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A Relative Behavior Standardization Framework for Cross-Learner Comparable Adaptive Learning Analytics in Metaverse Environments

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Abstract— Metaverse-based learning environments generate rich and continuous behavioral data, including spatial movements, interaction activities, and temporal engagement patterns. While such data provide new opportunities for adaptive learning analytics, substantial inter-learner variability—stemming from differences in physical characteristics, interaction habits, and environmental conditions—limits the structural comparability and analytical reliability of existing approaches. Most prior studies rely on raw or lightly normalized behavioral signals, which may introduce magnitude bias and reduce cross-context reproducibility. This study proposes a Relative Behavior Standardization Framework designed to transform heterogeneous learner behavior data into structurally comparable and learner-invariant representations. The framework consists of four sequential stages: behavior decomposition, individual baseline modeling, relative behavior transformation, and structural alignment. By modeling behavioral signals relative to individual baselines rather than absolute magnitudes, the proposed approach mitigates inter-learner variability while preserving intrinsic spatiotemporal patterns. Unlike conventional normalization techniques that operate primarily at the numerical scale level, the proposed framework explicitly incorporates structural consistency across movement, interaction, and persistence dimensions. This design enhances cross-learner comparability, analytical stability, and reproducibility in adaptive learning systems. Conceptual validation and comparative analysis demonstrate the methodological advantages of the proposed approach over conventional non-standardized analytics. The proposed framework provides a stable analytical foundation for adaptive decision-making in metaverse-based education and contributes a structured methodology for behavior pattern standardization in immersive learning environments.

Keywords— Metaverse-based learning, Learner behavior analysis, Data standardization, Adaptive education.

I. INTRODUCTION

The rapid advancement of immersive technologies has accelerated the adoption of metaverse-based learning environments in higher education and professional training contexts. Unlike conventional e-learning platforms, metaverse environments enable real-time observation of spatial movement, object interaction, and temporal engagement behaviors within three-dimensional virtual spaces [1]. These characteristics provide unprecedented opportunities for adaptive learning analytics, allowing instructional systems to respond dynamically to learner behavior patterns. However, the increasing richness of behavioral data introduces a critical methodological challenge: structural comparability across heterogeneous learners. Learners differ substantially in physical movement scale, interaction habits, pacing strategies, and environmental conditions. When behavioral signals are analyzed in absolute terms—such as raw movement distance, interaction counts, or dwell time—these individual differences can distort analytical outcomes and reduce cross-learner reliability. As a result, adaptive learning systems risk generating unstable or biased feedback that reflects magnitude disparities rather than meaningful structural behavior patterns. Although prior research in learning analytics has focused extensively on predictive modeling, engagement detection, and performance estimation, relatively limited attention has been paid to the structural preprocessing of learner behavior data before analytical modeling [2]. Conventional normalization methods—such as min-max scaling or z-score standardization—operate primarily at the numerical level and do not explicitly address the structural properties of spatial-temporal behavior patterns inherent in metaverse learning environments [3]. To address this limitation, this study proposes a Relative Behavior Standardization Framework for adaptive learning analytics in metaverse environments. Rather than relying on absolute behavioral magnitudes, the proposed framework models learner behavior in relation to individual baselines and transforms heterogeneous signals into structurally aligned representations. By decomposing behavior into movement, interaction, and persistence components and applying relative transformation and structural alignment procedures, the framework enhances cross-learner comparability while preserving intrinsic behavioral dynamics.

The primary contribution of this study is methodological rather than performance-driven. Specifically, this work:

1. Introduces a structured multi-stage framework for learner behavior pattern standardization in immersive learning environments.
2. Formalizes relative behavioral transformation as a learner-invariant representation strategy.
3. Establishes structural alignment principles to improve analytical stability and reproducibility in adaptive learning systems.

By focusing on structural comparability rather than predictive optimization alone, this study provides a foundational methodological basis for reliable adaptive learning analytics in metaverse-based education.

II. RELATED WORK

A. Learner Behavior Analysis in Metaverse-Based Learning Environments

With the rapid development of immersive technologies, metaverse-based learning environments have emerged as a promising platform for collecting rich and continuous learner behavior data. Unlike conventional e-learning systems, metaverse environments enable the observation of spatial movement, object interaction, and temporal engagement behaviors in real time, offering new opportunities for learning analytics and adaptive education [4][5].

