How are you Feeling? Inferring Emotions through Movements in the Metaverse

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Abstract

Metaverses are immersive virtual worlds in which people interact as avatars. There is emerging interest in understanding how metaverse users behave and perceive activities and tasks. Our understanding of users' behavior within metaverses is limited. This study examines the role of emotions in the movement of individuals. We therefore implement a metaverse setting using virtual reality technology and development tools. In our study, we manipulated negative emotions and tracked the movements of our participants. We show how negative emotion influences movements in a metaverse setting. Based on a literature review, we select and calculate movement features to train a support vector machine. As our result, we present a novel way to infer the negative emotions of metaverse users which will help create more engaging and immersive experiences that cater to user's emotions and behaviors. Our study provides preliminary evidence for the potential utilization of movement data in the metaverse.

Keywords: metaverse, virtual reality, experiment, attentional control theory

Introduction

The rising popularity of *the metaverse*, a virtual world where people can interact with each other, has created wide business opportunities (Davis et al., 2009; Nickerson et al., 2022). Even though there is no universally accepted definition of the metaverse (Lacity et al., 2023), we follow the concise definition of Mystakidis (2022) that aligns with our understanding of the concept:

> "*The Metaverse is the post-reality universe, a perpetual and persistent multiuser environment merging physical reality with digital virtuality. It is based on the convergence of technologies that enable multisensory interactions with virtual environments, digital objects, and people such as virtual reality (VR) and augmented reality (AR). Hence, the Metaverse is an interconnected web of social, networked immersive environments in persistent multiuser platforms. It enables*

> *seamless embodied user communication in real-time and dynamic interactions with digital artifacts. Its first iteration was a web of virtual worlds where avatars were able to teleport among them. The contemporary iteration of the Metaverse features social, immersive VR platforms compatible with massive multiplayer online video games, open game worlds, and AR collaborative spaces*".

As mentioned in the definition, a building block and current core technology of a metaverse is Virtual Reality (VR) which provides the possibility to completely immerse in a metaverse (Lee et al., 2021). A metaverse offers various user-related and organizational opportunities (e.g., defining a new customer journey and user experience or making online meetings richer and more collaborative experiences) and functional, social, and emotional ways of value creation (e.g., buying goods, meeting and communicating with others, experiencing positive emotions and feelings) (Schöbel & Tingelhoff, 2023).

Nevertheless, new technology needs to be accepted to be adopted. Emotions can play a role in the individual acceptance of new technology as they can be related to anxiety (Beaudry & Pinsonneault, 2010; Venkatesh, 2000). Thus, it is of emerging interest how users of a metaverse perceive activities and tasks under varying conditions and which emotional state they have in the meantime. Additionally, emotion recognition has further fields of application like marketing, education, or entertainment (Dzedzickis et al., 2020) which are also fields of application for the metaverse (Kamińska et al., 2019; Radianti et al., 2020; Schöbel & Tingelhoff, 2023).

Furthermore, as the utilization of virtual agents within the metaverse continues to expand (Dincelli & Yayla, 2022), there is an increasing need for these agents to be able to accurately perceive and understand the emotional states of the metaverse users (Seymour et al., 2018). This not only enhances the overall user experience by enabling more personalized and empathetic interactions but also has potential applications in fields such as mental health and customer service, where the ability to detect and respond to emotional changes or fluctuations is critical.

To the best of our knowledge, there has been no prior approach to infer emotions in a VR-provided metaverse except one that measures emotions by analyzing the voice of users (Daneshfar & Jamshidi, 2023). While the voice-based approach seems to be promising, it has two main weaknesses. People do not always speak, and the voice recording and processing needs additional user consent and permission. The additional permission for voice recordings might lead to decreased acceptance since one of the main user-related challenges of the metaverse is the fear of personal data misuse (Schöbel & Tingelhoff, 2023).

