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Virtual dance movement therapy for reducing anxiety, and artificial intelligence for monitoring the body and mind during therapy

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ABSTRACT

Dance Movement Therapy (DMT) is an established psychotherapeutic intervention that utilises movement to support emotional, cognitive, and physical well-being. While traditional DMT is practiced in physical settings, Extended Reality (XR) presents a new opportunity to expand accessibility by integrating immersive, interactive environments with structured therapeutic movement interventions. This study explores how XR-based DMT can serve as a preventative approach for anxiety by applying wearable biometric monitoring and AI-driven personalisation. Unlike recreational virtual dance activities such as Zumba or general movement-based fitness applications, XR-based DMT follows a structured therapeutic model, incorporating principles of mirroring, embodied cognition, and rhythmic synchronisation to enhance emotional regulation and engagement. The study employs real-time physiological feedback mechanisms, where biometric markers such as heart rate variability (HRV) and skin conductance inform dynamically adapted movement interventions. The findings suggest that XR-enhanced DMT provides a scalable, non-pharmacological intervention for individuals experiencing early-stage anxiety. This study contributes to the growing field of digital DMT by providing an evidence-based framework for integrating immersive technology into therapeutic movement practices, ensuring adherence to the core principles of dance movement therapy rather than generic dance-based interventions. Future research should address long-term efficacy, therapist-led versus AI-assisted interactions, and the potential for XR-DMT in community-based settings.

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Extended Reality (XR); Virtual Reality (VR); Artificial Intelligence (AI); Dance Movement Therapy (DMT); mental health and anxiety; non-pharmacological interventions

1. Introduction

Dance Movement Therapy (DMT) (Meekums, Karkou, and Nelson 2015; Payne 1992), is a well-established approach for alleviating anxiety and fostering emotional balance and has traditionally been implemented in physical settings (Millman et al. 2021). New technologies, such as Extended Reality (XR), including Virtual Reality (VR),

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Augmented Reality (AR), and Mixed Reality (MR), offer a potential solution by enabling remote access to immersive therapeutic environments.

When designed according to DMT principles, XR-based interventions can provide structured therapeutic movement experiences, rather than generic dance-based activities. This study explores how XR can be utilized to expand the reach of DMT while maintaining its core therapeutic integrity.

Unlike recreational dance programs such as Zumba, which focus on fitness and cardiovascular health, XR-based DMT is designed to facilitate emotional expression, self-regulation, and therapeutic engagement. By integrating wearable biometric feedback systems (e.g. HRV and skin conductance monitoring), XR-DMT sessions can dynamically adapt movement interventions based on participants' physiological stress responses. This personalised approach enhances therapeutic efficacy and engagement, offering a novel digital extension of DMT practices.

This study examines the use of biometric and AI-driven adaptations in XR-DMT, ensuring that movement-based interventions align with psychotherapeutic goals rather than recreational dance. The study also considers ethical implications such as participant privacy, data security, and the role of therapists in guiding AI-assisted interventions. Because XR platforms present opportunities for therapeutic innovation but also present risks (Xi et al. 2022), including the potential to intensify anxiety (ICO 2018). By clarifying the distinct role of DMT in XR environments, this research contributes to the evolving field of digital mental health interventions.

2. Literature review

When examining alternative therapies within Extended Reality (XR), it is crucial to approach the matter with the same level of rigour as traditional medical investigations (Xi et al. 2022). Even if these therapies are non-invasive, they require stringent adherence to medical guidelines. Ensuring that data protection principles (EUGDPR 2016; GDPR 2018; Voigt and von Dem Bussche 2017) are intrinsic to the research design is paramount. Before data collection can commence, every participant must grant explicit consent, typically documented via a participation consent form.

The research methodology standardised the data management by drawing from reputable clinical trials databases.[1] Among the database options considered are OMOP, CDISC, and SDTM. To further ensure consistency and clarity, the study incorporated recognised clinical vocabularies such as LOINC, SNOMED-CT, and NCIT.

