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Analyzing Social Dynamics In Virtual Reality: Towards a Data-Driven Framework

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ANALYZING SOCIAL DYNAMICS IN VIRTUAL REALITY: TOWARDS A DATA-DRIVEN FRAMEWORK

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Abstract

The increasing accessibility of Virtual Reality (VR) applications leads to the emergence of novel products and services, especially in the context of interacting with applicants, consumers or employees. Technological developments such as eye- or body-tracking enable new analytical insights about team interaction or customer relationship formation, causing organizational and academic interest. However, conceptual and technical frameworks that effectively integrate multimodal data of spatial virtual environments are still lacking. To close this gap, we bring together a systematic literature review of scientific VR experiments with a cross-case analysis of organizational social VR application scenarios and reflective expert interviews. We reveal and conceptualize the important data category of virtual sensors. We outline how such virtual sensors are useful for augmenting physiological data and ex-post perception surveys of social VR experiences to offer a systematic and effective approach to study virtual social interactions in immersive environments.

Keywords: Social Virtual Reality, Data Collection Framework

1 Introduction

In recent years, virtual reality (VR) applications have gained significant traction, particularly within the context of the metaverse and HCI. This is indicated by the emergence of new products and services, especially in the context of social interactions or collaboration (Egliston & Carter, 2021). The increasing popularity of VR is catalysed by progress in hardware development and investments by major technology companies, resulting in accessible and cost-effective VR (Egliston & Carter, 2021; Brookes et al., 2020). These developments motivated considerable organizational interest, as customers or virtual teams can utilize novel opportunities to adopt immersive technologies to enhance remote relationships and attain a greater sense of social presence (Bailenson, 2008).

As a side effect of the steady proliferation of VR technologies and application scenarios, novel analytical insights become possible within HCI. With data tracking features like eye-tracking and avatar monitoring via embedded *virtual sensors* (Grübel et al., 2017a) to enhance the analysis of users' spatial behaviours and physiological responses (Weibel, 2018), thus enabling the study of perceived presence illusions as an influence on particular usage outcomes such as trust or customer satisfaction (Trier & Steiger, 2023). Due to its ability to provide precise control over virtual environments and simulate both complex and realistic scenarios, the analysis of user behaviours in VR offers unique advantages as a research and analysis method (Innocenti, 2017; Halbig & Latoschik, 2021).

Prior approaches of measuring presence in digital experiences are mostly based on scales and methods such as self-reports, behavioural observations and physiological measurements (Biocca, 2002; Grassini, 2020; Kreijns, Xu, Weidlich, 2022). However, these approaches are susceptible to the 'break in presence' effect, in which participants experience brief interruptions in their sense of presence when moving from the virtual environment to questionnaires or surveys, which can affect the accuracy of the measurements (Putze et al., 2020; Slater & Wilbur, 1997). Previous research often focuses on individual data sources such as questionnaires or physiological measurements and manual data collection is often faulty or time consuming, while existing models fail when combining different data sources in an integrated framework (Bowen, 2017; Wölfel, 2023).

Against this backdrop, Sterna and Zibrek (2021) describe VR as a promising methodological tool for social presence research, allowing for the integration of multiple indirect and direct measures to capture the complexity of interactions in virtual environments. Despite the significant potential of VR, such as the ability to simulate realistic reactions and the possibilities for data collection (Marín-Morales et al., 2020), systematic frameworks that effectively integrate multimodal data of spatial virtual environments are still underdeveloped (van Kerrebroeck et al., 2021). Existing approaches have not yet fully covered a holistic framework that incorporates available virtual sensors of VR environments. For example, while Steptoe and Steed (2012) have already worked on a similar framework, they focus on exploring general communication patterns with a limited coverage of the spatial dynamics of social interaction. Furthermore, both the EVE and UXF frameworks lack comprehensive data collection capabilities tailored specifically for social virtual environments (Grübel et al., 2017a; Brookes et al., 2019). Similarly, Bailenson (2008) concludes that there is no standardised holistic framework that integrates various data sources to allow comprehensive data collection. Such a framework can provide an important foundation for systematically deriving and protecting against user privacy risks in future virtual environments. To close this gap, we systematically identify and derive main data categories from existing VR experiences and integrate them into a comprehensive framework for VR data analysis in social virtual environments. This framework is intended to fill the current research gap with providing a comprehensive data structure. To guide our work, we have formulated the following research question: *RQ: What data categories are collected in existing social VR environments and how can they be integrated into a systematic data framework that incorporates multiple data modalities, enhancing spatial data collection?*

To approach this question, we first systematically screen and analyse existing application scenarios used for innovative research experiments, using a systematic literature review. While these studies often intend to examine presence illusions and not some organizational and individual output they serve as a valuable approximation of our intended analytical context. To ensure the applicability of these findings to the organizational context, we then engaged in a systematic qualitative cross-case analysis of self-developed organizational application scenarios that have been tested within different user groups. Finally, we refined the data category model through reflective expert interviews and finally link these findings with the technological architecture of 3D models (in Unity) to develop a technological data model specification. This resulting data model makes a significant contribution by offering the conceptual and technological basis for a standardised and scalable data analysis of virtual experiments. Based on our results, researchers can systematically identify relevant metrics and data sources for subsequent analysis. We facilitate data collection and analysis in virtual reality and enable reproducible research designs. This is particularly important since VR is increasingly being integrated into organisational contexts. Here, precise data models are needed for the analysis of social interactions as well as team processes. Our findings further enable a systematic discussion of the risks of analysing virtual data, e.g. in the context of understanding virtual privacy requirements. In the remaining article, we now first introduce the theoretical background and explicate the foundation of social virtual reality covering the different data metrics. Subsequently the framework is derived from a systematic PRISMA literature review, cross-case analysis of organizational social VR applications and expert interviews. Then, the results are further discussed regarding research and practical implications. Finally, the conclusion summarizes the key findings and provides an outlook on future research directions.