To solve these issues, we propose another way of assessing the emotional state of users as our research goal: *analyzing the movements of tracked body parts since they are already tracked for the main metaverse application*. While previous research has focused on movement-based behavior recognition in traditional Human-Computer-Interaction (HCI) settings, such as using the computer mouse and keyboards (Hibbeln et al., 2017; Jenkins et al., 2019; Weinmann et al., 2022; Williams et al., 2017), little is known about how and if emotions influence movements in the metaverse. We pioneer in this area by investigating if negative emotions influence movements in the metaverse and whether the tracking of body parts in virtual reality (VR) can be used to infer negative emotions. The theoretical lens explaining how emotions influence movements originates from the attentional control theory (Eysenck et al., 2007). Hibbeln et al. (2017) used the theory to explain the influence of emotions on mouse movements.

To analyze the movements, we developed an experimental simulation in a metaverse setting using VR technology and conducted an experiment to measure movements in the metaverse setting after manipulating negative emotions. We employed an unfair intelligence test as our manipulation (Zuckermann, 1955) and a shopping setting as the metaverse setting. The self-developed simulation enabled us to capture movements as accurately as possible with the given hardware. From the three-dimensional trajectories (six degrees of freedom – x, y, z and α, β, γ) of both hands and the head we calculated features describing the movements. We used machine learning algorithms using our manipulation as the label to infer negative emotion from the movement features. Our findings contribute to the fields of HCI and metaverse research by providing new insights into the relationship between negative emotion and movements in a metaverse. The main contribution is the presentation of a method to infer emotions in metaverse settings. Moreover, our work highlights the need for ethical considerations in this emerging area of research due to the privacy implications of using emotion recognition in a metaverse.

Background

Influence of Emotions on Movements

Emotion is conceptualized as a transient psychological state that arises from cognitive appraisals of external stimuli or internal thoughts (Averill, 1980; Lazarus, 1991). Following Bradely and Lang (1994), the classification of emotions can be based on three dimensions: pleasure, arousal, and dominance. Pleasure ranges from extreme unhappiness to extreme happiness, arousal ranges from sleep to excitement, and dominance ranges from feelings of a total lack of control to extreme feelings of influence and control. The measurement of pleasure is most relevant for our study since low pleasure can be seen as a negative emotion.

Humans express their feelings through multiple channels: facial expressions, body language, voice, and different types of physiological changes (Sapiński et al., 2019). Mehrabian (2017) proposed the 7-38-55 principle for emotional messages humans (sub-)consciously exchange with each other: 7% verbal signs, 38% strength, height, and rhythm, and 55% body movements and facial expressions. Based on this, a human observing another individual can usually identify the emotional state of the observed individual rapidly and accurately through nonverbal cues, without the need for explicit communication. One of the nonverbal cues is movements of different body parts (Melzer et al., 2019; Morton & Johnson, 1991. Recent neurological research suggests that negative emotions influence movements by having direct connections to brain structures that mediate motor responses (Coelho et al., 2010). Negative emotion can also influence motor track excitability, the electrical stimulation in the nerves that initiate movement, and elicit motor-evoked potentials, which are electrical stimulations recorded in the muscles indicating potential movement (Coelho et al., 2010). Furthermore, negative emotions can affect motor movement reaction times and the amount of muscle force produced. Studies on emotion-influencing movements specifically address arm and head movements (Michalak et al., 2009) or eye movements (Schurgin et al., 2014). Research has shown that bodily movements, particularly those of the head and hands, are frequently utilized to convey one's emotional state. Observers naturally direct their attention toward these regions of the body when attempting to accurately infer the emotional state of others (McNeill, 1992). Attentional control theory (Eysenck et al., 2007) proposes that negative emotions can influence cognitive control, leading to changes in attentional focus and subsequent behaviors. Thus, negative emotions affect attentional control which impacts movements (Hibbeln et al., 2017). Overall, these findings suggest that emotions can have a significant influence on movements in the real world. We argue that this also translates into virtual environments such as metaverses.