One core aspect of our findings emphasises the influence of individual predilections and intrinsic personality traits on therapy efficacy (Meekums, Karkou, and Nelson 2015; Shuper Engelhard and Yael Furlager 2021). Recognising that not all subjects may resonate with traditional expressive therapies like music or art, the study broadened the scope to include therapies like cardiovascular techniques (Payne 1992). The rationale behind this eclectic mix is simple: to offer a varied palette of therapeutic options that can address the diverse tastes and requirements of the population (Chaiklin and Wengrower 2015; Levy 1988; Paulus 2013; Schaaf 2019; Yohannes et al. 2010).

One emerging query is the efficiency of the methodology when integrating an increasing number of therapies. While establishing a direct linear relationship between the number of therapies and their collective efficacy can be challenging, assuming a cumulative advantage is plausible (Coelho and Balaban 2015; Gorman and Sloan 2000; Xia and Kheirbek 2020). Each treatment, by design, targets different sides of mental health (Day 1964; Friedman and Thayer 1998; Giannakakis et al. 2017; Gilbert 2003; Jacob, Redfern, and Furman 2009; Jerath et al. 2015; Liu et al. 2018; Mallorquí-Bagué et al. 2016; Tiwari, Narayanan, and Falk 2019). When combined, they could offer a more holistic and well-rounded therapeutic intervention.

Any methodology's efficiency is invariably influenced by individual-specific variables such as the severity of mental health issues, the personal affinity towards a particular therapy, or the existence of other medical conditions. These variables underscore the need for more expansive research and trials to validate the methodology's effectiveness across a broader demographic.

3. Research methodology

The study applied the 'FAIR by design[2] method, which underscores the commitment to ensuring the developed applications are Findable, Accessible, Interoperable, and Reusable. By integrating existing ontologies like STATO,[3] the methodology adheres to established research paradigms on data storage and management. The proactive pre-registration programme[4] of the clinical trials with the Open Science Foundation and the transparent declaration of analytical methods underscore the planning of data management and metadata tracking.

The methodological approach, particularly the precise sample size calculations grounded in Human Phenotype Ontology classifications, ensured that the study's findings advance the understanding of non-pharmacological interventions in mental health. The research outlined in this paper combines the detailed nature of data recordings with a methodical approach to studying alternative therapies for mental health using XR. Grounded in the hierarchical classification derived from HPO 9, this methodology was used to assess the effectiveness of various interventions, such as cardio activity, free movement, and conscious dance.

3.1. Primary data collection and management

The primary data acquisition centres predominantly on quantitative metrics collected from an array of wearable medical devices and body-worn sensors, all centralised within a Testbed. This Testbed is equipped with cutting-edge XR technologies such as VR, AR, and MR headsets, complemented by haptic gloves, body sensors, and advanced wearables. The following delineates the types of data procured:

(1) Physical Activity Correlation: Accelerometers and heart rate monitors data that charts the relationship between heightened physical activity and the consequent anxiety levels, gauged during and post-present activities. This data is further complemented by questionnaires, offering a more comprehensive understanding.
(2) Skin Conductance: Leveraging wearable patches, skin conductance is meticulously documented, serving as a potent biomarker of anxiety levels in subjects.
(3) Heart Rate Variability (HRV) Meta-analysis: HRV, coupled with spontaneous heart rate fluctuations, offers invaluable insights into the workings of the

autonomic system, especially concerning anxiety-afflicted patients who are not simultaneously grappling with cardiovascular ailments.

(4) Photoplethysmography (PPG) Metrics: HRV is also quantified using PPG, a method geared towards capturing shifts in microvascular perfusion by inundating the skin with light and subsequently quantifying either the transmitted or reflected intensities.

To improve the value and strength of the data collected, wearable and sensor metrics are paired with qualitative insights from case study interviews and structured questionnaires. Only anonymised data classifications are electronically documented; this information is securely stored on encrypted computer systems. These precautions are required because of the sensitive nature of the data, especially regarding health-related parameters.

3.2. Analysis methodology for primary data

The accurate interpretation of the collected data was considered as crucial to the success of this study, especially considering the potential confounding factors that could influence skin conductance measurements, a key biomarker of anxiety. To mitigate these challenges, rigorous data collection protocol was established to maintain consistency and minimise external influences. Participants were instructed to avoid activities that could induce excessive sweating, adhere to a standardised diet, and account for environmental factors such as weather conditions before data collection sessions. This protocol ensured that all measurements are obtained under controlled conditions, thereby reducing variability caused by extraneous factors.

