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Visualizing Multimodal UX and Human Motion data in 3D scenes

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Abstract. Understanding user experience (UX) in immersive and interactive media increasingly involves rich embodied interactions, where human motion, encompassing both human position and human body kinematics, evolves alongside multimodal UX data streams over space and time. While visualization techniques play a central role in supporting the analysis of such data, existing approaches typically scatter these individual dimensions across detached views, failing to examine how physiological and experiential signals relate directly to their embodied context. Immersive analytics opens perspectives by allowing dimensions to be displayed in context directly within the 3D environment in which the experience takes place. In this paper, we address how the combined visualization of human motion and multimodal UX data streams in 3D scenes contribute to immersive analytics. We structure our investigation around three core elements: data synchronization, body-linked immersive representation, and analytical perspectives. Specifically, we present an approach that synchronizes body kinematics within a 3D scene while establishing a direct data-to-body mapping that binds physiological and contextual UX signals directly onto moving 3D skeleton. To support discovery of complex behavioral patterns, we combine complementary analytical perspectives, including exocentric viewpoints for spatial overviews, egocentric viewpoints for situated inspection, and abstract temporal views for focused trend analysis. We demonstrate the analytical potential of our approach through a systematic heuristic walkthrough and task-oriented scenarios based on an existing human motion dataset. By bridging the spatial-physiological correlation gap, this work contributes an exploratory framework for investigating the dimensions of immersive systems and informs future research on visualization designs for examining embodied interaction in XR.

Keywords: Human-Centered Computing, Immersive Visualization, Visual Analytics, Human Computer Interaction, Interaction Paradigms, Virtual Reality

1 Introduction

Human motion can be understood either as the position of a user within an environment, or as their detailed full-body kinematic data. While tracking position is often sufficient to analyze navigation patterns, observing the full-body kinematics (i.e., the spatial configuration, joint angles, and transformations of the skeletal system) provides a much richer understanding of physical embodiment. Our work addresses both dimensions of human motion, with a notable focus on full-body kinematics, an area that remains significantly less explored in immersive analytics. Analyzing this kinematic layer alongside user-related signals (UX data, such as physiological responses) contributes to a deeper understanding of user experience across domains such as psychology [Yu *et al.*, 2024], human–computer interaction (HCI) [Xu, 2024], and rehabilitation [Wei *et al.*, 2023]. In extended reality (XR) experiences, where interaction, perception, and environment are interwoven, the user experience is directly related to multiple dimensions: the kinematic data, UX data, contextual data (interactions, tasks, events occurring during the experience), and scene data (describing the 3D space and its state). These dimensions evolve over space and time and, considered together, open new perspectives for characterizing user experience in XR [Robert *et al.*, 2023; Javerliat *et al.*, 2024].

In this work, we focus on the analysis of human full-body kinematic data coupled with UX data. Analyses of UX data often begin with the inspection of temporal variations, providing initial insight into changes in user experience. Prior work has coupled such signals with contextual information, for example by aligning task phases or events along temporal representations to clarify how user responses relate to what is occurring during an activity [Robert *et al.*, 2024; Lee *et al.*, 2015], enabling richer interpretation. However, many human activities are inherently spatial and embodied, involving body movement and interaction within three-dimensional environments. Building on these earlier analytic steps, this work explores how immersive visualization can extend existing analytic practices by situating user-related signals within kinematic data and scene context, enabling analysts to examine behavior as it evolves over space and time.

Beyond methodological considerations, this work is motivated by the needs of users who analyze behavior and user experiences in situated and embodied contexts. Such analyzes arise across multiple domains, including ergonomics, training, rehabilitation, and clinical assessment, where understanding how individuals react and interact within an environment is central to interpreting user experience [Pervin and Lewis, 1978]. Prior work has shown that immersive visualization can effectively replicate 3D conditions allowing to assess reach ability and scale from a 1:1 perspective, enabling analysts such as ergonomists to study space occupation and workload without being constrained to on-site observation [Aupetit *et al*., 2023]. Similarly, review of embodied activity in virtual environments has been shown to support reflection and interpretation in training, rehabilitation, and clinical contexts, where replaying motion and associated signals can reveal atypical patterns and their possible underlying causes [Guths *et al*., 2025]. These use cases motivate the exploration of immersive visualization approaches that support flexible replay, filtering, and multi-perspective analysis of multidimensional data such as the motion, user-related signals, and the context.

In this paper, we explore the potential of an immersive visualization approach, integrating not only human position, but also kinematics, UX, and contextual data directly in the 3D scene. By situating multidimensional data directly within the spatial and temporal context of the activity, users can reconstruct the full-body kinematic of the studied individuals to observe their interactions with the environment, postures, and UX data over space and time. This aim to address a research gap in traditional 2D visualization tools, where flat charts or decoupled videos isolate spatial, temporal, and physiological signals, preventing a situated understanding of embodied user experiences. Our approach, exemplified in Figure 1 enables embodied interactions to be studied in relation to UX data and contextual information through filters and flexible interaction that supports switching between immersive exocentric views (observing the individual's movements from afar), egocentric views (from the individual's own perspective), and summarized representations of the data (graph generation, space-time path (STP)), which supports a multi-perspective exploration of the data.

To guide this investigation, we address a central Research Question:

- **RQ:** How can we leverage immersive visual analytics to support the co-located exploration of human motion and multimodal UX data streams in 3D environments?

To answer this question, we structure our exploration around three elements:

- **Data Synchronization:** Aligning kinematic body tracking with UX and contextual data.
- **Immersive Representation:** Designing body-linked visual encodings (e.g., joint-color mapping) to display multimodal metrics directly onto moving 3D skeleton.
- **Analytical Perspectives:** Assessing the combinations of viewpoints to help analysts discover complex behavioral patterns.

In particular, our contribution is twofold:

- **Design and implementation of a multi-perspective immersive visualization approach,** that integrates full-body kinematic, UX signals, and contextual data, enabling users to explore embodied activity in space and time through different perspectives within immersive environments.
- **Insights from applying the approach to a large, real-world dataset** of individual movements and human motion in a virtual environment that inform future research in immersive analytics for understanding human activities and behaviors.

The remainder of this paper is organized as follows. Section 2 establishes the fundamentals of embodied UX analytics, defining our taxonomy of human motion, human position, and body kinematics alongside multimodal UX signals. Section 3 presents previous works on the spatio-temporal visualization of human motion and multivariate UX data. Section 4 presents the design rationale and cognitive principles that guided our visual representation choices. Section 5 details the technical approach, data synchronization, and visualization capabilities. Section 6 illustrates its practical application through representative task-driven scenarios, and Section 7 presents our heuristic walkthrough. Section 8 discusses the analytical implications of our approach, its limitations, and future work. Finally, Section 9 concludes the paper by highlighting future directions for the immersive analysis of multidimensional human activity.

2 Fundamentals

To investigate information visualization opportunities within immersive analytics, it is important to establish a vocabulary of human motion and its intersection with user experience (UX). Prior literature in spatial visualization frequently uses terms like motion data or behavior tracking, which can obscure the differences between tracking a user's location versus tracking their kinematics. Under this work, human motion serves as the concept that encompasses both human position (where the user is) and human body kinematics (how the user is moving). In this framework, we explicitly categorize and separate these multi-modal behavioral data streams into three distinct layers based on their data granularity and utility:

1. **Human Position (Spatial Trajectory):** This represents the base level of spatial tracking, recording the user's coordinate inside a three-dimensional reference space over time. While spatial position data is effective for mapping navigation trends, it treats the human body as a point. It reveals where an individual traveled.
2. **Human Body Kinematics (Full-Body Posture):** This layer forms the core focus of our work. It involves the observation of joint angles, bone positions, and physical orientations of the user's skeletal system (e.g., via 3D joint-based skeletons). Body kinematics reveal how an activity physically happened, making visible postures and reach issues.
3. **Multi-Modal UX and Contextual Signals:** This layer captures concurrent non-spatial records that explain the internal state of the user and the environment. It includes physiological indicators of internal experience (e.g., heart rate, electrodermal activity) alongside environmental state (e.g., interactive events, object collisions). This layer provides the data required to interpret

Figure 1. Overview of the 3D visualization. (A) Observe and explore the motion and physiological data in-situ. (B) Use space-time path visualization to explore the variation of multiple attributes. (C) Use 2D visualization to perform quantitative analysis.

why an observed movement behavior happened.