Tracking Movements in an HMD-provided Metaverse

VR is a computer-generated simulation of a three-dimensional environment that can be interacted with by a user (Wohlgenannt et al., 2020). The metaverse, which is an online space where users can engage with a virtual world, is often provided by VR devices. VR devices typically take the form of head-mounted displays (HMDs), which are worn on the head and cover the user's eyes (Lee et al., 2021; Peukert et al., 2022). HMDs are usually equipped with hand controllers that allow the user to interact with the virtual environment. In the metaverse settings, the movements of the head using an HMD and the hands using handheld controllers are tracked and digitally translated onto an avatar in real time. This enables users to interact with the virtual environment and with other avatars in a more immersive and natural way (Slater & Sanchez-Vives, 2016). By leveraging advanced motion tracking technologies and algorithms, the avatar movements can closely match the user's actions and expressions, providing a more seamless and intuitive user experience. Additionally, this technology allows for increased social presence as users can engage in social interactions with others through their avatars, further blurring the lines between physical and virtual reality (Oh et al., 2023). The movements of the user are either tracked by sensors located on the HMD and hand controllers or from external sensors. This process, known as motion tracking, allows the user to move around and interact with objects in the virtual world as if they were actually present in that environment (Slater, 2003, 2009). Additionally, these movements can be recorded and analyzed, providing valuable data for researchers and developers. For example, Loske et al. (2022) measured times as an indicator of performance in a VR experiment to validate their field data. Table 1 shows exemplary data points that can be recorded in a usual metaverse setting.

Measurement	Detail
Position / Movement	Head
Position / Movement	Hand left
Position / Movement	Hand right
Position / Movement	Object in simulation
Time	Event A until Event B

Table 1. Exemplary Datapoints Generated in a Metaverse

Emotions in a Metaverse

Emotions serve as a central point in social interactions, conveying important information about an individual's internal states and shaping the nature and outcomes of social interactions (Averill, 1980; Lazarus, 1991). Given the fundamental role of emotions in human communication, the accurate capture and analysis of emotional data represents a crucial area of socio-technical research (Yu et al., 2023).

Emotions can significantly influence a user's behavior and decision-making in the acceptance of IT (Beaudry & Pinsonneault, 2010) like a metaverse. Understanding a user's emotional state can provide valuable insights into how they are likely to interact with the virtual environment and the decisions they are likely to make. Peukert et al. (2019) showed that perceived enjoyment has a positive influence on the intention to reuse a shopping environment. One core value driver of the metaverse is shopping (Kliestik et al., 2022). Yu et al. (2023) showed the importance and economic value of emotions in online reviews. Emotions during a shopping experience might be even more useful for managerial decisions (Magids et al., 2015). Inferring the emotions of users can also have practical applications in areas such as mental health and therapy (Chau et al., 2020).

Research Design and Methodology

The present study aims to investigate the impact of negative emotion on movements in the metaverse, utilizing virtual reality (VR) technology. The Unity3D platform was employed to develop an experimental setting and to facilitate the collection of movement data. This section provides a detailed account of the data collection procedures, including information about the study sample, the experimental conditions, the manipulation check, and the measures employed during the experiment and post-experimental survey. By leveraging state-of-the-art VR technology and experimental methods, this study represents a contribution to the scientific literature on emotion recognition in virtual environments.[1]

Data Collection Procedure and Sample

We recruited our participants by inviting mainly experienced VR users to take part in our study. We specifically targeted this group to reduce the novelty effect of metaverse applications. All participants received the same information as a briefing for the experiment (Dennis & Valacich, 2001). The participants were informed that they would be immersed in a "metaverse-supermarket," a virtual reality environment tailored to their unique intelligence levels, as determined by an intelligence assessment. Before entering the experimental metaverse setting, all participants received a comprehensive tutorial to ensure they were proficient in utilizing the VR controls. Upon completing the tutorial, the participants underwent the intelligence test to determine their cognitive abilities, which was said to be used to tailor the virtual environment to each individual's intellectual capacity. Within the metaverse supermarket, the participants were tasked with retrieving items from shelves and transporting them to the checkout. This approach aligns with previous research on emotions (Hibbeln et al., 2017). Upon completion of the goal-directed tasks, participants were administered a questionnaire as a final component of the experiment. Overall, the participants took around 18 minutes each to complete the experiment (2 minutes tutorial, 1 minute

[1] A video from the view of an exemplary study participant can be found here: https://youtu.be/xTAez3qh_6I

intelligence test, 10 minutes task completion, 5 minutes questionnaire). Our participants' age ranged from 18 to 30 years (mean: 24.75 years), and 22% identified as female. 23 participants were the final sample size.