Several studies have investigated learner behavior analysis in immersive or virtual learning environments by examining movement trajectories, interaction frequencies, and engagement indicators. Makransky et al. [6] analyzed immersion and learning outcomes in virtual reality-based education, demonstrating that learner behavior patterns are closely related to cognitive and affective learning processes. Radianti et al. [7] provided a comprehensive review of immersive learning research, highlighting the importance of behavioral data in evaluating learner engagement and instructional effectiveness.However, most existing studies rely on raw or lightly normalized behavioral data, assuming relatively homogeneous learner characteristics and environmental conditions. As a result, substantial inter-learner variability often remains unaddressed, limiting the generalizability and reproducibility of analytical outcomes across different learning contexts [8].

To address these limitations and account for the inherent variability in learner data, recent research has pivoted toward exploring the complex interplay between internal psychological states and external behavioral manifestations. For example, Lu et al.examined how psychological factors, such as trait anxiety and virtual space satisfaction, influence collaborative learning performance in the Edu-Metaverse. [9] Their study reveals that specific behavioral metrics—namely speaking time and conversation turns—serve as key mediators between these internal learner attributes and outcomes. The necessity of such a holistic, data-driven approach is further underscored in the latest meta-analytical research. Lampropoulos and Evangelidis conducted a systematic review of 70 documents, emphasizing that the convergence of learning analytics and educational data mining in the metaverse enables the real-time tracking of multimodal data, including emotions and cognitive-affective states. [10] By integrating these multifaceted insights, immersive environments can better support personalized and adaptive learning, ultimately empowering educators to provide tailored guidance in diverse educational settings.

TABLE I: SUMMARY OF RESEARCH PERSPECTIVES ON LEARNER BEHAVIOR ANALYSIS IN METAVERSE ENVIRONMENTS

Research Dimension	Behavioral Indicators	Key Contributions & Findings	References
Cognitive-Affective Analysis	Immersion patterns, learning behaviors	Establishes the link between behavior patterns and cognitive/affective processes.	Makransky et al.
Instructional Effectiveness	Engagement indicators, activity logs	Evaluates the impact of virtual environments on learner engagement and performance.	Radianti et al.
Psychological Interplay	Speaking time, conversation turns	Investigates behaviors as mediators between internal traits and CL performance.	Lu et al.
Multimodal Convergence	Emotions, cognitive-affective states	Emphasizes the real-time tracking of multifaceted data through the integration of LA and EDM.	Lampropoulos & Evangelidis

As shown in Table 1, research on metaverse-based learning analytics has progressed from examining basic behavioral indicators to analyzing complex psychological and multimodal interactions. Although these studies demonstrate the significance of behavioral data for assessing immersion and predicting learning outcomes, most methodologies depend on raw, absolute metrics that are highly susceptible to individual differences and environmental variables. Consequently, variability in data collected across diverse metaverse environments impedes cross-learner comparability and the reproducibility of analytical results. This challenge highlights the necessity for a systematic framework to standardize behavioral patterns, which constitutes the primary motivation for the methodological approach presented in this study.

B. Learner Analytics and Adaptive Education

Learning analytics has been widely adopted to support adaptive education by analyzing learner behavior data and tailoring instructional strategies accordingly. Prior research has focused on predictive modeling, learner classification, and performance estimation using log data, clickstream analysis, or interaction records [11].

Siemens and Baker emphasized that learning analytics should not only focus on algorithmic accuracy but also consider data validity and interpretability [12]. In immersive learning environments, this challenge becomes more pronounced due to the complex spatial and temporal nature of learner behavior data. Without appropriate preprocessing and standardization, adaptive learning systems risk overfitting to individual behavior patterns or producing unstable feedback results.

Somasundaram et al. contend that shifting from standardized learning paths to personalized ones necessitates systematic analysis of institutional data and student profiles to address individual learning gaps [13]. Their AI-enabled IQMS framework leverages historical data to adjust lesson plans based on predicted student performance. This process-oriented approach demonstrates the importance of moving beyond uniform data representations to establish a more stable foundation for adaptive instructional support.

