Virtual Reality (2025) 29:173
https://doi.org/10.1007/s10055-025-01246-6

ORIGINAL ARTICLE

Benefits and privacy in virtual reality commerce: a comprehensive review and data-driven assessment

Salah Hassanin[1] · Yun Fu[2] · Jella Pfeiffer[3] · Martin Meißner[2]

Received: 6 March 2025 / Accepted: 9 October 2025 / Published online: 20 November 2025

Abstract

Virtual reality (VR) commerce has immense potential for immersive and personalized shopping but also invites crucial privacy issues through exhaustive user data collection. The paper analyzes the technical aspects of VR data collection, such as multimodal sensory inputs and behavior tracking, to develop a data-driven privacy-benefit analysis (PBA) framework. Our approach links VR data attributes to psychologically derived constructs, outlining their business and user value along with privacy risks implicated. By integrating knowledge from information systems, behavioral sciences, and marketing, we present a framework highlighting the double-edged role of VR data in enhancing user experience along with subjecting consumers to privacy vulnerabilities. Our findings emphasize the importance of privacy-preserving design strategies and regulatory measures for fostering ethical and responsible innovation for VR commerce. The study contributes to the discourse on VR-based consumer interactions and digital privacy by offering practical insights for industry, policymakers, and academia, demanding interdisciplinary collaboration to balance technological advancements with user protection.

Keywords Virtual reality · Virtual reality commerce · User data collection · Sensor data · Privacy challenges · Privacy protection

1 Introduction

Virtual Reality (VR) allows elevating 2D shopping experiences, such as traditional e-commerce shopping on Amazon, to computer-simulated, interactive, real-time 3D shopping experiences. Prior research has argued that VR allows creating more functional, interactive, realistic, and engaging virtual commerce environments (v-commerce) (Xue et al. 2020). In this paper, we define v-commerce as electronically mediated commercial transactions that originate from cross reality technologies, particularly VR, and involve the exchange of either digitally generated or real-world goods and services. We refer to v-commerce as the subset of the broader concept of e-commerce that leverages VR to enhance the online shopping experience by creating immersive virtual marketplaces (de Regt and Barnes 2019; Luna-Nevarez and McGovern 2021). V-commerce research in this journal (Adhanom et al. 2023) has pointed out that the availability of new data sources, eye tracking (ET) in particular, provides exciting new uses cases for research and practice. For example, Pfeiffer et al. (2020) have shown that marketers can identify shopping motives (goal-directed and experiential search) by tracking and analyzing ET data in VR. The identification of shopping motives thus allows personalizing v-commerce applications. In addition, there are a few notable real-world pilot studies that demonstrate the application of utilizing such data in v-commerce. For instance, Hershey's and Kellogg using devices such as the Vive Pro Eye to track eye gaze and dwell time for optimizing product placement and shelf layout in retail environments (Nantelle

✉ Salah Hassanin
salah.hassanin@wirtschaft.uni-giessen.de

✉ Yun Fu
yun.fu.hn@tum.de

Jella Pfeiffer
jella.pfeiffer@kit.edu

Martin Meißner
martin.meissner@tum.de

1 Chair for Digitalization, E-Business and Operations Management, University of Giessen, Giessen, Germany

2 Center for Digital Transformation, Technical University of Munich, Munich, Germany

3 Institute for Information Systems, Karlsruhe Institute of Technology, Karlsruhe, Germany

2021). Similarly, Alibaba's Buy+VR shopping experience allowed users to interact with virtual products via gaze-based selection in commercial VR platforms (Hines 2016). While v-commerce shopping is still in a nascent stage, v-commerce represents a significant potential shift in the retail landscape. Forecasts predict a significant growth in the v-commerce market, with a CAGR of 34.7%, elevating its revenue from $18.60 billion in 2022 to $201.80 billion by 2030 (Statista 2023).

Despite the enthusiasm resulting from creating so-far unseen consumer benefits, researchers emphasized that v-commerce diffusion is challenged by various technical, ethical, and societal challenges (Dwivedi et al. 2022; Giaretta 2024). For creating a fully immersive environment with smooth interactions for the user, sensor-based data is needed to an extent that goes beyond what consumers are used to from e-commerce or brick-and-mortar shopping environments. The interactive data captured through VR technology is crucial for its functionality and for being able to offer the outlined benefits, such as presenting tailored recommendations based on identifying shopping motives (Pfeiffer et al. 2020). As a result, companies implement data-driven strategies by utilizing user-related data to generate personalized and interactive services for consumers (Saura et al. 2021). However, the literature provides little insights and guidance how multi-sensory data is connected to both benefits and privacy risks. Prior research either approached the topic from a technical (Garrido et al. 2024), theoretical (Reinartz et al. 2019) or privacy risks (Karwatzki et al. 2022) perspective. What is missing to the current day, is a framework that provides a comprehensive understanding of the topic.

This paper contributes to closing the outlined research gap by critically analyzing the intersection of VR technology and its application in v-commerce. We bring together the three outlined perspectives by reviewing the literature and developing a data-driven privacy-benefit assessment (PBA) framework. We start by describing from a technical perspective which data must and can be collected in VR. We then describe from a theoretical perspective which benefits and privacy risks may arise in the v-commerce context. Finally, we approach the empirical perspective by pointing readers to prior empirical findings about what can be learned from the VR data on the user level (we refer to this as psychological constructs).

This paper makes three key contributions. Firstly, it provides an understanding which data is used to infer which constructs that ultimately lead to knowledge about the user. Secondly, our paper outlines the benefits and privacy risks tied to various types of data and constructs. As these risks and benefits are context-specific, we, thirdly, illustrate the implications in the context of v-commerce highlighting implications for companies as well as users.

From a practical perspective, our framework provides valuable insights for companies seeking to leverage VR technology in v-commerce, policymakers tasked with regulating its use, and researchers focused on further advancing the VR technology field. Our work serves as a guide to the development of privacy-preserving strategies that balance innovation and user protection, contributing to the accelerating discussion on privacy in virtual reality (Giaretta 2024).

This study follows a conceptual theory synthesis approach (Jaakkola 2020), which is well-suited for synthesizing insights across diverse and overlapping research areas. Our goal is to integrate knowledge from technical, psychological, and ethical domains into a unified framework for assessing data practices in v-commerce. Accordingly, we selected literature relevant to the dimensions of our PBA framework from Scopus, Web of Science, AIS eLibrary, IEEE Xplore, ACM Digital Library, SpringerLink, and ScienceDirect. To complement this, we included selected industry reports, technical documentation, and authoritative web sources where relevant. Additionally, we applied backward and forward citation tracking to ensure comprehensive coverage across technical, psychological, and HCI-related domains. We prioritized foundational, recent, and domain-representative works that contribute to understanding key aspects such as data types, behavioral inference, consumer value, and privacy risks.

The rest of this paper is organized as follows: Sect. 2 explores the data collected in VR (technical perspective). Section 3 examines the interplay between v-commerce benefits and privacy risks (theoretical perspective). Section 4 bridges the technical and theoretical perspectives by linking VR data to psychological constructs, drawing on empirical findings (empirical perspective). This section highlights how the data can suggest psychological constructs and provide deeper understanding of consumers. The section also discusses potential use cases of business benefits and privacy risks of such insights.

2 Data collection in VR (technical perspective)

From a technical perspective, VR environments exhibit numerous advanced features that distinguish from traditional human–computer interaction (HCI) interfaces (Doerner et al. 2022). Among these is the multimodal presentation, which synchronizes various sensory channels—visual, auditory, and haptic, to produce realistic virtual experiences. These different channels are needed because the technology relies on interaction in a 3D world, leveraging body, hand, head movements and gestures. As a result, high-end VR devices are incorporating features such as room-scale tracking, hand tracking, and high-resolution displays, with plans to include extensive biometric measurements (Kröger et al. 2020a) such as electromyography (EMG) and electroencephalography (EEG).

We categorize data recorded in VR into three main types (see Fig. 1): primary, secondary and inferable data. Primary data attributes are directly observable and derived from data sources (e.g., sensors or devices). Secondary data attributes are deterministically generated from the primary data sources (e.g., body pose inferred from head and hand positions). Inferable data attributes are statistically estimated from primary and/or secondary data attributes (e.g., inferring personality traits from gaze and posture). Primary and secondary data, that are outlined further in the following sub-sections, present an immediate privacy risk due to their direct observability or deterministic nature, while the risk from inferable data is less apparent and depends on contextual analysis. We therefore offer a general overview of primary and secondary data attributes in this section and outline which data have been used to infer constructs that are particularly interesting in the v-commerce context as further outlined in Sect. 4.

Building on Garrido et al. (2024), we differentiate primary data attributes into static and dynamic privacy data types (see italics in Fig. 1 and Table 2 in Appendix 1). Privacy regulators mainly focus on personally identifiable information (PII) which is associated with static private information and revolves around identity. The static privacy dimension includes context-independent personal data that can currently be regulated and does not change (dramatically) over time, such as name, billing information, health information, beliefs, and personal documents (Bailenson 2018; Gulhane et al. 2019; Wang et al. 1998). The dynamic privacy view includes transit data which refers to real-time emotion and sensor data that changes substantially over time (Bailenson 2018; Gulhane et al. 2019). Being dynamic involves non-verbal behavioral cues that are meaningful and unique. These cues include unconscious interactions beyond the user's conscious awareness. Dynamic private information is primarily context-dependent and can be collected and analyzed to generate a well-informed individual profile (Wang et al. 1998). Heller (2020) calls the concept of creating such a profile within VR "biometric psychography". Biometric psychography involves using bodily-centered data to uncover deep insights into an individual's preferences and interests (Heller 2020).