Experimental Design and Conditions

For the experiment, we created the intelligence test and the metaverse supermarket using Unity3D (Unity, 2023). Unity3D is a game engine that is commonly used for research in VR and provides the technical capabilities to record movements of the tracked body parts. To design the metaverse experiment, we carefully followed the design principles of Menck et al. (2023) for VR experiments to collect transferable and relevant data.

We chose to do the experimental manipulation in VR to avoid the possible effect of a "break in presence" (Slater & Steed, 2000) that might lead to a reduced effect of our manipulation. Thus, we designed two versions of an intelligence test in VR. After the briefing, the participants were randomly assigned to either a negative emotion or a nonnegative emotion condition. The negative emotion was induced through an unfair intelligence task (Zuckermann, 1955). The other group did a fair intelligence task. Both groups had one minute to finish the test that included common questions used in intelligence tests.

The unfair test included two hard questions and unnecessary waiting times where participants lost time by "accepting cookies". This manipulation made it impossible to answer all questions. Thus, the shown result in the unfair group was always "very low". The result of the fair test was at least "average", the questions were easy to answer, and no waiting times were included. Table 2 shows the experimental groups and shows screenshots of fair and unfair elements.

<table>
<tr><th colspan="2">Intelligence test</th></tr>
<tr><td>Fair
(Normal intelligence test)

(Minimal possible IQ Level was "average")</td><td>Unfair
(Artificial waiting times between Questions)
(Participants had to accept Cookies)
(IQ level was always "very low")</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">Table 2. Experimental Conditions</td></tr>
</table>

After completing the (unfair) intelligence test, the participants (virtually) went to the metaverse supermarket and were provided with a shopping list. They were asked to pick items from the shopping list and bring each one to the checkout. At the checkout, predefined slots were prepared for the items. To move around in the metaverse-supermarket we enabled teleporting, a common way of moving in metaverse settings.

Measures

We employed two primary measurement tools in our study: the experimental artifact, namely the metaverse supermarket in which we recorded the movements of our participants, and a questionnaire designed to assess various constructs and demographics as well as the manipulation check. The following sections will provide a detailed explanation of our measurement approach.

Figure 1. Screenshot of the Metaverse-Supermarket

Experimental Artifact – Recording Movements of Goal-Directed Tasks

To capture precise and detailed data on participant movements during the goal-directed tasks in the metaverse supermarket, we utilized the Meta Quest 2, a standalone virtual reality device that does not require a computer and is capable of tracking the controllers/hands and the head of participants in 6 degrees of freedom (Meta, 2023). In the supermarket, our participants performed a series of tasks by picking an object from their shopping list and bringing it to a predefined laydown slot. Our recording process began as soon as an object was picked, enabling us to capture data on all relevant movements. We recorded the x, y, and z coordinates and rotation around the x, y, and z axis (α, β, γ) of both hands and head of each participant, at a rate of approximately 90 frames per second. This high level of detail allowed us to collect accurate and reliable data on participant movements, enabling us to analyze them with a high degree of precision. An overview of the recorded data is given in Table 3.

During the tasks, participants underwent three stages of action – picking an item, teleporting to the counter and/or shelf, and laying down the item on the checkout counter. To ensure that our recorded data accurately reflected actual participant movements, we filtered out teleportation movements. This ensured that our results accurately reflected participants' movements during the tasks. Figure 2 shows the path of the gripping hand in the 3-dimensional space for one item.

By leveraging the Meta Quest 2 and implementing a rigorous data collection process, we were able to obtain detailed and reliable data on participant movements during the tasks in the metaverse supermarket. This data formed the foundation of our analysis with the goal of drawing meaningful conclusions regarding participant performance and behavior within the virtual environment.