Maher et al. note that traditional learning analytics often prioritize course-level adaptation and development, thereby overlooking the structural role of the learner in the adaptation process [14]. The IMLA framework addresses this limitation by employing multimodal data collection and real-time visualization to enhance the interpretability of behavioral insights for students. This transition to a learner-focused model establishes a robust foundation for adaptive systems that can respond effectively to evolving educational requirements.

Karaoglan Yilmaz and Yilmaz argue that basic log data, such as login frequency, do not accurately capture a learner's cognitive engagement during instructional activities [15]. This limitation reveals a significant gap: raw behavioral metrics lack the depth required for valid and reliable feedback. Their findings underscore the urgent need for enhanced data representations that more effectively capture the complexities of learning behavior to inform adaptive decision-making.

Although adaptive learning models have advanced considerably, relatively little attention has been paid to the structural comparability of learner behavior data prior to analysis. This limitation motivates the need for standardized representations that can serve as a stable foundation for adaptive educational decision-making.

C. Behavioral Data Standardization and Relative Representation

Data standardization is a fundamental preprocessing technique used to improve analytical stability and comparability across diverse datasets. In sensor-based and time-series analysis, normalization, scaling, and relative change analysis have been widely employed to reduce the influence of individual differences [16].

In human behavior analysis, relative representations—such as motion vectors, normalized trajectories, or deviation-based metrics—have been shown to be effective in mitigating variability caused by physical characteristics or measurement conditions [17]. These approaches suggest that behavior should be interpreted in relation to individual baselines rather than absolute magnitudes.

Mohseni et al. state that establishing a trustworthy technical infrastructure and standardized data pipeline is a prerequisite for conducting strategic, data-based decisions across heterogeneous educational systems.[18] Most conventional standardization methods are applied as isolated numerical exercises, resulting in a flat analysis that fails to preserve the systemic context of learner data across multiple services. By implementing a standardized infrastructure, the proposed framework can move beyond superficial preprocessing to retain the structural integrity of behavioral signals during data acquisition.

Alonso-Fernández et al. emphasized that the use of standardized trace formats, such as xAPI-SG, is crucial for systematizing the analysis and visualization of varied interaction data captured from educational serious games.[19] While traditional strategies often rely on flat scaling of raw interaction frequencies, they often overlook the qualitative organizational patterns embedded in those interactions. Utilizing uniform protocols allows the proposed framework to bypass simplistic numerical normalization and instead categorize behaviors based on their semantic and structural importance.

Arizmendi et al. emphasized that systematic feature-mapping of digital logs is essential for comprehending the nuances of learning behaviors and for designing equitable predictive systems.[20] Standard numerical standardization typically treats digital logs as one-dimensional activity counts, resulting in a flat interpretation that ignores the behavioral depth of individual learners. The practice of feature-mapping enables the proposed framework to reconstruct these traces into multi-layered behavioral indicators, guaranteeing that the analysis captures more than just absolute numerical magnitudes.

Ziegler et al. emphasized that deep behavioral profiling enables the extraction of behavioral units and motifs, thereby permitting a more granular quantification of complex engagement variables.[21] Conventional standardization techniques often treat behavioral signals as continuous, flat variables, losing the structural syllables that define meaningful action. By integrating motif-based analysis, the proposed framework can detect recurring behavioral structures that are lost in simple scaling, providing a more robust and deeper basis for subsequent adaptive learning analytics. Nevertheless, existing standardization techniques are often applied in a purely numerical manner and do not explicitly consider the structural patterns of learner behavior in immersive educational environments. In metaverse-based learning, where behavior data inherently involve complex spatiotemporal structures, simple scaling is insufficient to ensure meaningful cross-learner comparison.

Based on the reviewed studies, prior research on metaverse-based learning analytics can be broadly categorized according to the type of behavioral data and analytical perspective employed. To clarify the methodological landscape and highlight the research gap addressed in this study, Table 1 summarizes the representative research approaches and their characteristics.