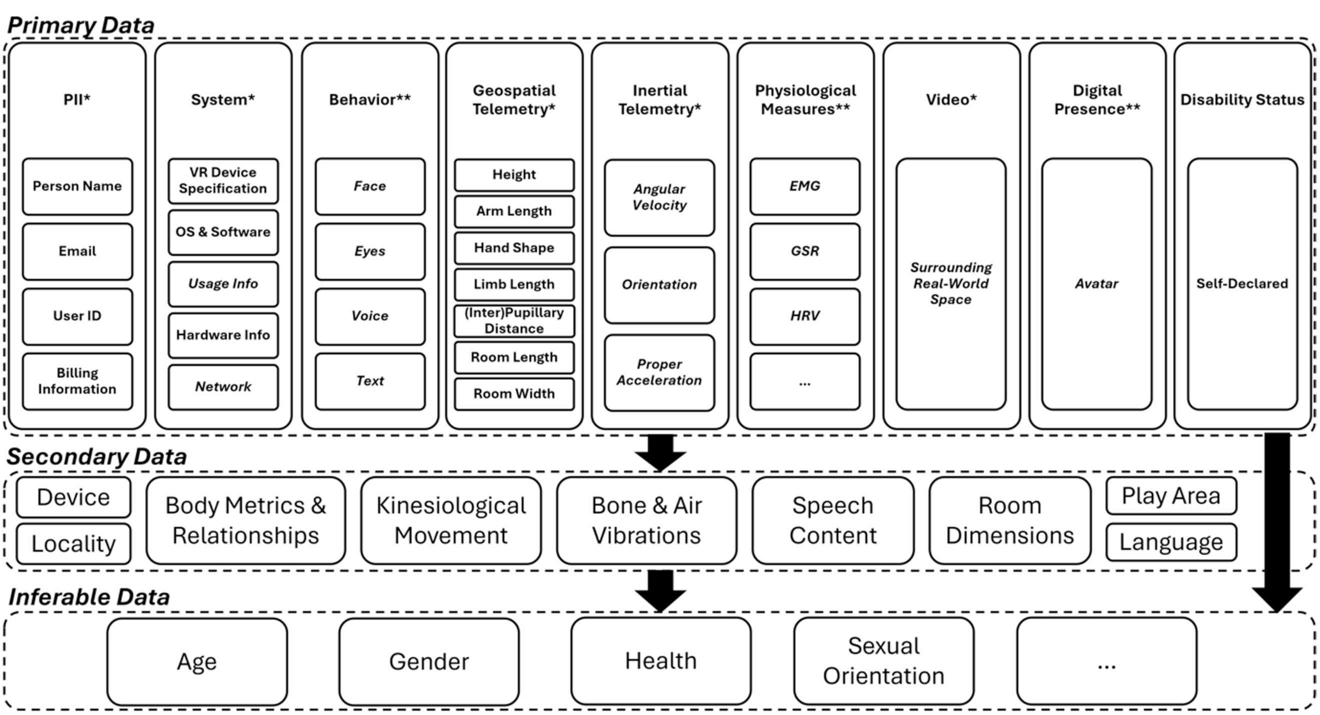

Fig. 1 Overview of categorized primary, secondary, and inferable data attributes and the associated content. Extended, modified, and based on Garrido et al. (2024), Nair et al. (2023a), Nair et al. (2023b), and Trimananda et al. (2022). Categories, marked with an asterisk, flag data that is essential to the functionality of the VR technology. Double asterisks (**) mark categories that are only contextually required, depending on the application. Data attributes in italics are dynamic and otherwise static. It is worth noting that any specifications and markings in the table are subject to change at any time as VR technology and regulations evolve. For a comprehensive overview, refer to Table 2 and Table 3 in Appendix 1

2.1 User identifiers

This primary data attribute category only includes static components and is used in all digital environments where users must at least provide personally identifiable information (PII) name and email registration, licensing, and in-app purchases. For this purpose, upon registration, a unique user ID is usually created once for the user on the respective central platform (e.g., Oculus Store).

2.2 System

The user identifiers can also be collected and accessed via network data flow (Trimananda et al. 2022). The network data flow enables collecting and accessing system information (see Table 2). This information encompasses device identifiers, geographical location either directly through IP address or indirectly through hyperbolic positioning using latency information, as well as virtual space location through obtaining the hostname in virtual space by capturing the IP address. Additionally, usage information, hardware information, and operating system and software information can be collected through this data flow (Nair et al. 2023b; Trimananda et al. 2022). Web trackers can create individual user profiles, called fingerprints, by utilizing system parameters and settings such as OS and software, hardware and usage information (Trimananda et al. 2022). This practice of fingerprinting enables trackers to monitor users for long periods of time, even if the users delete their traces (e.g., cookies) or utilize private modes (Vastel et al. 2018). Although there is unanimous consensus among standards bodies and browser vendors that fingerprinting is detrimental, its utilization on the internet has progressively risen throughout the last decade (Apple 2019; Das et al. 2018; Englehardt and Narayanan 2016; Google 2019; MozillaWiki 2022; W3C, 2015, 2021). Always-on cameras and sensors, especially inside-out tracking VR devices (Meta 2023) observe the surrounding real-world space to ensure the user's safety from physical collision. These cameras and sensors can expose the real-world environment around users, which may contain sensitive information (e.g., personal objects or bystanders).

2.3 Behavior: face and eyes

The face serves as the foremost instrument for facial expressions. The face and eye are closely connected by muscles, and movements of the face, including the eyebrows, eyelids, and mouth, and can provide valuable information about where a person is looking at as well as emotions (Schwartz et al. 2020). Both face and eye movements can be detected by (infrared) cameras such as implemented in the Meta Quest Pro (face and eye movements), HTC Vive Pro Eye (only eye movements; in combination with HTC Vive Facial Tracker also with face movements), and Playstation VR 2 (only eye movements) (Meta 2023; PlayStation 2023; VIVE 2023a, 2023b). ET technology has become an essential component of VR technology, enhancing the immersive and interactive experience for users (Adhanom et al. 2023). Its integration is primarily driven by foveated rendering, as highlighted by Godin et al. (2004). Many recent VR head-mounted displays (HMDs) incorporate ET technology to achieve this effect because manufacturers have made significant advancements in ET, making it cost-effective, portable, and highly proficient, as emphasized by a study conducted by Grand View Research (2022). Additionally, eye- and face-tracking technology (e.g., HTC Vive Pro Eye and HTC VIVE Facial Tracker) can be used to provide more personalized and adaptive content based on this information, such as (photo-realistic) facial expressions (Chu et al. 2020).

ET constructs and inferences can be derived from a combination of fixation-related, saccade-related, pupil-related, iris-related, or face-related data streams (Kröger et al. 2020a; Pfeiffer et al. 2020). Fixation-related ET measurements involve tracking the duration and location of fixations, which are periods of relative visual stability during which the eyes are focused on a specific point in the visual field. Saccade-related ET measurements involve tracking the speed, amplitude, and direction of saccades, which are rapid, abrupt eye movements that occur when a person shifts their gaze from one point of interest to another. Pupil-related ET measurements involve tracking pupil size and dilation. Yet, while data on fixations and saccades is standard in ET, not all ET systems measure pupil dilation. Kröger et al. (2020a) presented an extensive analysis outlining the multitude of insights that can be derived from ET. ET data can yield various inferences, including cultural and linguistic aspects (e.g. knowledge), expertise and performance, interests and preferences, emotional states and physical conditions and health-related information (e.g., drug addiction).

The human face has other essential physiological functions that only physiological tracking systems can track by applying physiological measures. For example, physiological measures such as photoplethysmography (PPG), EEG and galvanic skin response (GSR) become necessary to track microexpressions accurately (Saffaryazdi et al. 2022).

2.4 Behavior: communication (voice and text)

HMDs usually have microphones integrated and allow for voice input. Controllers, virtual keyboards or eye-movements further allow for text inputs. These multimodal ways of direct communication help users with disabilities or mobility impairments who may have difficulty with one or the other input device (Mott et al. 2019). Moreover, voice and text inputs can be faster and more efficient than traditional input methods, allowing users to perform more quickly and easily (Baxter et al. 2021; Jiang et al. 2019). Natural language processing (NLP) techniques can be used to analyze voice and text inputs to extract meaning and intent (Acosta & Reinhardt 2022). Audio data, such as voice, can provide vast information about the speakers and their surroundings. Kröger et al. (2020b) provide a plethora of sensitive information that can be derived from linguistic and acoustic patterns in recorded audio through advanced data analysis methods. Voice recordings may allow inferences about the user's personal characteristics, psychological states, linguistic and cultural aspects, health-related information, socioeconomic status and environmental information (e.g., background noise).

2.5 Geospatial and inertial telemetry

Using geospatial and inertial telemetry information gathered from end-users uncovers sensitive anthropometric measurements. Body tracking devices can reveal various continuous (e.g., arm-length and height) and binary anthropometric measurements (e.g., longer-arm and dominant handedness), which can be combined (e.g., wingspan) or compared to reveal additional biometrics or asymmetries in the user's body (Garrido et al. 2024; Nair et al. 2023a). In addition, kinesiological movements revealing unique gestures (Figueiredo et al. 2016) and biometric movements such as gait can also be recorded (Olade et al. 2020; Shen et al. 2019). Geospatial and inertial telemetry data can also be used to infer a user's full-body pose (Winkler et al. 2022) and even derive speech from bone and air-borne vibrations registered by an HMD's IMU inertial measurement unit (IMU) telemetry data (Shi et al. 2021). An IMU, a combined electronic sensor with accelerometers, gyroscopes, and magnetometers, tracks velocity, orientation, and gravity forces (Shi et al. 2021). For instance, it is used in headsets for head orientation and in controllers for hand movement detection.

2.6 Physiological measures

Physiological measures present a nonintrusive approach for assessing various task-related variables (Halbig & Latoschik 2021; Riedl & Léger 2016), such as heart rate variability (HRV) (Marín-Morales et al. 2021), electrograms by using EEG (Bin Suhaimi et al. 2020), and EMG (Lou et al. 2020). They provide objective assessments of autonomic (organic activations involuntarily and subconsciously controlled responses by the autonomic nervous system) and deliberate processes (intentional responses). HRV enables the quantification of autonomic processes like fluctuations between heart beats due to emotional arousal (Marín-Morales et al. 2021), while EMG enables capturing deliberate processes like facial muscle movements (Lou et al. 2020). Physiological measures allow inferring a user's inner state and can provide insights into cognitive and affective responses (Riedl & Léger 2016). The quantitative nature of the data obtained from physiological measurements makes it suitable for analysis and utilization in machine learning and deep learning algorithms, enabling insights and inferences to be drawn from the collected data. In the context of VR, physiological measuring is enabled by integrated sensors or wearables in VR headsets or on the user's body.

However, it is important to note that mainstream consumer VR headsets generally do not come equipped with built-in physiological sensors (except for ET, which some researchers consider to be a physiological measure). Instead, consumer-grade VR headsets focus primarily on delivering immersive visual and auditory experiences, relying on external devices or separate accessories, such as the Meta EMG Wristband (Meta 2021), for physiological monitoring if required.

2.7 Video

HMDs in VR systems often include sensors and cameras that capture the surrounding real-world space to enable spatial awareness, prevent collisions, and support functionalities such as passthrough vision or mixed reality overlays. This environmental recording enhances user safety and interaction fidelity. However, such continuous data may inadvertently capture the presence and distance of bystanders, private spaces, or sensitive contextual information (e.g., recording individuals without consent, revealing personal items or documents, or exposing confidential workspaces) (Y. Zhang et al. 2020b; Garrido et al. 2024). Even non-privileged applications can exploit side channels (side-channel attack) to infer real-world details (Y. Zhang et al. 2020b).

2.8 Avatar: non-verbal behavior and digital assets

Avatars may collect and transmit sensitive personal data, including biometric and behavioral data (Dwivedi et al. 2022; Giaretta 2024). An avatar is a visual representation of a user within the VR environment, and it is typically used to participate in social activities, driven by the user's movements (Bailenson et al. 2004). In the case of the upcoming Metaverse, the avatar is a medium that projects one's identity within virtual spaces (Park and Kim 2022). The primary means of controlling virtual avatars is through body movement. For this, professional motion-capture systems and suits are typically used in avatar-related research to achieve high-quality embodied experiences (Kilteni et al. 2013; Roth et al. 2016; Spanlang et al. 2014; Wu et al. 2021). Although these systems provide high accuracy and potentially large tracking areas, they are expensive and cumbersome to wear (Wu et al. 2021). An alternative solution for tracking body parts is consumer VR devices such as the Oculus Rift or HTC Vive with spatial controllers or hand tracking such as for the Meta Quest 2. However, the majority of VR systems currently rely on three-point tracking solutions (HMD plus two controllers), which necessitate additional sensors and trackers to convey movements of the arms, legs, or feet, as well as complex inverse kinematic algorithms (Aristidou et al. 2018; Caserman et al. 2019; Wu et al. 2021). Avatars have a crucial function in social VR, and their degree of realism significantly impacts the sense of presence, interpersonal interactions, and copresence (Jung et al. 2017, 2018; Jung and Hughes 2016; Steed and Schroeder 2015; Wu et al. 2021). When engaging in social interactions, people often communicate more through nonverbal cues than through verbal means (Matsumoto et al. 2013). According to Navarro and Karlins (2008), nonverbal cues account for about 60–65% of communication. Consequently, non-verbal social presence cues (proximity, orientation, eye contact and gaze, and physical appearance) are important for communication (Aburumman et al. 2022; Bente et al. 2004; Rae et al. 2008; Swinth and Blascovich 2002). Non-verbal behavioral data could easily be used to infer user facts, behaviors, or behavioral trends that are not visible to the user's eyes (Dwivedi et al. 2022; Dick 2021). Furthermore, the choice of avatar representation and digital assets the user owns can also reveal information such as their demographics and financial status (Dick 2021; Garrido et al. 2024; John et al. 2020).