To further address the impact of sweating on skin conductance readings, baseline measurements were established for each participant prior to any activity (Alm 2004). These baselines serve as critical reference points, enabling the identification of anomalies specifically related to anxiety rather than physiological responses to sweating (Nelson et al. 2015). The skin conductance patches selected for this study were chosen for their ability to minimise interference from external factors such as profuse sweating, thereby ensuring the integrity of the data (Yohannes et al. 2010).

To enhance the robustness of the findings, a multi-method analytical approach was employed, integrating quantitative data from wearables and sensors with qualitative data obtained from case interviews and structured questionnaires. This comprehensive approach allows for data triangulation, providing a more detailed understanding of the relationship between skin conductance and anxiety. The qualitative insights derived from interviews and questionnaires help to contextualise the quantitative findings, reducing the risk of misinterpretation due to confounding variables.

A detailed statistical analysis was conducted to identify correlations between skin conductance measurements and potential confounding factors, such as sweat levels, dietary habits, and prevailing weather conditions (Licht et al. 2009). By incorporating these variables as covariates in the analysis, the specific impact of anxiety on skin conductance was isolated. This rigorous approach mitigates the risk of drawing incorrect conclusions from the data, ensuring that the results accurately reflect the studied areas.

To uphold the highest standards of research integrity, all potential confounding factors encountered during data acquisition and analysis were documented. This documentation includes detailed records of participant activities, dietary intake, and environmental conditions, providing a comprehensive backdrop against which the data can be interpreted. Through this commitment to transparency, the study aims to eliminate premature or flawed conclusions and bolster the credibility of its findings. By combining a stringent data collection protocol with a multi-faceted analytical strategy and a strong emphasis on transparency, this study strives to eliminate the influence of confounding factors on skin conductance measurements, ensuring that the correlations observed between anxiety levels and skin conductance accurately reflect the true nature of their relationship.

3.3. Sessions structured according to established movement therapy frameworks

Unlike general dance-based applications, XR-DMT sessions are structured according to established movement therapy frameworks. The methodology involves the following key elements:

- Participants & Data Collection

• Participants included individuals experiencing mild-to-moderate anxiety, recruited through mental health clinics and community wellness programs.

• Movement interventions were designed following DMT principles, focusing on expressive movement, mirroring techniques, and rhythmic entrainment to promote emotional regulation.

• Sessions were conducted in immersive XR environments using VR headsets, motion sensors, and wearable biometric devices to monitor physiological stress responses.

- Therapeutic Adaptation via AI and Biometric Monitoring

• Biometric data, such as Heart Rate Variability (HRV) and Skin Conductance, were monitored to assess participants' anxiety levels in real-time.

• AI-driven adaptive systems adjusted movement interventions dynamically, ensuring that therapeutic sequences aligned with physiological responses.

- Therapist-Guided vs. AI-Assisted Interventions

• Some sessions were therapist-guided, where a trained DMT practitioner interacted with participants through XR platforms.

• Other sessions were AI-assisted, where movement sequences were adapted based on biometric data without live therapist input.

- Ethical Considerations

• The study adhered to data privacy regulations, ensuring that biometric and movement data were securely stored and anonymised.

• Participant consent was obtained, with clear guidelines on how XR-based interventions align with traditional DMT practices

3.4. Using secondary data for insights

While primary data serves as the basis of this research, integrating secondary data sources significantly enhances the study by adding depth and context. These pre-existing data reservoirs provide a broader perspective, allowing for a more comprehensive analysis. Open-Source Intelligence (OSINT) is utilized to gather data from publicly accessible sources, including media, academic publications, and government databases. This approach enables the incorporation of historical context, the comparison of emerging trends, and the benchmarking of findings against established studies, thereby offering a macro-level understanding of the subject matter.

In addition to OSINT, new and emerging forms of data (NEFD) from interconnected systems like the Internet of Things (IoT) are leveraged to provide large-scale real-time data streams. This data offers fresh insights into user behavior, preferences, and broader trends in device usage, which can be correlated with mental health indicators, opening new avenues for exploration. A qualitative review of secondary data is conducted using comprehensive academic databases such as Web of Science, Scopus, CSA Illumina, and Google Scholar. This review helps map the landscape of existing research, identify gaps, and contextualise the primary research findings, ensuring a thorough and nuanced understanding of the subject.