2.1 Information Silo vs. Spatial Contiguity

Across analytical domains, multi-modal behavioral streams are almost exclusively explored through isolated, decoupled methods that create information silos. While human motion is inherently three-dimensional, traditional analysis routinely splits this data into fragments: biomechanics commonly employs detached stick figures or path lines to depict human body kinematics [Choi *et al.*, 2012], psychophysiology relies on independent 2D time-series plots to analyze physiological measures like HR and EDA [Cowley and Torniainen, 2016; Gkikas *et al.*, 2025], and HCI frequently isolates contextual interaction events through linear timelines [Schmidt *et al.*, 2012]. While these decentralized approaches support the isolated analysis of individual metrics, they disconnect abstract UX signals from the spatial representation of movement. Consequently, it becomes challenging for an analyst to interpret internal states within the embodied context in which the interaction occurred.

This traditional workflow directly violates the *Spatial Contiguity Principle* [Mayer and Fiorella, 2014; Schroeder and Cenkci, 2018], which establishes that humans process information more effectively when related visual channels are physically integrated close together rather than separated across different windows. Forcing an analyst to mentally align a physiological spike from a detached 2D graph with a specific bodily adjustment imposes an unnecessary cognitive load.

By defining human body kinematics as our central visual anchor, our framework directly resolves this information silo through spatial contiguity. Instead of rendering independent scattered charts, we encode UX data directly onto the limbs and joints of the replayed 3D skeleton (e.g., mapping EDA intensity to joint color variations). This design preserves the direct spatial relationship between physical posture, internal physiological reactions, and the specific environmental event that triggered them, satisfying the requirements for complex embodied analysis that cannot be realized by trajectory paths or flat 2D charts alone.

3 Related work

The analysis of human motion and UX data together in-context remains a challenge [Zhang *et al.*, 2023], particularly when aiming to support visualization, navigation and interaction with the data to capture spatio-temporal dynamics and their relation with contextual data. In this section, we first review methods for visualizing human motion, then turn to immersive visual analytic tools designed for behavior analysis.

3.1 2D-based Human Motion Representation

Non-immersive visualization techniques typically represent motion compactly to support large-scale analysis. Hu *et al.* [2010] proposed a static "motion track" visualization approach to represent variations in human motion data in a 2D reference space. Their method transforms time-based animation sequences into sequential curves within a 2D space, making subtle variations perceptible and enabling the analysis of large-scale motion datasets. The approach emphasizes spatio-temporal trajectories (i.e., users' positions over space and time), represented as sequences of line segments connecting 3D points. Body movement is encoded at different timestamps through 2D body poses defined by joints and limbs. Similarly, Arpatzoglou *et al.* [2021] designed an interactive visual analytics tool for dance movement analysis that integrates 2D representation of human motion through a temporal sequence of skeleton poses. They further combine this tool with 2D charts that support comparison of dance moves and poses through qualitative and quantitative metrics such as angle and velocity similarity.

3.2 3D-based Human Motion Representation

Initial research in this area focused on developing spatial abstractions to visualize the volumetric properties of motion within both desktop and immersive settings. Oshita [2019] proposed a 3D visualization for exploring the volume of gestural trajectories through interactive "motion volumes", which comprise (i) representative key poses selected at specific key timings, (ii) geometric volumetric shapes representing each body part, encompassing the time-varying spatial trajectories from all input motions, and (iii) geometrical shapes (i.e., convex hulls) to represent the orientations of a body part at different timestamps.

To enrich the analysis and understanding of user experiences in XR, previous research has advocated integrating human body kinematics into visualizations [Kloiber *et al.*, 2020; Zhang *et al.*, 2026]. However, representing the 3D human body alongside position trajectories and UX data across space and time remains particularly challenging. Relying on a single visualization technique is impractical, as the multiple data dimensions and volume can lead to cognitive overload and visual clutter [Munzner, 2025]. Combining complementary visualization techniques has therefore emerged as a promising approach. For example, the Space-time Cube (STC, [Hägerstrand, 1970]) represents individual trajectories over space and time by encoding 2D spatial information on the cube's base and time along its height. When combined with 2D visualizations, STC has been shown to support analysis effectively and is often preferred by users because it provides multiple perspectives on the data [Kveladze *et al*., 2015; Gonçalves *et al*., 2016]. Another similar approach is the space-time path (STP), which allows us to represent individuals' trajectories over time, depicting the three spatial dimensions (latitude, longitude, altitude) [Büschel *et al*., 2021; Luo *et al*., 2023; Lammert *et al*., 2024]. However, the STP is limited as it does not support time integration; additional visualization techniques are necessary.

Early efforts in body kinematics visualization [Alallah *et al*., 2022; Browen *et al*., 2024] demonstrate the potential of combining motion with UX data, enabling the exploration of these attributes to discover their links across spatial and temporal dimensions. Recent tools such as HybridAxes [Seraji *et al*., 2024] also highlight the value of connecting immersive environments with analytic workflows, enabling flexible switching between embodied and abstract perspectives. Immersive visual analytics approaches have been recently proposed in an attempt to bridge analysis and embodied context, providing views of both the human kinematics and UX data at the same time (Reipschläger *et al*. [2022], Jansen *et al*. [2023]). With a specific focus on gesture-level motion, GestureExplorer (Li *et al*. [2023]) supports the exploration of large sets of 3D temporal gesture data, through a combination of joint-based skeleton, trajectory representations of body part movements, and clustered gesture abstractions.

Several systems leverage Augmented Reality (AR) to overlay behavior information directly onto the physical environment where the movements occurred. For example, SVATA [Ren *et al*., 2026] tracks eye movement and spatial position to analyze the mechanisms of embodied cognition in reconstructed spaces. AvatAR [Reipschläger *et al*., 2022] utilizes an AR headset to display 3D avatars reconstructed from tracking sessions, allowing analysts to isolate specific limbs or view gaze trails. Similarly, SSCA [Alallah *et al*., 2022] projects spatio-temporal trajectories in 3D environments, supporting proxemic interactions and path filtering. While these tools demonstrate the advantages of situated review, they focus mainly on representing spatial trajectories rather than visualizing full-body kinematics alongside multi-modal UX data.

3.3 Multimodal Human Motion Representation

Beyond pure spatial mapping, recent frameworks have transitioned into Virtual Reality (VR) environments to explore multi-modal data integration and comparative analysis. AutoVis [Jansen *et al*., 2023] introduces a mixed-immersive setting to analyze user and vehicle interactions during driving scenarios. In creative and analytical domains, the MoViAn system [Browen *et al*., 2024] incorporates interactive annotations, colored trails, and flexible timeline controls to examine 3D gaze, hand positioning, and environmental interactions. To facilitate cross-session comparison, Kloiber et al. [Kloiber *et al*., 2020] utilize specialized trajectory markers and terminal filtering to map individual paths across multiple immersive sessions. Similarly, recent attempts to integrate Large Language Models (LLMs) into XR analytics [Kim *et al*., 2025] focus primarily on text-based session interpretation and data organization rather than the direct spatial visualization of human movement. However, these systems often restrict their analytical scope to abstract spatial tracks and isolated UX metrics. They leave data fragmented across the information silos outlined in Section 2, presenting a clear opportunity for frameworks that concurrently unify full-body kinematics with rich physiological indicators.

In summary, while existing immersive approaches demonstrate clear values of embodied motion exploration, they rarely aim for a scope that allows the holistic analysis of user experiences. As shown in Table 1, most previous works focuses on isolated trajectories or narrow UX metrics, frequently overlooking the integration of multivariate data within the immersive context. This creates an information silo, making it difficult to understand motion and physiology over space and time. Pioneering immersive analytics platforms such as AvatAR [Reipschläger *et al*., 2022], ReLive [Hubenschmid *et al*., 2022], and Kloiber et al. [Kloiber *et al*., 2020] have successfully demonstrated the value of 3D spatial tracking; however, as structured in Table 1, they rely on decoupled data streams and remain strictly focused on trajectories (e.g., spatial paths) or single isolated metrics (e.g., gaze or positional data) without body-linked encoding. Our framework addresses a fundamentally different analytical paradigm: the concurrent, visual mapping of continuous, highly volatile physiological signals (such as synchronized electrodermal activity) directly encoded onto a fully articulated 3D joint-based skeleton models. By unifying multi-modal UX data streams directly with fine-grained postural kinematics, our approach enables analysts to intuitively correlate internal physiological reactions with physical bodily posturing. This allows researchers to discover rich, synchronized spatio-temporal UX relationships that remain entirely obscured when using trajectory-only or decoupled 2D visualization setups.

