoso et al. 2020). Apart from highlighting technical issues such as integration into the existing information technology (IT) infrastructure and technological maturity, these studies indicate that technology acceptance poses a bottleneck for the diffusion of AR in industrial environments. In particular, safety and privacy concerns constitute major challenges to the adoption of AR (Berkemeier et al. 2019; Egger and Masood 2020). The restricted field of view associated with the devices can increase the risk of accidents in industrial environments (Holm et al. 2017; Maly et al. 2017), and the sensors might enable supervisors to monitor employees by recording location, performance and error rates (Syberfeldt et al. 2016; Tunçalp and Fagan 2014). Thus, Amazon's filing of a patent to monitor warehouse staff through the use of AR glasses raised major privacy concerns among the public (Bernal 2018).

However, little is evident about users' concrete attitudes towards head-worn AR systems in industrial settings (Egger and Masood 2020; Grubert et al. 2010; Jetter et al. 2018). Prior research indicates that technology acceptance models (TAMs) are scarcely transferrable to AR systems due to their novelty (Leue and Jung 2014; Rauschnabel and Ro 2016). Experiments involving end-users in production settings, in turn, have so far mainly examined the impact on task outcome taking into account time, error rates and cognitive demand (e.g. Bottani and Vignali 2019; Theis et al. 2015). These experiments reveal that AR systems particularly facilitate the work for young and inexperienced employees (e.g. Jetter et al. 2018; Masood and Egger 2020). To the best of our knowledge, there is only one study examining preferences of AR systems in production settings. Jetter et al. (2018) found that reduction of time and errors constitutes a key benefit influencing the perceived usefulness and the attitude towards using AR systems.

However, this study did not examine the roles of safety and privacy due to its focus on mobile devices. As a result, the questions of how employees perceive AR adoption, in particular with regard to safety concerns or privacy violations, and which countermeasures might reduce these barriers remain unanswered (Syberfeldt et al. 2016; Masood and Egger 2019; de Souza Cardoso et al. 2020).

A promising approach to clarify these issues is conjoint analysis (CA) (Naous and Legner 2018). CA enables the extension of TAMs by combining factors such as usefulness with attributes such as monitoring or safety to obtain a more contextual view of user attitudes. In contrast to TAM studies, CA provides information on the value that the respondents attribute to specific artifact characteristics and enables the identification of trade-offs among attribute levels (Bajaj 1999; Davis 1989; Krasnova et al. 2009). Complementary clustering can reveal sub-segments with similar utility patterns (Burda and Teuteberg 2014). These insights can assist companies to implement AR on a large scale by enabling them to appropriately address user needs. In addition, these findings can help the research community to explain the use of augmented reality glasses on the user level (Bajaj 1999). Given these capacities, we aim to investigate the utility structures of AR systems in industrial settings from the employee perspective by conducting a choice-based conjoint study. To this end, we surveyed 204 students, as they represent future employees and are thus considered a particular target group of AR systems (Kinsey and Asif 2018). Thereby, the primary focus of our study is to answer the following research question (RQ):

> **RQ:** What preferences do future employees have when choosing AR assistance systems, what is the relative importance (RI) of certain attributes and what trade-offs can compensate for privacy violations?

To answer the RQ, we analyzed the trade-offs between productivity gain, performance monitoring, safety enhancement and ease of use resulting from the use of an AR system. We also included a financial incentive to determine compensation payments for privacy violations. Based on the results, we segmented the respondents into three clusters to enhance the understanding of different attitudes within the workforce. To the best of our knowledge, we are the first to address this research problem using CA and, in so doing, to assess financial compensations for the deployment of monitoring capabilities and identify clusters of adopters.

The remaining parts of this work are organized as follows: Sect. 2 introduces the concept of AR, provides an overview of technology adoption theories and summarizes prior research on AR adoption in workplace settings. Section 3 presents the research design of this investigation. The results obtained from the data analysis are explained in Sect. 4. Section 5 discusses these results as well as the implications and limitations of this study. Finally, we conclude by summarizing our findings.

2 Background and related work

2.1 Augmented reality

In general, AR describes a technology that supplements the user's natural perception with virtual information in real-time (Azuma 1997). AR is closely related to the concepts of assisted reality, mixed reality and virtual reality. However, the distinction between these concepts is sometimes ambiguous in public discussion (Berkemeier et al. 2019; Dwivedi et al. 2020). To resolve this inconsistency, Dwivedi et al. (2020) recently proposed an industry-specific classification scheme for extendes realities (XR, see Fig. 1).

According to this conceptualization, AR is an umbrella term that ranges from assisted reality to mixed reality. While assisted reality enhances the user's field of view by displaying 2D information, mixed reality defines a very mature form of AR technology, where virtual and real objects are no longer distinguishable for the user. To provide additional information via AR, devices such as smartphones, tablets and glasses can be used (Carmigniani et al. 2011). Following Dwivedi et al. (2020), this paper limits AR to the use of head-worn displays in the form of augmented reality smart glasses (ARSG). These glasses-like devices include cameras and sensors to detect the environment, thereby showing context-sensitive information on transparent displays in the user's field of vision (Rauschnabel et al. 2016; Ro et al. 2018).

With the launch of Google Glass in 2013, ARSG became available on the consumer market. However, barriers such as societal privacy concerns and a lack of fruitful use cases hindered widespread adoption in the consumer market (Koelle et al. 2017). In response, Google retreated from the consumer market and began specializing exclusively in B2B customers in 2017. Since then, numerous suppliers like Microsoft and MagicLeap have joined these developments by providing devices that are dedicated to corporate requirements (Magic Leap 2019; Microsoft 2019). Concurrently, a comprehensive enterprise AR solution ecosystem emerged (AREA 2020; Schuir et al. 2020). As a consequence, many use cases have been developed within the production context. These use cases can be divided into the areas of production support, quality control, safety management, maintenance, training, logistics, human–machine collaboration and design (Egger and Masood 2020; Pierdicca et al. 2017). For instance, in production support, AR assistance systems can

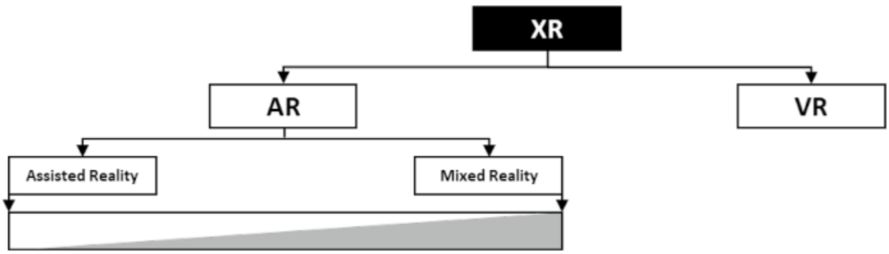

Fig. 1 Conceptualization of extended realities in accordance with Dwivedi et al. (2020, p. 16)

help lower the human-induced error rate by applying object recognition techniques (Westerfield et al. 2015). Likewise, the display of packing lists in the field of vision of logistics staff improves process efficiency (Reif and Günthner 2009).

In view of these potential uses, smart manufacturing associations and further stakeholders of the AR ecosystem promote ARSG as a "key component in modern manufacturing environments, production labs … and engineering organizations" (Vital Enterprises 2020, p. 7) as they can seamlessly connect workers and the smart factory (AREA 2018; Kaul and Wheelock 2016; Oesterreich et al. 2020, Vuzix Corporation 2018). However, the diffusion of ARSG technology is still in a formative stage: A recent survey by Capgemini Research (2018) reveals that two thirds of German AR adopters still undergo the pilot phase with small-scale implementations. As a result, large-scale adoptions remain a rarity (Palmarini et al. 2018; Staufen AG 2019).

2.2 Technology adoption

To explain the adoption of IT such as AR, information systems (IS) research has developed various technology adoption and acceptance models (King and He 2006; Oliveira and Martins 2011). In this section, we will briefly provide an overview of these models before discussing prior research on AR adoption. In line with prior studies (e.g. Hein and Rauschnabel 2016), we distinguish between the organizational and the user level, where the former refers to the decision-making of stakeholders such as top managers. This decision-making, in turn, influences the user level (i. e. workers wearing the devices).

A widespread approach to explaining technology adoption on the corporate level is the technology–organization–environment (TOE) framework, coined by DePietro et al. (1990). The TOE framework postulates that the technical, organizational and environmental contexts of an enterprise influence the decision on technology adoption. Thereby, the technological context reflects technical, functional and other qualitative properties of innovations (e.g. relative advantage); the organizational context targets the company's own resources and characteristics (e.g. structure) and the environment represents the external influences on an organization (e.g. legal requirements). The TOE framework has already been applied to study adoption decisions in cloud computing (Alshamaila et al. 2013), RFID systems (Wang et al. 2010) and industrial AR (Egger and Masood 2020). However, the TOE framework provides little information about what factors explain the adoption of technologies among individuals (Oliveira and Martins 2011).

On the individual level, acceptance models postulate that a number of factors influence the intention to use a technology. Drawing on the theory of reasoned action (Fishbein 1979), Davis (1989) developed the TAM, which predicts the dependent variable intention to use based on the two independent variables that describe the perceptions of a user towards a technology, namely perceived ease of use and perceived usefulness. While the ease of use refers to the degree to which the system can be intuitively controlled, the usefulness refers to the functional benefits for job performance (Davis 1989). Given its simplicity, TAM has become the most widespread model in IS research (King and He 2006). However, it is subject to serious limitations since it only integrates two key attitudes to explain the intention to use (Bagozzi 2007; Benbasat and Barki 2007). Therefore, prior studies with different types of users and technologies have found a wide variation in the robustness of the model (Legris et al. 2003). As a consequence, researchers have extended TAM by including latent determinants such as demographics, job relevance and experience, social influence and culture (Van Der Heijden 2004; Venkatesh and Davis 2000; Venkatesh and Morris 2000). Among the most popular extensions is the unified theory of acceptance and use of technology (UTAUT), which postulates that facilitating conditions and a user's behavioral intention to use a technology predict the use behavior. The behavioral intention, in turn, is predicted by the performance expectancy, social influence and effort expectancy. In addition, factors such as age, gender, experience with the technology and voluntariness mediate the relationships of these constructs with the behavioral intention to use and the use behavior (Venkatesh et al. 2003).

However, prior research indicates that these extensions are not sufficient to explain the acceptance of ARSG, as this technology combines unique characteristics of wearable technologies and AR systems (Rauschnabel and Ro 2016). For instance, Masood and Egger (2019, p. 7) conclude that prior adoption models are "too limited" to explain the adoption of AR among employees within organizations. As a result, more research on AR acceptance at the individual level is required.

2.3 Augmented reality adoption on the corporate level

To fill the aforementioned research gap, we examined prior research at the beginning of our study. We began by reviewing scholarly and practical literature that deals with the adoption of ARSG in industrial environments on the corporate level.

Given the slow diffusion, Masood and Egger (2019, 2020), de Souza et al. (2020) and Danielsson et al. (2020) have recently shed light on the adoption barriers and implementation challenges regarding AR systems in industrial environments on the corporate level. In addition, associations such as the Augmented Reality Enterprise Alliance (AREA 2019) and consultancy agencies like Capgemini (2018) have published case studies and whitepapers examining adoption determinants from a managerial perspective.