2 Theoretical Background

In VR research, terminology is often ambiguous, with terms like XR used inconsistently across academic and commercial contexts. Major companies, such as Apple, also influence terminology; for example, Apple uses "Spatial Computing" instead of VR. Rauschnabel et al. (2022) highlight the lack of standardization, which affects user experience. This research paper adopts a broad interpretation of XR, covering all forms of immersive environments, including VR, AR, and mixed reality (MR), with VR representing fully virtual environments and AR as partially virtual, as per Milgram's Reality-Virtuality Continuum (1995). Social VR is defined here as VR environments enabling multi-user interactions, where collaboration is central. An essential aspect of Social VR and related immersive experiences is social presence, defined as the "sense of being with another" in a mediated environment (Biocca, 2003). It describes the perceived interpersonal connection among users in virtual environments with significant impact on communication and collaboration in VR settings (Sterna & Zibrek, 2021). Rauschnabel et al. (2022) describe VR on a spectrum of telepresence — from "atomic VR", where VR is used as a tool, to "holistic VR", an immersive experience mimicking real-life. The metaverse is conceptualized as the next evolution of the internet, blending physical and digital worlds through XR. Mystakidis (2022) defines it as a "post-reality universe," and Cheng et al. (2022) view it as a social media evolution, enabling a "universal virtual world" for social interactions. Its history began in the late 1970s with text-based games, advanced in the 2000s with virtual worlds like SecondLife, and now emphasizes VR technology. Enhanced by 5G and computing advancements, the metaverse's growth will parallel VR and Social VR tool development, as Cheng et al. (2022) suggest.

2.1 Data metrics in practice

There is a wide variety of data collected in virtual environments. For instance, physiological measures, such as heart rate and skin conductance have been captured in order to understand social phenomena related to stress and attention. Marín-Morales et al. (2020) note that such metrics link physiological signals with psychological states, which can further be augmented with methods like machine learning to classify emotions in virtual settings (Domínguez-Jiménez et al., 2020). While metrics like heart rate map intuitively to emotional arousal, studies have also shown that metrics such as eye-tracking in VR can reveal emotional response to peripheral images (Nummenmaa et al., 2006). Questionnaires are also widely adopted sources of data collection in VR. They are typically conducted before or after VR experiences. Standard tools include the System Usability Scale (SUS) for usability or NASA-TLX for workload. The Presence Questionnaire (Witmer & Singer, 1998) gauges the user's feeling of "being there" (Schloerb, 1995). Cybersickness questionnaires like SSQ and VRSQ assess user comfort, essential for VR acceptance (Gallagher & Ferrè, 2018). Breaks in immersion when switching to paper or web-based surveys can impact data quality, motivating the use of in-VR questionnaires as more effective alternatives that enable improved data accuracy and user satisfaction (Alexandrovsky et al., 2020). Another important distinction in the design of VR questionnaires is made by Wagener et al. (2020), who classify VR questionnaires into two categories: extradiegetic user interfaces (UI), which appear in the VR environment but are not integrated into the immersive experience, and intradiegetic UIs, which are fully incorporated into the VR experience itself. Users generally prefer intradiegetic UIs, as they offer a more seamless and immersive experience (Wagner et al., 2020).

2.2 Hardware and Virtual Sensors

Various types of hardware-based sensors are utilized for automated eye, face, hand and body tracking data. Eye-tracking plays an important role in VR social research, allowing precise monitoring of gaze within virtual environments, which is useful for assessing attention, fatigue, and learning outcomes (Marín-Morales et al., 2020). Despite its benefits, conventional challenges remain, such as tracking difficulties with darker eyes or glasses-wearing participants (Clay et al., 2019). Face-tracking significantly enhances social interactions in VR by enabling emotion detection and realistic avatar expressions. Modern head-mounted displays (HMDs) for VR may be equipped with integrated face-tracking sensors, reducing the need for additional hardware modifications. These sensors use blend shapes to transfer facial data to virtual avatars, resulting in a more lifelike social experience (Lou et al., 2019). Similarly, hand-tracking has also become essential for natural interactions, allowing users to engage in VR without controllers and making gestures appear more realistic (Buckingham, 2021). High-precision hand-tracking in modern HMDs increases immersion and presence, allowing users to interact in a way that feels natural. However, reliance on such personal data can also lead to privacy concerns, as it allows individual identification (Liebers et al., 2024). Body-tracking further supports immersion through a comprehensive body ownership illusion (BOI), in which users feel their virtual avatar as an extension of their own body. This effect is beneficial in social VR, as it influences behaviour and empathy perceptions (Mottelson et al., 2023). While inverse kinematics (IK) solutions help simulate realistic body movements, additional trackers, like Vive Trackers, may improve accuracy (Ponton et al., 2024). Finally, controller and HMD tracking provide six degrees of freedom (6DoF) for both position and rotation, essential for spatial awareness in VR. Although controllers can simulate certain hand poses, fully tracked hands offer a more natural experience (Voigt-Antons et al., 2020).