4 Design rationale

To understand immersive experiences including motion behavior, we identify the following analytical goals:

1. **Detecting behavior anomalies.** This involves understanding how an individual's kinematic data varies and whether corresponding UX data such as physiological data, reveal unusual or noteworthy behavioral patterns.
2. **Relating context, interactions, and human behavior.** This requires situating kinematic data and user-related signals within the temporal and spatial context of an activity.
3. **Comparing human behavior.** This involves aligning kinematic data, trajectories, and user-related signals across individuals within a shared environmental frame.

Table 1. Comparison of immersive visualization approaches (Acronyms: STP: Space-Time Path; STC: Space-Time Cube; EDA: Electrodermal Activity; HR: Heart Rate). Unlike existing approaches where multi-modal UX attributes are scattered across detached 2D panels or separate views, our approach displays all attributes in context by directly binding physiological signals to the joints of an articulated 3D skeleton (Data-to-Body Mapping).

Reference	**Human Position**	**Human Body Kinematics**	**Multi-Modal UX Data**	**Distributed View of UX data**	**Data-to-Body Mapping**
Our approach	STP, Animation Time filtering	Joint-based skeleton models	Gaze, Physio. (EDA, HR), Context	**Displayed in Context**	**Dynamic (Direct joint-color mapping)**
Reipschläger *et al*. [2022]	STP, Animation	3D meshes	Gaze, Context	Scattered	None (Uncoupled environment overlays)
Jansen *et al*. [2023]	STP, Animation	Volumetric models	Gaze, Context	Scattered	None (Static path color-coding only)
Alallah *et al*. [2022]	STP, STC	None	Context	Scattered	None
Browen *et al*. [2024]	STP Temporal Tags	None	Context	Scattered	None
Kloiber *et al*. [2020]	STP, Animation	None	Context	Scattered	None
Hubenschmid *et al*. [2022]	STP, Animation	None	Gaze, Voice Context	Scattered	None

To ground the design rationale of our explored approach, we first articulate six analytical tasks that support users in reaching the aforementioned analytical goals, and that should be then supported by our approach. These analytical tasks cover intents observed across the presented analytical scenarios in Section 6 and reflect increasing levels of complexity following Shneiderman's Mantra [Shneiderman, 2003], from a broad signal-level inspection to a situated and comparative analysis.

The analytical tasks in Table 2 guide our visualization and interaction design. In particular, supporting tasks beyond signal-level analysis requires progressively richer representations of space and embodiment:

- **Task 1** focuses exclusively on the temporal dimension of a single signal, requiring only UX Data (**X**). At this stage, the analyst is looking for what happened and when, which can be achieved through a standard 2D visualization techniques, such as line graphs or histograms.
- **Task 2** introduces the contextual why by relating signal changes to scene events. This only strictly requires UX Data (X). An analyst can match a heart rate spike to a text-based event log without a 3D scene. However, including the Scene context is Recommended (O): omitting it force the analyst to guess the physical layout and structural triggers behind a participant's physiological spike.
- **Task 3** maps the spatial distribution of UX data, which requires both UX Data (X) and Spatial Position (X). The Scene context is Recommended (O) to ground this distribution. Without the 3D scene, spatial data points are rendered in a void, limiting the analyst's ability to identify points of interest and correlate physiological arousal with layout.
- **Task 4** shifts the focus to movement patterns. Analyzing a trajectory relative to the scene requires both the Scene (X) and Spatial Position (X) to understand if a user was navigating around an obstacle or hovering near an object.
- **Task 5** transitions to embodied analysis, requiring both UX Data (X) and joint-level Kinematic Data (X) to distinguish subtle behaviors (e.g., standing still versus looking around anxiously). While the analysis is technically possible with just these two streams, mapping the data recommends adding the Scene (O), Spatial Position (O), and Body Encoding (O). Omitting these attributes degrades the analytical workflow: it collapses the visual back to decoupled information silos, forcing users to look between a separate 2D chart and a 3D skeleton, introducing high cognitive load. Body encoding (e.g., color-mapping stress directly onto the 3D skeleton) allows the user to immediately perceive correlations, linking motion, signal, and context in a single gaze.
- **Task 6** is the most demanding task, requiring the concurrent correlation of Kinematic Data (X), UX Data (X), Spatial Position (X), and the Scene (X) to interpret behavior from an egocentric perspective. Here, the body acts as the coordinate anchor, while the head orientation shows the attention. Real-time Body Encoding (e.g., color-mapping physiological spikes directly onto the limbs of the first-person avatar) is Recommended (O). Omitting body encoding means the view loses its multi-modal contextual overlay, reducing the integrated behavioral replay into a spatial recording.

In our approach, we aim to understand user experience from the synthesis of three core dimensions: motion, user-related signals, and contextual information. While motion provides the structural backbone, ranging from spatial trajectories to full articulated body movements, user-related signals and contextual information provide the necessary layers to interpret the "why" behind an action. Integrating these signals reveals states not observable from movement alone, while environmental context situates this data within the specific conditions the individual experienced. Effectively supporting these interdependent dimensions requires a coordinated design strategy; therefore, the following subsections detail our approach through three key aspects: (1) representations of motion and embodiment, (2) thematic encoding of user-related and contextual attributes, and (3) representations of time. For each, we review existing alternatives and justify our design choices in relation to the analytical tasks established above.

Table 2. Task analytics and corresponding data requirements across physiological signals, scene context, and kinematic data representations. UX data refers to signals related to the user experience (e.g., heart rate, skin conductance). Scene data corresponds to the environmental context. Position represents the user's spatial location as a single point within the scene. Kinematic data refers to articulated body motion data. Body encoding denotes the visual encoding of UX-related signals onto scene or body elements (e.g., color mapping). **X** = Needed; **O** = Recommended.

Analytical Task	UX Data	Scene	Spatial Position	Kinematic Data	Body Encoding
1. Analyze temporal variations in UX.	X				
2. Relate UX changes to events in the scene.	X	O			
3. Explore the spatial distribution of UX.	X	O	X		
4. Detect patterns of individual trajectories relative to the scene.		X	X		
5. Explore correlations between body kinematics and UX over time.	X	O	O	X	O
6. Correlate first-person body kinematics and UX data with contextual data to interpret behavior.	X	X	X	X	O

4.1 Human Body Kinematics Representation

To support analytical tasks ranging from spatial distribution (Task 3) to the correlation of embodied behavior with environmental triggers (Task 6), a representation must balance anatomical clarity with the ability to support multivariate data overlays. The human body can be represented at varying levels of abstraction, depending on the analytical goals. Four main strategies are commonly found in the literature to represent a body moving over time: abstract representations, 3D meshes, voxel or volumetric models, and joint-based skeleton models.

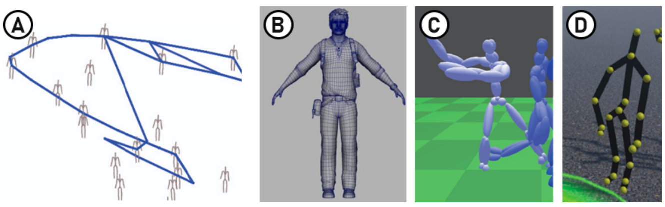

Figure 2. Overview of different kinematic body representation. A) Abstract representation Hu *et al.* [2010], B) 3D mesh Malta de La Plata [2013], C) Volumetric model Oshita [2019], and D) Joint-based skeleton model Li *et al.* [2023].

3D Mesh Representations: represents the body as a continuous surface, which improves the realism. This representation is used in film and biomedical contexts [Malta de La Plata, 2013; Palmas *et al.*, 2014] (Figure 2 B). These meshes can reveal detailed anatomy (skin, muscle, bone), but this high visual complexity can obscure movement patterns when the analytical focus is on body movement. Simplified meshes such as avatars are effective for posture and interaction studies [Reipschläger *et al.*, 2022].