Head	Left Hand	Right Hand
Current Picked Object		
Time		
Position (x, y, z)		
Rotation (α, β, γ)		

Table 3. Recorded Data (Each Frame ~90 Hz)

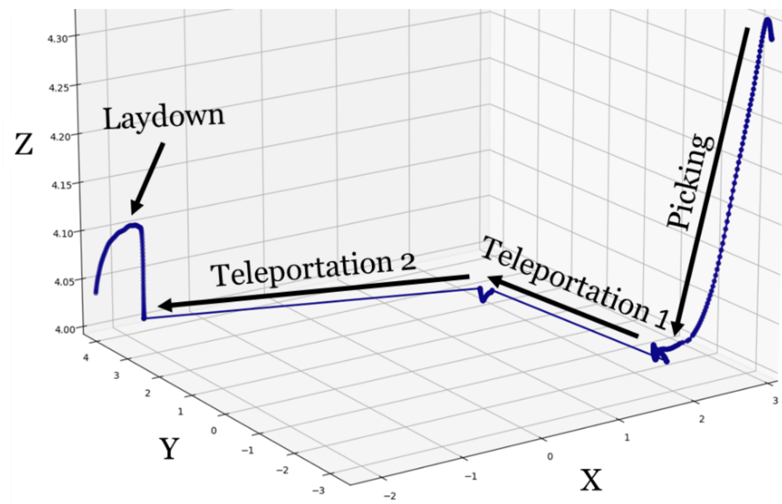

Figure 2. Movements of the Gripping Hand in the 3D-Environment

Questionnaire Measures

After completing the goal-directed tasks in the metaverse supermarket, participants were asked to complete the questionnaire. The questionnaire was designed to capture both positive and negative emotions that participants experienced during the experiment. Specifically, we measured pleasure and arousal using a 9-point Likert scale based on the Self-Assessment Mannekin (SAM) (Bradley & Lang, 1994) in line with IS research on emotions (Hibbeln et al., 2017; Sheng & Joginapelly, 2012; Valacich & Jenkins, 2021). The SAM test provides a means to assess emotions without the need for verbal expression, making it a convenient experimental strategy. Additionally, the use of pictorial assessments in the SAM test allows for cross-cultural and language-independent application (Morris, 1995).

Results

Feature Generation

We implemented Python scripts to analyze the data collected from our experimental artifact and questionnaire measures. Specifically, we developed custom scripts to preprocess and analyze the movement data captured by the VR devices, and subsequently integrated it with the questionnaire data for a comprehensive analysis. We separated the reported pleasure at the mean as a label (neutral/negative) and generated features to describe the motion of participants. Our recorded data from the experiments were divided by trials, products, and devices. One trial consisted of 8 carried products where each carried product contained between 2500 and 5000 rows of absolute world coordinates and rotations for each connected device (controller/hand left, controller/hand right, headset/head). Feature extraction was used to condense the data. Through our literature review, we identified that emotion could influence movements in numerous ways (see background section). Therefore, we selected multiple measures such as distance, speed, acceleration, jerk, and rotation smoothness to describe the motion of participants. These measures were selected as they are well-established in the field and have been previously utilized in similar studies investigating the relationship between emotion and movement in real life (Dzedzickis et al., 2020; Hibbeln et al., 2017; Melzer et al., 2019; Sapiński et al., 2019). By transferring these established measures from reality in a metaverse, we aimed to contribute to the scientific understanding of the complex and dynamic interplay between emotion and movement in a metaverse setting. To establish data representation, the mean, median, and standard deviation from the new columns were added to the features. Additionally, the same calculations were done regarding rotation and the distance from the carried product was appended.

We calculated the Euclidean distance in 3 dimensions between two points $P_i = (x_i, y_i, z_i)$ and $P_{i+1} = (x_{i+1}, y_{i+1}, z_{i+1})$:

$$d(P_i, P_{i+1}) = \sqrt[2]{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2 + (z_i - z_{i+1})^2}, [d] = \mathrm{m}$$

leading to a total movement distance of

$$D = \sum_{i=1}^{n-1} d(P_i, P_{i+1}), [D] = \mathrm{m}$$

between the recorded points $P_1, P_2, \dots, P_n$. For the speed of the motion, we divided the distance of the motion by the time $t(P_i, P_{i+1})$ between the two points:

$$v(P_i, P_{i+1}) = {d(P_i, P_{i+1})}\Big/{t(P_i, P_{i+1})}\ ; [t] = \mathrm{s}; [v] = {}^{\mathrm{m}}/_{\mathrm{s}}.$$

We analogously calculated the accelerations $a(P_i, P_{i+1})$ and jerks $j(P_i, P_{i+1})$; $[a] = {}^{\mathrm{m}}/_{\mathrm{s}^2}$; $[j] = {}^{\mathrm{m}}/_{\mathrm{s}^3}$.