From a technical perspective, these studies reveal that the integration of AR into the existing infrastructure and the level of technical maturity have so far deterred companies from adopting it. Thus, existing IT infrastructures need to be aligned to the devices (AREA 2019; Danielsson et al. 2020; Herzog and Beharic 2020). Likewise, user interface design, weight and tracking technologies still pose challenges (Danielsson et al. 2020; Koelle et al. 2017; Masood and Egger 2019, 2020; de Souza Cardoso et al. 2020). In addition, the hardware must be adapted to health safety standards (Hao and Helo 2017). Moreover, environmental aspects such as worker rights, standardization and the external support of industry associations and tech providers are relevant for adoption (AREA 2019; Masood and Egger 2020). From the organizational perspective, meanwhile, factors like resources, costs, the alignment of shop floor processes and organizational structures influence adoption (AREA 2019; Capgemini Research Institute 2018; Herr et al. 2018; Masood and Egger 2020; Porcelli et al. 2013).

As outlined in Sect. 1, also the acceptance of AR systems is an important influencing factor. Acceptance problems occur from the decision-maker level, with business line managers and corporate executives, down to the worker level. Thus, resistance factors such as uncertainty, fear of change and lack of trust can prevent business executives from adopting AR (AREA 2019; Masood and Egger 2020). For instance, uncertainty about benefits prevents managers from implementing the technology. Companies planning to adopt AR are therefore advised to early invest in market research to improve the managers' understanding of AR systems (AREA 2019). On the worker level, the lack of intention to use represents a barrier to the successful implementation of ARSG (Masood and Egger 2019). Workers initially have a positive attitude toward the technology, but then reject it (AREA 2019). However, dedicated investigations using TAMs tailored to ARSG in the industrial context are still rare (Egger and Masood 2020; Jetter et al. 2018).

2.4 Determinants of acceptance and resistance towards augmented reality

Despite the aforementioned research gap, the results of previous experiments and surveys on smart wearables and ARSG indicate some factors that are closely related to the intention to use AR systems (e.g. Holm et al. 2017), thereby providing an entry point for our study. In particular, previous research has highlighted four dimensions that drive both acceptance of and resistance towards AR systems: (1) the ergonomics of the devices, (2) the user interaction with the devices, (3) privacy and information security concerns and (4) functional benefits.

With regard to ergonomics (1), hardware characteristics such as the weight of headsets, the field of view, the presentation of information and health aspects are of particular importance to user acceptance (Masood and Egger 2019; Real and Marcelino 2011). For instance, Berkemeier et al. (2019) found that the lack of wearing comfort, resulting from the substantial weight of wearable devices, reduces the intention to use them in workplace settings. In addition, the restricted field of vision of ARSG can lead to disorientation, headaches, dizziness and visual problems (Hao and Helo 2017; Herzog and Beharic 2020; Real and Marcelino 2011; de Souza Cardoso et al. 2020; Yew et al. 2016). Further factors relating to ergonomics include battery life and incompatibility with conventional glasses (Berkemeier et al. 2019).

Concerning the interaction modalities[1] (2), a study by Basoglu et al. (2017) suggests that input using hand gestures is preferred to touchpads and voice control. In manual activities, however, hand gestures can turn out to be disruptive to the user and the task (Kammler et al. 2019; de Souza Cardoso et al. 2020). This misalignment between interaction and task, in turn, can result in rejection of the technology (AREA 2019). The ease of use resulting from the interaction modalities and user

[1] A detailed investigation of the interaction modalities can be found in Lik-Hang and Pan (2017), Lee and Hui (2018).

interface is an important aspect positively influencing the intention to use (Brancati et al. 2015; Stoltz et al. 2017). Although smart glasses were meant to be intuitive, users have complained about difficulties interacting with them (e.g. due to inaccurate input modalities, Lee and Hui 2018).

Privacy and information security risks (3) are mentioned and discussed most frequently in the literature examining employee acceptance of AR (Hofmann et al. 2017; Khakurel et al. 2018; Motti and Caine 2015). The sensors (GPS, motion and temperature) offer capabilities for monitoring health and activity (for instance by recording movement profiles), resulting in violations of users' privacy (Hobert and Schumann 2017; XR Safety Initiative 2020). Likewise, the built-in cameras enable the surveillance of employees by broadcasting, following and recording them while working (Tunçalp and Fagan 2014). These cameras can also invade the privacy of bystanders surrounding the users (Koelle et al. 2018). Thus, beta testers wearing Google Glass in public were insulted as "glassholes" because people in their surrounding area were afraid of being filmed (Kudina and Verbeek 2019, p. 428). To understand how the privacy of users and bystanders influence ARSG adoption decisions, Rauschnabel et al. (2018) developed and tested a theoretical model incorporating these privacy risks as a predictor of the adoption for ARSG among consumers. The authors found the degree to which the privacy of others is threatened has a strong impact on adoption decisions. In contrast, the degree to which one's own privacy is threatened by ARSG does not have an impact on ARSG decisions. However, these results are not fully transferable to business contexts. The requirements analysis conducted by Berkemeier et al. (2019) revealed that privacy by design is an important design goal for ARSG destined for the workplace. Of course, employers must observe locally applicable laws. In Germany, for example, the Federal Data Protection Act and the EU General Data Protection Regulation (GDPR) provide the legal scope for processing personal data (Custers et al. 2018). The GDPR applies the guiding principles of data minimization, data transparency and data security, such that employee data on performance profiles may only be processed anonymously (Berkemeier et al. 2019). In addition, personalized performance profiles may only be created with the employee's explicit consent (XR Safety Initiative 2020). Jacobs et al. (2019) found that the introduction of monitoring measures reduces the intention to use wearables in workplace settings. The results of their study suggest that a financial incentive of between \$100 and \$200 may foster adoption among employees. Likewise, Hein and Rauschnabel (2016) discussed the implementation of financial incentives to motivate active use of ARSG. In fact, prior research from the consumer sector has already proven that users might trade their privacy against other benefits (Hui et al. 2006).

With regard to functional benefits (4), AR systems can increase safety, health and productivity of workers by displaying additional information (Maltseva 2020; Tatić and Tešić 2016, 2017). According to a survey by Jacobs et al. (2019), employees are most likely to use smart devices when these improve work safety. When the devices are to increase productivity or control worker activities only, employees are less willing to use them. In contrast to this finding, a recent survey by Jetter et al. (2018) indicates that the productivity increase is the most important benefit of AR systems from the employee point of view. They found that the respective key performance indicator, reduction of time and errors, positively influences the perceived usefulness and the intention to use ARSG. However, if these benefits are not evident, users may reject the use of ARSG (AREA 2019).

To summarize, both hardware- and software-induced factors contribute to acceptance of and resistance towards AR systems in production environments. The former have already been addressed by various studies (e.g. Basoglu et al. 2017), and they can be expected to continuously improve (Bezegová et al. 2018; Kumar et al. 2018). However, employers can make their own contribution in the selection of the software and its benefits. Therefore, we investigate the utility structures of AR systems on the basis of a CA, taking into account different benefits as well as privacy configurations, and comparing them to factors such as ease of use to gain a more holistic view.

3 Research approach

In general, CA is based on the work of Green and Rao (1971). It can be applied to experimentally obtain preference judgments about competing product alternatives by uncovering the hidden rules individuals use to decide between different products or services. The main assumption behind CA is that consumers see a product as a combination of attributes (e.g. price) that have different levels (e.g. €10, €20). Based on different attributes with varying levels, various product alternatives can be defined in the form of stimuli (Green and Rao 1971).

In traditional conjoint analysis (TCA), respondents are asked to rank stimuli. Based on these rankings, the part-worth and the RI of the individual attributes with their levels can be calculated (Chrzan and Orme 2000; Green and Rao 1971). However, several adaptations of the method have emerged in research over the past four decades (Steiner and Meißner 2018). In this study, we apply a choice-based-conjoint analysis (CBCA), which is among the decompositional approaches of CA (Green and Srinivasan 1990). Compared to TCA, CBCA offers the advantage of simulating real choices as respondents face various choice situations and select the alternative that is most attractive to them. In addition, respondents can select no alternative (no-choice option) (Wittink et al. 1994). Based on the answers, the aggregated utility values for the individual product alternatives, the RI of the attributes and the part-worth utilities of the individual levels can be estimated (Green and Srinivasan 1990).

Following Burda and Teuteberg (2014, 2016), we proceeded by applying a four-step research approach. First, we conducted a pre-study to determine the appropriate attributes and to define the respective levels (cf. Section 3.1). We then designed and implemented the experiment using an online survey (cf. Section 3.2). Third, we collected the data by applying a student sample strategy (cf. Section 3.3). Finally, we used R Studio to obtain the results using a hierarchical Bayesian estimation. In addition, we clustered the respondents based on their preferences (cf. Section 3.4).

3.1 Selection of attributes and definition of attribute levels

To derive the attributes, we first reviewed relevant literature (cf. Section 2). Based on these results, we conducted semi-structured interviews with six employees of production companies that had already experimented with AR systems to determine the main drivers for the adoption of ARSG among employees, following Green and Srinivasan (1990). Next, to define levels, we followed the guidelines of Orme (2002), who recommends formulating unambiguous and assessable properties that are mutually exclusive. In addition, the number of levels per attribute should be approximately equally distributed to avoid the "number-of-levels effect" (e.g. Verlegh et al. 2002). Moreover, a moderate (< 5) number of levels for CBCA assures the predictive model quality by collecting high numbers of data per attribute level. Considering these guidelines, we opted for a maximum of three levels per attribute, each containing a short textual description and, wherever possible, a figure to facilitate the respondents' decision-making process. For the specification of the attribute levels, we used existing literature and analyzed the state of practice based on whitepapers and company websites.

During the interviews, the participants emphasized the importance of the usefulness of the assistance system. In line with Jetter et al. (2018), we found that productivity gains were of particular importance in production environments. In addition, the respondents indicated that impact of the system on user safety was of particular interest to perceived utility. Thus, we integrated productivity gains and impact of the system on user safety as attributes in the present study. In operationalizing the levels for the attribute productivity gain, we integrated values that have been reported in the scientific literature and company reports. For instance, Bassan and Vancluysen (2018, p. 3) state that smart "glasses are proven to provide 15 percent efficiency improvements … by effectively guiding workers and avoiding mistakes," whereas a laboratory experiment by Westerfield et al. (2015) reveals productivity gains of up to 30%. However, there are also studies indicating that employing ARSG does not lead to any productivity gains (de Souza Cardoso et al. 2020). Based thereupon, we defined the three levels no increase, slight increase and high increase and complemented them with the respective numeric figures (0%, 15% and 30%). In operationalizing the levels for the attribute of safety enhancement, we decided to integrate the two levels presence of safety and non-presence of safety since safety-enhancing solutions are currently still under development and have not yet been studied in-depth (Pierdicca et al. 2020; Rosi et al. 2018).

In addition, ease of use constitutes another important factor. The respondents noted that the specific input modalities used by the system—such as speech, gestures or facial expressions—are less important than how long it takes the user to learn how to handle the system. This finding is in line with previous studies that have attributed great importance to perceived ease of use in determining the utility of systems in general (Davis 1989; Venkatesh et al. 2003) and the utility of wearables in particular (e.g. Brancati et al. 2015; Cha et al. 2015; Kim and Park 2014). To operationalize the corresponding levels, we followed prior studies by integrating the levels easy to use and complex to use into our survey (Luo et al. 2013).

Finally, the respondents confirmed the role of performance monitoring policies on ARSG acceptance among employees. As outlined in Sect. 2, personalized performance profiles may only be recorded with the explicit consent of employees, whereas anonymous monitoring is legitimized in Germany. Jacobs et al. (2019) found that financial incentives are an effective instrument to promote adoption among employees. We discussed this option and decided to investigate the trade-off between monitoring and financial compensation by including both attributes. To operationalize the monitoring attribute, we followed the considerations of prior studies (e.g. Berkemeier et al. 2019) and integrated the levels none, recording of anonymous performance and movement profiles and recording of personalized performance and movement profiles. In addition, the study of Jacobs et al. (2019) inspired us to integrate financial incentives of €0, €100 and €200. Table 1 summarizes the five attributes, their descriptions and corresponding levels.

