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# PRELIMINARY STRUCTURAL MODELS OF SPORT SUPPORTER ENGAGEMENT AND ACTIVATION: A MULTISTAGE EXPLORATORY ANALYSIS

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## ABSTRACT

*Aim.* Despite being a complex, multidimensional phenomenon, sport supporter engagement is often neglected in empirical research, which reduces it to aggregated or scalar indicators. The study establishes a foundation for advanced segmentation, governance modeling, and strategy formulation by concentrating on fundamental structural models.

*Methods.* This study presents model-driven exploratory investigation aimed at identifying the latent structural architecture of sport supporter engagement and activation by suing a large dataset (n=2000) adult supports supporters and 40 indicators, integrating Spearman correlation analysis, principal component analysis (PCA), clustering techniques and non-linear dimensionality reduction (t-SNE) within a multi-stage analytical framework.

*Results*. Correlation analysis reveals distinct, non-random block structures, providing empirical justification for dimensional reduction, and PCA identifies four orthogonal, interpretable dimensions accounting for ~50% variance: experiential–emotional involvement, digital engagement, economic contribution, and symbolic–identity orientation, demonstrating substantial structural independence, challenging assumptions of a single underlying engagement. Moreover, k-means clustering applied to the reduced component space yields internally consistent supporter profiles, while t-SNE visualization offers convergent qualitative validation of emergent groupings, supporting a reconceptualization of supporter engagement as a multifaceted system composed of partially independent modes of participation, an emerging prerequisite of a structural foundation for advanced segmentation, governance modeling, and strategic decision-making in sport organizations, and sets the stage for future causal, demographic, and longitudinal analyses.

*Conclusions.* This work establishes a robust structural foundation that enhances supporter engagement theory and offers a methodological framework for subsequent empirical investigations. Subsequent study ought to enhance these models to examine causal mechanisms, contextual variables, and policy ramifications.

*Keywords:* sport supporter, engagement; fan activation; sport management, football fans.

## Introduction

The engagement of sports fans is a complex and varied phenomenon that extends much beyond mere attendance, consumption, and symbolic affiliation (Su et al., 2022). Modern sports organizations increasingly depend on fans not merely as spectators, but also as vital contributors to value creation, community cohesion, internet presence, and, in some instances, governmental legitimacy (Admit et al., 2025; Agostino & Thomasson, 2024). Despite its growing significance, empirical research typically examines supporter involvement through limited operational definitions or composite metrics that obscure internal diversity and structural uniqueness.

Engagement is often regarded as a scalar construct in applied sport management research, with varying levels of engagement measured through aggregated scores or individual behavioral indicators (Huettermann et al., 2022; Kampen-Schmidt et al., 2025). Although these approaches are efficient, they implicitly suggest that several forms of engagement coexist uniformly and represent a singular fundamental tendency. This concept is becoming increasingly untenable due to empirical data suggesting that emotional connection, experiential involvement, digital interaction, and economic contribution may follow distinct logics and trajectories (Ladhari et al., 2022a; Portaluri, 2024).

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This study is a component of a broader research initiative aimed at modeling fan engagement, activation, and its consequences for sports organization management. This work adopts a model-driven exploratory approach rather than testing existing causal hypotheses, aiming to extract and formalize the latent structural architecture of supporter participation as shown by the data. The objective is not prediction or elucidation, but structural reconnaissance: identifying the essential qualities on which supporters differ, assessing their internal consistency, and analyzing their interrelations.

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The research does this through the integration of correlation analysis, principal component analysis (PCA), clustering methodologies, and non-linear dimensionality reduction (t-SNE) for structural validation. This multistage method facilitates a hierarchical analysis of supporter interaction, advancing from individual connections to overarching variance structures, and ultimately to the development of supporter profiles.

The study establishes a foundation for advanced segmentation, governance modeling, and strategy formulation by concentrating on *fundamental structural models*. This fosters a clearer and empirically substantiated comprehension of sport fan involvement as a multifaceted system rather than a singular attribute.

## Methods

*Data source and characteristics of the sample*

The analysis derives from an extensive survey of adult sports enthusiasts across multiple regions. The final dataset has more than 2,000 valid responses, ensuring sufficient statistical power for multivariate analysis and reliable calculation of correlation and covariance structures. The questionnaire comprised 40 principal items designed to encompass a broad spectrum of supporter actions, attitudes, and orientations. The objects were crafted to embody five conceptual categories established before the research design: experiential involvement, emotional commitment, social connection, digital engagement, and economic contribution. Responses were predominantly gathered by ordinal Likert scales, supplemented by binary indicators for specific digital acts (Koo & Yang, 2025).