Since substantial parts of a VR experience happen inside of the virtual environment, data from the virtual entities can also be directly collected via software-side sensors from inside the virtual environment. Examples are insights about interpersonal distances (Bailenson et al., 2003) or mutual gaze (Fehlmann et al., 2020). We refer to this type of data source as virtual sensors. Collection of such virtual sensors generally starts from within a 3D engine like Unity. Alongside VR-specific libraries, such as the Meta Interaction SDK, the 3D engine provides essential functionalities like HMD support and object interactions for virtual environments. Unity is the dominant tool for VR development, valued for its extensive libraries and flexibility. Another relevant alternative is the Unreal Engine due to its improving VR capabilities (Ashtari et al., 2020). In the context of scientific experiments, structured approaches to data collection via virtual sensors are still needed. Frameworks such as EVE and UXF offer first advances by integrating pre-built data collection functions into the VR application. For example, UXF enables large-scale data collection and automating experiment steps that would otherwise be complex (Brookes et al., 2020). Other frameworks like ManySense VR cater to context-aware applications, collecting data from sensors to allow real-time adaptation of the VR experience. ManySense VR, for instance, gathers data from sources like eye-tracking and physiological sensors, enriching the experiment environment by responding dynamically to user and environmental inputs (Moon et al., 2022). This multi-layered software stack, combining development engines, libraries, and data collection frameworks, forms a robust foundation for data collection from VR applications in research and beyond. However, these frameworks lack a holistic perspective, particularly regarding virtual sensor data, highlighting a research gap that now needs to be addressed.

3 Deriving a systematic Data Framework

The previous section highlights the many unsystematically applied opportunities for collecting data in virtual environments as well as first advances to augment 3D models with corresponding data collection functions. To attain a systematic overview of these data categories and their potential use in organizational application scenarios, we conducted a rigorous survey of relevant literature on VR experiments to identify potential metrics which we further clustered into distinct categories. We then assess how the derived categories correspond to three organizational application scenarios for VR in sales, human resources and team collaboration. Finally, the framework is refined through expert interviews. We will now introduce this research approach and its outcome in more detail.

3.1 Systematic PRISMA literature review

To capture the breadth of data used for analysing VR experiences, we first conducted a comprehensive literature analysis, following the guidelines set by the PRISMA framework by Moher et al. (2009) and Page et al. (2021). This approach was chosen to give transparency on the paper selection process and to show the thoroughness of the methodology. For diversity in the body of literature multiple search engines were used: Scopus and Web of Science. The research goal was to identify relevant publications that involved experiment-based research that had both a focus on VR and on social aspects of the experience. From these experiments the data types that were used to draw their findings, were collected and analysed. For the Scopus search engine, the following query was used: *(TITLE-ABS-KEY("VR"), OR TITLE-ABS-KEY(„Virtual Reality")), AND TITLE-ABS-KEY(„experiment"), AND TITLE-ABS-*

KEY("social"). For Web of Science the following search query was chosen*: (TS = ("VR" OR "Virtual Reality")), AND TS = ("experiment"), AND TS = ("social").*

Both queries were designed to only include papers that focused in some way on Virtual Reality or the abbreviation VR. They then also had to include social in their abstract, title or keywords to focus on social VR experiences. Lastly, they had to include the keyword experiment in their abstract, keywords or title to focus the results on experiment-based research. Both search results were sorted by relevance to focus on more relevant, influential or more newly published research. To ensure manageability, both queries retrieved only the top 100 articles based on relevance, e.g. term matching, resulting in 53 journal articles from Scopus and 58 from Web of Science, spanning from 2005 to 2024 across diverse disciplines. For the detection of duplicates the web application Rayyan was used. A total of 41 papers were removed as they were duplicates from the two search queries. Out of the 159 remaining papers that were screened, 55 were excluded based on the exclusion criteria or because the paper was not available to the author. To be included in this analysis the papers had to pass three filters. First, they needed to include an experiment, since non-experiment-based research was not applicable to the data model the author evaluated. Second the papers had to measure and write about some data from their experiments in a meaningful way, that was detailed enough to warrant an analysis of what exactly they measured. This could include a wide range of data metrics, like technical implementations of user's locations or eye-tracking, or more subjective data like nausea, trustworthiness of other participants or usability scores collected by questionnaires. Third the experiment had to have a social focus. This could be fulfilled in two main ways, either the experiment had multiple actors interacting with each other or it had a single actor that was placed in a social situation. The resulting set of included papers was then analyzed more closely, and the types of data used or measured in the experiment were deducted as well as common research themes were identified. A table with all included papers is included in Appendix A. Due to the high number of included papers from the initial search a citation search for the inclusion set was skipped. An overview of the review process can be seen in Figure 1.

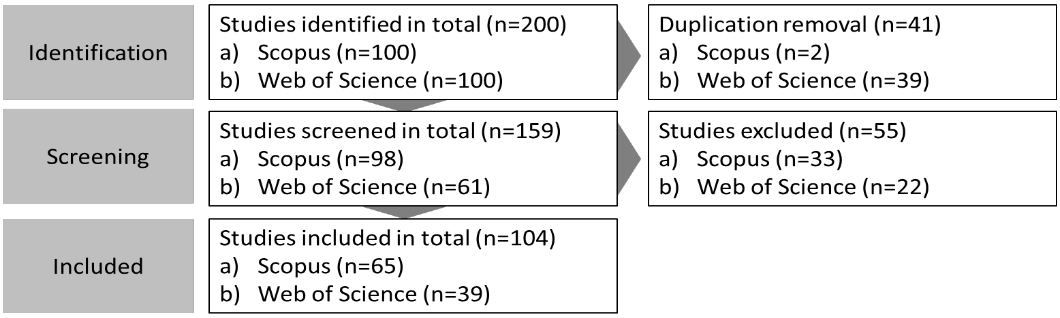

Figure 1. Systematic PRISMA flowchart of the literature review process.