As our analytical goals focus on body parts' position and movement rather than surface, this technique is not appropriate. We also aim to maintain a level of abstraction that supports the integration of multiple user-related signals (e.g., physiological or contextual data) through overlays, resize, and recolor encoding, which would be less effective on visually detailed meshes.

Voxel-Based & Volumetric Models: represent the body through volume derived from depth sensors, such as voxel grids or point clouds. Mikić *et al.* [2003] used voxels to automatically track and acquire kinematics data. Shen *et al.* [2023] demonstrated gait recognition using LiDAR point clouds. Oshita [2019] condensed body motion into compact volumetric manifolds, showing its potential for movement analysis, see Figure 2 C. These models are particularly successful at capturing fine-grained spatial detail of the body without skeleton fitting.

Volumetric reconstructions can capture fine spatial detail; however, they quickly become cluttered when multiple individuals are present, leading to significant performance loss as the rendering of high-density point clouds increases computational overhead. Interpreting these models often requires heavy post-processing to extract meaningful patterns from the raw data, which can hinder real-time behavioral analysis.

Joint-Based Skeleton Models: represent body kinematics as a set of connected joints, encoding the different body parts (e.g., pelvis, limbs, head, etc.). This structure is widely used in motion capture (MoCap) systems due to its efficiency and interpretability [Rokoko, 2020]. In the animation domain, skeletons ensure realistic movement through articulated pivots [Brusi, 2021]. In artificial intelligence, skeleton models are preferred for motion prediction and recognition tasks because of the reduced complexity while retaining essential movement patterns [Corona *et al.*, 2020]. Visualization systems such as GestureExplorer [Li *et al.*, 2023] rely on skeletons to simplify gesture-level analysis (Figure 2 D).

We adopt joint-based skeletons as our core representation to support the comparative and correlation-based goals of our analytical framework (Tasks 5 and 6). Unlike volumetric or mesh models, skeletons provide a clear view of the relational positioning of body parts without the visual "noise" of surface data. Most importantly, this abstraction provides discrete visual regions for encoding user-related data (e.g., mapping EDA intensity to joint color or scale). By avoiding the occlusion inherent in realistic surfaces, skeletons allow for salient data encoding while preserving high fidelity in motion behavior.

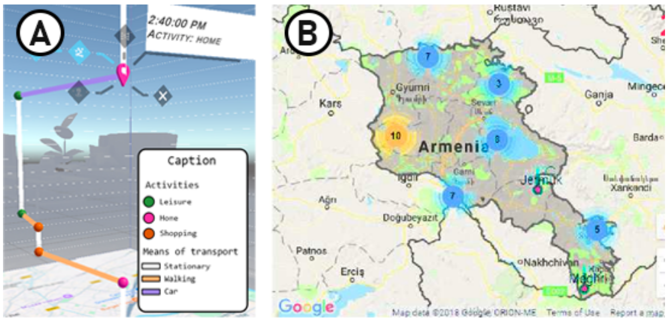

Figure 3. Overview of user-related data and the related contextual information. A) Body-linked attributes Quere *et al.* [2025], and B) Environment-linked attributes Astsatryan *et al.* [2018].

4.2 Multi-Modal UX Representation

Body-linked attributes: (e.g., stress level, heart rate) are often mapped onto motion data to provide behavioral insights [Wijntjes *et al.*, 2021]. While color is a common encoding for these attributes across various 3D visualizations, including space-time cubes and trajectory trails [Vrotsou *et al.*, 2010; Quere *et al.*, 2025] (Figure 3 A), the perceptual limits of color channels [Munzner, 2025] can restrict the number of attributes that can be interpreted without creating confusion.

Environment-linked attributes: describe contextual data such as a traffic light color or object interaction, encoded via icons, colored elements, markers, or annotated layers [Climavision, 2025; Astsatryan *et al.*, 2018; Contributors, 2025; League and Kennelly, 2019] (Figure 3 B). These approaches help contextualize user behavior; however, overloading a single view with multiple attributes risks occlusion and increased cognitive load.

In our approach, we address these limitations by integrating UX data through body encoding that exploit the skeleton's structural abstraction. To support Tasks 5 and 6, specific body joints can be recolored by physiological intensity or interaction status. Simultaneously, to support Task 6 without cluttering the primary view, the body's shadow is used as a ground-plane heatmap to reveal contextual information such as the state of traffic lights directly beneath the user's position. By constraining the visualization to a focused set of attributes per view, we leverage the effectiveness of color and spatial mapping while ensuring the analytical precision required for multi-perspective behavior analysis.

4.3 Human Position Representation

Common strategies to visualize time include **space-time paths**, **temporal animations**, and **juxtaposition**.

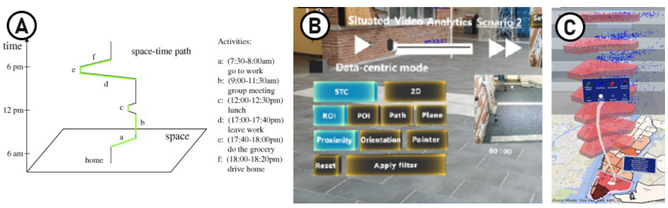

Figure 4. Overview of different time representation. A) Space-time Path Chen *et al.* [2011], B) Temporal Animation Alallah *et al.* [2022], and C) Juxtaposition Wagner *et al.* [2024].

Abstract Representations: summarize motion by compacting the body as a simplified key poses that can highlight a trajectory. Hu *et al.* [2010] for example divided motion data into representative poses for static visualization, see Figure 2 A. This is an effective method for illustrating the overall trajectory of a user or comparing simple movements across individuals. However, by condensing the motion into a set of discrete poses, these methods often lose the temporal flow and the verticality of posture transitions, limiting their usefulness for analyzing how an individual's height or reach changes relative to the environment during a specific action.

STP: highlight spatial information, often by displaying trajectories in a 3D cube [Vrotsou *et al.*, 2010; Chen *et al.*, 2011, 2018] (Figure 4 A). It is an effective approach to identify temporal patterns. However, trajectory occlusion can increase with dataset size, and interpreting it on 2D screens can be challenging [Poirel *et al.*, 2011].

Temporal Animation: presents the body dynamically, replaying actions over time [Gao, 2015; Alallah *et al.*, 2022; Hubenschmid *et al.*, 2022], see Figure 4 B. This is an intuitive representation that supports storytelling, but it limits comparison across time steps, as past information disappears over time.

Juxtaposition: displays time slices side by side for direct comparison [Wagner *et al.*, 2024] as shown in Figure 4 C. While this method preserves detail and serves as a great support for retrospective review, it can break the perception of continuous motion, requiring users to consciously integrate patterns across views. Furthermore, in a 3D context, juxtaposition would require duplicating the virtual representation of the 3D environment for each time slice, which is often unfeasible due to spatial constraints and the potential visual confusion.

In our approach, we combine STP and Temporal animation to balance abstraction and detail: STPs enable comparative analysis of trajectories (Tasks 3 and 4) without requiring playback, while animation supports immersive, body-level inspection of motion anomalies (Tasks 5 and 6). Juxtaposition was not adopted as our primary choice, as replicating multiple body instances and scene environments would overwhelm the visual field. Instead, we provide temporal animation and filtering such as time-window sliders and synchronized progress bars to facilitate temporal comparisons within a single context. By allowing users to move through time or isolate specific temporal segments, our approach supports comparative analysis (Task 6) without the overhead of scene duplication. Nevertheless, juxtaposition remains a meaningful direction for future work, as it could open possibilities of more systematic cross-comparisons of behavior across individuals by placing key poses side-by-side outside the 3D environment.

5 Our Approach

Our approach is instantiated through a Unity-based 3D/immersive visualization prototype using a Meta Quest 3 headset. It supports the exploratory analysis of multidimensional user-related data (UX) by enabling the integration and coordinated exploration of heterogeneous data streams within an immersive environment.