Quantitative analysis is also employed, utilising bibliometric tools like R-Studio (Charpentier 2014) and VOSviewer (Jan van Eck and Waltman, n.d.) to analyze extensive datasets, including the Web of Science Core Collection. This analysis helps identify influential publications, track trends, and provide an analytical overview of the existing literature, revealing patterns that may not be immediately evident through qualitative reviews. Additionally, secondary open-access data, including previously conducted interviews, surveys, and other anonymised records, are incorporated to validate primary findings and align the research with existing knowledge. This approach reduces redundancy and ensures consistency across different studies.

By synthesising primary data with these diverse secondary sources, the research gains a richer understanding of context, validation, and analytical depth. This integration allows for a more holistic and well-rounded examination of the focus area, ultimately enhancing the reliability and relevance of the study's findings.

3.5. Understanding data dimensions: types, classifications, and scale

For a comprehensive evaluation and interpretation of the findings, it was essential to classify and understand the nature and dimensions of the data. This classification ensured that the data analysis methods applied were appropriate, yielding meaningful and reliable insights. The data were categorised into distinct types, classifications, and scales, each playing a crucial role in the analytical process.

1. Data Types were categorised as follows:

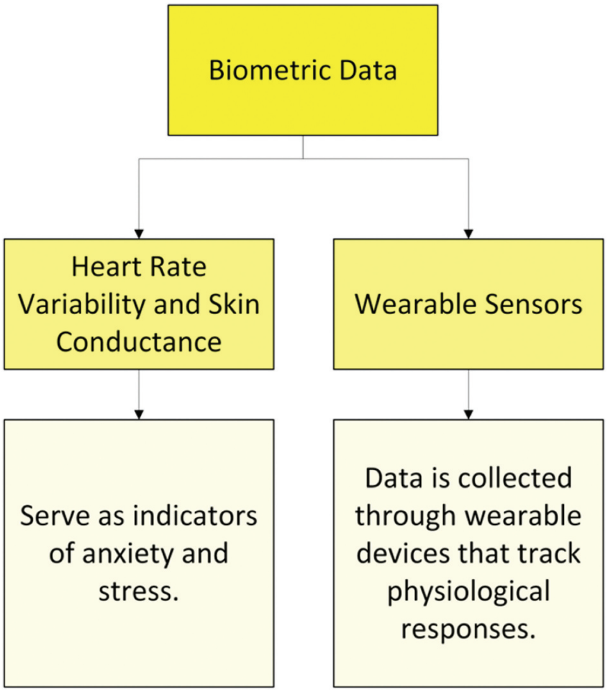

Figure 1. Biometric data and wearable Technology: this figure represents the types of biometric data (such as heart rate variability and skin conductance) collected through wearable sensors, crucial for evaluating and personalising mental health interventions.

(a) **Cross-Sectional Data**: This type of data provided a snapshot of specific attributes at a particular point in time, focusing on variables such as participants' age, medical conditions, or other demographic information (Figure 1). Cross-sectional data were instrumental in capturing the state of the participants at a given moment.
(b) **Time-Series Data**: This data type tracked the evolution of a single variable over a series of time points, making it invaluable for identifying trends and predicting future patterns (Figure 1). It allowed the observation of how variables such as anxiety levels fluctuated over time.
(c) **Panel Data**: Serving as a hybrid of cross-sectional and time-series data, panel data captured information on multiple entities over multiple time periods (Figure 1). For instance, the anxiety levels of a group of participants were tracked over several months, providing a more comprehensive view of temporal changes and variations across individuals.

2. Data Classifications included:

(a) **Structured Data**: This category comprised organised data with a predefined schema, making it amenable to analysis using AI and ML techniques. Examples included metrics from wearable devices, demographic data, and other systematically organized information. The structured nature of this data facilitated efficient and accurate analysis.

(b) **Unstructured Data**: In contrast, unstructured data lacked a fixed format and included elements such as open-ended survey responses and transcribed interviews. To extract meaningful insights, AI and ML models were employed to identify patterns, while Grounded Theory was applied to systematically derive theories from these data. This approach enabled the research to draw robust conclusions even from data that were not inherently organized.