Our literature survey highlights that social VR research is a diverse field, spanning areas like healthcare, manufacturing, and education. VR offers unique advantages, such as simulating high-risk scenarios for training or exposure therapy without actual danger. A common method of data collection in VR studies is through subjective questionnaires, though In-VR questionnaires, which could enhance immersion, remain underused. While intradiegetic (immersive) questionnaires could improve data quality, they are not frequently implemented, as most questionnaires remain external to the VR experience. Standardized perception data tools, such as the IGroup Presence Questionnaire, NASA TLX for task load, and PANAS for emotional valence, are widely used for metrics like presence, valence, and anxiety. Even when objective measures for concepts like anxiety exist (e.g., heart rate variability), researchers still favour subjective questionnaires to obtain additional insights, possibly due to the ease and accessibility of such tools. Presence is a particularly important metric in VR, since the sense of "being there" is crucial for VR's effectiveness, especially in applications like exposure therapy. Hence, it is common to measure presence along with other metrics to validate the immersive experience. Other critical metrics in social VR include empathy, social anxiety, and cybersickness, with questionnaires like the Simulator Sickness Questionnaire ensuring that symptoms do not interfere with data validity. Usability and mental workload questionnaires (e.g., SUS and NASA TLX) were less prevalent in Social VR studies, reflecting the focus on interactions rather than application evaluations in this field. Customizable questionnaires are important for researchers, as many studies adapt these tools to fit specific research goals. VR is particularly beneficial for studying conditions like autism and anxiety disorders, where safe, controlled simulations are important. VR scenarios like the Trier Social Stress Test illustrate VR's value in replicating social stressors efficiently. Education, especially with vulnerable populations like children or individuals with autism, is another prominent area of interest. VR can provide safe training grounds for social skills, and its application in workplace training and collaboration is growing. Eye-tracking remains the most commonly used tracking method but often requires additional hardware, as built-in eye-tracking is still new in most VR headsets. As newer models with integrated eye-tracking, such as the Meta Quest Pro and Apple Vision Pro, become more common, eye-tracking is likely to see increased use in VR research. To analyse similarities between the identified metrics and to condense them into distinct categories and dimensions, we segmented the data into data dimensions based on a Design-Structure-Matrix (DSM). For example, physiological metrics such as skin conductance, EEG, and heart rate were considered to be strongly interrelated because they all measure direct physical reactions to a VR environment. This resulted in formation of three data main dimensions: *Physiological Data*, *Virtual Sensor Data* and *Perception-oriented Ex-Post Survey Data*. We further assigned the identified data categories, data metrics and concepts to their respective data dimensions, as presented in table 1. In 29 papers, *Physiological Data* was collected. Commonly measured metrics included heart rate, skin conductance, and brain activity, often used together, with heart rate variability and skin temperature also frequently measured. Saliva samples were collected for biomarkers like cortisol, alpha amylase, and oxytocin. Additionally, microphones and cameras recorded behaviour such as yawning and hand gestures, requiring manual coding post-experiment. *Virtual Sensor Data*, collected in 30 papers, was generally reported with less precision than perception-oriented ex-post survey data. Unlike questionnaires, virtual sensor data lacked standardized descriptions. Some data collection methods were broadly categorized, such as "task completion", encompassing actions like passing a virtual door or interacting with an object, typically linked to specific research tasks. Eye-tracking data was frequently used, with analyses covering saccade duration, occurrence time, blink rate, and gaze direction. Head, hand, and body movements were also tracked, as was spatial data on actor or object positioning. Some data collection methods were either highly specific or too vague for straightforward categorization, with certain activities grouped under "task completion/other". The majority of the surveyed studies focused on *Perception-oriented Ex-Post Survey Data*, with 90 papers gathering perceptual data. Presence was a prominent theme, often measured through specific questionnaires. Researchers frequently specified the questionnaires they used, with common types including cybersickness, presence, and anxiety, measured by tools like the Simulator Sickness Questionnaire (SSQ) and the iGroup Presence Questionnaire (IPQ). Other notable concepts included valence, empathy, motivation, engagement, usability, embodiment, and stress. Demographic questionnaires were omitted from the canvas to avoid clutter. An overview of the dimensions, categories and metrics is provided in table 1.

Data Dim	Data Category	Related Metric (Concept)	References
Physio-logical Data	Skin Conductance	Attention, Arrousal, Social Stress/Anxiety, Cybersickness	(5, 8, 24, 30, 69, 81, 83, 93, 95, 102)
	Heart Rate	Social Stress/Anxiety	(24, 43, 56, 69, 81, 83, 95, 102)
	Brain Activity	(Cognitive) Attention, Empathy, Synchrony	(11, 33, 51)
	Audio & Video Recording	(Learning) Engagement, Social Presence	(7, 16, 20, 58, 72)
	Saliva Sample	Pain Tolerance, Social Stress/Anxiety	(61, 83, 95, 102)
	Task Completion/Other	Social Stress/Anxiety, Social Presence, cybersickness, Synchrony, Honesty, Physical Endurance, Social Simon Effect	(5, 8, 16, 20, 21, 24, 30, 33, 36, 55, 57, 62, 71, 75, 93)