5.1 Data Description

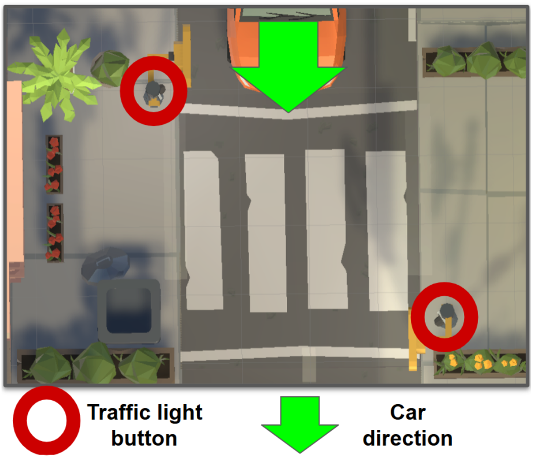

Figure 5. One of the 3D scene models used during the experience. Individuals have to press traffic light buttons to turn the traffic light green and cross safely the road.

To illustrate the application of our approach, we use the open CREATTIVE3D dataset [Wu *et al.*, 2025], which contains a wide variety of UX data relevant for our use case. The data collection and baseline experiment setup are outside the scope of this paper's contributions and are summarized briefly here to provide context for the visualization scenarios. All data used to demonstrate our visual analytics approach were collected anonymously during a prior, ethics-approved protocol providing an openly available dataset.[1]

The data was collected during a VR experiment with a total of 40 participants performing 24 road-crossing scenarios in 3D environments following the model shown in Figure 5. The environment layout was constructed using assets purchased under standard commercial licensing from the Unity Store. Each scenario was one to two minutes long, consisting of a list of interactive task to perform in a given order, such as: (1) Get the Box, (2) Interact with the Traffic Light Button, (3) Cross the road, (4) Place the box in the Trashcan, (5) Cross the road again. Participants had to walk in a 10 by 4 meters environment during the scenarios. In this paper, we use a subset of each dimension contained in this dataset to illustrate the possibilities of our approach:

- Human Position data: the position and the rotation of the participant in the VR space, captured with the position of the HTC Vive Eye Pro headset.
- Human Kinematics data: the position and rotation of 17 sensors on the body of the participant, captured using the XSens motion capture system.
- Multi-Modal UX data: the EDA and HR, captured using Shimmer GSR+ system.
- Contextual data: the interactive task to perform, the interaction of the participant with the environment, the state of the traffic light, and the position of cars.

5.2 Data Integration

The proposed approach supports the integration of multivariate datasets: kinematic data, contextual data (e.g., environmental states and task events), and user-related signals (e.g., EDA, HR, respiration rate, step speed) into a unified spatio temporal representation. Since these modalities are collected through diverse sensors with different sampling rates and formats, a synchronization step is required to align everything within a common timeline. In addition, space alignment can be necessary, as kinematic data and VR data are often captured using different coordinate systems, requiring a transformation into a shared spatial reference frame. All abstract overlays, spatial heatmaps, space-time ribbons, and data-encoding scripts were generated using custom scripts and base functionalities of Unity.

The data is provided under a BVH format, where all entries are already synchronized temporally at a frequency of 125Hz. However, the motion data and the spatial data use different spatial reference frames, which prevents the motion data from being directly overlaid in the virtual scene. To support coherent exploration, we applied a spatial alignment step. First, we aligned the origins by placing the origin of the motion body at the same position as the origin of the spatial data. Then, we adjusted the trajectory of the motion data to match the individuals's tracked trajectory in the 3D environment, ensuring that movements captured by the motion sensors corresponded precisely to the individual's navigation and interactions within the space of the virtual scene.

While the approach is illustrated using a specific dataset, the underlying design principles are applicable to other multivariate datasets combining kinematics, UX signals, and scene information. This enables the exploration of similar analytic questions across different experimental settings without assuming a fixed data collection protocol.

5.3 Visualization Approaches

We propose three exploration strategies based on the user's point of view, thus supporting a multi-perspective exploration of data. These are defined as follows:

- **Exocentric visualizations**: individuals' full-body kinematics is reconstructed and projected directly within the experimental scene where it happened. Users can visualize full-body kinematics over time to trace trajectories, study postures, and inspect motion behaviors such as hesitations or abrupt stops. The data can be filtered over time or over the contextual data (e.g., "current task") to display only kinematic data during a road crossing task. Shadows and body recoloring can be applied to highlight physiological data values over time, creating spatial heatmaps of stress as shown in Figure 8. This view provides a natural sense of scale and spatial relations, supporting the visual identification of potential behavioral anomalies, such as unsafe road crossings.
- **Egocentric visualizations**: The environment is rendered from the individual's perspective, by placing the camera of the user directly in the position and rotation of the selected individual's head. This allows users to see exactly what the individual perceived at key moments (e.g., the state of a traffic light or the approach of an oncoming car). Users can then view the animation of the scene temporally, to help them create links between

[1] `https://doi.org/10.5281/zenodo.8269108`

perceptual factors and changes in physiological data. By exploring from this perspective, users can better understand whether stress responses (e.g., EDA peaks) align with a defined environmental factor, and how perception may have influenced decision-making.

- **Summarization and abstract visualizations**: To complement the ego and exocentric explorations, data can be condensed into abstract representations such as time-series plots or individual-centered ribbon timelines. These views summarize the evolution of UX data (physiological responses) or contextual data (tasks, actions) over time. For example, ribbons can show when an individual pressed the traffic light button, waited, and crossed, with EDA and HR levels superimposed. Such visualizations support quantitative inspection and cross-individual comparison for patterns first identified in egocentric and exocentric exploration.

Taken together, these representations offer complementary entry points for exploratory analysis. While ego/exocentric perspectives allow an intuitive exploration of the data, grounded in the spatial and perceptual context of the individual, the summarized perspective support more abstract view, to perform quantitative follow-up. By moving fluidly between these views, users can progress from rich experiential understanding to a systematic analysis, ensuing the motion and physiological behavior of the individual can be captured more broadly.

5.4 Exploratory Interaction and Analytic Operations

We describe the interaction mechanisms that support exploratory analysis and iterative refinement of hypotheses across motion, user-related, and contextual data.

Selection and Filtering: Users can filter the data based on multiple criteria. They can filter by time by interacting with the time range bar in Figure 7 A to define the beginning and the ending of the data displayed in the environment. This time filter is applicable to exocentric view and summarized view (graph, abstract ribbon). The Figure 6 B highlights the application of a timer filter to only keep road-crossing portion of the data. For example, the user select only the time intervals corresponding to the moment the user is on the road, they can isolate the motion during the road-crossing task to enable investigations of behavior in that precise context. User can additionally filter the body parts displayed.

Highlighting and Summarizing: UX and contextual data can be encoded visually through recoloring or resizing the spheres composing the body parts. Through the attribute menu shown in Figure 7 D, the user can define if they want to recolor the sphere of the body, or the shadow of the body, by which UX data (i.e, EDA, HR), and in which color. The color encoding takes the normalized data value, where the higher the value, the darker the color, as shown in Figure 6 C: the body color was encoded following EDA value, we observe a darker color at the end of the crossing, meaning the individual's EDA did rise during the crossing task. For the case of current task, the color change every time the task name change. The shadow of the user can be recolored the

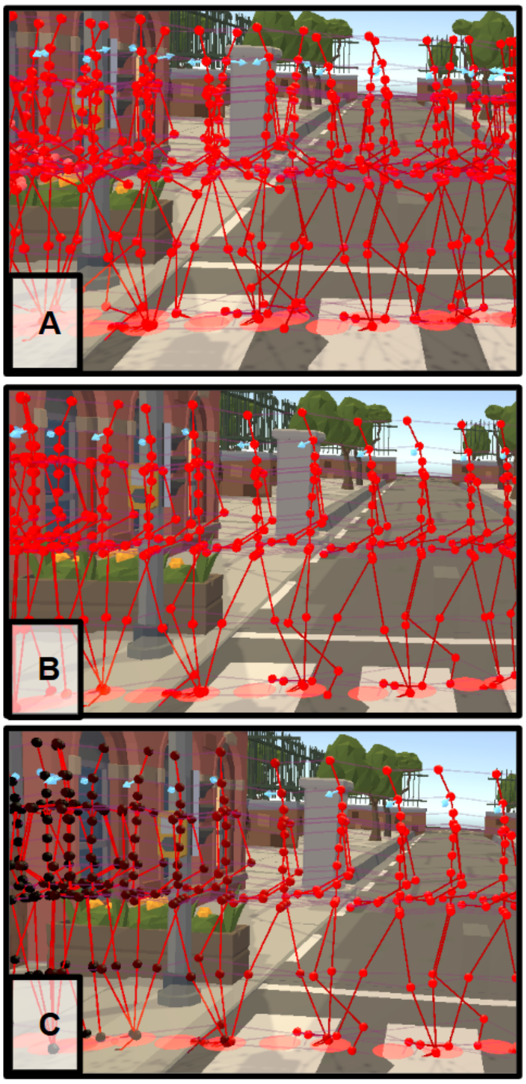

Figure 6. The kinematic data displayed in the virtual environment. Figure A shows the raw kinematic data, down sampled at three bodies displayed per second for visibility purpose. Figure B shows the data after a time filter, to only display the data at the end of the experience, when the individual cross from the right to the left. Figure C shows the data with a color encoding based on a UX data value, in this case the EDA: the darker the sphere, the higher the value.

same way to create a spatial heatmap of UX data as shown on the Figure 8. These visual encodings facilitate the recognition of spatial patterns, deviations from expected behavior, and correlations between motion and physiological data.