We calculated the same features with the rotation data.

Table 4 gives an overview of the generated features.

Head	Left Hand	Right Hand
(Rotation-)Speed (V) (Mean, Median, Standard deviation)		
(Rotation-)Acceleration (A) (Mean, Median, Standard deviation)		
(Rotation-)Jerk (J) (Mean, Median, Standard deviation)		
Distance (D)		

Table 4. Features Generated from Recorded Data

Training the Classifier

First, we tested our manipulation using a t-test. We compared the pleasure (as an indicator of negative emotion) for both groups. The results are shown in Table 5.

	Test	t-value (df)	p-value	Result
Manipulation	Pleasure(neutral) > Pleasure(negative)	-1.98 (21)	<.03	Manipulation successful

Table 5. t-test for Manipulation Check

After extracting the features from the dataset, they need to be used to recognize negative emotions. A support vector machine (SVM) is a supervised machine learning algorithm that takes features as training data and calculates a separating line or other shapes depending on the kernel, that classifies the input features. After fitting the SVM to the features, the accuracy is calculated by reading new data that has not been used before by the algorithm, predicting the class of its features, and comparing it to the true labels of them. To further improve the accuracies, the optimal value of the parameter gamma is obtained by iterating over the range of 0.001 to 1, running the SVM, and evaluating the resulting accuracies.

To further demonstrate the accuracy of the predictions, the k-fold cross-validation (CV) is used. This algorithm offers different train- and test-sets for every iteration of creating and evaluating an SVM model. It separates the input data into k splits and trains the SVM on all but one of them, which is then used for testing the accuracy. After testing every split once, the mean of the resulting accuracies is returned. K-fold CV calculates the evaluation of the features which is less biased by chosen train- and test-sets. Since the algorithm picks random samples with their labels, it is not guaranteed the trainset contains the same amount of negative and neutral samples. For that reason, a stratified k-fold CV is used, which balances the input labels (classes) for training. After applying dimensionality reduction on the features, the returned accuracy from stratified k-Fold CV is 54% when used in combination with an SVM running on a linear kernel. The optimal parameters are evaluated by iterating over a range of values between 0.001 and 10 for gamma and 2 to 100 for dimensionality reduction. Table 6 shows the importance of choosing optimal gamma values after applying principal component analysis (PCA) to the dataset.

The dots show the projected coordinates on the 2-dimensional coordinate system using PCA. Red circles are negatively labeled features, and the green are marked as baseline. The black shape separating the two classes is the fitted SVM onto the points. Higher gamma values tend to overfit the samples so it should stay low to allow generalizability. The images in Table 6 show acceptable results since most of the red dots are included inside the separation border for gamma values over 10.

When the samples are labeled and classified using emotion data collected by the survey, the accuracy increases to 66%. The following confusion matrix (Figure 3) shows the returned predictions with an accuracy rating of 66% highlights the issue of features with negative emotion labels being misclassified. Considering the small number of participants, the result is a big step toward classifying users' emotions in the metaverse, as more training data would likely lead to clearer results. Our artifact can serve as a tool to collect more data in the future.

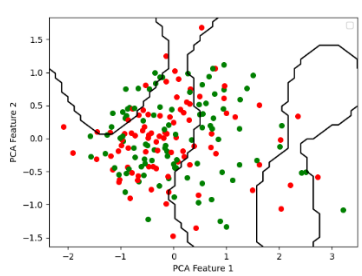	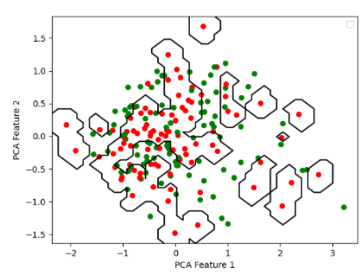	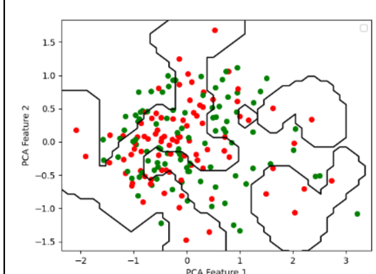
Gamma = 1	Gamma = 40	Gamma = 10