3.2 Conjoint questionnaire design and implementation

The survey is divided into four parts: (1) introduction, (2) choice scenarios, (3) questions about attitudes toward different constructs and (4) demographic questions.

To first familiarize the respondents with AR systems and the application context, we used scenario-based methods (Sutcliffe 2003). More precisely, we adopted the vignette technique developed by Atzmüller and Steiner (2010). The participants were asked to imagine they worked for an automobile manufacturer in a car assembly position. Due to an increasing number of accidents, long breaks taken by employees and high error rates, the manufacturer had decided to implement an AR-based assistance system. The participants were also asked to watch a video showing the user interface and the operational mode of smart glasses. They were told that the employer had already selected the best hardware available and that only the software remained to be chosen. In this context, the participants were to engage in the decision-making process on behalf of the employees. This approach represents a common practice in industrial digitization projects, as companies are advised to actively involve the staff in decision-making processes from the very beginning instead of using top-down approaches (Hirschheim and Newman 1988; Merhar et al. 2018; Rizzuto and Reeves 2007). Before proceeding to the conjoint part of the survey, participants were given instructions. The individual attributes and levels were explained in a table.

Subsequently, the respondents were asked to select their decisions with a full profile design in the second part of the survey, each involving two different stimuli (Chrzan and Orme 2000). Overall, the literature does not provide a clear recommendation on the best number of choice sets for a study (Burda and Teuteberg 2014): some scholars state that validity grows with an increasing number of choices due to learning effects, others argue that too many choices carry the risk of cognitive burdens (c.f. Hess et al. 2012). In view of these inconsistencies, we were guided by the results of a meta-study on the use of CA that indicated a median of 16 choice sets (Wittink et al. 1994). Thus, we synthesized a design consisting of 15 stimuli that we randomly combined in the survey. We also integrated two further choice scenarios

Table 1 Attributes and attribute levels

Attribute	Attribute description	Attribute levels
Productivity gain	Impact of the system on the quality of the work results, taking time into account	*1) No Increase:* The system does not lead to a productivity increase *2) Slight Increase:* The system leads to a slight productivity gain of 15% *3) High Increase:* The system leads to a strong productivity gain of 30%
Safety enhancement	Presence of safety enhancement capabilities (i.e. collision detection)	*1) No safety enhancement:* The system has no safety enhancement functions *2) Presence of safety enhancement:* The system increases users' safety (e.g. by warning of moving forklift trucks and robots)
Ease of use	User's perspective on the degree to which the system can be intuitively controlled	*1) Easy to use:* The system is easy to use, so that users are familiar with the operation of the system after a few minutes *2) Complex to use:* The operation is difficult for users, and they need several days to get used to it
Performance monitoring	Possibilities for monitoring the performance, error rates and location of employees on the shop floor	*1) None:* No performance and movement profiles are stored *2) Recording of anonymous performance and movement profiles:* The employer (i.e. supervisor) can assess anonymous movement and performance profiles of employees (i.e. to assess error rates) *3) Recording of personalized performance and movement profiles:* The employer (i.e. supervisor) can assess personalized movement and performance profiles of employees (i.e. to assess error rates)
Financial compensation	Additional financial incentive the employees receive each month for wearing the system	*1) €0/month* *2) €100/month* *3) €200/month*

to serve as hold-out sets that could be used later to evaluate how well the calculated conjoint utilities predict the responses (McCullough 2002). Following the recommendation of Haajer et al. (2001), we additionally integrated a *no-choice* option into every choice set to ensure a realistic selection situation. Thus, for each question, the respondents were given two different AR system stimuli and a no-choice option. To create these choice situations, we used the statistics software R with the extension Algorithmic Experimental Design for the production of a reduced factorial design from our full factorial design ($3 \times 2 \times 2 \times 3 \times 3 = 102$ stimuli, Wheeler 2019) and adopted the R script by Burda and Teuteberg (2014). According to Chrzan (1994), the order of selection situations represents a further source of data bias in CBCAs because cognitive performance declines toward the end of the study and participants use different heuristics at the beginning than at the end. To address these issues, we implemented a function that randomly divided the participants into two groups that completed the 17 selection situations in opposite orders (Chrzan 1994; Chrzan and Orme 2000). In concluding the preparations in R, we applied effects coding for the translation of the questionnaire for the data analysis step (Hensher et al. 2005).

To obtain a more detailed understanding of CA results, cluster analyses often accompany these studies in marketing practice (DeSarbo et al. 1995). We applied clustering to identify different adopter groups with similar attitudes towards AR systems. In order to draw a coherent picture of these clusters, we measured the respondents' attitudes towards different constructs and collected the user characteristics (e.g. gender) at the end of the survey. As CAs do not permit conclusions about the general attitude towards the technology under consideration, we focused on the respondents' opinions towards ARSG. In addition, we integrated constructs that stem from findings of the related studies (see Sect. 2) or were emphasized during the interviews (e.g. perceived privacy risk). The operationalized constructs are presented in Table 2 and were surveyed using a 7-point Likert scale (see Appendix A).

Concluding the design phase, we implemented the questionnaire in the form of an online survey using the software Limesurvey (2020). To ensure the clarity of the questions, 10 research colleagues pretested the survey, responded to all questions, provided feedback on survey duration, wording and item measurement and suggested improvements. Based on these responses, the survey was revised, validated and finally reviewed by three other colleagues.

3.3 Data collection

Subsequently, we invited students in our faculty via email to participate in the survey. Although subject to criticism (see Compeau et al. 2012), we opted for the student sample strategy for several reasons: First, younger people, known as "digital natives" (Prensky 2001), are considered early innovators in terms of adopting new technologies. Therefore, they can be regarded as the accelerators of digitization by demanding innovative support tools in working environments. Simultaneously, younger people are considered change agents with regards to digitization in workplaces (Biahmou et al. 2016; Kinsey and Asif 2018). Second, strategic whitepapers and industry association reports advocate recruiting employees with a positive

Table 2 Operationalization of constructs and measurement items

Construct	Description	Items
Attitude Toward Using ARSG	Refers to positive or negative feelings with regard to the use of ARSG in the workplace (Venkatesh et al. 2003)	(Rauschnabel and Ro 2016; Venkatesh et al. 2003)
Intention to Use	Refers to the individual willingness to use ARSG in the workplace (Ajzen 1991)	(Ajzen 1991)
Personal IT Innovativeness	Describes the individual willingness to experiment with innovations and adopt them (Agarwal and Prasad 1998)	(Agarwal and Prasad 1998)
Perceived Privacy Risk	Describes the individual willingness to share personal data in view of a possible invasion of privacy (Li et al., 2014; Malhotra et al. 2004)	(Li et al. 2014; Malhotra et al. 2004)
Legal Trust	Refers to the level of confidence that the laws protect one's privacy (Mcknight et al. 2002)	(Mcknight et al. 2002; Krasnova et al. 2009)

attitude towards IT such as ARSG as key users to encourage adoption (AREA 2019; Kinsey and Asif 2018). Third, as traditional factory jobs are rather unattractive for digital natives, the use of AR systems is encouraged as a means of increasing the attractiveness of work for younger workers (Kinsey and Asif 2018; Vuzix Corporation 2018). Thus, innovative technologies such as ARSG are regarded as a powerful instrument to "engage and train tomorrow's digital workforce" (World Economic Group 2017, p. 30). Fourth, many students have experience in the industrial sector as a result of previous education, internships or side jobs. Over half of university students in Europe work alongside their studies, many of them in manufacturing settings (Masevičiūtė et al. 2018). Finally, given the projection that the diffusion of AR systems may continue for another decade (Bezegová et al. 2018; Rüßmann et al. 2015), the respondents are likely to be exposed to AR systems over the course of their careers (e.g. in the role of decision makers).

Thus, we collected a total of 218 completed questionnaires. As an incentive for detailed responses, participants could win an Amazon gift card (Porter and Whitcomb 2003). In the subsequent screening process, we excluded 14 respondents due to very short processing time or incomplete answers. The average respondent processing time, including reading the introductory vignette and viewing the video, was 34.2 min. Table 3 provides an overview of the sample characteristics. More than half of the participants (57.84%) already had experience working in an industrial environment (e.g. on shop floors) as part of vocational trainings, holiday jobs or other experiences.

3.4 Preference model specification and data analysis

Prior to analyzing conjoint data, it is necessary to define the underlying preference model (Naous and Legner, 2018), for the operationalization of which a corresponding preference function needs to be specified. This preference function defines the valuation of the individual levels by attributing a parth-worth utility value (Green and Srinivasan 1978).

Marketing research suggests three different types of preference functions: (1) ideal point models, (2) vector models, and (3) part-worth function models (Green and Srinivasan 1978). The distribution of an ideal point model can be compared to a bell curve on account of the quadratic function. Therefore, there is only one utility-maximizing property level (e.g. the sugar concentration of yogurt). If a property takes on a value that is above or below the optimal value, a reduction in utility results. Vector models, in turn, expect a proportional and linear relationship between the increase of levels and the increase of their perceived utility. Consequently, they are exclusively suitable for quantitative attributes such as fuel consumption (Green and Srivivasan 1990). However, this linear relationship hardly manifests itself since even numerical factors such as money were found to exhibit diminishing marginal utility (Eggers and Sattler 2011). In addition, both of the aforementioned preference functions are highly dependent on a priori assumptions (Green and Srinivasan 1978). By contrast, part-worth function models are not fixed to a specific function curve, but instead are mapped as piecewise continuos curves. To operationalize individual

Table 3 Survey sample characteristics

Gender	Female: 83 (40.69%)		Male: 121 (59.31%)	
Age	18–19 years: 70 (34.31%)	20–21 years: 77 (37.75%)	22–23 years: 40 (19.60%)	> 24 years: 17 (8.33%)
Occupation	Student: 180 (88.23%)		Employee: 24 (11.77%)	
Industrial work experience	Yes: 118 (57.84%)		No: 86 (42.16%)	

levels in part-worth models, dummy variables are used. As part-worth models are capable of representing both linear and non linear functions, they are not dependent on a priori assumed correlations. Rather, they are more flexible than ideal-point and ideal-vector models (Green and Srinivasan 1978; Steiner and Meißner 2018).