Virtual Sensor Data	Eye Tracking	Gaze Direction (e.g. Visual Attention, Engagement, Synchrony, Social Presence, Gaze Duration & Frequency (Social Presence, Co-Presence), Blink Rate (Cognitive Load), Fixation Duration(Cognitive Load, Anxiety)	(3, 13, 21, 34, 44, 51, 54, 90, 94)
	Hand Tracking	Hand Gestures (Quality of non-verbal communication), Hand-Movement (Synchrony)	(27, 61)
	Head- & Body Tracking	Head Movement (Predicting Heart-Rate, Synchrony), Head Rotation (Social Presence, Gaze Following), Head Direction (Avoidance)	(43, 54, 61, 83, 94)
	Orientation (Position)	Position (Task Performance, Place Familiarity), Movement Path (Task Performance, Social Influence), Proximity, Synchrony	(17, 18, 25, 44, 47, 50, 53, 59, 65, 76)
	Video-/Audio Recording	Manual Coding (Task Performance, Turntaking, Task Cooperation)	(27, 28, 65, 66)
	Task Completion	Task Performance (e.g. Travel Success, Completion Time, Failure Rate, Attentional Bias, Evacuation Decision Time)	(3, 4, 17, 18, 19, 25, 27, 29, 44, 67, 77, 98)
Percep-tion-oriented Ex-Post Survey Data	Perceived Anxiety	FNE Scale Questionnaire, Spielberger Trait-State Anxiety Inventory STAI questionnaire for anxiety, LSAS-FR social anxiety, State Trait Anxiety Inventrory STAI, SPAI Social Phobia and Anxiety Inventory	(8, 24, 56, 61, 67, 68, 81, 83, 84, 85, 90)
	Perceived Presence	social presence questionnaire SPQ, iGroup presence questionnaire (IPQ), Nasa TLX, Networked Minds Measure of Social Presence (NMQ), Networked Minds Social Presence Inventory (NMSPI)	(5, 9, 15, 16, 25, 27, 29, 30, 31, 32, 38, 48, 49, 50, 52, 53, 54, 55, 58, 60, 61, 62, 70, 72,...)
	Perceived Cybersickness	Fast Cybersickness Scale (FMS) survey, simulator sickness questionniare (SSQ), simulator sickness questionnaire SSQ, Motion Sickness Questionnaire	(1, 28, 30, 31, 32, 63, 73, 83, 86, 95, 98)
	Perceived Empathy	affective empathy scale, social closeness index, Parasocial Interaction PSI Process Scales, Empathy Questionnaire (EQ), Likert Scale, Affective Empathy Scale (AES)	(10, 15, 21, 33, 42, 52, 76, 80, 86, 89, 91)
	Perceived Usability	System usability and acceptability, Slater-Usoh-Steed SUS scale	(19, 93, 98, 99, 103)
	Perceived Workload	NASA-TLX cognitive load, Subjective Mental Effort Questionnaire (SMEQ),	(22, 30, 31, 32)
	Perceived Engagement	parasocial interaction, likert scale for engagement, Confirmatory Factor Analysis (CFA)	(6, 14, 26, 82, 97, 103)
	Perceived Valence	Positive and negative effect PANAS, Self Assessment Manikin SAM,	(39, 40, 53, 63, 85)
	Perc. Immersion	Transportation Scale-Short-Form TS-SF	(5, 9, 19, 46, 70, 101)
	Other	game experience questionnaire GEQ, questionnaire on virtual body ownership (IVBO), questionnaire on customer experience, TSST-VR, Revised Social Connectedness	(1, 2, 5, 6, 9, 10, 12, 14, 18,..)

Table 1. Identified and clustered Data Dimensions, Categories and Metrics from Systematic Literature Review.

3.2 Case Vignettes

Most of the identified VR settings relate to experimental research contexts. To examine the applicability to an organizational context, we conducted an ex-post analysis of three different organisational application scenarios that we created and tested with users for the purpose of observing what behaviours can be measured via virtual sensors. The following case vignettes were selected based on two criteria: (1) relevance to current organizational uses of social VR and (2) their potential to reflect a diverse spectrum of application areas. They are structured based on the virtual social interaction triangle (VISIT; Trier et al., 2024) which offers a useful lens through which to examine social VR as an interaction phenomenon. It draws on the key elements of Goffman's interaction framework – social occasion, gathering, and (spatial) situation – serve as foundational components in understanding virtual social interactions. Where social occasion refers to the planned event or unit of social interaction, which sets the context for the interaction, gathering represents a group of individuals in a given moment, where all of them are in one another's immediate presence. The situation encompasses the spatial environment in which the interaction occurs. This framework effectively captures the core constituents of social interactions in virtual environments.

Figure 2. Impression of the three analysed organizational VR application scenarios. Sales interaction in VR (left), job interview (middle), team meeting (right).

VR-based Sales Situation: Starting with (Trier & Steiger, 2023), an innovate VR commerce scenario, where we have created an immersive customer interaction. Here, the *social occasion* is a virtual sales scenario, where the customer interacts with a salesperson avatar in an immersive environment. The customer has the ability to explore products and make purchase decisions through dynamic conversation with the salesperson. The *gathering* takes place in a virtual sales environment, where the participant and the sales avatar interacts in real time. This creates a feeling of co-presence and social presence, which was confirmed by the participants during the interviews. In terms of the *situation*, the customer enters the virtual salesroom as an avatar and meets a virtual salesperson, which is represented as a human actor. During a one-on-one consultation, the salesperson shows products, answers questions and uses both verbal and non-verbal cues such as pointing gestures to create a realistic interaction. The participants can observe and interact with the digital product from different positions. Participants then were asked to evaluate how the virtual environment design and sales avatar interaction influences perceptions of immersion, social presence and media richness (e.g. possibility for real time conversations and nonverbal gestures). With this application scenario, we could successfully demonstrate the value of VR commerce as a driver of customer satisfaction and capture participants' reaction and perception of VR-based social interactions.

VR-based Job Interview: A second application scenario was created to analyse user behaviours a simulated a job interview. The *social occasion* involves a structured scenario where the participant interacts with a virtual agent. The setting involves a proxemics experiment, where the participants interacted with a virtual agent to collect data on interpersonal distances and nonverbal communication to analyse social presence, interaction and user acceptance. The *gathering* consists of the participant and a virtual agent, whereas the agent maintains eye contact with the participant or not. The spatial *situation* refers to the virtual environment, where varying objects (e.g. standing table and a reception desk) in a virtual office environment influences the participants proxemics. The situation is designed to test how proximity and gaze behaviour affects the participants comfort and response.