Table 6. Different Gamma Values

True Label	0	98	14
	1	51	21
		0	1
		Predicted Label	

Figure 3. Confusion Matrix of the SVM

Discussion

Our results have the potential to change the way of thinking about and measuring metaverse adoption by introducing the role of emotions. We measured actual behavior in a metaverse setting (Williams et al., 2017) to infer negative emotions. We introduced a method that allows researchers and developers to assess negative emotions in metaverse settings without the need to elicit additional data. Thus, there is no need for users to provide additional permissions. Our study shows that negative emotion also influences movements in the metaverse. Our findings have implications for companies engaged in developing a metaverse, IS research, and metaverse users. We contribute by using a machine learning approach with a distinctive method (an experiment in VR) for a novel phenomenon (emotions in the metaverse) with a reflective framing (Leidner, 2020).

Implications for Research

Emotions are communicated by the body and VR translates certain aspects of human bodies into virtual worlds like the metaverse (Schultze, 2010). Especially movements are translated in the metaverse. Our main contribution from the IS research perspective lies in the demonstration of a tool that uses the movements of the translated bodies for emotion assessment in the metaverse. To our knowledge, our work is pioneering in analyzing motions in a metaverse setting to infer emotions. Thus, the results of our study can contribute to research on multiple metaverse activities and experiments in VR.

Analyzing movement and other data generated in a metaverse setting provides an opportunity for extensive research in areas like HCI (Hibbeln et al., 2017) or marketing (Dwivedi et al., 2023). With the ability to assess emotions in real time, researchers can investigate the impact of emotional states on user behavior and engagement. For instance, studies could examine how emotional states affect interactions within the metaverse. Moreover, analyzing data from metaverse shopping experiences can provide insights into user behavior and preferences, which in turn can inform product design and marketing strategies. For example, understanding how emotions influence purchasing decisions in the metaverse could lead to more effective targeted advertising and personalized product recommendations. Additionally, emotion detection can aid in HCI studies by providing objective measures of user emotional states. Researchers can use this data to evaluate the effectiveness of various design features, such as user interfaces or avatars, in eliciting desired emotional responses.

The contemporary research landscape highlights the potential misuse of data streams originating from the metaverse (Lacity et al., 2023). Our contribution highlights this concern by exemplifying a specific data stream and its capacity to deduce personal information like emotional states. This is in line with one of the main user-related challenges of the metaverse: misuse of personal data (Schöbel & Tingelhoff, 2023). The possibility to assess emotions from existing data opens a new possibility for privacy discussions and research (Lacity et al., 2023)

Our study can also inspire research interest in emotional distress, as we showed that movement analysis can predict negative emotion. This could be used for the early detection of high-risk individuals (Chau et al., 2020).

Lastly, our findings can be extended to VR applications other than the metaverse. Experiments in VR can easily record movements and generate a deeper understanding of the role of emotion in the data, especially when physical movement is included (e.g., Loske et al., 2022). VR-gaming apps can, for instance, measure the effect of lootboxes (Larche et al., 2021).

Practical Implications

We demonstrated a way to collect data and assess emotions without necessitating additional permissions from users. All data points we used would have been collected and transmitted to the servers that run a metaverse anyhow. This means metaverse providers can implement it immediately. This way of assessing the emotions of users has multiple implications for companies engaged in the metaverse:

Marketing: Dwivedi et al. (2023) describe how the metaverse will shape the future of consumer research and practice. A central position of their conceptual paper is that enhanced tracking and monitoring of individuals will increase dense streams of customer data and generate new metrics regarding interactions with users and objects. Our proposed approach does not need additional data streams to provide new, valuable metrics. Since leveraging emotion can be used to engage customers with advertisements (Teixeira et al., 2012) studying emotions is of great value in marketing.