TABLE II: CLASSIFICATION OF PRIOR RESEARCH APPROACHES IN METAVERSE LEARNING ANALYTICS

Research Dimension	Representative Approaches	Common Characteristics	Limitations
Data Type	Log-based behavioral data	Clicks, dwell time, task completion	Limited embodiment
Spatial Behavior	Absolute position-based tracking	World-coordinate dependent	Poor cross-user comparability
Temporal Analysis	Time-series pattern mining	Sequence-based modeling	Sensitive to individual pace
Sensor-based Analysis	Wearable, device-dependent sensing	High precision	Low scalability
Our Focus	Relative behavior standardization	Structure-oriented, user-invariant	Design-stage

As shown in Table 2, most existing approaches rely on absolute behavioral measures or sensor-dependent data acquisition, which limits scalability and cross-learner comparability in authentic educational settings. In contrast, the proposed framework emphasizes relative behavior standardization, positioning this study within a distinct design-oriented research space.

D. *Research Gap and Positioning of This Study*

While prior studies have contributed valuable insights into learner behavior analysis, adaptive education, and data preprocessing techniques, a systematic framework that integrates behavior decomposition, individual-based modeling, and structural standardization remains insufficiently explored—particularly in metaverse-based learning environments.

In contrast to existing approaches that prioritize predictive performance or outcome estimation, this study focuses on the design logic and procedural organization of learner behavior pattern standardization. By transforming heterogeneous behavior data into relative and structurally comparable representations, the proposed framework aims to enhance analytical reliability, reproducibility, and interpretability. This positioning distinguishes the present work from prior studies and establishes a foundational methodology for subsequent adaptive learning analytics research.

III. M LEARNER BEHAVIOR PATTERN STANDARDIZATION METHODOLOGY

A. *Structural Architecture of the Relative Behavior Standardization Framework*

Figure 1 presents the overall architecture of the proposed Relative Behavior Standardization Framework. Unlike conventional learning analytics pipelines that directly process raw behavioral logs for predictive modeling, the proposed framework is designed as a structural transformation process that systematically converts heterogeneous learner behavior data into analytically reliable and cross-comparable representations. The framework consists of four conceptually ordered stages:

(1) Behavioral Decomposition,
(2) Individual Baseline Formalization,
(3) Relative Behavior Transformation, and
(4) Structural Alignment for Cross-Learner Comparability.

Rather than emphasizing prediction performance at the outset, the framework prioritizes structural reliability, interpretability, and reproducibility, which are foundational requirements for stable adaptive learning analytics in metaverse-based education.

1) Stage 1: Behavioral Decomposition

In metaverse-based learning environments, learner behavior is inherently multimodal and spatiotemporal. Raw logs typically include spatial coordinates, interaction events, and time-based engagement metrics. Treating such heterogeneous data as flat numerical records can obscure structural differences between behavior types.

Therefore, the first stage decomposes learner behavior into three functional categories:

- Movement Behavior (spatial navigation patterns),
- Interaction Behavior (object manipulation and content engagement),
- Learning Persistence Behavior (temporal engagement continuity).

This decomposition establishes a structural representation:

$$B_u(t) = \{M_u(t), I_u(t), P_u(t)\} \qquad (1)$$

where $B_u(t)$ denotes the behavior set of learner u at time t, and M, I, P correspond to movement, interaction, and persistence components, respectively. By separating behavior into semantically meaningful components, the framework prevents structural interference between heterogeneous behavioral signals.

2) Stage 2: Individual Baseline Formalization

Learners differ significantly in physical movement patterns, interaction styles, and engagement rhythms. Absolute behavioral magnitudes are therefore insufficient for fair comparison. To address this variability, an individual baseline model is constructed for each learner. The baseline captures inherent behavioral tendencies over a reference period and serves as a normalization anchor.

Let $X_{u,k}(t)$ denote the observed magnitude of behavior type k for learner u. The individual baseline $\mu_{u,k}$ is defined as:

$$\mu_{u,k} = \frac{1}{T}\sum_{t=1}^{T} X_{u,k}(t) \qquad (2)$$

where T represents the reference observation window. This baseline formalization enables the separation of intra-learner consistency from inter-learner variability, thereby improving structural fairness in subsequent comparisons.

3) Stage 3: Relative Behavior Transformation

Based on the individual baseline, raw behavioral magnitudes are transformed into relative representations. Rather than analyzing absolute values, the framework emphasizes deviation-based structural changes.