Temporal Animation and Navigation: Temporal animation of the experience can be viewed frame-by-frame. As shown in Figure 7 C, the user can select the automatic animation. User can pause at any moment, and select one timestamp to teleport at the individual position and head rotation, to enter in egocentric view. User can also modify the animation speed, or mark a precise timestamp for later in-depth analysis. The displayed frequency of the motion data can be adjusted, to define how many body instances are rendered per second, which helps maintain clarity when examining high-resolution datasets. This supports revisiting the experience as it unfolded, detect some unexpected body motion behavior, mark them, and perform more in-depth analysis afterward using summarized views. Users can additionally adjust the rendering frequency from the full sampling rate (125 body instances

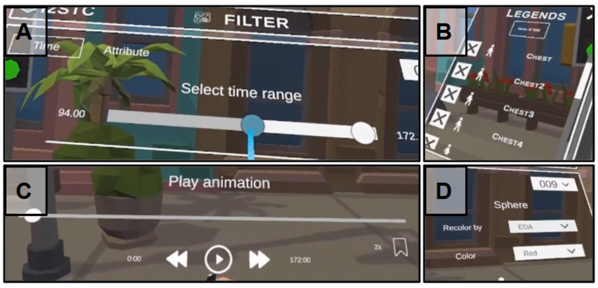

Figure 7. Our workflow enables: (A) The filtering of data on a specific time range, (B) The filtering of data for a specific body part, (C) The temporal animation frame by frame of the body motion data, and (D) The encoding of parameters (ux, context) through color and size.

per second) down to a single body instance per second, to reduce visual clutter linked to data quantity.

Generation of graph: Users can generate quantitative visualizations through line charts or bar charts based on selected temporal intervals and UX data. Users can choose one or multiple variables, such as HR or EDA, along with the corresponding timestamps, to create precise plots of physiological trends over time. The data displayed in the graph will exclude data filtered out (for example, outside the current time filter). The user noticing an individual getting honked at by a car can generate a line graph of EDA to identify peaks corresponding to moments of surprise in the environment.

Space-Time Path Visualization: STP in the form of ribbons allows simultaneous visualization of multiple individuals can be done for compact visualization that summarize UX and contextual variables over time. Each ribbon is divided into three horizontal bands, where users can assign a different parameter (e.g., traffic light color, HR, EDA, or timestamp) to each band. The value of each parameter is a color gradient, ranging from clear to dark color according to the parameter's normalized value. This allows users to quickly identify peaks in a given parameter, and the potential link with the other parameters. For example, a ribbon showing a traffic light (bottom band), HR (middle band), and EDA (top band) allows immediate recognition of stress responses coinciding with observed task-relevant events in the 3D scene, such as crossing during a red light.

Multi-individual visualization. Simultaneous visualization of multiple individuals within the same environment can be performed. Users can select a set of individuals, for which they display the data in the environment, and apply any filter or any visualization method presented previously for individual data individually. For example, by performing a recolor of all shadows based on a UX value, users can create intuitive spatial heatmaps that reveal group-level patterns or outliers.

6 Task-Oriented Analysis Scenarios

In this section, we present a series of illustrative analysis scenarios that demonstrate how progressively richer visual representations support increasingly complex reasoning about user experiences. The scenarios are organized to reflect a gradual transition from abstract, body-less visualizations toward fully embodied and situated analysis. Each scenario highlights the precise steps to go through in order to reach the intended visualization. Early scenarios rely on spatial and trajectory-based representations to explore UX data and navigation patterns. Subsequent scenarios introduce articulated body motion in the 3D context to relate internal data to task execution. Finally, the last scenarios combine embodied motion, contextual events and perspective shifts to support individual and group-level exploration of perception and behavior in context. Together, these scenarios illustrate how different visualization choices enable distinct analytical tasks, and how increasing representational richness supports deeper exploratory analysis.

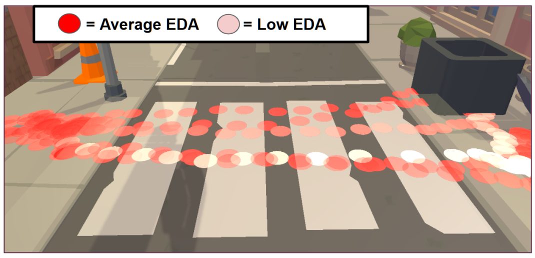

Figure 8. Aggregated spatial heatmap of normalized EDA for participants 009, 047 and 053 over one complete scenario. Shadows are recolored based on EDA (0 = light red, 1 = dark red). Elevated arousal appears mostly in anticipation before the road crossings.

Scenario 1: Spatial distribution of UX data

Motivation question (TA 1, 2, 3): How to relate the UX data variation with events in the scene and its spatial distribution?

Scenario description:

1. Select participants data to visualize.
2. Enable the Space-Time Heatmap view.
3. Use the Exocentric View to get a bird's-eye perspective of the tracking volume.
4. Recolor in red the heatmap by the Arousal (EDA) attribute to highlight areas where the user experienced high physiological stress.

As shown in Figure 8, this produces a spatial heatmap revealing areas of heightened physiological response. Elevated arousal consistently appears in waiting zones prior to road crossings, suggesting anticipatory effects related to the upcoming task. This scenario illustrates how spatialized UX data placed in the 3D environment support reasoning about environmental influences on behavior across multiple individuals.

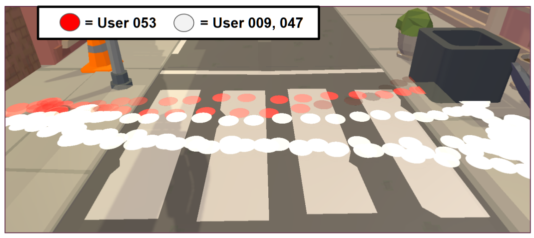

Figure 9. Trajectory comparison highlighting participant 053 (red) against participants 009 and 047 (white). Participant 053 exhibits a deviation by crossing without interacting with the traffic light button.

Scenario 2: Trajectory deviation

Motivation question (TA 3, 4): How to identify deviation in spatial distribution across multiple individuals relative to environmental context?

Scenario description:

1. Select a single participant's session from the scenario 1 heatmap visualization.
2. Recolor heatmap data of this participant in a different color.

In this scenario, shadows are recolored to contrast individual trajectories within the same environment. As shown in Figure 9, individual 053 exhibits a clear deviation from the expected navigation strategy followed by other individuals, which highlight the fact individual 053 crossed the road back without interacting with the traffic light, resulting in a potential unsafe crossing. This deviation becomes immediately visible through spatial trajectory comparison, illustrating how exocentric representations support the identification of atypical navigation behavior relative to contextual constraints.

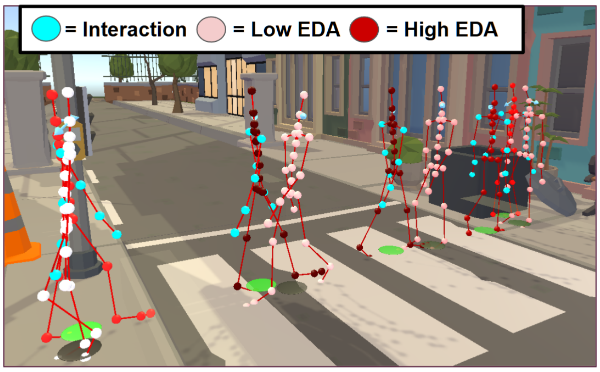

Figure 10. Visualization of participant 544 during two road crossings. The torso is recolored by normalized HR, arms are highlighted during object interaction, and shadows are recolored by timestamp.