User Experience: Emotion, especially negative emotion, plays a central role in user experience (Hassenzahl & Tractinsky, 2006). Detecting a user's emotional state can provide a fast way to evaluate advertisements, different designs, and enable A/B testing. This would allow companies to evaluate different designs and find failure points in designs.

Customer support: Detecting negative emotions can help companies in the metaverse to proactively reach out to (potential) customers to care for their needs. Possible actions include giving an opportunity to express concerns, providing apologetic statements, or even offering compensations (Hibbeln et al., 2017).

Privacy: Due to the additional data points and the possibilities arising, firms will have to deal with increasing privacy concerns compared to traditional online environments (Dwivedi et al., 2023).

Designing metaverse applications: Designers could prioritize eliciting standardized movements from users. This approach enhances the collection of precise and comparable data across diverse interactions. By enforcing consistent gestures and expressions, practitioners can ensure a robust foundation for reliable emotional analysis and evaluation within the metaverse environment. This method optimizes the accuracy of emotional responses and facilitates cross-application comparisons, ultimately advancing the quality and depth of emotional insights derived from user interactions within the metaverse.

Overall, the assessment of negative emotion can result in a higher revenue for companies by enabling them to tailor a marketing campaign for a tailored user experience with proactive customer support. The inferred emotion can further inform product development or further business decisions. Nevertheless, companies must care about the privacy concerns of their customers.

Limitations and Opportunities for Future Research

Our design exhibits different limitations and offers opportunities for future research on emotions in the metaverse. Our experimental setting allowed us to foster high levels of control and precision to investigate our research goal. There was also a high degree of realism since the object of interest was a metaverse setting. Thus, we followed a "lab in the field" approach (Karahanna et al., 2018) by conducting our study in a metaverse setting using VR technology. Nevertheless, conducting experiments in VR takes more resources than online experiments that can be distributed using online platforms like Qualtrics or Prolific. Like other studies using VR, our sample size might raise issues regarding generalizability (Vankov & Jankovszky, 2021). The age range of 18 to 30 year-old participants and the imbalance of male and female participants can be potential points of concern. We utilized an SVM for our analysis, but it is important to note the limitations of machine learning, especially in the context of our small sample size. This approach provides just one perspective on machine learning, and there are various other approaches concerning features, algorithms, and evaluation. Given our current dataset, we can expect limited accuracy, though the results are promising. For a more generalized and precise model, a larger dataset would be essential to review and analyze.

To promote transparency and reproducibility in our research, we make our experimental artifact, which includes the executable file and source files, available to interested researchers upon request. By sharing our experimental artifacts, we enable the replication and extension of our findings, as well as further exploration of the research addressed in our study. We specifically followed the design principles of Menck et al. (2023) to design our artifact to enable future research on the basis of our artifact. The sharing of experimental artifacts is becoming increasingly important in scientific research as it promotes openness, transparency, and the advancement of knowledge in the field (Dennis et al., 2020). By providing access to our experimental artifact, we hope to contribute to these goals and promote the use of open science practices in the IS community.

Our study provides preliminary evidence for the potential utilization of movement data in the metaverse for emotion recognition. However, the accuracy of our results is currently limited. Despite this limitation, our findings represent a crucial first step toward the development of emotion recognition techniques in the metaverse. As there are already approaches for using smartphone-based interaction data as an identification tool (Bo et al., 2014), we assume the analyses of metaverse movement data can be an even better estimator for the identification of individuals (Nair, Guo, et al., 2023; Nair, Rack, et al., 2023) and their emotions. Further research could investigate the use of physiological measures such as changes in the breathing pace and heart rate to further validate our approach and provide even more accurate labels for the machine learning algorithms.

Conclusion

The assessment of emotions in the metaverse has the potential to shape the development of new metaverse applications and future research on and in the metaverse. As a first step, we implemented an experimental artifact and a manipulation to induce negative emotion. We collected movement data of study participants. From this data, we extracted features and trained an SVM to classify our dataset. We tested this SVM through stratified k-fold cross-validation. This approach allows us to predict users' emotional states with a promising level of accuracy that could be improved by more extensive data collection. Our findings have strong implications for metaverse development and research.

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