We would like to point out that we consider only the directly observable (inter)actions (e.g., choices and human-to-human interaction) and appearance of avatars (e.g., gender identity and species). Therefore, we limit possible digital assets that belong to an avatar contributing to its appearance, such as wearables (e.g., clothing).

2.9 Disability status

Self-declaring a disability in VR environments enables people with disabilities (PWD) to shape their virtual identity authentically, access tailored social experiences, and foster representation through avatar design that reflects their real-world conditions (Zhang et al. 2022). While self-declaration promotes visibility and agency, it requires safeguards that ensure PWD retain control over what they disclose and are protected from potential misuse or harm. Such safeguards may include selective disclosure settings, anonymous identity layers, and protective measures against risks like targeted harassment or the misinterpretation of disability-related avatar features (Zhang et al. 2022, 2023a; Stendal & Bernabe 2024).

3 Privacy risks and benefits (theoretical perspective)

Information systems need extensive personal data to develop and deliver benefits based on personalized services. The use of data for personalization, however, often brings along a loss in information privacy. The following example illustrates the close connection between benefits and privacy concerns: In v-commerce, companies can utilize ET to discern consumers' attention patterns. Companies create benefits for consumers if they tailor product displays to individual search motives (Pfeiffer et al. 2014) or determine the point in time when assistance is needed (Weiß and Pfeiffer 2024). However, the same data potentially reveals how price-focused or -sensitive a consumer is. A company may use this information against the interest of consumers and implement price discrimination. The example outlines that the same process of data collection, inferred by the same construct (attention patterns) but used in different contexts, can yield benefits as well as risks associated with data misused. Consumers, when facing such benefit-risk trade-offs, are expected to assess privacy risks dependent on the context as risk perception originate from the nature, causes and consequences inherent to each context.

When evaluating whether to disclose personal data, consumers do not rely on a fixed set of preferences. Instead, their privacy decisions are context-dependent (Acquisti et al. 2015). For instance, even if consumers express concern for their information privacy, they may still choose to share behavioral data in specific contexts such as travel. This dynamic also applies to sensitive data types like biometric information—studies have shown that consumers' willingness to disclose such data is heavily influenced by the benefits they expect to receive in return (Ioannou et al. 2020). Therefore, the trade-off between perceived benefits and privacy risks plays a central role in shaping consumers' disclosure decisions (Wang et al. 2016). Given the growing depth and scope of data collection driven by digital technologies in retail, it becomes increasingly important to systematically outline and categorize the potential benefits that can result from data disclosure. This is especially relevant in v-commerce, where the understanding of customer value and future customer shopping experiences are essential. In response to this need, marketing scholars have discussed regarding opportunities in future retail stores (e.g., Szocs et al. 2023; Grewal et al. 2023; Reinartz et al. 2019).

While much of the frameworks provide valuable insights by examining the evolution of retail formats—such as the distinction between physical and online stores (Szocs et al. 2023) or purely focus on future online retail stores (Grewal et al. 2023), they do not address how digital transformation fundamentally reshapes value creation itself. In particular, we adopted the framework by Reinartz et al. (2019) for illustrating the benefits in v-commerce for our work. Reinartz et al.'s framework explains how digital transformation opens up new sources of value by meeting customer needs in novel ways through the lens of value creation (see Table 1 for the categorization of benefits used for companies and consumers). This perspective aligns closely with our focus on VR technology in commerce, where consumer interaction often involves the disclosure of biometric data. We argue that such data serves as a key driver of value such as enabling personalization and convenience for consumers, and offering retailers new avenues for business growth. At the same time, these data introduce privacy risks. By building on Reinartz et al.'s lens, we highlight data disclosed as a fundamental mechanism through which digital transformation generates both value and vulnerability. Secondly, the distinction between firm-level and consumer-level benefits from Reinartz's framework is especially useful in our analysis. Because the use of consumer data in VR can lead to either mutually beneficial outcomes (e.g., enhanced shopping experience) or one-sided advantages (e.g., price discrimination). Categorizing benefits at both levels helps us more clearly capture the complex trade-offs and ethical implications of data-driven value creation in VR commerce. Consequently, we will refer to these different categories of benefits and discuss their magnitude and relative importance in the light of our v-commerce context.

Consumers' decision whether to share private data in a particular context is the outcome of a trade-off between potential benefits and risks (Dinev et al. 2013; Hui et al. 2007; Kaur et al. 2024). Information systems research showed that a loss of information privacy can increase privacy concerns and privacy risks perceptions, in case users feel that organizations could misuse their data (Al-Natour et al. 2020; Smith et al. 1996). Research focused on better understanding user's privacy risk perceptions resulting from external (parties) access to users' personal information (Karwatzki et al. 2022) or privacy concerns stemmed from literature and interviews (Kummer et al. 2021; Yun et al. 2019).

Privacy perceptions and behaviors are not only situational but also shaped by individual and cultural differences. For example, Fleming et al. (2021) demonstrate that self-construal and cultural orientation significantly influence how individuals value personal data and, consequently, how they manage privacy behaviors. In addition, a meta-analysis by Bauer and Schiffinger (2016) confirms that cultural factors, such as individualism and uncertainty avoidance, significantly moderate how individuals assess privacy risks and benefits. This reinforces the importance of integrating cultural context in privacy-related research. Consequently, scholars have examined various strategies to safeguard

Table 1 Overview of potential benefits and privacy risks of data and constructs

Data and construct		Benefits for companies and consumers			Privacy risks for consumers	
Data attributes	Constructs	Benefits for (source of value creation) company (Reinartz et al. 2019)	Benefit for consumers (Reinartz et al. 2019)	Concrete examples of benefit	Concrete examples of negative consequences	Risk dimensions (Karwatzki et al. 2022)
Eyes	Attention patterns	Individualization	convenience, relevance	AP1, AP2	APN1, APN2	Freedom-related, Resource-related
		Automation	convenience	AP3		
		Transparency and control	empowerment	AP4		
Eyes, HR	Attention directed to stimuli	Individualization	relevance or convenience	ADS1	ADSN1	Psychological, Prosecution, Freedom-related
			relevance, experience	ADS2		
Eyes	Level of processing	Interaction	relevance, empowerment	LP1	LPN1	Resource-related, Psychological
Eyes, ECG	Cognitive load	Interaction	relevance, experience	CL1	CLN1, CLN2	Resource-related, Social, Psychological, Freedom-related
			Empowerment	CL2		
		Ambient embeddedness	relevance	CL3		
Eyes, EMG, HR, SCR, Voice	Emotional arousal	Interaction	relevance, experience	EA1, EA2	EAN1, EAN2	Resource-related, Freedom-related, Psychological, Social
Eyes, EMG, HRV, Kinesiological Movements, SCR, Voice	Personality traits	Individualization	relevance, experience	PT1	ETN1, ETN2	Psychological, Resource-related
		Individualization Interaction	relevance, experience, empowerment	PT2		
			relevance, experience	PT3		

The example abbreviations in the table correspond to examples discussed in Sect. 4 (e.g., AP1 denotes the first example under the Attention Patterns subsection in Sect. 4). Note: Not all data attributes mentioned in Table 1 are required to infer the respective construct consumer privacy and reconcile the industry's data collection needs, through the angle of regulation, trust, ethics, and justice (Ashworth and Free 2006; Liu et al. 2022), a point that we will come to at the end of this paper.

As the assessment of privacy risks requires a solid understanding of the benefits and is also highly context-specific, we assess privacy risks through the multidimensional framework proposed by Karwatzki et al. (2022). Karwatzki and colleagues conceptualized privacy risks according to the context-specific negative consequences as perceived by consumers. They identified seven distinct privacy risk dimensions: physical, social, freedom-related, resource-related, prosecution-related, career-related, and psychological (Table 4 in Appendix 1 provides an overview of these dimensions and possible use cases in VR). By knowing the consequences they would be encountering, consumers may vary in privacy risk perceptions due to different contexts when the data is used and aggregated. This framework provides a foundation to our work as we aim to outline the potential privacy risks for consumers and the benefits derived from companies' value creation.

4 Constructs (empirical perspective)

4.1 Data and construct

As discussed in previous literature (Meißner and Oll 2019), psychological constructs are frequently operationalized and measured using attentional or sensory data. Building upon the discussion of VR data attributes in Sect. 2, this section discusses how user's psychological constructs can be inferred in v-commerce and further present the potential values for companies, benefits for consumers, and privacy risks stemming from the analysis of the inferred constructs by applying Reinartz et al. (2019) and Karwatzki et al. (2022)'s framework. Table 1 summarizes the explanations given in the following paragraphs and gives readers the opportunity to directly link data attributes, constructs, as well as benefits and risks.

We acknowledge that it is not feasible to include all possible constructs in our assessment, especially given the rapid advances in computational modeling. In this paper, we focus on constructs that (1) are directly inferable from observable VR data attributes, as categorized in Sect. 2, (2) are supported by robust empirical evidence—either in VR or related contexts, and (3) are uniquely relevant to the immersive and embodied nature of VR.

For instance, as we discussed in the following section, *attention patterns* can be directly inferred from ET data and have been extensively validated in decision-making and information search contexts. *Personality traits* are included due to existing strong evidence in the literature supporting its possibility to be inferred directly from VR observable data such as body movements, ET data, voices. Moreover, personality plays a central role in social VR interactions, making it a particularly relevant construct for this context.

4.2 Attention patterns

The investigation of attention patterns has a long tradition in decision-making research. The adaptive decision-making framework developed by Payne et al. (1993) has strongly stimulated decision-making and information processing research. In an overview of attention in decision-making theories, Orquin and Loose (2013) suggest that decision-makers tend to form patterns when making decisions, particularly segmented into 'overview', 'comparison', and 'checking' phases, as indicated by ET data. Furthermore, ET data can reveal how the context of search tasks influences attention patterns. For example, Shi et al. (2013) introduce a hierarchical hidden Markov model using ET data and suggest that consumers switch between attribute-based and product-based information acquisition strategies during online decision-making environments. Their study particularly emphasizes and challenge the traditional notion of deliberate and conscious strategic decision-making because the role of over-learned and largely unconscious routines in information overload and time pressure context are significant. Attention patterns can further be used to distinguish goal-directed and exploratory search motives (Janiszewski 1998). Findings by Pfeiffer et al. (2020) suggest that search motives can be identified based on ET data with 85% accuracy after observing the first 15 s of search behaviour in a VR shopping context.