Scenario 3: Human kinematics linked to interactions

Motivation question (TA 5): How do interactions influence UX data and body motion relative to environmental context?

Scenario description:

1. Display the full kinematic data for one participant.
2. Recolor the body in red by the EDA attribute to highlight where the user experienced stress.
3. Recolor body-part to highlight arms in blue when participants interact.

As shown in Figure 10, arm posture and EDA differ when the participant carries an object versus when no interaction is present. We observe a clear higher EDA during the crossing with interaction than during the crossing without interaction. Body-part filtering can be applied to reduce visual clutter, or to a body part encoded by a defined UX data.

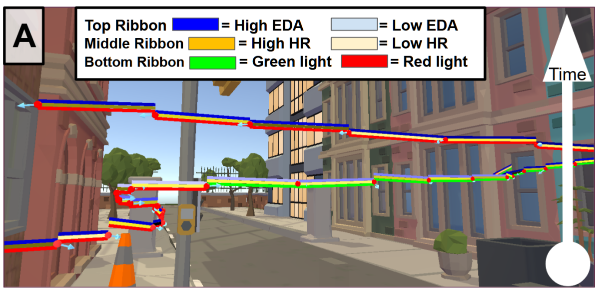

Figure 11. Space-time ribbon visualizations. Single-participant ribbon showing traffic light state, normalized HR, and normalized EDA over time.

Scenario 4: Alignment of contextual and UX data

Motivation question (TA 2, 3, 5): How do contextual conditions influence multiple UX data over space and time?

Scenario description:

1. Enable the Space-Time Ribbon view (Figure 11) to align different signals.
2. Map the Traffic Light State, Heart Rate (HR), and EDA onto the ribbon's layers.
3. Compare the physiological peaks with the color-coded state of the traffic signal.

This alignment reveals that the participant attempted to cross during a red light, resulting in a car honking. The ribbon clearly shows that the "honk" event immediately preceded the EDA and HR spikes. This scenario demonstrates how the ribbon summarizes complex causal relationships between environmental triggers and physiological responses.

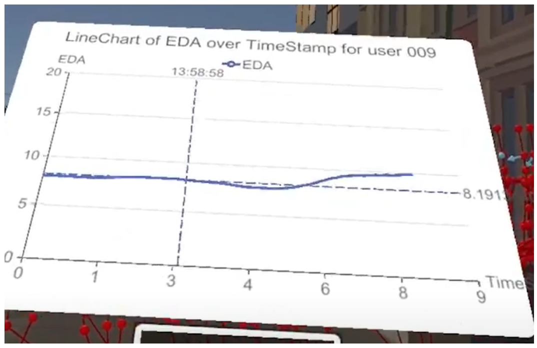

Figure 12. Time-series visualization of EDA corresponding to the temporal segment shown in Figure 13. Only data within the active time filter are displayed. The marker highlights the timestamp associated with the selected body instance.

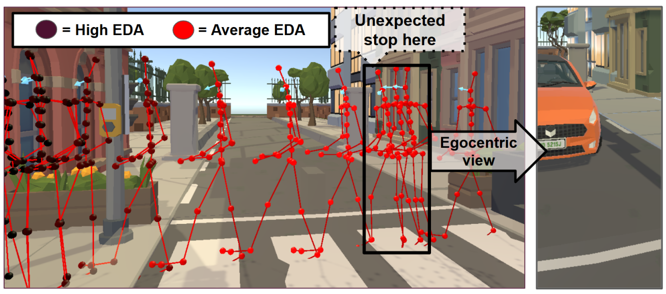

Figure 13. Visualization of the body movement of participant 009 during a road crossing task. The body is recolored based on normalized EDA (0 = light red, 1 = dark red). An unexpected stop occurs in the middle of the road, followed by an increase in EDA.

Scenario 5: Correlating kinematics and UX data

Motivation question (TA 5, 6): How do contextual conditions influence perception, posture, and UX data from an individual's perspective?

Scenario description:

1. Run an Exocentric Temporal Animation to observe movement flow and identify unexpected pauses.
2. Use Temporal Filtering to isolate the specific moment of the pause.
3. Generate a Signal Plot for the specific moment (Figure 12).
4. Switch to the Egocentric Perspective to replicate the user's field of view at the timestamp of the pause.

This multi-view approach reveals that participant 009 paused mid-crossing as a car approached (Figure 13), followed by a sharp increase in EDA (darkening of body segments). The egocentric view confirms that the user was looking at the car, allowing us to conclude that the surprise was linked to the car. This scenario demonstrates how embodied motion representations and egocentric view help discover and relate signal variation to specific events in space and time.

7 Analysis of Visualization Support

This section demonstrates the utility of the presented approach framework presented in Section 6 by illustrating how different visualization support distinct forms of reasoning about human behavior. Table 3 summarizes the scenarios and highlights how exocentric, egocentric, and summarized views contribute complementary analytic affordances. Taken together, these scenarios illustrate how visualization choices shape the types of insights that can be explored and uncovered when analyzing multidimensional behavioral data.

Exocentric visualizations (Scenarios 1 to 3) support spatial reasoning by UX data, trajectories, and human motion directly within the 3D environment. In early scenarios, bodyless representations such as shadows enable users to explore spatial distributions of UX data and navigation strategies across individuals. As representational richness increases, kinematic data is introduced, allowing users to relate UX variations to posture and interaction phases. Recoloring strategies applied to bodies, shadows, or paths help maintain a tight coupling between movement, context, and UX data within the spatial frame of reference.

Summarized visualizations (Scenarios 3 to 5) complement immersive exploration by providing temporal abstraction and focused inspection of UX and contextual data. Time-series plots support precise examination of signal variations during selected events, while space-time ribbon representations integrate multiple data dimensions along an individual's trajectory. These summarized views can be consulted after patterns observed in the 3D scene, enabling users to refine interpretations and confirm temporal relationships between UX data, contextual conditions, and motion.

Egocentric visualization (Scenario 5) introduces a perception-centered perspective that builds on prior exocentric and summarized analyses. By switching to the individual's point of view, users can examine how environmental cues and events such as approaching vehicles or traffic light states are experienced. This perspective adds interpretive depth by aligning perception, posture, and UX variations within the lived spatial context of the experience.

Across the scenarios, no single visualization approach is sufficient alone. Exocentric and egocentric perspectives support a more intuitive and embodied understanding of behavior in the 3D context. On the other hand, the summarized representations enable focused inspection and comparison. The scenarios verify how fluid transitions between these views support exploratory analysis of complex behavioral data.

Central to this approach is the use of **in-context visualization**, which place motion, UX data, and contextual information within the 3D environment where the experience happened. By maintaining spatial and temporal coherence, the approach supports forms of reasoning that are difficult to achieve using more traditional and more abstract visualizations.

8 Discussion and future work

The designed approach is intentionally structured to minimize extraneous cognitive load: the mental effort spent on processing the interface rather than the data itself [Skulmowski and Xu, 2022; Cabouat, 2024]. Traditional 2D analysis of immersive UX data typically asks researchers to maintain a high split attention to correlate 2D data on graphs with 3D spatial replay. This requires a high-effort mental mapping to synchronize the UX data with the specific environmental trigger.

By applying the Spatial contiguity principle, our framework reduces this load by co-locating multivariate signals directly within the spatial context of the experience [Johnson and Mayer, 2012; Ginns, 2006]. Specifically, in the exocentric view, the motion trajectory is the graph. When a researcher observes a color shift in the participant's encoding (e.g., from clear red to dark red due to EDA variation), the signal and the context are naturally perceived as a single unified visual object. This integration removes the need for mental alignment, allowing analyst to focus on higher-level pattern recognition.