In light of this flexibility, we decided to use a part-worth model in the present study. Therefore, we define the part-worth utility of an alternative k with a level m (u_{km}) as the sum of the products of the estimated coefficients (b_{jm}) of attribute level m of attribute j and its binary dummy variable (x_{kjm}), taking the value 1 if the characteristic is present and 0 otherwise. Against this background, we define the part-worth utility for a level m of an alternative k (u_{km}) as follows:

$$u_{km} = \sum_{m=1}^{M_j} b_{jm} \times x_{kjm} \tag{1}$$

In order to calculate the total utility of an alternative k based on the individual partial utility values, a model linkage function needs to be defined. For this purpose, the vast majority of conjoint analyses employ linear additive part-worth models (Cui and Curry 2005). These models are based on the assumption that individuals conduct mathematical calculations by comparing the expected utility of different alternatives when making choices. Thus, a less preferred characteristic of one attribute (e.g., high price of a computer) can be compensated by a preferred characteristic of another (e.g., more computing power) (Steiner and Meißner 2018). Even though this assumption might not always hold in reality (e.g., for ad hoc purchase decisions), prior research demonstrates that the linear additive model is very resistent to deviations from this postulation (Cui and Curry 2005). Since, in our case, we draw on prior findings (e.g. Hui et al. 2006) and assume that respondents accept a trade-off between privacy violations and monetary compensation, the additive part-worth model turns out suitable (Steiner and Meißner 2018). The additive model postulates that the total utility of an alternative k (u_k) results from the sum of the products of the relevant part-worth of an attribute level m of attribute j (b_{jm}) and their dummy variable (x_{kjm}). Thus, the equation can be formalized as follows:

$$u_k = \sum_{j=1}^{J} \sum_{m=1}^{M_j} b_{jm} \times x_{kjm} \tag{2}$$

After formulating these preference model specifications,[2] we proceeded to the data analysis step. The overarching goal of analyzing CBCA data involves determining the part-worth utility values for individual levels based on the empirically obtained choices. Using these results, researchers can subsequently calculate the RI of individual attributes. To compute the results of a CA, the literature suggests a variety of estimation aproaches such as McFadden's multinomial logistic regression (MLR), latent class (LC) analysis or hierarchical bayes (HB) approaches, depending on the objective of the subsequent analysis (Agarwal et al. 2015; Hensher et al. 2005).[3]

The most straightforward approach involves using the identified preferences of all subjects to estimate aggregate part-worth utilities using MLR. However, if there are segments with different preferences, an aggregate analysis may provide distorted findings, thereby reducing the predictive quality of CBCA models (Natter and Feuerstein 2002). To encounter these issues, prior research recommends LC analysis and HB analysis as they can incorporate heterogenous attitudes (Hensher et al. 2005). LC analysis performs part-worth calculations and respondent segmentation based on multinomial logit regressions. As a result, LC analysis leads to different segments, each with uniform part-worth values (Agarwal et al. 2015). However, since LC analysis estimates aggregate part-worth values for each segment, it neglects individual-specific heterogeneity within the segments (Natter and Feuerstein 2002). In contrast, HB models enable the estimation of individual-specific part-worth coefficients, which is advantageous in heterogeneous samples with an unknown number of segments (Howell 2009).

To estimate individual-specific part-worth values, HB analyses employ hierarchical multinomial logit models that are specified at two levels: 1) a higher level model that fits to the population (i.e. prior distribution) and 2) a lower level model that fits to each individual's data (i.e. posterior utilities) (Allenby and Ginter 1995). At the higher level, HB models assume that the part-worth utilities follow a multivariate normal distribution. This distribution, in turn, is characterized by a vector of means and a matrix of covariances. At the lower level, HB models hypothesize that, given an individual's part-worth values, his or her probabilities of choosing certain alternatives are specified by a multinomial logit model. The estimation of the HB model parameters follows an iterative approach using Markov chain Monte Carlo (MCMC) algorithms (Allenby and Ginter 1995; Hensher et al. 2005). These algorithms aim to find a balance between estimating model parameters that fit to the average population (i.e. means and covariances) and calculating model parameters tailored to each respondent's data (i.e. posterior utilities). In each iteration, the model parameters are re-estimated using probability rules until the coefficients converge to the optimal distribution (Allenby and Ginter 1995; Howell 2009). HB models have proven to be more accurate and robust compared to the LC method (Agarwal et al. 2015; Moore 2004). Thus, Agrawal et al. (2015, p. 30) conclude that, in almost all cases, HB "has been found to be comparable or even superior to traditional methods both

[2] A holistic overview of the utility functions can be found in Appendix B.

[3] A detailed review of these estimation techniques can be found in Elshiewy et al. (2017).

in part-worth estimation and predictive quality." For instance, HB is less sensitive to the so-called independence from irrelevant alternative (IIA) problem[4] and still permits post-hoc segmentation of respondent data based on cluster analysis (Orme and Baker, 2000).

Considering these advantages, we opted for the HB approach. Given the complex nature of HB model specifications (cf. Allenby and Rossi 2006), commercial vendors such as Sawtooth provide pre-built models that can be tailored to user requirements. Likewise, the R package *bayesm* contains a set of HB models and functions that are frequently employed in quantitative marketing (Rossi 2019). In the present study, we carried out all estimations using a hierarchical multinominal logit model routine from the R package *bayesm* (i.e. *rhierMnlRwMixture*). This routine includes an MCMC algorithm for hierarchical multinomial logit models that also accounts for mixtures of normal distributions in the priors and has contributed to high hit rates in prevous CBCA (e.g. Burda and Teuteberg 2014).[5]

To prepare the estimation, we first combined the empirically obtained choice data and conjoint survey design, which had been effect-coded during the preparation of the survey (cf. 3.2). Subsequently, we estimated the model parameters by deploying a MCMC algorithm. Following the recommendations of Rossi (2019), we used 10,000 iterations to achieve convergence and to obtain the parameter estimates. To ensure that the approximation converged, we examined the histograms of the coefficients post analysis. In addition, we employed a thinning parameter as the draws of an MCMC are autocorrelated (Rossi et al. 2005; Rossi 2019). In accordance with Rossi (2019), we set this parameter (i.e. *keep*) to 5, which means that every 5th draw is used for the analysis.[6] Using the individual estimates as a basis, we subsequently applied the analytic framework employed by Krasnova et al. (2009) as well as Burda and Teuteberg (2014, 2016). First, we calculated the aggregate results by averaging the individual coefficients per level (Krasnova et al. 2009). In addition, we calculated the standard deviations of the coefficients across the sample. To produce the RI value of an attribute j (O_j), we calculated the ratio of a single attribute's utility bandwith to the sum of the utility bandwiths of all attributes (Cattin and Wittink 1982, Steiner and Meißner 2018):

$$O_j = \frac{(\max u_j - \min u_j)}{\sum_{j=1}^{J} (\max u_j - \min u_j)}. \tag{3}$$

After the initial estimation of the individual part-worth utilities and the subsequent computation of the RI values, we calculated the euro equivalents for the utility shifts between the individual attribute levels. Finally, we performed a cluster

[4] IIA is a property of the logit model where the ratio of the proportions of any two product alternatives is fixed, independent of changes in other product alternatives. In MNL models, covariance structures with mixture distributions assist in solving this problem (see Agarwal et al. 2015).

[5] A comprehensive specification of the model can be found in Rossi (2019).

[6] The script, which draws on Burda and Teuteberg (2014), can be accessed here https://github.com/uwi-uos.

analysis to identify patterns in the utility structures using SPSS. The clustering procedure is outlined in Sect. 4.2.

4 Results

4.1 Aggregated findings

4.1.1 Model quality, average utility and relative importance of attributes

To assess the predictive quality of our model, we estimated the results of the last two hold-out tasks with our model and compared them to the choices actually made. Based on our estimation, we were able to predict 368 of 408 (204 * 2) hold-out tasks, thus yielded a hit rate of 90.20%, which indicates an acceptable predictive validity. To examine the quality of our model in greater depth, we also performed a likelihood ratio test. This test compares the quality of the estimated parameters in the present model with those of a model in which all parameters are zero (Vuong 1989). Our findings indicate that the estimated model is statistically reliable in that it exceeds the critical χ^2 value with LR = 27.32, which allows the null hypothesis to be rejected at a significance level of 0.01.

Returning to our research question, Table 4 displays the estimated part-worth utilities with their standard deviation for the respective attribute levels. As expected, the parameter estimates indicate that the individual level rankings were ordered appropriately (see Appendix B), thereby indicating face validity (Green and Srinivasan 1978). In considering the estimated part-worth utilities, we found that the optimal AR system leads to a high productivity gain (max [−2.076, −0.532, 2.608] = 2.608), does not include monitoring capabilities (max [1.263, −0.052, −1.211] = 1.263), increases work safety (max [−1.898, 1.898] = 1.898) and is easy to use (max [−1.091, 1.091] = 1.091). Additionally, companies should provide employees with monthly incentives of €200 to maximize utility from the employees' point of view (max [−2.134, 0.311, 1.823] = 1.823).

In addition, the results also allow us to determine the RI of each attribute from the respondent's perspective (Cattin and Wittink 1982). The three most important attributes are: (1) productivity gain (RI = 27.40%), (2) financial incentive (RI = 23.15%) and 3) safety enhancement (RI = 22.21%). While these attributes are almost equally distributed, monitoring capabilities (RI = 14.48%) and ease of use (RI = 12.77%) rank last. Thus, with reference to our RQ, the following key findings can be derived:

Key finding 1 The perfect AR system significantly increases productivity, enhances user safety and is easy to use. Additionally, it does not allow user monitoring, and employees receive monthly incentives of €200.

Key finding 2 Apart from financial incentives (RI = 23.15%), functional benefits such as productivity gains (RI = 27.40%) and the impact on personal safety (RI = 22.21%) are main drivers for AR adoption decisions from the users' perspective. These

Table 4 Attributes, aggregated part-worths and relative importance

Attribute	Levels	Final Utilities	Std. Deviation	Rel. Importance
Productivity gain	No Increase	−2.076	1.156	27.40%
	Low Gain	−0.532	0.447	
	High Gain	2.608	0.895	
Performance monitoring	None	1.263	1.291	14.48%
	Anonymous	−0.052	1.010	
	Transparent	−1.211	1.831	
Safety enhancement	No safety enhancement	−1.898	0.807	22.21%
	Presence of safety enhancement	1.898	0.807	
Ease of use	Complex to use	−1.091	0.579	12.77%
	Easy to use	1.091	0.579	
Financial compensation	€0/month	−2.134	0.988	23.15%
	€100/month	0.311	0.423	
	€200/month	1.823	1.104	

factors are considered more important in adoption decisions than monitoring capabilities (RI = 14.48%) and ease of use (RI = 12.77%).

4.1.2 Trade-offs among attribute levels and level changes in reward equivalents

To gain a deeper understanding of our results, we further assessed the utility changes between the individual attribute levels, as outlined in Table 5. The table presents the utility changes that result from comparing two AR systems with heterogeneous levels. Additionally, we report the p-values of the dependent sample t-test, which measures whether the utility changes between two levels differ significantly from each other.

Based on the results in Table 5, users perceive the highest utility gain from a change in productivity from low to a high increase for this attribute; this utility gain is more than twice the utility delta resulting from a change from no increase to a low increase ($\Delta u = 3.139$ utility units vs. $\Delta u = 1.544$ utility units). These results indicate that a high increase in productivity would be important for employees to accept an AR system in this respect. With regard to monitoring, the change from no monitoring capabilities to anonymized recording of performance profiles leads to the highest loss of utility for this attribute ($\Delta u = -1.316$ utility units). The results also indicate a diminishing marginal utility: A change from none to anonymized monitoring exhibits a greater utility loss ($\Delta u = -1.316$ utility units) than a change from anonymized to personalized monitoring ($\Delta u = -1.158$ utility units). This suggests that employee monitoring is generally rejected, regardless of whether it is anonymous or transparent. Although only third with an RI of 22.21%, safety enhancement leads to the largest increase

Table 5 Attributes, part-worths, relative importance and financial compensations

Attribute	Level change	Utility delta	*p*-value (*t*-test)	Level change in reward equivalent (Euros)
Productivity gain	No Increase → Low Increase	+1.544	0.00[a]	
	Low Increase → High Increase	+3.139	0.00[a]	
Performance monitoring	None → Anonymous	−1.316	0.00[a]	−53.67 – (−87.03)
	Anonymous → Transparent	−1.158	0.00[a]	−47.19 – (−76.59)
Safety enhancement	No safety enhancement → Presence of safety enhancement	+3.796	0.00[a]	154.68 – 251.08
Ease of use	Complex to use → Easy to use	+2.183	0.00[a]	
Financial compensation	€0/month → €100/month	+ 2.445	0.00[a]	
	€100/month → €200/month	+ 1.512	0.00[a]	

(Significance level: [a] = 1%)

in utility among all of the attributes (Δu = +3.796 utility units). Similarly, although the factor with the lowest RI is ease of use, the results show that the loss of utility in moving from an easy system to a complex system is considerably higher than, for example, moving from no monitoring to the introduction of anonymous monitoring measures (Δu = 2.183 utility units vs. Δu = 1.316 utility units). Regarding monetary incentives, the greatest utility increase occurs when the incentive increases from €0 to €100/month (Δu = 2.445 utility units vs. Δu = 1.512 utility units), which implies that already a financial compensation of €100 could nearly compensate for recording transparent performance and movement profiles (Δu = 2.445 utility units vs. −2.474 units). In short, financial rewards for wearing AR systems are generally perceived as positive and might be considered as compensation for privacy violations.