VR-based Team Meeting: The third case scenario investigates spatial positioning and visual attention in immersive environments. We examined, how spatial positioning of participants and their closeness to each other affect attention during a presentation. The *social occasion* involves participants engaging with a virtual presentation. Various elements, such as proximity and seating arrangements are manipulated in order to test how these factors influence visual attention and learning outcomes. While the *gathering* comprises the participants and a virtual presentation avatar, interaction is primarily supported by spatial positioning, movements, and eye-tracking. The presence of other avatars in the surroundings will either enhance or detract participants focus, depending on their proximity and perceived social dynamics. The *situation* involves a virtual classroom environment, where participants are placed in various situations, which allow different spatial arrangements. These arrangements include fixed positions (e.g. seated at a desk) or more dynamic (e.g., ability to move freely within the virtual space). The studied case vignettes show how, in organizational settings, different concepts like social presence, attention or proxemics can be quantified through virtual sensor data like eye-tracking, hand tracking or spatial orientation. For instance, the virtual sales scenario not only measures how participants interact with avatars but also how such interactions influence customer satisfaction. Our analysis has shown that the data categories from the literature survey fully apply the organisational setting. They enable a systematic analysis of operationalized metrics that can describe relevant virtual user behaviours and related outcomes of interest for organisations and researchers. The final overview of how data categories are useful to measure in organizational VR applications is provided in table 2.

Virtual Sensors	**Case Vignette 1 – Sales Situation**	**Case Vignette 2 – Job Interview**	**Case Vignette 3 – Team Meeting**
Eye Tracking	Social Presence: Fixation (Object, Actors) and Eye Contact relate to engagement Co Presence: Gaze Change and Actor Activation reinforce others presence awareness	Proxemics: direct or averted gaze and gaze collision were tracked	Attention: Fixation on objects and actors, -duration, gaze shifts and eye contact capture visual attention Personal Space: Combined with eye tracking leads to potential personal zones
Hand Tracking	Social Presence: Head-hand synchronization & symbolic gestures allow expressions Co Presence: symbolic gestures and motoric activity enhance sense of shared space		Attention: Gestures like pointing serve as an indicator for attention Personal Space: Gestures combined with interpersonal distance shows critical distances
Head- & Body Tracking	Social Presence: Orientation towards others supports sense of being there Co Presence: Synchronized body movement to a shared Point of Interest help establish co presence	Proxemics: Orientation between participant and agent was tracked	Attention: Orientation toward objects and actors indicate participants attention Personal Space: Body orientation towards others maintain personal spac
Orientation (Position)	Social Presence: Orientation tracking to face each other naturally Co Presence: Movement paths and proximity tracking foster co presence	Proxemics: Steps and Distance were tracked to analyze the movement path and Proximity	Attention/Personal Space: Proximity to objects and other actors identify social distances and can influence attention. Personal Space: Movement paths and distance analyse spatial arrangement

Video-/Audio Recor-ding	Social Presence: Audio recording for conveying emotions Co Presence: Activity coding reinforces sense of togetherness		
Task Completion/Other	Social Presence: Completing presentation task builds sense of mutual support	Proxemics: Button press to identify preferred proximity	Attention: time spent on specific objects like presentation or other participants

Table 2. Case Vignettes Virtual Sensor Overview.

3.3 Semi-structured interviews

To refine and contextualize the results of the systematic literature review and the cross-case analysis, we conducted four expert interviews from the field of XR experiment-based research. Following the methodological approach of Mayring (1994), these experts were interviewed following a semi-structured interview guide. All interview partners were researcher from within the field of XR and have published several papers on experiments or studies conducted with VR or AR and were chosen to represent a variety of viewpoints from within the research community. They were chosen to represent a range of disciplinary perspectives: from cognitive neuroscience with a focus on social interaction (P1), to human-machine interaction and applied XR (P2), to privacy and security in AR (P3), and finally education research with focus on chemical process visualization in AR (P4). The interviews were, with permission of the interviewees, recorded and subsequently transcribed. After anonymization, the interview data was prepared for a qualitative content analysis, applying an inductive coding approach. To add a level of reflection to contextualize our derived data model, the experts' interview guide was not only capturing views on the general data collection, but also included questions on general potentials and limitations of VR data collection; benefits and drawbacks of in-VR questionnaires; and implications of eye- and face-tracking, along with privacy and security considerations. The experts acknowledged several potentials and limitations of using VR for data collection. The biggest advantages were the high level of *control* and engagement, as well as their precision and objectivity. However, VR research requires technical skills, posing challenges for non-technical researchers as stated by P1: *"Many researchers who don't have a computer science or engineering background want to work with humans in VR but do not have the technical ability to get the output of the data that might be of interest."* Experts concluded that perception data is central in VR research primarily because surveys and questionnaires offer valuable insights into participants' mental states. Additionally, standardized, widely tested questionnaires make data collection simple, affordable, and accessible, with minimal technical requirements. P2 expands on this point by a potentially comparing the gathered data: *"In this respect, I think the idea of actually collecting data in the virtual environment or data in reality during interactions and then comparing it with the perception border is a good one."* Additionally, in-VR questionnaires present a promising tool to enhance data quality, as they minimize immersion breaks and align data collection with the experimental context, reducing recall bias. Collecting data immediately post-exposure also limits interference from unrelated stimuli, resulting in more accurate responses as stated by P1: *"Also, it's a time and recency thing. If we ask people in the moment, they are experiencing something the answers likewise will also be more valid and reliable because if there is time in between people are getting in touch with other stimuli and forget certain emotions.* A data framework should also allow for diverse eye-tracking metrics based on the study's goals and sensor capabilities, as mentioned by P4: *"Another thing that is on the rise, at least in the field of science or chemistry didactics, is eye-tracking, because it's a bit different from surveys or questionnaires."* Privacy and security are also crucial. An ideal framework would offer anonymization tools, introducing statistical noise to biometrics to protect identity, and notifies participants about the collected data for transparency purposes. These tools could alert researchers if selected data types (e.g., eye- and face-tracking) might compromise anonymity, ensuring comprehensive data protection declarations. Technical challenges remain a barrier in VR research, especially for non-technical fields like neuroscience, healthcare, and education. Cross-disciplinary collaboration between computer scientists and social scientists could help bridge this gap, by developing user friendly tools and leveraging diverse expertise.