3. Data Scale classifications were as follows:

(a) **Nominal Scale**: This scale was used for qualitative data points that were categorical in nature, such as the classification of participants based on different Human Phenotype Ontologies (HPO). It was essential for categorising and comparing distinct groups within the study.
(b) **Ordinal Scale**: Data on this scale were ranked, allowing for the evaluation of participant responses in an ordered manner. For example, post-activity comfort levels rated on a scale from 1 to 5 provided insight into participant experiences and areas for improvement.
(c) **Interval Scale**: Interval scale data were characterised by consistent intervals between measurements, such as heart rate or body temperature. This scale was particularly useful for analysing physiological data where the differences between values were meaningful.
(d) **Ratio Scale**: This scale provided quantitative data that allowed for comparative analysis, such as comparing heart rate measurements with perceived improvements in anxiety. The ratio scale facilitated the derivation of meaningful relationships between variables, enhancing the depth of the analysis.

Sample Size Consideration was carefully developed in accordance with existing literature, to ensure the statistical validity of the research. The sample size was estimated based on expected effect sizes, data variability, and the desired confidence level. Additionally, the categorisations from the HPO hierarchical classification were incorporated to refine these estimates further. This methodical approach to sample size estimation ensured that the study was both robust and representative. This structured approach ensured that the analytical methods were aligned with the inherent nature of the data, leading to accurate, insightful, and reliable conclusions.

4. Findings on XR-Based alternative mental health therapies design

Designing studies involving human participants, particularly in the sensitive area of mental health, requires a detailed, carefully planned and ethically correct approach (Figure 2).

The section of the study described in Figure 2, began by determining an appropriate sample size, where prior research parameters and effect size considerations indicated that a minimum of 102 participants would provide sufficient statistical power without

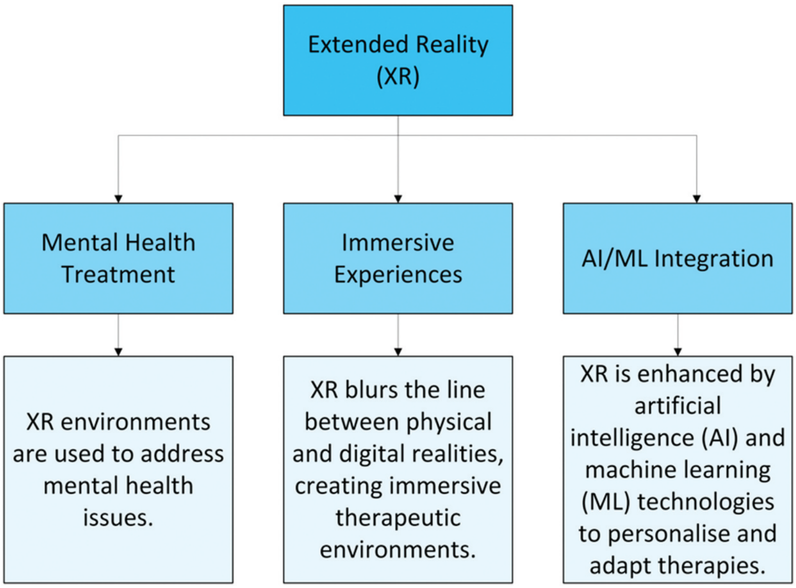

Figure 2. Extended reality (XR) and mental health Treatment: this figure illustrates how XR environments provide immersive experiences that enhance mental health treatment, integrating virtual and augmented reality for therapeutic interventions.

overburdening the research process. This sample size allowed for meaningful insights while maintaining the feasibility of the study.

Participants were then classified using the Human Phenotype Ontology (HPO) for anxiety, ensuring that individual symptoms were accurately represented within the study. Categories such as 'episodic paroxysmal anxiety' provided a structured framework for group allocation. Additionally, 20% of the participants were assigned to an alternate therapy group, which included activities like Zumba, adding a comparative dimension to the study. This approach facilitated the evaluation of different therapeutic interventions within the XR environment.