Observing attention patterns in v-commerce could yield several benefits for both users and companies (see Benefits for Companies and Consumers column in Table 1). V-commerce environments can be individualized to enrich user experience, offering consumers significant convenience. This individualization facilitates attribute-wise search in complex situations through methods like product highlighting or sorting by frequently observed attributes, saving consumers' time and ensuring a tailored search experience (AP1). Furthermore, the identification of search motives can be used by recommender systems that aid in line with search motives, enhancing the relevance of the shopping experience (AP2). Furthermore, it increases convenience to consumers by providing better recommendations based on their past shopping habits (AP3). Pfeiffer et al. (2020) found that users prefer product filters and social network recommendations in goal-directed search and collaborative filtering recommendation systems. In contrast, more special offers are preferred in exploratory search situations. Matching offers provided by the company with the consumer's goal further empowers consumers by providing automated comparisons for items of interest to simplify their choices, and it also increases the company's transparency and control over consumer's needs (AP4).

However, a system that infers attention patterns will also make users more vulnerable. Companies may infer consumers' price sensitivity by quantifying how often they search by brand or by price and adjust the visual store layouts with the intention to personalize brand and pricing information presentation in real-time (APN1). Sorting of products on the shelf can also be adapted to individual needs. This customization can also pose threats on freedom-related privacy. For example, fostering brand-focus by enhancing space for products of a particular brand might reduce price focus and make impulsive buying more likely (Zhao et al. 2022). Consequently, the outlined application would result in unexpected resource-related privacy risks. Second, retailers detecting consumers' attentional biases (Chen et al. 2021) may strategically place high-margin products at eye level to maximize profits. Similarly, recommender systems could be set up to influence user preferences based on presenting selective information in a certain order or limiting the number of options in personalized consideration sets (APN2).

4.3 Attention directed to stimuli

The measurement of attention towards a stimulus can be quantified by various methods, such as tallying the number of fixations or accumulating fixation durations. Findings by Meißner et al. (2016) support a strong correlation between the utility of alternatives and their attention, known as the "alternative focus effect." Similarly, the attention that an attribute receives can signify the attribute's relative importance in the decision-making process. Moreover, neurophysiological methods also reveal consumers' preference (Venkatraman et al. 2015) and attention. For example, changes in heart rate (HR) and skin conductance response (SCR) have been shown to distinguish levels of viewer attention, specifically detecting the shift from preattention to focal attention during ad exposure (Bellman et al. 2019). Furthermore, Walla et al. (2011) found that significant reductions in eye blinks, SCR, and HR occur when consumers view brands they favor, compared to those they dislike.

Analyzing the attention to stimuli in real-time in v-commerce could aid consumers in forming their consideration set, thereby enhancing convenience and relevance in shopping experience (ADS1). For instance, making decision-relevant information visually salient, such as highlighting products that so far got most consumer attention, may prevent information overload and enable consumers to form consideration sets more efficiently. Given the strong correlation between attention to stimuli and preferences, recommender systems could use the amount of attention directed to stimuli to create real-time product recommendations, enhancing engagement by providing content matching consumer interests. Furthermore, retailers could leverage information on consumers' response to stimuli by identifying highly engaged consumers and sending them promotional codes to incentivize immediate purchases (ADS2).

Although identifying preferences may be relatively unproblematic within a marketing context if the goal is to create additional consumer value, inferencing preferences outside the marketing context has stronger privacy implications. Attention paid to political statements or sexual content could potentially reveal a person's political views or sexual orientation (Wenzlaff et al. 2016) (ADSN1). This exposure could lead to negative outcomes such as discrimination and surveillance inducing mental discomfort and a feeling of being watched, leading to psychological privacy risks. Moreover, if religious beliefs, political views, or sexual orientation is accidentally exposed, it could present significant prosecution risks, particularly in countries with extreme conservative stances on these matters.

4.4 Level of processing

Stimulus information processing occurs at levels from shallow (focuses on physical attributes), to deep processing (meaningful connections are formed) (Craik and Lockhart 1972). Typically, fixation durations between 200-250 ms are associated with scanning and automatic processing, whereas deeper processing requires fixation durations exceeding 300 ms, indicative of a slower and more cognitively demanding process (Velichkovsky et al. 2002). ET can be used to identify processing strategies. For instance, print ads provoke longer processing times and larger pupil sizes, signalling stronger engagement and a broader range of attention, while digital ads receive shorter processing times but a higher proportion of long fixations, hinting at deeper processing (Venkatraman et al. 2021). Evaluation of high and low involvement product categories and their corresponding purchase risk (Rossiter and Percy 2017) might necessitate different processing levels. Researchers have found that individuals process stimuli differently depending on the complexity of the stimuli. They become aware of basic visual features, like color, before complex features, like categories (Jimenez et al. 2021). Ovalle-Fresa and colleagues (2021) extended these findings to visual associative memory, demonstrating the influence of level of processing framework to both verbal and perceptual stimulus.

Utilizing different presentation modes like print, digital, voice marketing, and other sensory marketing techniques, retailers can effectively customize the presentation of information to suit the target product category in a v-commerce context. This approach fosters interactions that benefits companies by engaging consumers in a more dynamic and personalized manner. Furthermore, personalized presentation assimilates relevant product information without additional mental effort for consumers, empowering them with the knowledge they need to make informed decisions and ensures effective delivery of product information for retailers. In line with the idea to change the design of nonverbal stimuli to enhance recall of decision-relevant product attributes (Krefeld-Schwalb and Rosner 2020), retailers may adapt stimulus presentation to the level of complexity experienced by users (LP1).

The privacy risk related to the given example is that retailers could use highly personalized and potentially sensitive information about the consumer's current level of processing to customize their sales tactics. For example, knowing that a consumer's cognitive processing abilities are currently diminished, a retailer could choose to present highly appealing, but potentially more expensive items or use other persuasive techniques that the consumer might be more susceptible to under these conditions, thereby generating freedom-related privacy risks (LPN1).

4.5 Cognitive load

Cognitive load, a multidimensional construct, refers to the allocation of working memory resources during mental activities (Paas et al. 2010). Gambiraza et al. (2021) indicate that oculometric data alone can be effectively used for cognitive load classification, for example by using machine-learning approaches (Bachurina et al. 2022). Luong et al. (2020), for instance, argued that blinks and pupil size are known to be affected by varying levels of cognitive activity. Weiß and Pfeiffer (2024) support the idea that ET measures, specifically, saccadic angular velocity and saccade duration are highly discriminative in cognitive load measurements. Also, ECG can be used to measure cognitive load (Haapalainen et al. 2010) and was tried as sensor (Weiß and Pfeiffer 2024).

High cognitive load reduces attention to negative information (Li et al. 2020), enabling retailers to adapt review displays accordingly, for example, by balancing positive and negative feedback. Moreover, cognitive load might also affect consumers' choice behavior. Shiv and Fedorikhin (1999) showed that individuals choose products superior to the affective dimensions but inferior to the cognitive dimensions when the cognitive load is enhanced. This knowledge can be used by retailers to recommend emotionally linked products to those experiencing high cognitive load, potentially improving interaction with consumers by providing relevant product recommendations and increasing consumer satisfaction (CL1). In essence, the combination of ET data and machine learning techniques has made it possible to predict cognitive performance and, in turn, quantify consumers' real-time cognitive load (Bachurina et al. 2022). Furthermore, cognitive load can help determine the optimal time for a decision support system or a digital sales agent to offer assistance (CL2), offering an individualized, stress-free shopping experience. Retailers can also provide selective discounts based on consumer cognitive states, offering them when consumers are most likely to respond to them (CL3).

Cognitive load positively influence how much time consumers spent in virtual stores in purchase stages, indicating that retailers could potentially identify who are more likely to stay longer in the store (Kakaria et al. 2023). Moreover, cognitive load can potentially be used to identify impulsive buyers (CLN1). Research has shown that people under high cognitive load are more likely to make impulsive decisions as their ability to self-regulate and make rational choices decreases (Vohs and Faber 2007). Consequently, retailers could exploit this finding by pushing flash sales, limited time offers, or suggesting more expensive products, playing into the impulsivity of these overloaded users. Moreover, high cognitive load has also been associated with risk-taking behavior when performing economic decision-making (Blaywais and Rosenboim 2019), suggesting that retailers could potentially promote high-risk content to those experiencing such cognitive strain (CLN2).

4.6 Emotional arousal

Emotional arousal, defined as a state that describes the level of calmness or excitation elicited by a stimulus (Skaramagkas et al. 2021), plays a significant role in understanding how we interact with our environment. Researchers have found that physiological measures like ET, HR, voice, and EMG serve as valid indicators of arousal. Skaramagkas et al. (2021) conducted a comprehensive review of ET metrics that can infer significant levels of emotional arousal, and Hildebrand et al. (2020) demonstrated how changes in voice dimensions can infer different types of emotions. Laukka et al. (2005) also showed the connection between slower speech rate with arousal ratings. Luangrath et al. (2022) found that those highly stimulated (based on the elevation of HR) in VR tend to experience a greater sense of psychological ownership when using virtual hands and tend to have a stronger impact on willingness to pay for products. In addition, social competition within the environments and time pressure could increase arousal states (based on HR and SCR) (Adam et al. 2015).

The given examples demonstrate that retailers can utilize physiological measures for identifying arousal levels. Virtual store atmosphere could then be adapted in line with the level of arousal measured, improving interaction with consumers. For instance, for consumers who show high arousal under social competition or time pressure (Adam et al. 2015), a limited promotion sales strategy could be utilized to enhance their shopping experiences and boost sales. This strategy underscores the relevance and experience benefits for consumers by customizing shopping environments to their real-time emotions (EA1) and presenting marketing stimuli based on their arousal levels (EA2). However, potential privacy risks exist. For instance, if a retailer wants to promote a poorly selling product, they could manipulate the tone and voice of marketing messages, based on data revealing which kind of voice features can increase or decrease arousal (EAN1). They could also create a scenario of social competition, increasing the arousal level through self-generated avatars, leading consumers to have a higher willingness to pay or purchase intention (Adam et al. 2015). This manipulation of arousal levels and incorporating with marketing tactics could result in unwanted impulsive purchases and unexpected financial loss for consumers. Furthermore, consumers may experience discomfort that companies have access to their arousal states and use that data to affect their (purchase) behavior. In combination with the information which stimuli a user looked at, retailers could potentially quantify and model the arousal level of each consumer for each stimulus, enabling them to determine which stimuli interest consumers (EAN2).

4.7 Personality trait

Personality traits refer to "consistent patterns in the way individuals behave, feel, and think" (Cervone and Pervin 2022). Berkovsky et al. (2019) have sought to predict these traits based on measurements of human physiological responses to external stimuli like eye saccades, brain activity, and skin conductivity. Using machine learning techniques, the authors report a remarkable overall accuracy rate of 85.71% in predicting 16 personality traits. Hoppe et al. (2018) further utilize eye movements during routine activities and successfully predicted four of the five Big-5 traits. Parallel research by Khatri et al. (2022) demonstrated that data from ET, head and hand postures (POS), and navigation behavior (interaction metrics, INT) could predict traits such as extraversion, agreeableness, and open-mindedness. Their work also suggests that, when combining results from both exploration and goal-oriented tasks, both ET data and a distinct set of posture and interaction metrics (POS + INT) can individually predict Big-5 personality traits with over 70% classification accuracy. Other researchers suggest that analyzing spoken content can unveil aspects of an individual's personality (Koutsoumpis et al. 2022; Stern et al. 2021). Stern et al. (2021) found voice pitch to be a valid indicator for identifying traits like extraversion, dominance, and sociosexual orientation. Studies suggest that physiological markers such as heart rate variability (HRV) could indicate individual mindfulness and emotion regulation, which could further describe one's personality (Watford et al. 2020). Moreover, Gil-López et al. (2023) found the potential to identify gender and age using kinematic movements such as hand gestures and head postures. They suggest that hand gestures may be more useful for identifying gender during free exploration tasks, while head postures may be more relevant for both free exploration and task-oriented search navigation tasks.