3.4 Operationalising the final Social VR Data Canvas

Based on the results of the literature review, the cross-case analysis and the reflections derived from the interviews, we can support the category system in Table 1 and derive the operationalized metrics or concepts for the main categories of virtual sensor data in Table 2. As a VR environment is essentially a technical context, a further step is needed to operationalize and technically implement these measures: For each data category a corresponding entity is created within the entity relationship model (Figure 4). As we actually identified the technical data collection process ourselves, *eye tracking* for example can be captured through measuring the exact orientation of the users' eyes, where 3D coordinates and angle of each eyeball is calculated, while the gaze pointer consolidates data from both eye pointers to establish a unified focus direction. The *voice* component collects the participants voice through the microphone and can be used for lip-syncing or facial expressions. Moreover, the *shoulder pointer* consists of a forward vector originating from the midpoint between both shoulders. It represents the general direction in which a person's body is facing. *Face tracking* data is applied to a user's avatar using blend shapes—textures that deform and transition between two states. For example, a smile from a user can range from 0 (no smile at all) to 1 (an exaggerated, wide smile), with all intermediate values representing different intensities. Different standards exist, with approximately 60 blend shapes being sufficient to capture most natural facial expressions. In *hand tracking* mode, the position and rotation of the users' hands and fingers is tracked through a script and captured through camera or depth sensors within the HMD with recognition of key points on the hands. This mode tracks each finger (e.g., thumb, index, middle, ring, pinky) and each finger joint (e.g., thumb1-4) separately, while in *controller tracking* mode, the interactions can be captured through the controllers. These interactions are further categorized into gripping, pointing, or pressing actions and the system also tracks whether a finger is removed from a button, resting loosely on it, or is actively pressing it. In addition to hand tracking, *index fingers* (e.g., LeftIndexPointer, RightIndexPointer) are key in non-verbal communication, often used to indicate directions. The LeftIndexPointer and RightIndexPointer are forward vectors originating from the index fingers. Although considered meaningless, the movement of the index finger while the rest of the fingers are closed is a unique gesture that gives a directional cue, which is detectable via virtual sensors for rotation on the other fingers. The *avatar* node represents the virtual embodiment of the participant, which stores attributes such as name, height and sex. The avatar node ensures that each participant´s virtual representation is consistent and includes a customizable appearance to reflect personal preferences or specific experimental parameters. To capture interactions within the virtual environment, *collider components* are used. They detect contacts between avatars and virtual objects. When interacting with a digital object the system registers the contact through a collider script and enables manipulation of transformation and rotation of the object. The *orientation* entity captures the users' position (e.g., x, y, z coordinates) and rotation (alpha, beta, gamma), represented in a quaternion format. In this representation, the additional value is included primarily for computational purposes. *Video and audio recordings* allow participants perspectives or to navigate freely through the environment on demand. Multiple camera angles can be used, allowing the flexibility to switch between viewpoints seamlessly during recording. These virtual recordings are akin to conventional ones; they can subsequently be utilised for manual coding or detailed analysis. This technical translation of the derived metrics leads to the final result of our research effort the social VR data canvas. The framework illustrates the integration of different data types, such as reality data, virtual reality data and perception data into a holistic data model. Figure 4 shows the final model, starting with the *Physiological Data*, which includes metrics such as brain activity, skin conductance and heart rate. These metrics represent the participants' physiological state during the experiment and are collected through physical sensors. These provide insights into how users physically react in virtual environments. Next, we have *Virtual*

Sensor Data, which covers metrics directly related to interactions within the virtual environment. These data metrics are captured through virtual sensors and consists of components like eye tracking (e.g., left and right pointer), gaze pointer and also voice data. It also includes avatar specific data like name, height, and sex as well as collider elements representing, how the user interacts with virtual objects within the spatial environment. The *Perception-oriented Ex-Post Survey Data,* shorted in figure 2 to *Perception-oriented Data*, due to limitations, involves data collection through surveys or subjective methods, which focusses on various psychological and perceptual measures, such as anxiety, presence, cybersickness, empathy, usability, workload, valence and immersion. The framework also incorporates a privacy label for sensitive data types, marking elements that require anonymization. P3 suggested further defining sensitivity based on data combinations, though this was not feasible within the current Entity-Relationship Model (ERM). Additionally, some brain activity data may be influenced by HMD types, a detail not represented in the canvas but considered for future versions.