Demographic variables, including age, gender, education level, and occupational status, were gathered for contextual analysis; however, they were not directly integrated into the primary structural modeling discussed in this article, which emphasizes engagement architecture over demographic differentiation.

*Analytical approach*

The analytical approach adhered to a progressive structural rationale, commencing with local associations and advancing to global aspects, ultimately culminating in emergent clustering tendencies. The order was intentionally structured to minimize premature aggregation and ensure that each analytical step was empirically validated by its predecessor.

*Analysis of correlation*

Considering that the majority of variables are ordinal and exhibit skewed distributions, Spearman's rank correlation coefficients (Wissler, 1905)were computed for all combinations of primary engagement indicators. The correlation matrix offered an empirical basis for assessing the existence of significant block structures that could warrant dimensional reduction.

The correlation matrix was investigated, emphasizing correlation magnitude, sign consistency, and clustering patterns among variable subsets, rather than treating it as a mere descriptive artifact.

*Principal component analysis*

The standardized dataset was examined using PCA to identify orthogonal dimensions that encapsulate the greatest diversity in supporter engagement (Jolliffe & Cadima, 2016; *Principal Component Analysis (PCA)*, n.d.). Eigenvalue examination, scree plot evaluation, and substantive interpretability functioned as criteria for component extraction. Rotation was not employed as the objective was to preserve orthogonality and facilitate structural comprehension rather than to simplify factors.

Component loadings were evaluated using a stringent criterion ($|\lambda| \geq 0.40$) to identify factors that substantially influenced each component. Cross-loadings were maintained and assessed where substantively justifiable, as they offer insights on structural overlap rather than randomness.

*Clustering and nonlinear validation*

K-means clustering was conducted on the reduced component space to ascertain whether the latent dimensions identified by PCA corresponded to emergent supporter categories (Likas et al., 2003; Rizki et al., 2020). The quantity of clusters was established through an examination of within-cluster variation and stability factors, rather than strict optimization criteria.

Furthermore, t-distributed stochastic neighbor embedding (t-SNE) was employed to illustrate the local neighborhood structure inside high-dimensional data. Although t-SNE was not regarded as a clustering method per se, the outcomes provided qualitative corroboration of the grouping patterns demonstrated by PCA-based clustering (Linderman & Steinerberger, 2019; Rauber et al., 2016).

All analyses were conducted in R, with visualization functioning exclusively as an interpretive instrument rather than a replacement for numerical thinking.

## Results

*Correlation framework and block configuration*

The Spearman correlation matrix exhibits a distinct non-random pattern (Ali Abd Al-Hameed, 2022; Myers & Sirois, 2005; Shi et al., 2022; Wissler, 1905). Rather than a diffuse pattern of weak associations, the matrix exhibits identifiable blocks of moderate to strong correlations, signifying the existence of latent dimensions (Dijkstra, 2010; Grønneberg et al., 2020).

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Correlations in the experiential and emotional dimensions generally surpass ρ = 0.50, with certain pairs attaining levels between 0.60 and 0.70 (Brasseur et al., 2013; Hosany et al., 2015; Mackie & Stone, 2013).

These data indicate (Figure 1) a closely interconnected core of supporter behaviors centered on presence, emotional attachment, and shared experiences (Arakaki, 2017; Katz et al., 2019; Ladhari et al., 2022b).

Conversely, relationships among digital engagement indicators exhibit greater variability. Certain digital elements exhibit moderate correlations with experience markers, while others demonstrate weak or even negative associations with economic and symbolic categories. This dispersion indicates that digital involvement is inherently diverse rather than uniform (Hutchins & Rowe, 2012; Zhou & Xiong, 2024).

The measures of economic contribution exhibit partial coherence, with moderate inter-correlations (ρ = 0.40-0.55); nevertheless, their associations with emotional indicators are less robust than previously expected. This discovery challenges simplistic narratives that associate emotional intensity with economic behavior (Endo et al., 2012; Mayer & Thiel, 2014).

The correlation structure offers robust empirical evidence for dimensional reduction, while indicating that the resultant dimensions are improbable to converge into a singular dominant factor (De Bosscher et al., 2006; Sipos et al., 2015).