By integrating these movements with ET, retailers could infer tailored search behaviors, enabling more individualized customer service. A potential application of identifying personality traits is the grouping of consumers with similar traits (PT1). Adamopoulos et al. (2018) has shown that similar personalities in word-of-mouth communication increased the likelihood of subsequent purchases by nearly 50%. This finding supports the benefit of leveraging word-of-mouth campaigns that resonate with consumer personalities, enhancing relevance, experience, and empowerment for consumers (PT2). In dynamic v-commerce environments, distributing product reviews based on recipients' personalities could significantly enhance sales. Furthermore, retailers can provide customized interaction, such as matching the preferred personality of a salesperson to the consumer based on their personality. For instance, extrovert consumers may prefer interacting with an extrovert salesperson (PT3).

However, there is also a privacy-related downside. Misinterpretation of personality traits could lead to an unwelcome shopping experience. For example, a retailer may increase the number of shoppers in a VR environment to enhance social presence, assuming that an extroverted consumer would enjoy a more crowded shopping environment. But if the consumer is not receptive to socializing at that time, the implementation could lead to discomfort and mental burden (ETN1). Moreover, awareness of consumers' personality traits could exacerbate impulsive buying tendencies (ETN2). As Olsen et al. (2016) showed, neuroticism correlates positively with impulsive buying behavior and has a negative correlation with variety-seeking. Retailers could exploit this correlation by targeting neurotic consumers with limited-time promotions to amplify impulsive purchasing. This practice could lead to undesired financial burdens for consumers, triggering resource-related privacy risks.

5 Discussion

VR technology is revolutionizing future commerce interactions between consumers and companies. It utilizes sensor-based data collection, including biometric and behavioral data, to enhance user interaction in virtual environments. This paper's uniqueness lies in detailing the data attributes that can be collected and linking these to higher-level psychological constructs inferred from these attributes. Our PBA (see Table 1) demonstrates how these connection between data attributes and constructs could result in value creation for companies, benefits for consumers, as well as privacy risks associated. For the data attribute, ET data is potentially one of the most important data attributes given its ability to measure attentional-based behavior, information processing, and the reaction of a stimuli. Individualization seems to be important for companies' value creation in v-commerce as it fosters relevance for consumers. Interaction for value creation is also indispensable as it enables real-time experiences for consumers depending on their states. However, our PBA also outlines the salient role of psychological and freedom-related privacy risk, mostly because companies are able to manipulate information and gain certain sensitive knowledge of consumers by analyzing the data collected.

The PBA contributes in three ways. Firstly, the technical perspective details the specific collectable data attributes in VR and their potential to reveal different facets of consumer. Our work highlights the importance of data management in future v-commerce by demonstrating how such huge amount of data could be valuable in understanding consumers. This understanding could further help companies on areas like product development. For instance, if consumers consistently show increased attention on certain product functions, such as paying lots of attention on the gamification features in a fitness app, companies can prioritize the development and improve such functions. Through integrating emotional arousal analysis, the company can also assess whether the attention is perceived in a positive or negative light. VR data can also be relevant for improving accessibility and inclusivity. For example, by understanding the level of processing and cognitive load, companies can provide more accessible personalized commerce environment for people with disabilities.

Second, our work also underscores the importance for companies to prioritize transparency and articulate their data collection and data usage methodologies clearly. Given most consumers' limited awareness of how their data is being used, even those informed about the risks face a tough decision: to accept a compromise on privacy risks for VR application benefits or to forego the benefits created by new applications. This trade-off creates the tension between the desire for personalized, immersive experiences and concerns over privacy. Our PBA contributes to educating companies (and potentially also consumers) to make better informed trade-off decisions by detailing the specific negative impacts stemming from potential data misuse. Notably, we emphasize the significance of understanding specific negative impacts, as opposed to a broad apprehension of privacy concerns (Karwatzki et al. 2022). Our PBA offers foundational knowledge on the origins of potential negative impacts (due to collecting respective data attributes), their composition (aggregating these data reveals sensitive personal information), and the resulting consequences (infringed privacy risk dimensions). Businesses can leverage our PBA to tailor data usage to individual consumer preferences in various contexts. For example, if a consumer particularly dislikes the sensation of being monitored (a freedom-related privacy risk) during their shopping experience, businesses could refrain from employing business practices that might trigger this privacy risk dimension. Therefore, our work provides companies a clear overview to enhance transparent communication with consumers regarding how their data will be used. Moreover, our PBA suggests that collaborative design of product or service interactions between companies and consumers would work best in this context, as business can ensure that activities uphold consumer ethics (Adams et al. 2018).

Third, our work supports policymakers to pave an effective way to protect VR data without hindering innovation in VR technology. Despite the tremendous opportunities ahead in VR, we advocate the consideration of the potential consequences of sensory manipulation on customers' self-image and the influence on possibly resulting real-world behavior. Studies have shown that virtual experiences can alter internal models and assumptions (e.g., stereotype priming) about the world, potentially leading to real-world changes in behavior (Doerner et al. 2022; Peck et al. 2013; Piryankova et al. 2014). For instance, VR technology can be used to nudge consumers towards sustainable consumption through multisensory experience (Laukkanen et al. 2022). However, these manipulations can have negative consequences if not used responsibly, as seen in cases of cyberbullying and immoral behavior in social VR, and escapism (Blackwell et al. 2019; Doerner et al. 2022). Effective management of psychological manipulation within VR experiences necessitates a responsible approach. Therefore, our work contributes to the balancing of innovation and potential risks by taking a first step to delineate possible business benefits and associated privacy risks stemming from the collection and aggregation of data in VR. With a comprehensive understanding, policymakers can better balance consumer and corporate perspectives, thereby crafting policies that harmonize innovation with risk management.

One limitation of our study is the evolving nature of VR technology. As this technology continues to advance, new privacy challenges and considerations may emerge. Future research should keep pace with these developments and further explore the privacy implications of VR in various domains beyond v-commerce. Additionally, the ethical dimensions of privacy in this virtual realm deserve closer attention, including issues related to consent, data ownership, and algorithmic bias.

Future research may address the challenges identified in this article. Firstly, there is a need for comprehensive and standardized privacy frameworks tailored specifically to VR environments. These frameworks should encompass technical, legal, and ethical aspects to ensure effective privacy protection. For instance, the idea of the Neuro-rights (right to identity, agency, mental privacy, fair access to neurotechnology, and protection from algorithmic bias) aims to protect fundamental human rights (dignity, freedom, security, non-discrimination, equal treatment, and privacy) in the context of neuroscience advancements (Yuste et al. 2021). Secondly, further studies should focus on developing privacy-preserving mechanisms and technologies that strike a balance between personalization and privacy, such as privacy computing technologies. Privacy computing technologies in VR employ methods like federated learning (McMahan et al. 2017) and differential privacy (Dwork et al. 2006; Dwork and Roth 2014) to secure data while enabling its use without additional privacy protection programs (Chen et al. 2024), such as the MetaGuard (Nair et al. 2023a). These technologies aim to protect sensitive information, enable anonymous interactions, and support data analysis without compromising privacy (Chen et al. 2024), thereby fostering user trust and addressing ethical concerns. Thirdly, interdisciplinary collaborations between researchers, policymakers, and industry stakeholders are essential for understanding the broader societal implications of VR privacy and formulating appropriate regulations and guidelines.

6 Conclusion

This article explores the intricate relationship between user privacy and business benefits in the context of v-commerce. The granular data collected through VR, ranging from biometric and behavioral data to geospatial telemetry, can enhance personalization and engagement but also poses substantial risks if not managed properly. Our PBA demonstrates the structural overview of which data available in VR will lead to which benefits for companies and consumers alongside the privacy risks it poses. This mapping serves as a crucial tool for both researchers and practitioners to understand the dual-edged nature of VR data collection. We emphasize the need for multifaceted privacy protection strategies to balance personalized and engaging shopping experiences with privacy preservation.

Appendix 1

See Tables 2, 3 and 4.

Table 2 Overview of categorized primary data attributes and the associated content

Category	Data attribute	Content (if necessary)	Static	Dynamic
Personal identifiable information*	Person name		x	
	Email		x	
	User ID		x	
	Billing information		x	
System*	VR device specification	VR device identifiers (android ID, device ID, serial number, device model, field of view,…)	x	
	OS & software	SDK, build versions, flags (rooted or not)	x	
	Usage info	Usage time, session info, app name, cookies		x
	Hardware info	Refresh rate, tracking rate, resolution, GPU power, CPU power	x	
	Network	Bandwith, Latency, IP Address		x
Video*	Surrounding real-world space			x
Geospatial telemetry*	Height		x	
	Arm length	Left arm, right arm	x	
	Hand shape		x	
	Limb length		x	
	(Inter)pupillary distance (IPD)		x	
	Room length		x	
	Room width		x	
Inertial telemetry*	Angular velocity			x
	Orientation			x
	Proper acceleration			x
Physiological measures**	Electromyography			x
	Galvanic skin response			x
	Heart rate variability			x

Extended, modified, and based on Garrido et al. (2024), Nair et al., (2023a), Nair et al. (2023b), and Trimananda et al. (2022). Categories, marked with an asterisk, flag data that is essential to the functionality of the VR technology. Double asterisks (**) mark categories that are only contextually required, depending on the application. It is worth noting that any specifications and markings in the table are subject to change at any time as VR technology and regulations evolve

Table 3 Overview of secondary data attributes and the associated content

Secondary data attribute	Required primary data attribute
Device	System*: VR Device Specification, Hardware Info
Locality	Network*
Body spatial measurements & relationships	Geospatial telemetry*: height, hand shape, limb length, (inter)pupillary distance (IPD)
Kinesiological movement	Geospatial telemetry*: height, hand shape, limb length, (inter)pupillary distance (IPD); inertial telemetry*: angular velocity, orientation, proper acceleration
Bone- and air-borne vibrations	Inertial telemetry*, kinesiological movement
Speech content	Bone- and air-borne vibrations, kinesiological movement, behavior**: voice
Room dimensions	Geospatial telemetry*: room length, room width
Play area	
Language	Self-declared; behavior**: voice, text, speech content

Extended, modified, and based on Garrido et al. (2024), Nair et al. (2023a), Nair et al. (2023b), and Trimananda et al. (2022). Categories, marked with an asterisk, flag data that is essential to the functionality of the VR technology. Double asterisks (**) mark categories that are only contextually required, depending on the application. It is worth noting that any specifications and markings in the table are subject to change at any time as VR technology and regulations evolve

Table 4 Overview of the privacy dimensions and corresponding exemplary use cases

Privacy dimensions	Possible use cases in v-commerce
Physical privacy risk	In the context of VR therapy, future treatments may leverage virtual environments to elicit and simulate patients' distress. However, the unauthorized access of physiological data by third parties could result in malicious use. For example, replicating such stimulation with the intention to trigger patients in other VR environments might pose a threat to their physical safety
Social privacy risk	Users may utilize VR as a platform for escapism and the exploration of identities or activities that they may be hesitant to express in reality. However, reputation damage could occur in VR if a user's actions, typically presumed private, become public due to data breaches or unauthorized data access. Consequently, users' social relationship would be negatively affected
Resource-related privacy risk	Users might worry that sharing personal physiological or biometric data in VR, like facial or voice data, could heighten the risk of identity theft. Such a breach could lead to financial losses if payment authentication details are misused
Psychological privacy risk	VR environments collect various types of personal information, encompassing both behavioral and biometric data. As the subsequent section will detail, this data consolidation facilitates real-time comprehension, analysis, and prediction of individual behavior and preferences. While this allows for hyper-personalization benefits, it may simultaneously heighten discomfort related to perceived surveillance and diminish personal information autonomy
Prosecution-related privacy risk	In the VR context, users may worry about legal repercussions if their identities are stolen by malicious actors who then commit crimes. The regulation of criminal activity in VR environments, including avatar misconduct that could harm individuals in the real world, remains unclear at the moment
Freedom-related privacy risk	ET data can reveal one's shopping behavior and attitude towards marketing stimuli. While in VR context, product display could be manipulated in a more salience way, consumers may fear that their options be limited because companies try to predict their preferences and only show options that have high margins
Career-related privacy risk	Various categories of data collected in VR could infer one's mental states, and when these kinds of information become available consciously or unconsciously to the employers, possible career discrimination may happen

Declarations

Competing interests The authors declare no competing interests.