With this potential in mind, we examined financial rewards more closely by deriving the euro equivalents of the utility trade-offs (Burda and Teuteberg 2014). In this context, we refer exclusively to invasions of privacy and occupational safety since it is also common to financially compensate such restrictions in other workplaces (e.g. in dangerous professions such as the military). As Table 5 shows, the total change in utility from a rise in monetary reward from €0 to €100 reduces to a change of 2.454/100 = 0.02454 units of utility per euro. Accordingly, the final utility change per euro for an increase from €100 to €200 implies a change of 1.512/100 = 0.01512 units of utility per euro. These values constitute the upper and lower boundaries for the utility-change-per-euro values and can be used to determine the euro equivalent for a change in the levels of the other attributes considered in our study.

Thus, the introduction of anonymous recording of performance profiles is worth the equivalent of between €53.67 and €87.03, while transparent recording of performance profiles is worth an equivalent of between €100.86 (-€53.67 + −€47.19) and €163.62 (-€87.03 + −€76.59). Accordingly, employers might consider paying their employees financial compensation within those ranges when introducing control mechanisms. Although safety enhancement exhibits an RI of only 21.7%, the results reveal a high monetary equivalent from employee perspective. In the fictitious scenario, for example, employees would forgo between €154.68 and €251.08 if the assistance system contributed to increasing occupational safety. Returning to our RQ, the following key findings can be derived:

Key findings 3 Privacy violations might be monetized and compensated. Anonymous monitoring requires less financial compensation than transparent monitoring. If no conclusions are to be drawn about individuals, a financial compensation of between approximately €50 and €90 per month is necessary to compensate the utility loss from privacy violation. For personalized profiles, the necessary monthly compensation ranges from approximately €100 to €160.

4.2 Cluster segmentation

To systematically identify distinct sub-groups with similar utility patterns, we additionally applied cluster analysis using SPSS (Hagerty 1985). Prior to clustering, we determined the input variables, following Balijepally et al. (2011). In line with earlier studies (e.g. Burda and Teuteberg 2014; Krasnova et al. 2009, 2013), we chose the individual coefficients per level as input for the subsequent clustering. However, too many input variables can trigger the so-called "curse of dimensionality," which describes a distortion of the algorithm (Assent 2012). Interdependent variables, in turn, can affect the weigthing of variables, thereby inducing multicollinearity (Balijepally et al. 2011). As in our case the part-worth values are interdependent, being inverted at the zero point due to effects coding,[7] we excluded the base level (i.e. the summand) for each attribute to avoid distortion. Besides, we found the lowest standard deviation for the RI of ease of use and safety enhancement, which indicates a homogeneous attitude among the respondents. Since the inclusion of these variables during the initial clustering attempts did not increase the subjective explanatory value, we excluded the levels for the attributes ease of use and safety enhancement. Ultimately, six coefficients[8] remained as input for the cluster analysis.

Subsequently, we proceeded to clustering. In general, clustering algorithms can be categorized in hierarchical (e.g. Ward 1963) and non-hierarchical procedures (e.g. K-means) (Hair et al. 2010). Prior CAs from the IS discipline applied Ward's

[7] For instance: 2.608 utility units = (−1) * (−2.076 utility units + -0,532 utility units) for the attribute productivity gain.

[8] The coefficients of the following levels were part of the final clustering: low gain, high gain, anonymous monitoring, personalized monitoring, 100 Euro and 200 Euro.

method and K-means to segment respondents (Burda and Teuteberg 2014; Krasnova et al. 2009, 2013). Although Ward's method is regarded as a valuable approach to determine the number of clusters (Balijepally et al. 2011), it is subject to serious limitations when applied for CA since it is sensitive to outliers (Punj and Stewart 1983). Non-hierarchical procedures such as K-means, in contrast, are less sensitive to outliers and are thus considered a more reliable and valid approach for cluster segmentation. Hence, researchers are advised to combine hierarchical and non-hierarchical algorithms to leverage the strengths of both approaches (Balijepally et al. 2011; Burns and Burns 2008). Thus, we followed the guidelines of recent IS publications by applying a two-step approach. First, we conducted a hierarchical agglomerative cluster analysis using Ward's linkage in SPSS, incorporating the individual utility estimates for each level to determine the number of clusters (Ward 1963). Based on this analysis, we studied the dendrogram changes and the agglomeration summary, applying the elbow criterion, which indicated that a three-cluster solution is suitable for our sample. Yet, since researchers are advised to also examine subjective explanatory values with fewer and more clusters (Balijepally et al. 2011), we separated the sample into two, three and four segments applying K-means clustering in SPSS. Finally, we compared the solutions with regard to their suitability to create mutually exclusive segments, taking into account the silhouette scores.

4.2.1 Relative importance, part-worth utilities and attribute-level changes per cluster

The three-cluster solution showed the highest subjective interpretability and the highest consistency between the hierarchical and non-hierarchical algorithms. The three clusters consist of 62 (C1, 30.39%), 69 (C2, 33.82%) and 73 (C3, 35.78%) members. Figure 2 and Table 6 present the clusters, including the RI of the individual attributes, the change in utility per level and the associated values of the latent variables.

The results indicate that the RI of the individual attributes differs significantly between clusters. While C1 attributes the highest RI to efficiency gain (RI = 40.72%), C2 focuses on financial rewards (RI = 31.25%). C3, in turn, attaches the greatest importance to monitoring (RI = 30.08%). In contrast to the aggregated results, the attribute ease of use is the least important attribute (RI = 8.60%) in C3, whereas C1 and C2 weight monitoring as the least important attribute with RIs of 4.58% and 10.27%, respectively.

Taking into account the part-worth utilities in Table 7, we observe that participants in all three clusters prefer AR systems that lead to a high productivity gain, enhance work safety and are easy to use. Additionally, all clusters prefer €200 per month in terms of monetary compensation. Concerning performance monitoring, however, cluster-specific differences can be identified: While C1 prefers the recording of transparent performance profiles, C2 and C3 favor systems without monitoring capabilities. Thus, C1 is the only cluster whose members perceive a positive utility from recording personal performance profiles (0.323 vs. −0.383 vs. −3.292 utility units). C1 also experiences a positive utility if no performance profiles are

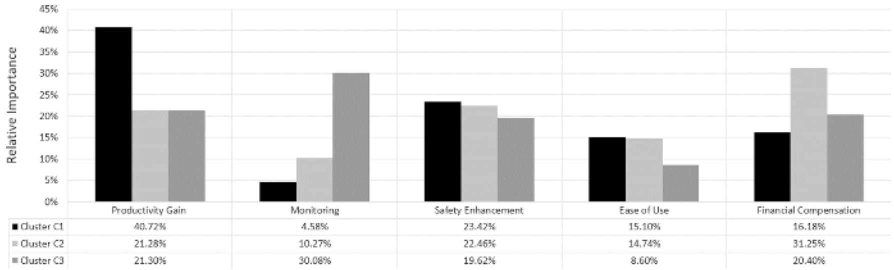

Fig. 2 Cluster analysis

Table 6 Pairwise *t*-tests of relative importance (*p*-value)

	Productivity gain	Monitoring	Safety enhancement	Ease of use	Financial compensa-tion
C1:C2	0.00^{a}	0.02^{b}	0.26	0.02^{b}	0.00^{a}
C1:C3	0.00^{a}	0.00^{a}	0.02^{c}	0.00^{a}	0.00^{a}
C2:C3	0.36	0.00^{a}	0.06^{c}	0.00^{a}	0.00^{a}

(Significance Levels: $^{a}=1\%$, $^{b}=5\%$, $^{c}=10\%$)

recorded (0.094 utility units). However, if performance profiles are recorded but cannot be traced back to the individual, C1 perceives a lower and negative part-worth utility in the present scenario (−0.417 utility units). In their case, however, the introduction of an incentive of €100 would suffice to compensate the privacy concerns due to monitoring. By contrast, C1 perceives the expected productivity gain as the most important factor influencing the adoption decision (RI = 40.72%), since among all individual levels it assigns the greatest part-worth to high productivity gains (3.376 utility units). Given their drive for productivity as well as their lack of privacy concerns, or willingness to share their performance with others, we refer to cluster C1 as *Strivers*.

In contrast, C2 is characterized by a greater orientation to financial rewards (RI = 31.25%). This cluster demonstrates a utility increase of 3.207 units as soon as an incentive of €100/month is offered for adopting an AR system. In line with this finding, an increase in the incentive to €200/month leads to the highest utility change per level across all clusters (2.160 utility units). We refer to this cluster as *Payroll Hunters* due to their pursuit of financial rewards. In addition, we note that all clusters incorporate safety enhancement into their choice-making processes with RIs of 23.42% for C1, 22.46% for C2 and 19.62% for C3.

Finally, C3 attributes by far the highest importance to monitoring mechanisms (RI = 30.09%), thereby significantly differing from the other clusters. The results indicate that recording of anonymous profiles would be sufficient for employees in C3 to form a rather positive opinion about monitoring capabilities (0.860 utility units). Nevertheless, C3′s members prefer not to be monitored (2.431 utility units). Yet, C3 suffers the highest utility loss among all clusters as soon as the performance

Table 7 Cluster segmentation

	Variable	Cluster		
		C1: Strivers (30.39%)	C2: Pay-roll hunters (33.82%)	C3: Privacy keepers (35.78%)
Relative importance	Productivity gain	40.72%	21.28%	21.30%
	Monitoring	4.58%	10.27%	30.08%
	Safety enhancement	23.42%	22.46%	19.62%
	Ease of use	15.10%	14.74%	8.60%
	Monetary rewards	16.18%	31.25%	20.40%
Part-worth utilities	*Productivity gain*			
	No increase	−3.196	−1.445	−1.721
	Low increase	−0.180	−0.765	−0.609
	High increase	3.376	2.210	2.330
	Monitoring			
	None	0.094	1.073	2.431
	Anonymous	−0.417	−0.691	0.860
	Transparent	0.323	−0.383	−3.292
	Safety enhancement			
	No safety enhancement	−1.890	−1.929	−1.866
	Presence of safety enhancement	1.890	1.929	1.866
	Ease of use			
	Easy to use	1.218	1.266	0.818
	Complex to use	−1.218	−1.266	−0.818
	Monetary reward			
	€0	−1.492	−2.858	−2.052
	€100	0.371	0.349	0.224
	€200	1.120	2.509	1.828
Utility change	*Productivity gain*			
	No increase → Low increase	+3.016	+0.679	+1.111
	Low gain → High gain	+3.556	+2.976	+2.939
	Monitoring			
	None → Anonymous	−0.511	−1.764	−1.571
	Anonymous → Transparent	+0.740	+0.308	−4.152
	Safety enhancement			
	No safety enhancement → Presence of safety enhancement	+3.780	+3.857	+3.732
	Ease of use			
	Difficult to use → Easy to use	+2.437	+2.532	+1.635
	Monetary reward			
	€0/month → €100/month	+1.863	+3.207	+2.276
	€100/month → €200/month	+0.749	+2.160	+1.604

profiles can be traced back to them personally ($\Delta u = -4.152$ utility units). Against this background, we refer to this cluster as *Privacy Keepers*, as its members have a strong drive to protect their privacy and avoid interference by third parties. C3 is also distinguished by the fact that ease of use (RI = 8.60%), safety enhancement (RI = 19.62%) and increased productivity (RI = 21.30%) are weighted lower than in the other clusters on account of the strong focus on privacy protection in C3. In this cluster, the introduction of a financial reward of €200 per month would not suffice to compensate for the privacy violation induced by the introduction of transparent monitoring (3.880 utility units $< -1 * -4.150$ utility units).