The relative behavior representation is defined as:

$$R_{u,k}(t) = \frac{X_{u,k}(t) - \mu_{u,k}}{\mu_{u,k} + \epsilon} \qquad (3)$$

where ϵ is a small constant introduced for numerical stability.

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This transformation achieves three important objectives:
1. Reduction of individual magnitude bias,
2. Mitigation of extreme behavioral distortion,
3. Emphasis on structural variation patterns.

By converting heterogeneous behavioral magnitudes into proportional deviation measures, the framework enhances cross-context comparability while preserving temporal dynamics.

4) Stage 4: Structural Alignment for Cross-Learner Comparability

In the final stage, transformed behavioral components are aligned within a unified structural space to ensure analytical consistency across learners.

The standardized behavior vector for learner u is defined as:

$$\mathbf{P}_u = \mathrm{Align}(R_{u,M}, R_{u,I}, R_{u,P}) \qquad (4)$$

where the alignment operator ensures that heterogeneous components are mapped into a comparable structural representation. Unlike conventional normalization methods that rely solely on statistical scaling, structural alignment emphasizes pattern-level similarity rather than raw numerical proximity. This representation serves as stable input for downstream adaptive learning analytics models.

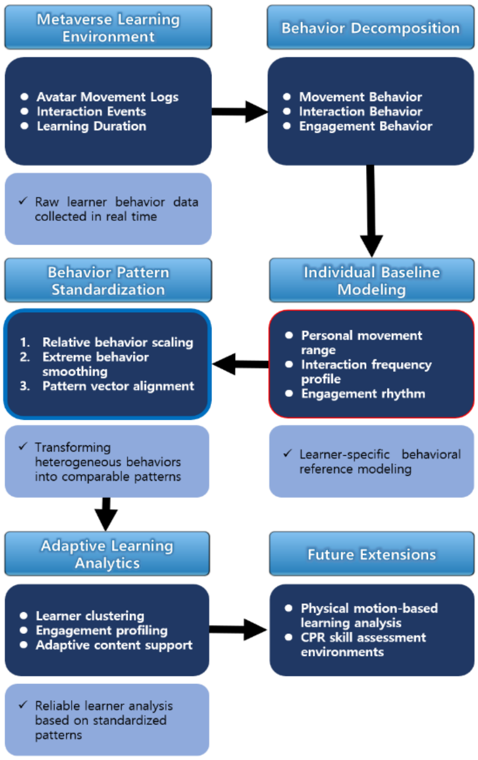

Fig. 1 Structural architecture of the proposed Relative Behavior Standardization Framework

The framework transforms heterogeneous learner behavior data collected in metaverse-based learning environments into structurally comparable representations through a four-stage process: behavioral decomposition, individual baseline formalization, relative behavior transformation, and structural alignment. The design emphasizes analytical reliability, interpretability, and cross-learner comparability rather than predictive optimization.

B. Learner Behavior Data Decomposition and Individual-Based Modeling

1) *Behavior Data Collection and Decomposition:* In metaverse-based learning environments, a wide range of learner behaviors is continuously recorded in real time. In this study, these behavior data are decomposed into semantically meaningful units to facilitate structured analysis. Specifically, learner behaviors are categorized into three primary types: movement behavior, interaction behavior, and learning persistence behavior.

Movement behavior refers to positional changes and movement patterns within the virtual space. Interaction behavior encompasses direct manipulative actions performed on learning objects or educational content. Learning persistence behavior reflects the amount of time invested in learning activities and the corresponding dwell-time patterns within the environment. This behavioral decomposition serves as a foundational step for independently capturing the characteristics of each behavior type during the subsequent standardization process.