Author contributions The authors S.H. and Y.F. contributed equally to all parts (including tables and figures) of this work and should be considered co-first authors. All authors reviewed the manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data availability No datasets were generated or analysed during the current study.

References

Aburumman N, Gillies M, Ward JA, Hamilton AFdeC (2022) Nonverbal communication in virtual reality: nodding as a social signal in virtual interactions. Int J Hum Comput Stud 164:102819

Acosta LH, Reinhardt D (2022) A survey on privacy issues and solutions for voice-controlled digital assistants. Pervasive Mob Comput 80:101523

Acquisti A, Brandimarte L, Loewenstein G (2015) Privacy and human behavior in the age of information. Science 347(6221):509–514

Adam MTP, Krämer J, Müller MB (2015) Auction fever! How time pressure and social competition affect bidders' arousal and bids in retail auctions. J Retail 91(3):468–485

Adamopoulos P, Ghose A, Todri V (2018) The impact of user personality traits on word of mouth: text-mining social media platforms. Inform Syst Res 29(3):612–640

Adams D, Bah A, Barwulor C, Musaby N, Pitkin K, Redmiles EM (2018) Ethics emerging: The story of privacy and security perceptions in virtual reality. In: Proceedings of the fourteenth USENIX conference on usable privacy and security. pp 443–458

Adhanom IB, MacNeilage P, Folmer E (2023) Eye tracking in virtual reality: a broad review of applications and challenges. Virtual Reality 27(2):1481–1505

Al-Natour S, Cavusoglu H, Benbasat I, Aleem U (2020) An empirical investigation of the antecedents and consequences of privacy uncertainty in the context of mobile apps. Inform Syst Res 31(4):1037–1063

Apple (2019) Safari privacy overview [PDF-Document]. Safari Privacy Overview. Retrieved 27 Jun 2023, from https://www.apple.com/safari/docs/Safari_White_Paper_Nov_2019.pdf

Aristidou A, Lasenby J, Chrysanthou Y, Shamir A (2018) Inverse kinematics techniques in computer graphics: a survey: inverse kinematics techniques in computer graphics. Comput Graph Forum 37(6):35–58

Ashworth L, Free C (2006) Marketing dataveillance and digital privacy: using theories of justice to understand consumers' online privacy concerns. J Bus Ethics 67(2):107–123

Bachurina V, Sushchinskaya S, Sharaev M, Burnaev E, Arsalidou M (2022) A machine learning investigation of factors that contribute to predicting cognitive performance: difficulty level, reaction time and eye-movements. Decis Support Syst 155:113713

Bailenson J (2018) Protecting nonverbal data tracked in virtual reality. JAMA Pediatr 172(10):905–906

Bailenson JN, Beall AC, Loomis J, Blascovich J, Turk M (2004) Transformed social interaction: decoupling representation from behavior and form in collaborative virtual environments. Presence Teleoperators Virtual Environ 13(4):428–441

Bauer C and Schiffinger M (2016) Perceived risks and benefits of online self-disclosure: affected by culture? A meta-analysis of cultural differences as moderators of privacy calculus in person-to-crowd settings. In: Proceedings of the 24th European conference on information systems (ECIS), Istanbul, Turkey. http://aisel.aisnet.org/ecis2016_rp/68

Baxter M, Bleakley A, Edwards J, Clark L, Cowan BR and Williamson JR (2021) "You, move there!": investigating the impact of feedback on voice control in virtual environments. In: Proceedings of the 3rd conference on conversational user interfaces

Bellman S, Nenycz-Thiel M, Kennedy R, Hartnett N, Varan D (2019) Best measures of attention to creative tactics in TV advertising: when do attention-getting devices capture or reduce attention? J Advert Res 59(3):295–311

Bente G, Rüggenberg S and Krämer, NC (2004) Social Presence and interpersonal trust in avatar-based, collaborative net-communications. In: Proceedings of the seventh annual international workshop on presence, pp 54–61

Berkovsky S, Taib R, Koprinska I, Wang E, Zeng Y, Li J and Kleitman S (2019) Detecting personality traits using eye-tracking data. pp 1–12.

Bin Suhaimi NS, Mountstephens J and Teo J (2020) Emotional state classification with distributed random forest, gradient boosting machine and Naïve Bayes in virtual reality using wearable electroencephalography and inertial sensing. In: 2020 IEEE 10th symposium on computer applications and industrial electronics (ISCAIE). pp 12–17.

Blackwell L, Ellison N, Elliott-Deflo N and Schwartz R (2019) Harassment in social VR: implications for design. In: 2019 IEEE conference on virtual reality and 3D user interfaces (VR). pp 854–855.

Blaywais R, Rosenboim M (2019) The effect of cognitive load on economic decisions. Manag Decis Econ 40(8):993–999

Caserman P, Garcia-Agundez A, Konrad R, Göbel S, Steinmetz R (2019) Real-time body tracking in virtual reality using a Vive tracker. Virtual Real 23(2):155–168

Cervone D and Pervin LA (2022) Personality: theory and research. John Wiley & Sons

Chen C, Li Y, Wu Z, Mai C, Liu Y, Hu Y, Kang J, Zheng Z (2024) Privacy computing meets metaverse: necessity, taxonomy and challenges. Ad Hoc Netw 158:103457

Chen M, Burke RR, Hui SK, Leykin A (2021) Understanding lateral and vertical biases in consumer attention: an in-store ambulatory eye-tracking study. J Mark Res 58(6):1120–1141

Chu H, Ma S, De la Torre F, Fidler S, Sheikh Y (2020) Expressive telepresence via modular codec avatars. In: Vedaldi A, Bischof H, Brox T, Frahm J-M (eds) Computer Vision – ECCV 2020. Springer International Publishing, pp 330–345

Craik FIM, Lockhart RS (1972) Levels of processing: a framework for memory research. J Verbal Learn Verbal Behav 11(6):671–684

Das A, Acar G, Borisov N and Pradeep A (2018) The web's Sixth sense: a study of scripts accessing smartphone sensors. In: Proceedings of the 2018 ACM SIGSAC conference on computer and communications security. pp 1515–1532.

de Regt A, Barnes SJ (2019) V-Commerce in retail: nature and potential impact. In: Tom Dieck MC, Jung T (eds) Augmented reality and virtual reality: the power of AR and VR for business. Springer International Publishing, New York, pp 17–25

Dick E (2021) Balancing user privacy and innovation in augmented and virtual reality. Information Technology and Innovation Foundation. Retrieved 27 Jun 2023, from https://www2.itif.org/2021-ar-vr-user-privacy.pdf

Dinev T, Xu H, Smith JH, Hart P (2013) Information privacy and correlates: an empirical attempt to bridge and distinguish privacy-related concepts. Eur J Inf Syst 22(3):295–316

Doerner R, Geiger C, Oppermann L, Paelke V and Beckhaus S (2022) Interaction in virtual worlds. In: Virtual and augmented reality (VR/AR) foundations and methods of extended realities (XR). Springer. pp 201–244

Dwivedi YK, Hughes L, Baabdullah AM, Ribeiro-Navarrete S, Giannakis M, Al-Debei MM, Dennehy D, Metri B, Buhalis D, Cheung CMK, Conboy K, Doyle R, Dubey R, Dutot V, Felix R, Goyal DP, Gustafsson A, Hinsch C, Jebabli I, Janssen M, Kim

Y-G, Kim J, Koos S, Kreps D, Kshetri N, Kumar V, Ooi K-B, Papagiannidis S, Pappas IO, Polyviou A, Park S-M, Pandey N, Queiroz MM, Raman R, Rauschnabel PA, Shirish A, Sigala M, Spanaki K, Wei-Han Tan G, Tiwari MK, Viglia G, Wamba SF (2022) Metaverse beyond the hype: multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int J Inf Manag. https://doi.org/10.1016/j.ijinfomgt.2022.102542

Dwork C, McSherry F, Nissim K, Smith A (2006) Calibrating noise to sensitivity in private data analysis. In: Halevi s, Rabin T (eds) Theory of cryptography. Springer, Berlin Heidelberg, pp 265–284

Dwork C, Roth A (2014) The algorithmic foundations of differential privacy. Found Trends Theor Comput Sci 9(3–4):211–407

Englehardt S and Narayanan A (2016) Online tracking: a 1-Million-site measurement and analysis. In: Proceedings of the 2016 ACM SIGSAC conference on computer and communications security, pp 1388–1401.

Figueiredo LS, Livshits B, Molnar D, Veanes M (2016) Prepose: privacy, security, and reliability for gesture-based programming. IEEE Symposium on Security and Privacy (SP) 2016:122–137

Fleming P, Bayliss AP, Edwards SG, Seger CR (2021) The role of personal data value, culture and self-construal in online privacy behaviour. PLoS ONE 16(7):e0253568

Gambiraza M, Kesedzic I, Sarlija M, Popovic S, and Cosic K (2021) Classification of cognitive load based on oculometric features. In: 2021 44th international convention on information, communication and electronic technology (MIPRO), pp 377–382.

Garrido G, Nair V, Song D (2024) SoK: data privacy in virtual reality. Proc Priv Enhancing Technol 2024(1):21–40

Giaretta A (2024) Security and privacy in virtual reality: a literature survey. Virtual Reality 29(1):10

Gil-López C, Guixeres J, Moghaddasi M, Khatri J, Marín-Morales J, Alcañiz M (2023) Recognizing shopper demographics from behavioral responses in a virtual reality store. Virtual Reality. https://doi.org/10.1007/s10055-023-00767-2

Godin G, Massicotte P, and Borgeat L (2004) Foveated stereoscopic display for the visualization of detailed virtual environments. In: Proceedings of the Tenth Eurographics conference on virtual environments. pp 7–16.