8.1 Feature Analytical Trade-offs

Our approach aims to provide a variety of representations because human behavior analysis is rarely a one-size-fits-all task. As demonstrated in the use case scenarios, each feature offers a specific trade-off between spatial, temporal or postural depth. For example, the Space-Time Heatmap (Scenario 1) is highly efficient for identifying global spatial trends and hotspots of physiological arousal across a population, however, it is insufficient for posture analysis as it collapses body posture into abstract points. Skeleton animation and Body-part Filtering shown in Scenario 3 provide the highest resolution for ergonomic assessment but can lead to significant visual clutter if applied to multiple participants simultaneously. The Egocentric Perspective (Scenario 5) serves as a unique tool to validate the why behind a data spike by aligning the user's field of view with their physiological response. Table 4 summarizes these analytical affordances, providing a mapping between the visualization features and the specific tasks they are best suited to support.

8.2 Heuristic Walkthrough

We performed a heuristic walkthrough across the five analytical scenarios presented in Section 6 to highlight the value of the proposed approach. This evaluation focuses on the Information Gain and the specific insights uncovered with immersive analysis, compared to 2D representation.

Scenario 1, 2, 4 (Global patterns): These scenarios demonstrate the effectiveness of the overview first heuristic. By visualizing heatmaps and STP in-situ, analysts can move beyond identifying when a signal varies to identify the

Table 3. Illustrative analysis scenarios, their analytical focus, required data, visualization approaches, and associated task analytics (TA).

Scenario	Analytical Focus (TA)	Data Used	Visualization Approach
1	Spatial distribution of UX data within the environment (TA1,2,3)	UX data (EDA), human position, scene layout	Exocentric view; Shadow recoloring; Aggregated spatial heatmap
2	Identification of trajectory deviations relative to environmental constraints (TA3,4)	Human position, trajectories, scene context	Exocentric view; Trajectory and shadow comparison; Spatial filtering
3	Relationship between human kinematics, interaction, and UX variation (TA5)	Kinematic data, contextual events, UX data (EDA, HR), timestamp	Exocentric replay; Body-part filtering; Body encoding by UX and interaction
4	Temporal alignment of contextual events and multiple UX signals (TA2,3,5)	UX data (EDA, HR), contextual events (traffic light)	Summarized space-time ribbon; Multi-attribute encoding; Temporal navigation
5	Situated interpretation of perception, posture, and UX from the individual perspective (TA5, TA6)	Kinematic data, UX data, contextual events	Exocentric replay; Egocentric perspective; Temporal filtering; Signal plots

Table 4. Suitability of visualization features for specific analytical tasks.

Feature	Spatial Trends	Temporal Flow	Physio. Correlation	Body Posture	User Perspective
Heatmap (Shadows)	O	X	o	X	X
Space-Time Ribbon	o	O	O	X	X
Skeleton Animation	X	o	o	O	o
Body-part Filtering	X	X	o	O	X
Egocentric View	X	o	X	o	O
Signal Plots (2D)	X	O	O	X	X

O = High Suitability, o = Partial Suitability, X = Low Suitability

spatial trigger. While a 2D environment might show a heart-rate spike at a specific timestamp, the immersive overview reveals the environmental context that caused it. This provides an immediate explanation for data variation that would otherwise require manual cross-referencing between temporal logs or videos.

Scenario 3 & 4 (Embodied coorrelation): In these scenarios, we observe high information gain regarding reach and posture. While 2D joint coordinates can quantify arm extension, the 1:1 scale of immersive playback facilitates action-specific perception. Analysts can inhabit the participant's view to perceptually assess ergonomic strain or the scale of an obstacle. The walkthrough reveals that a physiological spike was not a random outlier, but a direct response to a physical interaction, an insight regarding the spatial side of the interaction that can be inaccessible on a flat monitor.

Scenario 5 (Details-on-demand): Finally, the integration of spatial filters and situated time-series fulfills the details-on-demand requirement. By allowing analysts to hold a 2D graph next to the 3D embodied representation, we supports high-confidence verification of trends without breaking the immersive context. This seamless transition from broad pattern observation to granular analysis ensures a rigorous analytical workflow following Shneiderman's Mantra [Shneiderman, 2003], grounding numerical data in the lived experience.

8.3 Analytical Opportunities

Our analytic approach provides a couple of benefits to uncover insights in immersive user experiences compared to 2D approaches. First, situating synchronized motion, physiology, and contextual data directly within the virtual environment allows users to interpret human behavior in its original spatial and temporal context. This facilitates the perception of anomalies such as hesitations, skipped interactions, or atypical trajectories, which would otherwise remain hidden in log files or time-series plots.

The presented approach leverages complementary viewpoints (exo-egocentric, summarized visualization). Researchers can fluidly move between embodied exploration and abstract quantitative investigation, supporting both hypothesis generation and systematic analysis. This combination is particularly powerful when linking motion anomalies with physiological data to efficiently compare group-level trends with individual deviations.

Beyond the methodological interest, such visualization enables users to study embodied activities over space and time with direct relevance across various research domains. For instance, in HCI, this can support the connection of the user actions with the system interaction in realistic settings; for rehabilitation, it can support clinicians in intuitive analysis of multivariate data to diagnose atypical movement patterns associated with certain conditions such as anxiety or stress.

Finally, this workflow encourages the development of new analytical questions. Visual inspection of postures during waiting tasks inspired the idea of body inclination and arm orientation as a potential behavioral marker. Similarly, aggregated heatmaps across individuals revealed anticipatory stress patterns, opening avenues for group-level behavioral modeling. By acting as a catalyst for methodological innovation, we can support an easier generation of hypotheses linking motion anomalies with physiological data, a task that can be particularly time-demanding with more traditional visualization tools.

8.4 Limitations and Challenges

While promising, the approach also comes with specific limitations. First, regarding visual clutter and scalability, human motion data is particularly dense: simultaneously visualizing more than two or three of individuals' skeletons quickly becomes cluttered. Our filtering tools mitigate this by allowing task or time-based selection, but large-scale comparison of the raw motion data across dozens of individuals still requires abstraction into representations such as ribbons or statistical plots.

Second, rendering high-frequency motion and physiology records presents scalability challenges that can overload the visualization system. With a dataset proposing a native resolution of 125 Hz, displaying every single body instance produces significant visual clutter and undesirable rendering lag. Adjusting the data frequency and filtering the data addresses this issue, but at the cost of losing temporal granularity.

Third, extended analytics sessions introduce risks of interaction fatigue due to the strong cognitive demands placed on the researcher. Navigating virtual space, switching between perspectives, and managing multiple interconnected views can be satisfying but also exhausting and ergonomically taxing over time. Careful design of interaction techniques and interface ergonomics is necessary to balance analytical depth with usability. Thus, future work include user-based evaluations to verify the usability of our approach both in terms of task resolution support and user experience.

Finally, there is a limitation concerning dataset specificity; while our implementation was designed in a generic manner, we have tested it exclusively on a single specialized, interactive dataset. Future work is required to test the cross-platform generalizability of the tool through the integration of new datasets with different motion capture or sensor systems. Such processes would aim to result in data standards shared with the community to help make comparable visualization more widely available.

9 Conclusion

We presented a visual analytic approach for analyzing multi-dimensional user experiences that combine human motion, multi-modal UX data, and contextual information. By situating embodied activity within the spatial and temporal environment and complementing it with summarized views, our approach enables users to detect anomalies, explore relationships between movement and internal responses, and generate new hypotheses about embodied user experience. Our work highlights that immersive multi-perspective analysis can be a valuable complement to traditional analytical methods, particularly for exploratory investigations of motion-UX relationships. Immersive visualization opens additional perspectives that help analysts reason about experience as it evolves in space and time, supporting comprehension that can be difficult to achieve with 2D representations alone.

Supporting quantitative comparisons represents a promising direction. Addressing this challenge requires further exploration of how multidimensional data can be represented and managed at large scale. Future works should investigate adaptive levels of abstraction and interaction techniques to allow users to navigate between individual and population-level views. In particular, balancing performance and cognitive load remains a challenge to enable the exploration of larger user populations in 3D and immersive environments.

Declarations

Authors' Contributions

Conceptualization: All authors;
Software: C.Q, F.R;
Analysis: C.Q, F.R ;
Writing: All authors.

Competing interests

The authors declare that they have no competing interests.

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Availability of data and materials

The study utilized the CREATTIVE3D dataset, which is openly available at https://zenodo.org/records/14514163 .

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