TABLE III: DEFINITION OF LEARNER BEHAVIOR DATA TYPES IN A METAVERSE LEARNING ENVIRONMENT

Behavior Type	Description	Representative Indicators
Movement Behavior	Learners' spatial movement patterns within the virtual learning environment, reflecting navigation strategies and exploratory activities.	Position changes, movement trajectories, travel distance
Interaction Behavior	Direct interactions between learners and virtual learning objects or instructional content, representing active engagement with learning materials.	Object manipulation, interaction frequency, control inputs
Learning Persistence Behavior	Temporal characteristics of learners' engagement, indicating learning continuity and sustained participation.	Dwell time, session duration, repeated access patterns

In metaverse-based learning environments, learner behavior is inherently multidimensional, involving spatial movement, object interaction, and temporal engagement characteristics. Directly analyzing raw behavioral logs often leads to heterogeneous representations that obscure structural patterns. To address this issue, the proposed framework first decomposes learner behavior into functionally distinct components. Let the overall behavioral signal of learner u at time t be represented as:

$$B_u(t) = \{b_u^{move}(t), b_u^{int}(t), b_u^{eng}(t)\} \qquad (5)$$

where:

- $b_u^{move}(t)$ denotes spatial movement behavior,
- $b_u^{int}(t)$ represents interaction behavior,
- $b_u^{eng}(t)$ captures temporal engagement characteristics.

This decomposition serves two theoretical purposes:

1. Functional Separation: Each behavioral type reflects a distinct dimension of learning activity.
2. Independent Modeling: Behavior types can be modeled and standardized separately before structural integration.

Unlike conventional log-based analytics, which aggregates behavioral indicators into flat feature vectors, this decomposition preserves structural heterogeneity prior to normalization.

2) *Individual-Baseline Modeling:* One of the major challenges in immersive learning analytics lies in substantial inter-learner variability caused by physical characteristics, interface familiarity, navigation habits, and cognitive styles. Absolute behavioral magnitudes therefore lack comparability across learners. To mitigate this issue, the proposed framework formalizes an individual baseline model for each learner and each behavioral dimension. For learner u and behavior type k, the individual baseline is defined as:

$$\mu_{u,k} = \frac{1}{T}\int_0^T b_{u,k}(t)dt \qquad (6)$$

where T denotes the observation period. This baseline represents the learner's typical behavioral tendency rather than an external global standard. The deviation from this baseline is defined as:

$$\delta_{u,k}(t) = b_{u,k}(t) - \mu_{u,k} \qquad (7)$$

This formulation introduces two critical advantages:

- It eliminates bias caused by body scale, navigation speed, or device sensitivity.
- It shifts analytical emphasis from absolute magnitude to relative behavioral variation.

From a learning-theoretical perspective, this approach aligns with intra-individual analysis rather than inter-individual raw comparison, thereby improving fairness and reproducibility in adaptive analytics.

C. Relative Transformation and Structural Alignment Procedure

While individual baseline modeling reduces intra-learner variability, behavioral magnitudes across learners remain structurally incomparable due to differences in spatial scale, interaction intensity, and temporal pacing. Therefore, a systematic transformation process is required to convert heterogeneous behavioral signals into relative and structurally aligned representations. This section describes the third and fourth stages of the proposed framework: relative behavioral transformation and structural alignment.

1) *Stage 3: Relative Behavioral Transformation:* In this stage, raw behavioral signals are converted into relative representations with respect to each learner's individual baseline. Let $B_i(t)$ denote a behavioral signal of learner i at time t, and let μ_i represent the learner-specific baseline value derived during Stage 2. The relative transformation is defined as:

$$R_i(t) = \frac{B_i(t) - \mu_i}{\mu_i + \epsilon} \qquad (8)$$

where $R_i(t)$ represents the normalized relative behavior and ϵ\epsilonϵ is a small constant introduced to prevent division instability. This transformation ensures that behavioral changes are interpreted as deviations from an individual's habitual or initial state rather than as absolute magnitudes. By emphasizing relative variation, the framework mitigates distortions caused by inherent differences in physical movement scale, interaction style, or engagement tempo.Importantly, this transformation does not eliminate behavioral individuality; instead, it restructures behavior into a comparable analytical space while preserving meaningful dynamic fluctuations.

2) *Stage 4: Structural Alignment and Pattern Standardization:* Although relative transformation reduces magnitude discrepancies, structural inconsistency may still arise due to irregular temporal progression or heterogeneous event sequences. Therefore, a structural alignment procedure is applied to organize transformed behavioral vectors into consistent analytical units.