Google (2019) Building a more private web. Building a More Private Web. Retrieved 27 Jun 2023, from https://www.blog.google/products/chrome/building-a-more-private-web/

Grand View Research (2022) Eye tracking market size worth $8.06 billion by 2030. Retrieved 27 Jun 2023, from https://www.grandviewresearch.com/press-release/global-eye-tracking-market

Grewal D, Breugelmans E, Gauri D, Gielens K (2023) Re-imagining the physical store. J Retail 99(4):481–486

Gulhane A, Vyas A, Mitra R, Oruche R, Hoefer G, Valluripally S, Calyam P, Hoque KA. (2019) Security, privacy and safety risk assessment for virtual reality learning environment applications. In: 2019 16th IEEE Annual consumer communications & networking conference (CCNC). pp 1–9

Haapalainen E, Kim S, Forlizzi JF, and Dey AK (2010) Psycho-physiological measures for assessing cognitive load. In: Proceedings of the 12th ACM international conference on ubiquitous computing. pp 301–310

Halbig A, Latoschik ME (2021) A systematic review of physiological measurements, factors, methods, and applications in virtual reality. Front Virtual Real. https://doi.org/10.3389/frvir.2021.694567

Heller B (2020) Watching androids dream of electric sheep: immersive technology, biometric psychography, and the law. Vanderbilt J Entertain Technol Law 23(1):1–52

Hildebrand C, Efthymiou F, Busquet F, Hampton WH, Hoffman DL, Novak TP (2020) Voice analytics in business research: conceptual foundations, acoustic feature extraction, and applications. J Bus Res 121:364–374

Hines A (2016). The strange, lonely experience of shopping in Alibaba's VR world. VICE. Retrieved 23 Jul 2024, from https://www.vice.com/en/article/alibaba-vr-shopping-buy-singles-day

Hoppe S, Loetscher T, Morey SA, Bulling A (2018) Eye movements during everyday behavior predict personality traits. Front Hum Neurosci. https://doi.org/10.3389/fnhum.2018.00105

Hui K-L, Teo HH, Lee S-YT (2007) The value of privacy assurance: An exploratory field experiment. Mis Quart 31:19–33

Ioannou A, Tussyadiah I, Lu Y (2020) Privacy concerns and disclosure of biometric and behavioral data for travel. Int J Inf Manage 54:102122

Jaakkola E (2020) Designing conceptual articles: four approaches. AMS Rev 10(1–2):18–26

Janiszewski C (1998) The influence of display characteristics on visual exploratory search behavior. J Consum Res 25(3):290–301

Jiang H, Weng D, Zhang Z, Chen F (2019) Hifinger: one-handed text entry technique for virtual environments based on touches between fingers. Sensors (Basel). https://doi.org/10.3390/s19143063

Jimenez M, Poch C, Villalba-García C, Sabater L, Hinojosa JA, Montoro PR, Koivisto M (2021) The level of processing modulates visual awareness: evidence from behavioral and electrophysiological measures. J Cogn Neurosci 33(7):1295–1310

John B, Jörg S, Koppal S, Jain E (2020) The security-utility trade-off for iris authentication and eye animation for social virtual avatars. IEEE Trans vis Comput Graph 26(5):1880–1890

Jung, S., & Hughes, C. E. (2016). The Effects of Indirect Real Body Cues of Irrelevant Parts on Virtual Body Ownership and Presence. Proceedings of the 26th International Conference on Artificial Reality and Telexistence and the 21st Eurographics Symposium on Virtual Environments, 107–114.

Jung, S., Sandor, C., Wisniewski, P. J., & Hughes, C. E. (2017). RealME: The Influence of Body and Hand Representations on Body Ownership and Presence. Proceedings of the 5th Symposium on Spatial User Interaction, 3–11.

Jung S, Wisniewski PJ and Hughes CE (2018) In Limbo: The effect of gradual visual transition between real and virtual on virtual body ownership illusion and presence. In: 2018 IEEE conference on virtual reality and 3D user interfaces (VR). pp 267–272.

Kakaria S, Bigné E, Catrambone V, Valenza G (2023) Heart rate variability in marketing research: a systematic review and methodological perspectives. Psychol Mark. https://doi.org/10.1002/mar.21734

Karwatzki S, Trenz M, Veit D (2022) The multidimensional nature of privacy risks: conceptualisation, measurement and implications for digital services. Inf Syst J 32(6):1126–1157

Kaur A, Maheshwari S, Bose I, Singh S (2024) Watch out, you are live! Toward understanding the impact of AI on privacy of employees. Commun Assoc Inf Syst 55(1):603–626

Khatri J, Marín-Morales J, Moghaddasi M, Guixeres J, Giglioli IAC, Alcañiz M (2022) Recognizing personality traits using consumer behavior patterns in a virtual retail store. Front Psychol. https://doi.org/10.3389/fpsyg.2022.752073

Kilteni K, Bergstrom I, Slater M (2013) Drumming in immersive virtual reality: the body shapes the way we play. IEEE Trans vis Comput Graph 19(4):597–605

Koutsoumpis A, Oostrom JK, Holtrop D, Van Breda W, Ghassemi S, De Vries RE (2022) The kernel of truth in text-based personality assessment: a meta-analysis of the relations between the big five and the linguistic inquiry and word count (LIWC). Psychol Bull 148(11–12):843–868

Krefeld-Schwalb A, Rosner A (2020) A new way to guide consumer's choice: retro-cueing alters the availability of product information in memory. J Bus Res 111:135–147

Kröger JL, Lutz OHM and Müller F (2020a) What does your gaze reveal about you? On the privacy implications of eye tracking. In:

Friedewald M, Önen M, Lievens E, Krenn S and Fricker S (eds) Privacy and Identity management. Data for better living: AI and privacy: 14th IFIP WG 9.2, 9.6/11.7, 11.6/SIG 9.2.2 International Summer School, Windisch, Switzerland, August 19–23, 2019, Revised Selected Papers. Springer International Publishing. pp 226–241
Kröger JL, Lutz OHM and Raschke P (2020b) Privacy implications of voice and speech analysis – information disclosure by inference. In: Friedewald M, Önen M, Lievens E, Krenn S and Fricker S (eds) Privacy and identity management. Data for Better Living: AI and Privacy: 14th IFIP WG 9.2, 9.6/11.7, 11.6/SIG 9.2.2 International Summer School, Windisch, Switzerland, August 19–23, 2019, Revised Selected Papers. Springer International Publishing. pp 242–258
Kummer T-F, Pelzl S, Bick M (2021) A conceptualisation of privacy risk and its influence on the disclosure of check-in services information. Int J Inf Manag 57:102266
Laukka P, Juslin P, Bresin R (2005) A dimensional approach to vocal expression of emotion. Cogn Emot 19(5):633–653
Laukkanen T, Xi N, Hallikainen H, Ruusunen N, Hamari J (2022) Virtual technologies in supporting sustainable consumption: from a single-sensory stimulus to a multi-sensory experience. Int J Inf Manag 63:102455
Li M, Peng H, Ji L (2020) Roles of cognitive load and self-relevance during emotional information searching on decision-making. J Behav Decis Making 33(4):463–476
Liu B, Pavlou PA, Cheng X (2022) Achieving a balance between privacy protection and data collection: a field experimental examination of a theory-driven information technology solution. Inform Syst Res 33(1):203–223
Lou J, Wang Y, Nduka C, Hamedi M, Mavridou I, Wang F-Y, Yu H (2020) Realistic facial expression reconstruction for vr hmd users. IEEE Trans Multimed 22(3):730–743
Luangrath AW, Peck J, Hedgcock W, Xu Y (2022) Observing product touch: the vicarious haptic effect in digital marketing and virtual reality. J Mark Res 59(2):306–326
Luna-Nevarez C, McGovern E (2021) The rise of the virtual reality (VR) marketplace: exploring the antecedents and consequences of consumer attitudes toward V-commerce. J Internet Commerce 20(2):167–194
Luong T, Martin N, Raison A, Argelaguet F, Diverrez J-M, Lécuyer A (2020) Towards real-time recognition of users mental workload using integrated physiological sensors into a VR HMD. IEEE International Symposium on Mixed and Augmented Reality (ISMAR) 2020:425–437
Marín-Morales J, Higuera-Trujillo JL, Guixeres J, Llinares C, Alcañiz M, Valenza G (2021) Heart rate variability analysis for the assessment of immersive emotional arousal using virtual reality: comparing real and virtual scenarios. PLoS ONE 16(7):e0254098
Matsumoto DR, Frank MG and Hwang HS (2013) Nonverbal communication: science and applications. SAGE.
McMahan B, Moore E, Ramage D, Hampson S, and Arcas BA (2017) Communication-efficient learning of deep networks from decentralized data. In: Singh A and Zhu J (eds), Proceedings of the 20th international conference on artificial intelligence and statistics. Vol 54, pp 1273–1282. PMLR.
Meißner M, Musalem A, Huber J (2016) Eye tracking reveals processes that enable conjoint choices to become increasingly efficient with practice. J Mark Res 53(1):1–17
Meißner M, Oll J (2019) The promise of eye-tracking methodology in organizational research: a taxonomy, review, and future avenues. Organ Res Methods 22(2):590–617
Meta (2021) Inside facebook reality labs: wrist-based interaction for the next computing platform. Tech at Meta. Retrieved 29 Jun 2023, from https://tech.facebook.com/reality-labs/2021/3/inside-facebook-reality-labs-wrist-based-interaction-for-the-next-computing-platform/
Meta (2023) Meta. Meta Quest Tech Specs | Meta Store. Retrieved 27 Jun 2023, from https://www.meta.com/us/en/quest/quest-pro/tech-specs/
Mott M, Cutrell E, Franco MG, Holz C, Ofek E, Stoakley R and Morris MR (2019) Accessible by design: an opportunity for virtual reality. In: 2019 IEEE international symposium on mixed and augmented reality adjunct (ISMAR-Adjunct) pp 451–454.
MozillaWiki (2022) Security/Anti tracking policy—MozillaWiki. Security/Anti Tracking Policy. Retrieved 27 Jun 2023, from https://wiki.mozilla.org/Security/Anti_tracking_policy
Nair V, Garrido G and Song D (2023a). Going incognito in the metaverse: achieving theoretically optimal privacy-usability tradeoffs in VR. In: Proceedings of the 36th annual ACM symposium on user interface software and technology. pp 1–16.
Nair V, Garrido G, Song D, O'Brien J (2023b) Exploring the privacy risks of adversarial VR game design. Proc Privacy Enhanc Technol 2023(4):238–256
Navarro J, and Karlins M (2008) What every body is saying: an ex-Fbi agent's guide to speed reading people, 1st edn. Collins.
Nantelle K (2021). Eye-tracking vr technology is changing the retail industry. ReadySet VR. Retrieved 11 Feb 2024, from https://readysetvr.com/2021/05/24/eye-tracking-vr-technology-is-changing-the-retail-industry/
Olade I, Fleming C, Liang H-N (2020) BioMove: biometric user identification from human kinesiological movements for virtual reality systems. Sensors. https://doi.org/10.3390/s20102944
Olsen SO, Tudoran AA, Honkanen P, Verplanken B (2016) Differences and similarities between impulse buying and variety seeking: a personality-based perspective. Psychol Mark 33(1):36–47
Orquin JL, Loose SM (2013) Attention and choice: a review on eye movements in decision making. Acta Psychol 144(1):190–206
Ovalle-Fresa R, Uslu AS, Rothen N (2021) Levels of processing affect perceptual features in visual associative memory. Psychol Sci 32(2):267–279
Paas F, van Gog T, Sweller J (2010) Cognitive load theory: new conceptualizations, specifications, and integrated research perspectives. Educ Psychol Rev 22(2):115–121
Park S-M, Kim Y-G (2022) A metaverse: taxonomy, components, applications, and open challenges. IEEE Access 10:4209–4251
Payne JW, Bettman JR, Johnson EJ (1993) The adaptive decision maker. Cambridge University Press
Peck TC, Seinfeld S, Aglioti SM, Slater M (2013) Putting yourself in the skin of a black avatar reduces implicit racial bias. Conscious Cogn 22(3):779–787
Pfeiffer J, Meißner M, Brandstätter E, Riedl R, Decker R, Rothlauf F (2014) On the influence of context-based complexity on information search patterns: an individual perspective. J Neurosci Psychol Econ 7:103
Pfeiffer J, Pfeiffer T, Meißner M, Weiß E (2020) Eye-tracking-based classification of information search behavior using machine learning: evidence from experiments in physical shops and virtual reality shopping environments. Inform Syst Res 31(3):675–691
Piryankova IV, Stefanucci JK, Romero J, De La Rosa S, Black MJ, Mohler BJ (2014) Can i recognize my body's weight? The influence of shape and texture on the perception of self. ACM Trans Appl Percept. https://doi.org/10.1145/2641568
PlayStation (2023) Shop PS VR2 now | PlayStation® (UK). Retrieved 27 Jun 2023, from https://direct.playstation.com/en-gb/playstation-vr2
Rae J, Guimaraes E, and Steptoe W (2008) Simulation versus reproduction for avatar eye-gaze in immersive collaborative virtual environments. In: PRESENCE 2008-proceedings of the 11th annual international workshop on presence