Given the geographical distribution of participants, a clustered sampling approach was employed, and a control group was included to account for placebo effects and other non-specific influences. The interventions focused on exploring the therapeutic potential of conscious movement in virtual dance settings (Rothbaum and Hodges 1999), with adjustments made according to participants' backgrounds, such as differentiating between those with and without prior dance experience (Levy 1988). Regular interviews and observations, lasting between 15 minutes to an hour, were conducted to gather qualitative insights into the efficacy of the interventions (Chaiklin and Wengrower 2015). These observations were key in capturing the impacts of XR-based therapies.

The statistical design, including power calculations, was developed to ensure that the study's conclusions were valid and reliable. Given the sensitive nature of the participant population (Re 2021), regular follow-ups were scheduled at six-month intervals, with each session consisting of one hour of virtual therapy followed by a 30-minute post-therapy interview. Monitoring participant stress levels was a critical component of the study, ensuring that the research process did not exacerbate anxiety or other mental health conditions (Millman et al. 2021).

Participant safety remained the primary concern throughout the study. Established anxiety measures, such as the Beck Anxiety Inventory (BAI), Generalized Anxiety Disorder 7-item scale (GAD-7), and the Penn State Worry Questionnaire (PSWQ), were integrated into the research to provide a standardised assessment of anxiety severity and related symptoms. Additionally, qualitative methodologies were employed, including case study research with interviews, group discussions, and statistical tests like the Kruskal–Wallis H, Mann-Whitney U test, and Pearson's chi-square Test, to offer a holistic view of participant well-being.

The study also used HPO classifications for anxiety to align interventions and evaluations with established medical frameworks. Anxiety was classified according to the Diagnostic and Statistical Manual of Mental Disorders (DSM), ensuring that the research adhered to widely recognized diagnostic standards. This approach to study design balanced scientific methodology with a commitment to participant welfare and successfully explored the therapeutic potential of XR in addressing complex mental health challenges.

4.1. New discoveries in XR-Based alternative mental health therapies design

By integrating DMT and advanced biometric and AI technologies, the research demonstrates the transformative potential of XR in addressing mental health challenges.

Table 1 presents a structured analysis of the key discoveries in the integration of DMT within XR environments. Table 1 summarises the core findings, their innovative contributions, and their implications for the future of digital movement-based interventions.

Table 1 illustrates how technological advancements can reinforce rather than dilute the therapeutic foundations of DMT. The comparison with alternative dance modalities, such as Zumba, reinforces the importance of structured therapeutic frameworks in movement-based interventions. Crucially, the balance between therapist-led and AI-driven adaptations suggests that while automation enhances accessibility, professional oversight remains essential for deeper emotional processing. These findings collectively demonstrate the potential of XR-DMT to bridge the gap between traditional therapeutic practices and digital innovation while maintaining scientific and ethical integrity.

5. Conclusion

This study demonstrates that XR-based Dance Movement Therapy (XR-DMT) can serve as a structured, accessible, and effective intervention for anxiety prevention. By incorporating real-time biometric feedback and AI-driven movement adaptation, XR-DMT ensures that therapeutic sessions align with individual physiological responses, enhancing engagement and efficacy.

The study reinforces the distinct role of DMT in digital environments by differentiating structured therapeutic movement from general virtual dance interventions. Unlike recreational dance programs, XR-DMT adheres to psychotherapeutic principles, incorporating expressive movement, mirroring, and rhythmic engagement to support emotional well-being.

Table 1. Analytical summary of key discoveries in XR-Based Dance Movement Therapy (DMT) and their implications.