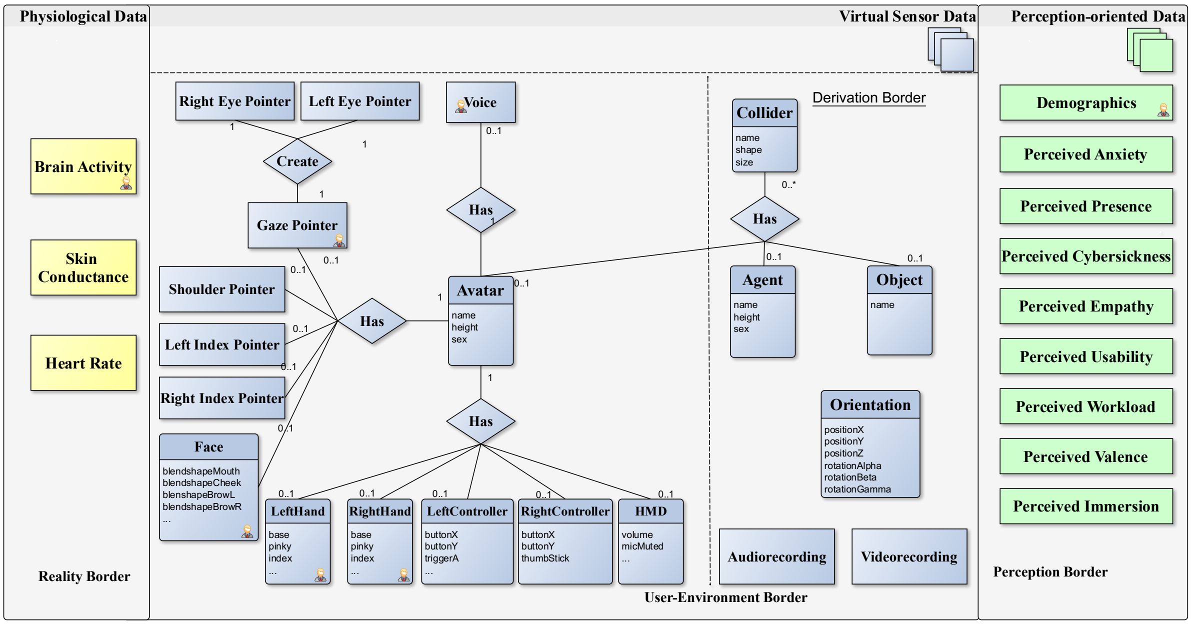

Figure 3. *Social VR Data Canvas.*

4 Discussion

By deriving the Social VR Data Canvas from the identified and assessed data dimensions, categories and metrics, we comprehensively answer our research question and developed a systematic data framework that incorporates multiple data modalities to enhance spatial data collection. With this framework we can contribute to research and practice in various ways. First, the framework synthesizes an overview of relevant and practically proven data categories that are linked to conceptual measures. These data types offer an effective and coherent approach to determine useful constructs for VR-based research or for organizational analytics of novel application scenarios. It also enables a holistic overview of concurrent analytical perspectives, which is important for comprehensively investigating and understanding complex social phenomena, such as the experience of presence in a group-based virtual environment. Further, our analysis helped to identify three important data collection dimensions that reach from physiological measures to perception-oriented ex-post surveys. Virtual sensor data emerged as a third dimension and mediating link between the two other realms, highlighting the comprehensive opportunities that lie in actually collecting data from virtual actor behaviours in a VR environment. Potential AI applications for pattern recognition in virtual sensor data, sentiment analysis, and behavioral clustering could further extend the analytical scope, while, interdisciplinary collaboration could additionally enhance analytics. Our expert interview results underlined the value and further point out that perception-oriented survey can also directly be integrated into the VR experience to increase data validity and minimize disruptions. The three data dimensions are often used in combination, suggesting that collecting virtual sensor data may eventually become an effective predictor of manually collected survey data. By relating the measures identified in the literature review with our organizational application scenarios, we were able to demonstrate that VR data analysis is extendable to corporate settings and can be used to automate and quantify the current manual observations of user behaviours. A further contribution arises from our operationalization of the data categories to a technical level that now can be implemented in 3D models and development environments such as Unity. This enables researchers to establish a link between a technical data source in a 3D model and user perceptions, offering a very systematic and grounded starting point for advancing VR analytics. The expert surveys point to the fundamental importance of determining suitable limitations to meet privacy needs in VR contexts. Despite the positive results, there are several limitations remaining. First, while the model was assessed through case analyses and interviews, further validation checks through actual measurement and analysis are needed to prove generalizability and robustness. Future research should assess the extendibility of the framework from its current narrow focus on VR to related technologies such as augmented reality as well as mixed reality and identify similarities and differences in terms of data modalities. Another important issue relates to data protection. Collecting biometric data, such as eye movement and facial expressions can expose the users to the risk being identifiable. Implementation of privacy mechanisms which anonymize or aggregate individual user data, or which produce statistical noise are therefore a crucial topic for future research. Aggregation, for example, will not necessarily limit the practical insights, as still a level of user engagement, trust or presence can be measured for a social VR experience. This helps making the framework more applicable in practice. Another potential limitation lies in the difficulties of integrating data from multiple different sources. Finally, at this stage, many researchers from non-technical disciplines will find it difficult to implement the metrics, which is why we work on a user-friendly software tool that will be easy to use, making the framework more accessible to a wider audience.

5 Conclusion

We believe that our data framework offers an important point of departure for researchers in areas such as Human-Computer-Interaction or Computer-supported cooperative Work. Our contribution supports researchers in structured conceptualization of experiments in social virtual reality and gathering of relevant data. The data canvas especially helps understanding social interactions on a deeper level, specifically in organizational contexts, which can lead to increased quality and reproducibility of experiments. Building on these foundations, future research could explore how different data modalities influence social presence, whether real-time biometric feedback enhances collaboration effectiveness, or the evolution of social norms in digital space and ethical implications of prolonged immersion.

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