4.2.2 Latent variables per cluster

To deepen the understanding of the utility-specific clusters, we additionally asked the participants about their attitudes towards different latent constructs. Before interpreting the results, we first examined the item reliability and validity. We chose Cronbach's alpha (α) and composite reliability (CR) to assess the scale reliability and the internal consistency (Santos 1999). To complement this assessment, we computed the average variance extracted (AVE) and its square root to specify the goodness of the constructs. The values for α range from 0.76 to 1 in all cases, thus remaining within the acceptable range (Santos 1999). Simultaneously, CR values exceed the critical mark of 0.7 (Straub et al. 2004). In addition, the AVE values surpass the threshold value of 0.5, while the square root of each construct exceeds the values of the inter-construct correlations (Straub et al. 2004). Table 8 presents the findings of this assessment.

Once the reliability and validity of the constructs were assessed, we continued with the analysis of the items per cluster. To do this, we calculated the mean values of each construct per cluster. We also studied the gender distribution per cluster. Table 9 displays the mean values per construct for each cluster.

We found that C1 (*Strivers*) exhibits the highest index values for attitude toward using AR glasses (max [5.944, 5.587, 5.548] = 5.944) and intention to use (max [5.435, 5.268, 5.510] = 5.435). Thus, participants in this cluster expect AR systems to have a strong impact on their productivity and index the highest RI for productivity gain (40.72%) among the three clusters. C1′s low RI for the monitoring attribute (RI = 4.58%) is also reflected in the latent variables: Among the latent variable values for C1, perceived privacy risk has the lowest value (max [3.776, 3.355, 2.233] = 3.776). Among the three clusters, C1 has the highest index values for legal trust (max [4.573, 4.391, 3.966] = 4.573). These values suggest that C1 members assume that the laws protect their privacy, and thus they assign an RI of 4.58% to monitoring capabilities. Ease of use is considerably more important to C1 than to C3, which may be explained by the fact that this cluster's members assign themselves a slightly lower computer proficiency (min [3.737, 3.895, 4.012] = 3.737) than the other clusters.

In contrast, C2 (*Payroll Hunters*) shows a slightly more positive attitude toward the use of AR glasses and slightly higher values for intention to use than C3 (5.268 > 5.110). The high importance that its members place on monitoring

Table 8 Reliabilities, AVE and latent variable correlation

#	Construct	α	CR	AVE	1	2	3	4	5
1	Attitude toward using ARSG	0.76	0.79	0.65	**0.810**				
2	Intention to use	0.76	0.78	0.65	0.632	**0.810**			
3	Personal IT Innovativeness	0.84	0.84	0.83	0.249	0.275	**0.911**		
4	Perceived Privacy Risk	0.92	0.95	0.91	0.177	0.108	0.046	**0.954**	
5	Legal Trust	0.84	0.88	0.78	0.305	0.312	0.201	0.223	**0.883**

α Cronbach's alpha; *CR* composite reliability; bold cells, square root of AVE

Table 9 Latent Variables per Cluster

#	Variable	Cluster		
		C1: Strivers (30.39%)	C2: Payroll hunters (33.82%)	C3: Privacy keepers (35.78%)
1	Attitude toward Using AR Glasses	5.944	5.587	5.548
2	Intention to Use	5.435	5.268	5.110
3	Personal IT Innovativeness	4.581	4.607	4.918
4	Perceived Privacy Risk	3.776	3.355	2.233
5	Legal Trust	4.573	4.391	3.966
6	Computer Proficiency	3.737	3.895	4.012
7	Gender (Female/Male)	48.38%/51.61%	42.02%/57.79%	31.51%/68.49%

functionalities, compared to C1, is also reflected by this cluster's level of legal trust, with an index of 4.391, which is lower than that in C1 (4.573).

Proceeding to the analysis of C3 (*Privacy Keepers*), we found that members of this cluster show unique characteristics as the results indicate the lowest level of legal trust (min [4.573, 4.391, 3.966] = 3.966) and the highest perceived privacy risk (min [3.776, 3.355, 2.233] = 2.233). Members of C3 are consistent in their attitudes and assign the highest RI to the attribute related to monitoring capabilities. In addition, C3 exhibits a slightly higher level of personal IT innovativeness (4.918) than members of C1 (4.581) and C2 (4.607). In a similar vein, this cluster assigns itself the highest computer proficiency among all clusters (max [3.737, 3.895, 4.012] = 4.012) Returning to our RQ, the following key findings can be formulated:

Key findings 4 The attitudes influencing the adoption decision among users vary significantly and result in three adopter groups with different heuristics:

- *Key findings 4a* The members of group 1 (*Strivers*) intend to use AR systems if these generate high functional benefits.They are not concerned about privacy violations, as demonstrated by a willingness to share performance data with the employer. The explicit reporting of AR-induced benefits encourages them to adopt AR systems, as they share a strong interest in productivity gains (RI = 40.72%) and their own safety (RI = 23.42%).

- *Key findings 4b* The members of group 2 (*Payroll Hunters*) intend to use AR systems if these generate high functional benefits. They are somewhat concerned about privacy violations, as demonstrated by an unwillingness to share performance data with the employer. Financial rewards encourage the Payroll Hunters to adopt ARSG and diminish privacy concerns, as they have a strong interest in monetary incentives (RI = 31.25%).
- *Key findings 4c* The members of group 3 (*Privacy Keepers*) intend to use AR systems if these are compliant with current legal requirements, as shown by their unwillingness to enable supervisors to view their performance data and provide functional benefits. Emphasizing the absence of any tracking of performance data encourages the Privacy Keepers to adopt ARSG, as they have a strong interest in protecting their privacy (RI = 30.08%).

5 Discussion

The main objective of this study is to enhance the understanding of AR acceptance in workplace settings. Given this goal, we were interested in answering the question based on the preferences of future employees regarding AR systems and the relative importance of different attributes. In addition, we looked for trade-offs to compensate for privacy violations. To this end, we applied a CBCA with a sample of 204 respondents and analyzed the trade-offs between productivity gains, monitoring capabilities, safety enhancement, ease of use and financial rewards for adopting AR systems. Based on the estimated utility parameters, we subsequently conducted a cluster analysis to find distinct adopter groups whose members share the same utility patterns. In total, our study revealed four key findings, which we subsequently discuss in relation to previous research.

Key finding 1 The perfect workplace AR system provides contextual support to increase productivity and enhance safety without violating user privacy.

Based on the aggregated results, we define the optimal workplace AR system as follows: User assistance systems based on ARSG should provide a high productivity gain, enhance user safety, be easy to use and not allow monitoring of employees. Thus, we found that accessing sensor and camera data for performance measurement negatively impacts the utility of ARSG. This finding partly contradicts a study by Rauschnabel et al. (2018), who indicate that privacy concerns have no significant influence on the adoption decision. In contrast, we confirm the perception of Berkemeier et al. (2019), who stated that respecting user privacy is an essential design goal of AR-based support systems. However, Berkemeier et al. (2019) did not examine employee attitudes toward monitoring, instead relying on the GDPR. We complement this perspective by quantifying attitudes toward three different privacy configurations in monitoring in terms of utility units, namely: no monitoring (1.263 utility units), anonymized monitoring (−0.052 utility units) and personalized monitoring (-1.211 utility units).

As AR systems "must keep track of what the operator is doing and seeing" (Syberfeldt et al. 2016, p. 113), prior research has called for developing concrete policies regarding data access related to ARSG in workplace settings. Responding to this call, our findings suggest that collected performance data must not be accessible to others nor should they be saved at all. If stored, the data should only be accessible anonymized, as this privacy configuration provides more part-worth utility (−0.052 > −1.211 utility units). Considering this recommendation, our findings enhance the body of knowledge by providing user-centric guidance on how to manage privacy policies with regard to ARSG in the workplace. Returning to the example of Amazon, this recommendation implies that Amazon should refrain from recording performance data in order to roll out ARSG in an acceptance-oriented manner. Rather, companies are encouraged to carefully select use cases such as safety enhancement or context-sensitive support to increase productivity, as key finding 2 shows.

Key finding 2 Functional benefits constitute a main technical driver for wearable AR adoption decisions at the user level, while ease of use and monitoring play a minor role.

Drawing on the RI values, we found that functional benefits play the most important role in the user decision between different AR systems. In this context, the productivity gains, which refer to the impact of the system on the quality of the work results, taking time into account, constitute the most relevant factor impacting the adoption decision (RI = 27.40%). Thus, we confirm the findings of Jetter et al. (2018) who analyzed the most important key performance indicator of AR systems and concluded that usefulness in terms of an increase in efficiency and a decrease in errors constitutes the most important factor to consider when analyzing technology acceptance of AR in workplace settings. In addition, this finding is consistent with previous findings that perceived usefulness constitutes the most important factor to predict technology acceptance (Davis 1989; Venkatesh et al. 2003; Williams et al. 2015). Likewise, this finding supports the inherent role of relative advantage for technology adoption in the TOE framework and Rogers DOI (Depietro et al. 1990; Rogers 2003).

Apart from the productivity gain, the impact of AR systems on user safety, with an RI of 22.21%, forms another important functional benefit for AR adoption in the present scenario. Jetter et al. (2018) did not examine the role of safety for technology acceptance as they dealt with smartphone-based AR. However, ARSG face massive safety concerns resulting from the limited field of view, which may negatively influence acceptance (Holm et al. 2017; Maly et al. 2017). We found the highest utility change per level among all attributes when head-worn AR systems integrate safety features (Δu = 3.796 utility units). As a consequence, we propose to address the perceived usefulness of ARSG both in terms of productivity and safety in TAM studies (Davis 1989). This could lead to a better explanation of technology acceptance as previous research demonstrated that the initial draft of TAM is not suitable for ARSG (Rauschnabel and Ro 2016).

In light of its relevance in technology acceptance models such as UTAUT and TAM (Davis 1989; Venkatesh et al. 2012a, b), we expected ease of use to be of higher RI than the other attributes. However, in our study, this attribute plays only a minor role (RI = 12.77%). This finding also corresponds to the study by Jetter et al. (2018), who found that ease of use does not have a significant effect on intention to use mobile AR systems in production environments. One explanation for our outcome may be that the respondents consider their own work results and safety in working environments to be much more important than ease of use, thereby perceiving more utility (Jacobs et al. 2019; Jetter et al. 2018). Moreover, the majority of the respondents had little practical experience with the operation of ARSG before the experiment. Thus, they may not have been aware of usability issues. Despite the low RI value for ease of use, the part-worth utilities demonstrate a significant utility increase. Given the reported difficulties using ARSG, AR providers and researchers need to improve the ease of use of applications (Lik-Hang and Pan 2017). Otherwise, there is a risk that ARSG use disrupts work processes, which may result in resistance towards the technology.