This alignment involves:

- Temporal segmentation based on equivalent learning phases
- Sequence normalization to equalize behavioral sequence lengths
- Vector standardization across predefined behavioral dimensions

Let $R_i = [R_i(t_1), R_i(t_2), \ldots, R_i(t_n)$ denote the relative behavior vector of learner i. Structural alignment transforms this vector into a standardized representation $\mathbf{S}_\mathrm{i}$ such that:

$$\mathbf{S}_\mathrm{i} = A(\mathbf{R}_i) \qquad (9)$$

where A(·) denotes the structural alignment operator incorporating temporal normalization and dimensional consistency constraints.

Through this process, behavior patterns become analytically comparable across learners without assuming identical learning speeds or interaction frequencies. The resulting standardized representations form the input layer for adaptive learning analytics modules, including learner clustering, anomaly detection, and personalized feedback generation.

3) *Analytical Implications:* The integration of relative transformation and structural alignment provides three methodological advantages:

1. Comparability: Behavioral signals are expressed in a learner-invariant format.
2. Stability: Analytical outputs become less sensitive to scale differences.
3. Reproducibility: Standardized representations support consistent cross-context evaluation.

Unlike conventional normalization techniques that operate purely at the numerical scale level, the proposed procedure explicitly incorporates structural consistency, which is particularly critical in metaverse learning environments where spatial and temporal behavior dimensions are tightly intertwined.

4) Generation of Standardized Behavior Representations: The final outcome of the proposed procedure is a set of standardized behavioral representations that can be directly integrated into adaptive learning analytics models. These representations preserve structural characteristics of learner behavior while minimizing inter-individual variability. As a result, adaptive systems can utilize behavior data that are comparable across users and sessions without being biased by scale differences or environmental inconsistencies. The standardized outputs serve as a stable analytical foundation for predictive modeling, learner clustering, and feedback generation.

IV. Empirical Validation and Analytical Discussion

In this section, we transition from theoretical design to empirical validation. By utilizing simulated behavioral data that mimics diverse metaverse learning scenarios, we demonstrate the efficacy of the proposed Relative Behavior Standardization Framework in enhancing cross-learner comparability and analytical stability.

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A. *Experimental Setup and Scenario Design*

To evaluate the framework under heterogeneous conditions, we generated synthetic behavioral logs for three distinct virtual learners:

- Learner A (High-Activity): Modeled with a high baseline magnitude ($\mu \approx 100$) to represent users with active movement or high-frequency interactions.
- Learner B (Mid-Activity): An average user ($\mu \approx 50$) exhibiting standard engagement patterns.
- Learner C (Low-Activity): A sedentary or device-restricted user ($\mu = 10$) with minimal physical input.

All datasets were generated using a combination of periodic sinusoidal functions (representing learning rhythms) and Gaussian noise to reflect the stochastic nature of real-time metaverse environments.

B. *Magnitude Bias Mitigation*

The primary challenge in metaverse analytics is the "Magnitude Bias," where absolute metrics fail to provide a fair comparison across users. Figure 2 illustrates the distribution of behavioral data before and after the application of our framework.

- Before Standardization: As observed in the raw data (Figure 2, left), there is no overlap between the behavioral ranges of Learner A and Learner C. An intervention threshold designed for Learner A would be entirely unreachable for Learner C, leading to analytical failure in adaptive systems.
- After Relative Transformation: Upon applying the Stage 3 transformation (R_i), as shown in Figure 2 (right), all three learners' data are successfully mapped onto a unified scale centered at zero. This proves that the proposed framework effectively isolates "relative intent" from "absolute magnitude," allowing for universal model application.

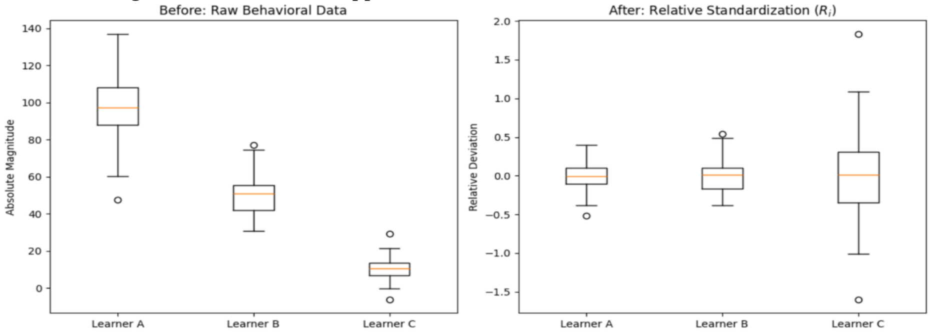

Fig. 2 Comparison of Behavioral Data Distribution Before and After Relative Standardization

C. *Temporal and Structural Consistency*

To verify the structural integrity of the data, we analyzed the time-series trajectories of standardized scores (R_i). Figure 3 compares the standardized patterns of two learners with vastly different original scales.