Aspect	Key Discovery	Implications for DMT
Dynamic Biometric Feedback Integration	Real-time biometric monitoring (HRV, skin conductance) personalises therapy within XR-DMT sessions, moving beyond static interventions.	Facilitates personalised, interactive therapy, shifting DMT from static to dynamic intervention models.
Hybrid Therapy Models	Integration of DMT into XR settings allows hybrid therapeutic models, combining immersive environments with structured movement therapy.	Expands the applicability of DMT, allowing remote, immersive therapy that aligns with traditional movement-based interventions.
Interdisciplinary Methodology	Cross-disciplinary synthesis of psychology, machine learning, and XR ensures scientifically rigorous interventions aligned with DMT principles.	Provides a framework for integrating computational models with established psychotherapeutic movement practices.
Comparative Insights Across Therapy Modalities	Comparison with alternative dance-based therapies (e.g. Zumba) highlights the superior engagement and effectiveness of XR-DMT.	Reinforces the distinction between structured DMT and general dance interventions in digital health research.
Ethical and Regulatory Frameworks	Adherence to GDPR and ethical frameworks ensures responsible biometric data usage and participant safety in XR therapeutic environments.	Ensures that digital DMT implementations adhere to high ethical standards, securing participant trust and regulatory compliance.
Scalability and Accessibility	XR-DMT extends access to therapy by removing geographical barriers, allowing participation from underserved populations.	Scalability supports mental health interventions for populations with limited access to traditional DMT sessions.
New Methodologies for Data Integrity	Robust data collection methods mitigate confounding factors, ensuring reliability and validity in digital DMT research.	Validates the methodological robustness of XR-DMT, ensuring its scientific credibility in digital therapy settings.
Structured Therapeutic Framework	Maintains core DMT methodologies (e.g. guided improvisation, mirroring, embodied cognition) within XR settings.	Preserves the psychotherapeutic essence of DMT within digital applications, preventing dilution into recreational movement.
Real-Time Biometric Adaptation	Physiological data enables adaptive interventions, ensuring that movement sequences align with real-time stress responses.	Enhances therapeutic precision, tailoring DMT sessions to individual physiological needs rather than generic movement sequences.
Therapeutic Engagement vs. Fitness-Oriented Dance	XR-DMT sessions show greater anxiety reduction compared to recreational virtual dance due to structured therapeutic movement.	Demonstrates the importance of structured therapeutic intent in movement-based digital interventions.
Therapist vs. AI-Driven Adaptation	Therapist-led XR-DMT enhances emotional processing, though AI-driven models improve accessibility and scalability.	Supports a hybrid model where AI enhances access while therapists remain essential for deep emotional engagement.

Future research should explore long-term efficacy, therapist-led versus AI-assisted XR-DMT interventions, and the integration of additional physiological biomarkers such as brainwave activity to further refine personalisation. Additionally, studies should investigate how XR-DMT can be integrated into clinical mental health care settings to provide complementary therapeutic options.

5.1. Limitations and further research

Despite the promising results, several limitations warrant further exploration. The dependency on high-performance computational resources and edge computing for real-time data processing presents a challenge for large-scale deployment. Additionally, the reliance on locally stored biometric data, while enhancing privacy, restricts the possibility of real-time cross-user adaptation and continuous learning from broader datasets.

Addressing these constraints will require advancements in hardware efficiency, computational optimisation, and federated learning techniques for decentralized AI training.

Future research should explore:

• The long-term efficacy of XR-based DMT interventions through extended follow-up studies.

• The impact of various XR modalities (e.g. Virtual Reality, Augmented Reality, and Mixed Reality) on different mental health conditions.

• The integration of additional physiological and neurological biomarkers, such as electroencephalography (EEG), to refine personalisation algorithms.

• The development of scalable and cost-effective XR solutions to ensure accessibility across diverse socio-economic groups.

Notes

1. https://clinicaltrials.gov.
2. https://fairbydesign.com/.
3. http://stato-ontology.org/.
4. https://www.cos.io/initiatives/prereg.

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Disclosure statement

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Petar Radanliev is a Member of Faculty in Artificial Intelligence and Cybersecurity at the University of Oxford's Department of Computer Science. Dr. Radanliev completed his PhD in 2013/14 and has since engaged in postdoctoral research at several prestigious institutions, including Imperial College London, the University of Cambridge, the Massachusetts Institute of Technology, and the Department of Engineering Science at the University of Oxford for 7 years, before moving to the Department of Computer Science. Dr. Radanliev specialises in artificial intelligence, cybersecurity, quantum security, and blockchain security.

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Authors' contributions

Dr Petar Radanliev – sole author, was responsible for all aspects of the manuscript.

Availability of supporting data/availability of data and materials

All data and materials are included in the article.

Ethical approval

The Central University Research Ethics Committee (CUREC), the University of Oxford, has granted ethical approval under reference R51864/002. All participants gave written informed consent. Participants with a 'lived experience' have been involved and all participants gave written informed consent.

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