In addition, we suspected respondents would rank their privacy as more important than attributes such as productivity gains, given the public debate about ARSG and privacy (cf. Rauschnabel and Ro 2016). Our results deviate from this expectation, with productivity gain (RI = 27.40%) found to be almost twice as important as monitoring (RI = 14.48%). There are several explanations for this finding. First, the low importance of monitoring can be interpreted as a result of the usage context studied. As Rauschnabel et al. (2018, p. 280) state, "supervisors and co-workers might observe one other, cameras might surveil the workspace or work behavior is tracked regardless." Thus, workers are used to having their performance reviewed by supervisors. Furthermore, as Rauschnabel et al. (2018) point out, mechanisms such as resignation, the abstractness of consequences and individual consciousness can explain the low RI of monitoring. With the increasing diffusion of digital technologies such as conversational agents (e.g. Alexa) and smartphones, people are accustomed to sharing personal data with third parties (e.g. Amazon). This familiarity leads to resignation. Others have "nothing to hide" (Rauschnabel et al. 2018, p. 376)—a clear conscience—and are therefore willing to share their data. Another explanation is the low average age of the sample, as research has indicated a greater willingness to share data among younger generations (Francis and Hoefel 2018). To conclude on this point, the performance and movement profiles referred to as performance data may not represent sensitive data from the perspective of respondents (Mettler and Wulf 2019). If we had integrated vital parameters (e.g. pulse, body temperature) into the study, the RI would probably have been higher for this attribute, as workers are more critical in sharing this data (Hofmann et al. 2017; Jacobs et al. 2019). Despite the low RI value for monitoring, anonymized monitoring is not positively assessed by the respondents on an aggregated level, while respondents perceive the incorporation of transparent performance profiles to be even slightly more negative. In this context, key finding 3 reveals a potential countermeasure to compensate for privacy concerns.

Key finding 3 User privacy might be monetized and compensated.

Drawing on the findings of prior studies (e.g. Hein and Rauschnabel 2016; Jacobs et al. 2019), we included a monetary reward in our study. Apart from the functional benefits mentioned above, these incentives had a major influence on the decision-making process. In fact, for the respondents they were more important (RI = 23.15%) than monitoring (RI = 14.48%) and ease of use (RI = 12.77%). In general, this finding confirms that incentives would foster adoption of ARSG among employees (Hein and Rauschnabel 2016; Jacobs et al. 2019).

Taking the perspective of Hui et al. (2006), who found that users might agree with trading their privacy for other benefits, i.e. the monetary reward, we applied the CA approach to calculate payments required to compensate for privacy violations. If no conclusions are to be drawn about individuals, a financial compensation of between approximately €50 and €90 per month is necessary. If personalized profiles are created, the necessary amount is between approximately €100 and €160 per month. Responding to the call for developing instruments to diminish privacy concerns among employees (e.g. Syberfeldt et al. 2016), our findings thus provide evidence that financial incentives might be a suitable instrument to compensate for the loss of utility induced by privacy violations. However, monetary incentives are associated with a variety of issues. From an economic point of view, incentivizing monitoring is not desirable as it leads to additional costs for deploying AR systems (Jacobs et al. 2019). In addition, monetary rewards are probably not going to improve the attitude towards using ARSG among employees in the long run either. Instead, companies need to intrinsically motivate their employees to use AR systems (AREA 2019). In this respect, our results suggest that the careful selection of ARSG features is a critical success factor to increase user acceptance (Jacobs et al. 2019). In our example, the introduction of safety features in hazardous situation can compensate for the loss of benefits caused by monitoring measures ($3.796 > 1.316 + 1.158 > 1.316$ utility units) and therefore increase the perceived utility of ARSG among employees. This strategy requires fewer incentives, as employees opt to use the technology for their own benefit. However, this perception about monitoring changes when considering the derived clusters.

Key finding 4 Breaking down the heterogeneity in preferences leads to three clusters with significantly different utility patterns each: Strivers (C1), Payroll Hunters (C2), and Privacy Keepers (C3).

Approximately one third of the respondents (30.39%)—namely, the members of C1 (*Strivers*)—intend to use AR systems if these generate high functional benefits and they are not concerned about privacy violations, as demonstrated by a willingness to share performance data with the employer. The explicit reporting of AR-induced benefits encourages the Strivers to adopt AR systems as they share a strong interest in productivity gains (RI = 40.72%) and their own safety (RI = 23.42%). Our complementary analysis indicates that members of this group rely on the legal system and that they tend to be less critical of sharing performance data with the employer via ARSG than the average. Therefore, a monetary incentive to compensate privacy concerns about personalized monitoring is not required. This cluster may reflect the "nothing to hide" attitude explored by Rauschnabel et al. (2018), leading to little or no loss of utility when monitoring is introduced.

By contrast, approximately another third of respondents—namely, the members of C2 (*Payroll Hunters*)—display a strong orientation to financial rewards and a preference for systems without monitoring possibilities due to their lower level of legal trust. However, privacy appears to be of minor importance for the Payroll Hunters (RI = 10.27%). The low importance of monitoring in this cluster can be caused by the resignation mentioned above (Rauschnabel et al. 2018). Thus, the members of C2 intend to use AR systems if they generate high functional benefits or receive a financial incentive. As a result, given their strong interest in monetary incentives (RI = 31.25%), financial rewards help to encourage the members of this group to adopt ARSG and diminish privacy concerns.

Overall, privacy is a major concern for only about one third of respondents. Thus, 35.78% of the respondents belong to C3 (*Privacy Keepers*) and would share only anonymized performance data with an employer. *Privacy Keepers* demonstrate a strong drive to protect their own privacy and avoid interference by third parties. They also exhibit the lowest legal trust and highest perceived privacy risk among the three clusters. This relation between legal trust and privacy risk reflects a recent study by Paul et al. (2020) who found that, when perceived effectiveness of privacy laws such as the GDPR is low, users exhibit a higher perception of privacy risks. Thus, even a higher amounts of compensation payments would hardly convince members of C3 to allow the recording of transparent profiles in the present scenario. The knowledge of adopter groups and their specific needs helps AR system providers and companies when adopting targeted AR systems (AREA 2019).

5.1 Implications for research and practice

Given the findings outlined above, this study is of interest for researchers and practitioners in several ways. First, from a theoretical perspective, our findings contribute to the little-explored research area of AR technology acceptance in production environments at the worker level. Previous research indicates that the lack of AR acceptance at the user level constitutes a bottleneck for the adoption of such technologies (Masood and Egger 2019; Rauschnabel and Ro 2016; de Souza Cardoso et al. 2020). To date, with few exceptions (e.g. Jetter et al. 2018), scientific examinations at the individual level have focused primarily on the impact of AR systems on work results and cognitive demands (e.g. Murauer et al. 2018; Bottani and Vignali 2019). We identified five important attributes and their RIs in the choice of head-worn AR systems when employed in production environments. Complementing the findings of Jetter et al. (2018), we found that, in addition to the productivity gain, the impact on personal safety is an important functional benefit influencing the adoption among employees in hazardous environments. Therefore, we recommend integrating this attribute into future TAM or UTAUT investigations concerning ARSG (Davis 1989; Venkatesh et al. 2003). This extension can be applied by adding safety-related aspects to the construct of perceived usefulness apart from the productivity gain, given that an AR system may have safety-enhancing mechanisms such as collision avoidance (cf. Choi et al. 2017). Linking this consideration with perceived vulnerability can provide further insights into the causal relationship between individual traits and the role of safety concerning acceptance of ARSG (Choi et al. 2017). Likewise, our results imply that perceived privacy is indeed a factor influencing technology acceptance. Prior research on the consumer sector has shown that user privacy concerns do not affect the intention to adopt ARSG (Rauschnabel et al. 2018). Our study partly contradicts these findings, as for one third of all respondents, privacy configurations are more important in the decision-making process than any other attribute. As a consequence, we encourage researchers to analyze the influence of perceived privacy risk on the intention to use ARSG in the workplace as a causal relationship in future studies of technology acceptance (Malhotra et al. 2004). We propose using legal trust as a moderating variable, as in our case it is related to privacy attitudes among adopter groups. From a methodological point of view, researchers can study these relationships, for example, using structural equation modeling and regression (Gefen et al. 2000).

Considering the aforementioned extensions, our study reflects the general criticism of "one-size fits all" (Head and Ziolkowski 2012, p. 2337) adoption theories such as UTAUT und TAM (Benbasat and Barki 2007; Davis 1989; Venkatesh et al. 2003). For example, prior research has criticized the uniform assumptions employed by technology acceptance models. Given the heterogeneity in preferences among respondents revealed in the cluster analysis, the question arises whether these theories are at all sufficient to explain the underlying heuristics affecting ARSG acceptance across different users. Until now, experiments based on the TAM or UTAUT often differentiated by socio-demographic characteristics (Davis 1989). Experiments with AR systems in the work environment, in contrast, distinguished between novice and experienced employees rather than considering individual preferences (e.g. Jetter et al. 2018). However, in line with Head and Ziolkowski (2012, p. 2337), we believe that "segmentation by perceived utility of technology features may yield a richer and deeper understanding of preferences and perceptions of feature-rich products." For decades, creating adopter groups has been considered an important tool to explain technology adoption within the IS discipline (e.g. Rogers 2003). Therefore, the second theoretical contribution of this study to the knowledge base on technology adoption and acceptance is the classification into three adopter groups synthesized on the basis of cluster analysis. Within the IS discipline, these groups can be used, for example, to develop user-centric implementation strategies tailored to AR. In addition, they serve as guidance in design science research to ensure real-world relevance of artifacts during requirements elicitation (Hevner 2007; Naous and Legner 2018). For example, the different privacy configurations per cluster provide inspiration for the implementation of privacy-by-design paradigms in AR systems (Schaar 2010). We found that safety is a highly important aspect across all clusters. To the best of our knowledge, however, the development of capabilities for safety enhancement (e.g. collision avoidance) of shop floor AR systems is underexplored. A recent example includes Pierdicca et al. (2020), who developed a safety-enhancing AR system for maintenance processes. Thus, we encourage design science researchers to incorporate our findings by exploring safety enhancing mechanisms. In this context, attention must also be paid to protecting the privacy of users despite the recording and processing of their sensor data (Syberfeldt et al. 2016).

We also provide an important contribution to the field of privacy research in the IS literature, in particular with regard to wearables and ARSG (Bélanger and Crossler 2011). To the best of our knowledge, there is only limited research on this topic related to ARSG in the workplace at the user level (e.g. Berkemeier et al. 2019; Rauschnabel et al. 2018). As a consequence, researchers called for specific privacy policies regarding data processing, storage and access (Syberfeldt et al. 2016). Responding to this need, Berkemeier et al. (2019) conducted a requirements analysis incorporating the GDPR. Our results constitute a first step towards closing this gap by involving end users. We recommend neither to process, nor to disclose or store productivity data. Moreover, by integrating financial incentives into the experimental setting, we provide an instrument to compensate privacy concerns and to promote adoption (Jacobs et al. 2019). However, as incentives lead to increased expenditures, we believe that this economic gap should be investigated by means of a cost–benefit analysis. We also found that one third of respondents (C1: Strivers) appreciated sharing personalized performance data. To overcome these conflicts of interest, self-determination to share data through control mechanisms is an interesting means. Future research in the IS discipline might study how these aspects are viewed from an employee perspective concerning ARSG.

Finally, we contribute to the methodological knowledge base in the IS discipline by demonstrating and providing a method for understanding trade-offs for adoption decisions, in particular in workplace settings. When reviewing the literature, we noted that the methodology has been deemphasized in recent years, although there are substantial methodological foundations within IS (e.g. Naous and Legner 2018). CA has already been successfully applied in marketing and privacy research within the IS discipline (Krasnova et al. 2009; Burda and Teuteberg 2014), but to our knowledge there have been only few CAs in the IS discipline with reference to IS in the workplace (e.g. Luo et al. 2013). A reason for this is that cost-intensive software tools such as Sawtooth are needed to analyze conjoint data (Krasnova et al. 2009). Moreover, the practical application of the method is very complex (McCullough 2002). To lower these barriers, we make a methodological contribution to the knowledge base by demonstrating and extending the R script by Burda and Teuteberg (2014).