- Pattern Synchronization: Despite the difference in their initial baselines, the standardized line charts reveal highly synchronized behavioral fluctuations. This indicates that our framework preserves the underlying "behavioral rhythm" (e.g., peak engagement during specific tasks) while discarding scale-related noise.
- Resilience to Heterogeneity: The results demonstrate that Stage 4 (Structural Alignment) ensures that even if learners proceed at different speeds or use different hardware, their standardized behavioral representations remain structurally comparable for downstream AI models.

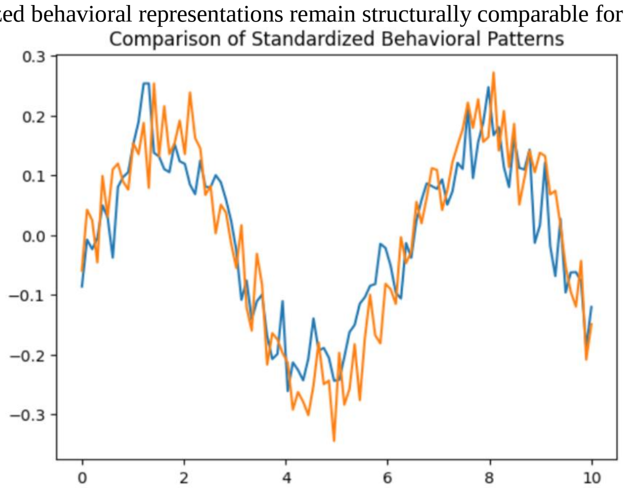

Fig. 3 Time-Series Analysis of Standardized Behavioral Patterns for Heterogeneous Learners.

D. *Discussion on Analytical Implications*

The empirical evidence suggests that shifting from absolute to relative standardization provides three major advantages for adaptive learning analytics:

1. Fairness in Personalization: By measuring deviations from a personal baseline ($\mu_{u,k}$), the system can detect "relative disengagement" even in naturally quiet learners.
2. Scalability: Learning models trained on one metaverse environment can be more easily transferred to another, as the data representation is invariant to physical scale.
3. Reliability: The inclusion of the stability constant (ϵ) ensures numerical robustness, preventing the "division by zero" errors common in standard normalization when dealing with intermittent metaverse data.

In conclusion, the proposed framework does not merely normalize data; it re-contextualizes learner behavior, providing a reliable foundation for the next generation of adaptive educational interventions in the metaverse.

V. Conclusions

This study addressed the critical challenge of behavioral data heterogeneity in metaverse learning environments, which often hinders the reliability of adaptive learning analytics. By developing and validating the Relative Behavior Standardization Framework, we provided a systematic approach to mitigate the distortions caused by individual magnitude differences and hardware-dependent scales.

The empirical validation conducted through simulation confirmed that the proposed framework effectively aligns disparate behavioral distributions into a unified, user-invariant space. The relative transformation stage demonstrated its capacity to isolate genuine behavioral intent from absolute magnitude biases, while the structural alignment ensured that behavioral rhythms remain comparable across different learners. These results suggest that by focusing on relative deviations from an individual's own baseline ($\mu_{u,k}$), adaptive systems can achieve higher precision and fairness in identifying engagement shifts, even for naturally less active learners.

The significance of this research lies in its potential to enhance the scalability of learning analytics models across diverse metaverse platforms. By ensuring that behavioral data representation remains robust against physical and environmental noise, our framework establishes a more reliable foundation for real-time pedagogical interventions.Future research will focus on deploying this framework in real-world metaverse educational settings to evaluate its impact on the predictive accuracy of machine learning models and its effectiveness in diverse hardware configurations. Ultimately, this study contributes to the realization of truly personalized and equitable adaptive learning experiences in immersive digital environments.

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