Reinartz W, Wiegand N, Imschloss M (2019) The impact of digital transformation on the retailing value chain. Int J Res Mark 36(3):350–366

Riedl R, Léger P-M (2016) Fundamentals of NeuroIS: information systems and the brain, 1st edn. Springer, Berlin Heidelberg

Rossiter JR, Percy L (2017) Methodological guidelines for advertising research. J Advert 46(1):71–82

Roth D, Lugrin J-L, Büser J, Bente G, Fuhrmann A, Latoschik ME (2016) A Simplified Inverse Kinematic Approach for Embodied Vr Applications. IEEE Virtual Reality (VR) 2016:275–276

Saffaryazdi N, Goonesekera Y, Saffaryazdi N, Hailemariam ND, Temesgen EG, Nanayakkara S, Broadbent E, Billinghurst M (2022) Emotion recognition in conversations using brain and physiological signals. In: 27th international conference on intelligent user interfaces. pp 229–242

Saura JR, Ribeiro-Soriano D, Palacios-Marqués D (2021) From user-generated data to data-driven innovation: a research agenda to understand user privacy in digital markets. Int J Inf Manag 60:102331

Schwartz G, Wei S-E, Wang T-L, Lombardi S, Simon T, Saragih J, Sheikh Y (2020) The eyes have it: an integrated eye and face model for photorealistic facial animation. ACM Trans. Graph. 39(4):91–101

Shen Y, Wen H, Luo C, Xu W, Zhang T, Hu W, Rus D (2019) Gaitlock: protect virtual and augmented reality headsets using gait. IEEE Trans Depend Secure Comput 16(3):484–497

Shi C, Xu X, Zhang T, Walker P, Wu Y, Liu J, Saxena N, Chen Y, Yu J (2021) Face-Mic: Inferring Live Speech and Speaker Identity via Subtle Facial Dynamics Captured by AR/VR Motion Sensors. In: Proceedings of the 27th annual international conference on mobile computing and networking. pp 478–490

Shi SW, Wedel M, Pieters FGM (2013) Information acquisition during online decision making: a model-based exploration using eye-tracking data. Manag Sci 59(5):1009–1026

Shiv B, Fedorikhin A (1999) Heart and mind in conflict: the interplay of affect and cognition in consumer decision making. J Consum Res 26(3):278–292

Skaramagkas V, Giannakakis G, Ktistakis E, Manousos D, Karatzanis I, Tachos N, Tripoliti EE, Marias K, Fotiadis DI, Tsiknakis M (2021) Review of eye tracking metrics involved in emotional and cognitive processes. IEEE Rev Biomed Eng 16:260–277

Smith HJ, Milberg SJ, Burke SJ (1996) Information privacy: Measuring individuals' concerns about organizational practices. MIS Quart 20(2):167–196

Spanlang B, Normand J-M, Borland D, Kilteni K, Giannopoulos E, Pomés A, González-Franco M, Perez-Marcos D, Arroyo-Palacios J, Muncunill XN, Slater M (2014) How to build an embodiment lab: achieving body representation illusions in virtual reality. Front Robot AI 1:9

Statista (2023) Metaverse: Market data & analysis. Statista. Retrieved 22 Feb 2024, from https://www.statista.com/study/132822/metaverse-market-report/

Steed A, Schroeder R (2015) Collaboration in immersive and non-immersive virtual environments. In: Lombard M, Biocca F, Freeman J, IJsselsteijn W, Schaevitz RJ (eds) Immersed in media: telepresence theory, measurement and technology. Springer International Publishing, New York, pp 263–282

Stendal K, Bernabe RDLC (2024) Extended reality—new opportunity for people with disability? Practical and ethical considerations. J Med Internet Res 26:e41670

Stern J, Schild C, Jones BC, DeBruine LM, Hahn A, Puts DA, Zettler I, Kordsmeyer TL, Feinberg D, Zamfir D, Penke L, Arslan RC (2021) Do voices carry valid information about a speaker's personality? J Res Pers 92:104092

Swinth KR and Blascovich J (2002). Perceiving and responding to others: human-human and human-computer social interaction in collaborative virtual environments. In: Proceedings of the 5th annual international workshop on PRESENCE, p 392.

Szocs C, Kim Y, Lim M, Mera CA, Biswas D (2023) The store of the future: engaging customers through sensory elements, personalized atmospherics, and interpersonal interaction. J Retail 99(4):605–620

Trimananda R, Le H, Cui H, Ho JT, Shuba A and Markopoulou A (2022) OVRseen: auditing network traffic and privacy policies in oculus VR. 31st USENIX security symposium (USENIX Security 22). pp 3789–3806. https://www.usenix.org/conference/usenixsecurity22/presentation/trimananda

Vastel A, Laperdrix P, Rudametkin W, Rouvoy R (2018) FP-STALKER: tracking browser fingerprint evolutions. IEEE Symposium on Security and Privacy (SP) 2018:728–741

Velichkovsky BM, Rothert A, Kopf M, Dornhöfer SM, Joos M (2002) Towards an express-diagnostics for level of processing and hazard perception. Transport Res F: Traffic Psychol Behav 5(2):145–156

Venkatraman V, Dimoka A, Pavlou PA, Vo K, Hampton W, Bollinger B, Hershfield HE, Ishihara M, Winer RS (2015) Predicting advertising success beyond traditional measures: new insights from neurophysiological methods and market response modeling. J Mark Res 52(4):436–452

Venkatraman V, Dimoka A, Vo K, Pavlou PA (2021) Relative effectiveness of print and digital advertising: a memory perspective. J Mark Res 58(5):827–844

VIVE (2023a) About the VIVE pro eye HMD [Customer Guide Website]. About the VIVE Pro Eye HMD. Retrieved 27 Jun 2023, from https://www.vive.com/us/support/vive-pro-eye/category_howto/about-the-headset.html

VIVE (2023b) VIVE Facial Tracker|VIVE United States. Retrieved 27 Jun 2023, from https://www.vive.com/us/accessory/facial-tracker/

Vohs KD, Faber RJ (2007) Spent resources: Self-regulatory resource availability affects impulse buying. J Consum Res 33(4):537–547

W3C (2015) Unsanctioned Web Tracking. Unsanctioned Web Tracking. Retrieved 20 Mar 2023, from https://w3ctag.github.io/unsanctioned-tracking/

W3C (2021) Mitigating Browser Fingerprinting in Web Specifications. Mitigating Browser Fingerprinting in Web Specifications. Retrieved 19 Mar 2023, from https://w3c.github.io/fingerprinting-guidance/

Walla P, Brenner G, Koller M (2011) Objective measures of emotion related to brand attitude: a new way to quantify emotion-related aspects relevant to marketing. PLoS ONE 6(11):e26782

Wang H, Lee MKO, Wang C (1998) Consumer privacy concerns about internet marketing. Commun ACM 41(3):63–70

Wang T, Duong TD, Chen CC (2016) Intention to disclose personal information via mobile applications: a privacy calculus perspective. Int J Inf Manag 36(4):531–542

Watford TS, O'Brien WH, Koerten HR, Bogusch LM, Moeller MT, Sonia Singh R, Sims TE (2020) The mindful attention and awareness scale is associated with lower levels of high-frequency heart rate variability in a laboratory context. Psychophysiology 57(3):e13506

Weiß T, Pfeiffer J (2024) Consumer decisions in virtual commerce: good help-timing and its prediction based on cognitive load. J Neurosci, Psychol Econ 17(2):119

Wenzlaff F, Briken P, Dekker A (2016) Video-based eye tracking in sex research: a systematic literature review. J Sex Res 53(8):1008–1019

Winkler A, Won J and Ye Y (2022) QuestSim: human motion tracking from sparse sensors with simulated avatars. In: SIGGRAPH Asia 2022 conference papers

Wu Y, Wang Y, Jung S, Hoermann S, Lindeman RW (2021) Using a fully expressive avatar to collaborate in virtual reality: evaluation of task performance, presence, and attraction. Front Virtual Real. https://doi.org/10.3389/frvir.2021.641296

Xue L, Parker CJ, Hart C (2020) How to design fashion retail's virtual reality platforms. Int J Retail Distrib Manag 48(10):1057–1076

Yun H, Lee G, Kim DJ (2019) A chronological review of empirical research on personal information privacy concerns: an analysis of contexts and research constructs. Inf Manag 56(4):570–601

Yuste R, Genser J, Herrmann S (2021) It's time for neuro-rights: new human rights for the age of neurotechnology. Horizons: J. Int. Relat. Sustain. Dev. 18:155–164

Zhang K, Deldari E, Lu Z, Yao Y, and Zhao Y (2022) "It's just part of me:" understanding avatar diversity and self-presentation of people with disabilities in social virtual reality. In: Proceedings of the 24th international ACM SIGACCESS conference on computers and accessibility. pp 1–16.

Zhang K, Deldari E, Yao Y and Zhao Y (2023) A diary study in social virtual reality: impact of avatars with disability signifiers on the social experiences of people with disabilities. In: The 25th international ACM SIGACCESS conference on computers and accessibility. pp 1–17

Zhang Y, Slocum C, Chen J and Abu-Ghazaleh N (2023) It's all in your head(set): Side-channel attacks on AR/VR systems. 32nd USENIX Security Symposium (USENIX Security 23). pp 3979–3996. https://www.usenix.org/conference/usenixsecurity23/presentation/zhang-yicheng

Zhao Y, Li Y, Wang N, Zhou R, Luo X (2022) A meta-analysis of online impulsive buying and the moderating effect of economic development level. Inf Syst Front 24(5):1667–1688