Apart from its theoretical relevance, our research is also helpful to practitioners. First, members of the AR ecosystem, including companies planning to adopt AR, industry associations (e.g., AREA) and AR system providers, can gain knowledge from our study as it creates transparency regarding workforce preferences on the benefits and RI of different criteria in AR system selection. In particular, given that companies planning to adopt are advised to select employees with a high digital affinity as the first adopters, our sample provides relevant insights concerning the target group (World Economic Group 2017). Thus, managers can study the findings to better understand the preferences of employees. In this regard, our study implies that careful selection of use cases and associated features of AR systems (e.g., safety enhancement, productivity enhancement through context-sensitive guidance) are key drivers of adoption. Although we found that financial incentives might increase adoption among employees, companies are advised to intrinsically motivate employees by suitable use cases. Further, we recommend companies to actively and transparently communicate the benefits as well as the privacy policies of AR systems to foster adoption, i.e. avoid rejection.

Likewise, the identified clusters give IT providers and user companies insights into how heterogeneous attitudes in employee groups can be. Based on the latent variables and the different utility estimates, these partial results can be used to yield personas of different interest groups represented in companies, which in turn can be considered when preparing for the introduction of AR systems (Aoyama 2005; Salminen et al. 2020; Thoma and Williams 2009). In addition, the ranking of the RI of the different attributes and the corresponding part-worth utilities may help IT companies specializing in AR to target their focus in future software development. For example, our results reveal that employees rate increased productivity more important than ease of use. In addition, occupational safety functions are of considerable importance. Although some solutions have already been developed in the research setting (e.g. Pierdicca et al. 2020, Tatić and Tešić 2016), they still constitute a rarity in practice.

Finally, our findings offer legislators and labor unions insights into preferences for privacy configurations in workplace settings. To the best of our knowledge, there are few data protection frameworks in practice that are tailored to AR. For instance, the XR safety initiative recently introduced the XRSI privacy framework and called for continuous improvement through participation (XR Safety Initiative 2020). Thus, the findings can help practitioners of this network to enhance and improve privacy frameworks to enable privacy by design.

5.2 Limitations and future research

Despite the knowledge gains outlined above, our study is subject to limitations that serve as a starting point for future research. First, the applied research method is a source of limitation. The results of CAs correlate strongly with the definition of attributes and levels (Beattie and Baron 1991). For example, a higher number of levels can trigger the "number-of-levels effect" (see e.g. Verlegh et al. 2002). To avoid this effect, we decided to create between two and three levels per attribute. Nevertheless, we cannot guarantee that the effect did not manifest itself. In addition, the attributes must be defined to be distinct and comprehensible (Orme 2002). Therefore, we had our formulations of the attributes checked in advance of the experiment. Another distortion of the results can arise from the order of the choice scenarios, given that cognitive performance often declines at the end of the choice scenarios, or participants use different heuristics at the beginning than at the end. Chrzan (1994) suggests three solutions to address these issues: rotating choice orders, rotating attribute order and stimuli. In this study, we followed his advice by randomly assigning the subjects to two groups that completed the 17 selection situations in opposite orders (Chrzan 1994; Chrzan and Orme 2000). We also removed some constructs after the pre-test to keep the survey length moderate.

Second, the selected attributes do not represent all relevant attributes of an AR-based assistance system. In our study, we excluded important factors such as brand, price and weight; neither did we integrate the privacy of others, which is relevant in the context of ARSG in the consumer sector (Rauschnabel et al. 2018). While we integrated monetary incentives, an attribute that is not itself a component of an assistance system, AR systems should be designed to intrinsically motivate their users, as such incentives are more effective in the long term. One possible starting point for this motivation is the gamification of user interfaces (Oliveira et al. 2015). However, since one focus of our study is to achieve trade-offs between monetary incentives and privacy, and between occupational health and safety and productivity gains, this selection seems appropriate. Still, when selecting the attributes, we were careful to achieve a balance between appropriate attributes and avoiding cognitive burdens for participants (Bansak et al. 2019). We focused in particular on qualitative attributes of the software, as we believe these can be better queried in an online survey than, for example, hardware characteristics, since many people have never worn AR glasses. Moreover, hardware specifics of ARSG have already been investigated in other studies using CA (Basoglu et al. 2017). Nevertheless, in view of the attributes not considered, there is a need for further research to be investigated with the help of CAs, e.g., the graphic design of user interfaces and the trade-offs between individual interaction modalities (Egger and Masood 2020).

Finally, the most serious limitation concerns the sample. Our survey was mainly completed by German students. In IS research, the generalizability of experiments with students has been controversial (Compeau et al. 2012). Nevertheless, recent research has shown that students do not differ significantly from other populations in investigations of technology decision-making (Mcknight et al. 2011; Sen et al. 2006). In consequence, students are often used in experimental studies to assess future work systems, for instance by Ellwart et al. (2019), Loose et al. (2013) and Weeger and Heiko (2014). In addition, in our case, 57.48% of the respondents already have industrial work experience, and we consider them as future employees. As outlined in Sect. 3.3, there are several rationales for choosing future employees with a high openness towards IT. For instance, companies are advised to first promote adoption by hiring digitally affine employees. Thus, the sample is likely to be exposed to AR systems in the workplace over the course of their careers (e.g. in the role of decision-makers). Given the projection that the diffusion of AR systems may continue for another decade, we are thus providing important insights into a later target group. In view of this sample-induced limitation, we propose and plan to conduct the survey again with a different sample consisting exclusively of current employees.

6 Conclusions

In this paper, we investigate the preferences of future employees with regard to AR systems in the production context. To this end, we conducted a choice-based conjoint study based on the attributes productivity gain, monitoring, safety enhancement and ease of use. In addition, we included a financial incentive for adopting AR systems to calculate the value of privacy violation compensations. From the respondents' perspective, the perfect AR system significantly increases productivity, enhances user safety, is easy to use and does not allow user monitoring. Additionally, an incentive of €200 maximizes the perceived AR utility. However, we found that attitudes toward the individual attributes vary significantly among employees. We identified three clusters that differ in their preferences and underlying utility structures: Strivers (C1), Payroll Hunters (C2) and Privacy Keepers (C3). In general, our findings encourage AR providers and user companies to carefully select well-accepted use cases and to transparently communicate privacy policies. Theoretically, our study reveals that safety enhancement and productivity gain constitute the two main drivers for technology acceptance of head-worn AR systems. In addition, privacy violations are indeed perceived negatively. Future research should examine the correlations between these factors, the perceived usefulness, the attitude towards using AR systems and the intention to use AR systems.

Appendix A

See Table 10.

Table 10 Item sources, item wording, item means, standard deviation

Construct	Reference	Item Wording	Mean	SD	α
Attitude toward using ARSG	(Rauschnabel and Ro 2016; Venkatesh et al. 2003)	ATTU1: Using augmented reality smart glasses in production environments is good.	5.54	0.89	0.76
		ATTU2: I have a positive attitude towards using augmented reality smart glasses in production environments.	5.81	1.08	
Intention to use	(Ajzen 1991; Davis 1989)	ITU1: Assuming I had access to augmented reality smart glasses in production environments, I intend to use them.	5.35	1.06	0.76
		ITU2: Given that I had access to augmented smart glasses in production environments, I predict that I would use them.	5.17	1.15	
Personal IT innovativeness	(Agarwal and Prasad 1998)	PIT1: I like to experiment with new technologies.	5.01	1.47	0.84
		PIT2: Among my friends, I am usually the first to try out new information technologies.	4.42	1.52	
Perceived privacy risk	(Malhotra et al. 2004)	PPR1*: It would not be risky to disclose my performance data and my movement profiles to my employer.	2.99	1.51	0.92
		PPR2*: There would not by any uncertainty associated with giving my personal performance data and my movement profiles.	3.17	1.62	
Legal trust	(Mcknight et al. 2002)	LT1: I feel confident that existing laws protect me against abuse of my information in workplace environments.	4.59	1.28	0.84
		LT2: Existing laws adequately protect my information in workplace environments.	3.99	1.46	

*Reverse Coded

Appendix B

Equation 2 describes the utility function to calculate the total utility of an alternative following Burda and Teuteberg (2014).

$$u_k = \sum_{j=1}^{J} \sum_{m=1}^{M_j} b_{jm} \times x_{kjm} \tag{2}$$

where.
u_k: Overall utility of an alternative k.
b_{jm}: Part-worth utility of attribute level m of attribute j.
x_{kjm}: Dummy variable for the attributes

$$x_{kjm} = \begin{cases} 1 & \textit{if alternative k contains level m of attribute j} \\ 0 & \textit{otherwise} \end{cases}$$

We define the dummy variables per attribute as follows:
Attribute 1: Productivity Gain

$$x_{j=productivity\_gain,m=0} = \begin{cases} 1 & \textit{if productivity\_gain} = 0 \\ & \textit{otherwise} \end{cases}$$

$$x_{j=productivity\_gain,m=15} = \begin{cases} 1 & \textit{if productivity\_gain} = 15 \\ & \textit{otherwise} \end{cases}$$

$$x_{j=productivity\_gain,m=30} = \begin{cases} 1 & \textit{if productivity\_gain} = 30 \\ & \textit{otherwise} \end{cases}$$

Attribute 2: Monitoring

$$x_{j=monitoring,m=none} = \begin{cases} 1 & \textit{if monitoring} = \textit{none} \\ & \textit{otherwise} \end{cases}$$

$$x_{j=monitoring,m=anonymized} = \begin{cases} 1 & \textit{if monitoring} = \textit{anonymized} \\ & \textit{otherwise} \end{cases}$$

$$x_{j=monitoring,m=transparent} = \begin{cases} 1 & \textit{if monitoring} = \textit{transparent} \\ & \textit{otherwise} \end{cases}$$

Attribute 3: Safety Enhancement

$$x_{j=safety\_enhancement,m=no} = \begin{cases} 1 & \textit{if safety\_enhancement} = \textit{no} \\ & \textit{otherwise} \end{cases}$$

$$x_{j=safety\_enhancement,m=yes} = \begin{cases} 1 & if\ safety\_enhancement = yes \\ & otherwise \end{cases}$$

Attribute 4: Ease of Use

$$x_{j=ease\_of\_use,m=complex} = \begin{cases} 1 & if\ ease\_of\_use = complex \\ & otherwise \end{cases}$$

$$x_{j=ease\_of\_use,m=easy} = \begin{cases} 1 & if\ ease\_of\_use = easy \\ & otherwise \end{cases}$$

Attribute 5: Financial Incentive

$$x_{j=financial\_incentive,m=0} = \begin{cases} 1 & if\ financial\_incentive = 0 \\ & otherwise \end{cases}$$

$$x_{j=financial\_incentive,m=100} = \begin{cases} 1 & if\ financial\_incentive = 100 \\ & otherwise \end{cases}$$

$$x_{j=financial\_incentive,m=200} = \begin{cases} 1 & if\ financial\_incentive = 200 \\ & otherwise \end{cases}$$

Applying Eq. 2 to our context, the overall utility of system k can be calculated as follows:

$$\begin{aligned} u_k = {} & -2.076 * x_{k,j=productivity_{gain},m=0} - 0.532 * x_{k,j=productivity_{gain},m=15} \\ & + 2.608 * x_{k,j=productivity_{gain},m=30} + 1.263 * x_{k,j=monitoring,m=none} \\ & + (-0.052) * x_{k,j=monitoring,m=anonymous} + (-1.211) * x_{k,j=monitoring,m=transparent} \\ & + (-1.898) * x_{k,j=safety_{enhancement},m=no} + 1.898 * x_{k,j=safety\_enhancement,m=yes} \\ & + (-1.091) * x_{k,j=ease\_of\_use,m=complex} + 1.091 * x_{k,j=ease\_of\_use,m=easy} \\ & + (-2.134) * x_{k,j=financial\_incentive,m=0} + (0.311) * x_{k,j=financial\_incentive,m=100} \\ & + (1.823) * x_{k,j=financial\_incentive,m=200} \end{aligned}$$

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