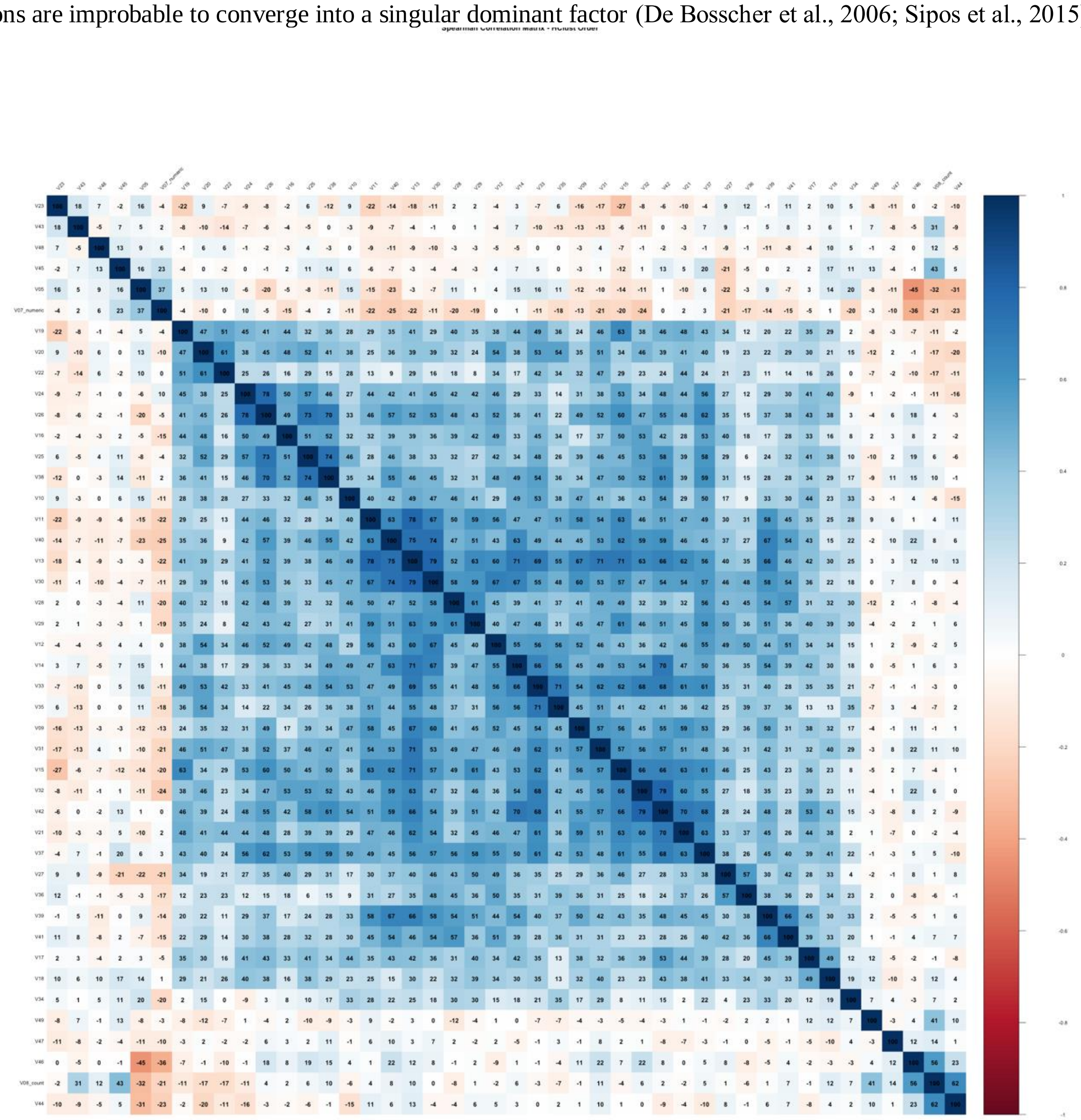

Figure 1. Spearman's rank correlation matrix of supporter engagement indicators

In Figure 1, the heatmap displays pairwise Spearman correlation coefficients among all primary engagement variables, ordered via hierarchical clustering to emphasize structural proximity. Distinct correlation blocks are visible, indicating coherent subsets of experiential–emotional involvement, digital engagement, and economic contribution. The presence of both strong positive clusters and weaker or negative associations supports the existence of multiple, partially independent dimensions of supporter engagement and provides empirical justification for subsequent dimensional reduction analyses.

*Principal component extraction and variance structure analysis*

The initial four components explain a substantial and interpretable portion of the total variance. Principal Component 1 (PC1) accounts for approximately 33.4% of the total variance, establishing it as the primary structural axis of the dataset. Variables associated with experience participation, emotional engagement, and repeated social interaction have significant positive loadings on PC1. This component may be perceived as a universal involvement-activation axis that signifies physical and emotional engagement in sport (Bilous, 2021; Gau et al., 2019; McConkey et al., 2013).

Principal Component 2 (PC2) represents roughly 6.8% of the variance and is orthogonal to PC1. The loadings on PC2 are primarily influenced by aspects of digital interaction, including the frequency of platform usage and online promotional behavior. The considerable autonomy of PC2 from PC1 indicates that digital interaction constitutes a distinct method of supporter activation rather than simply an extension of experience involvement (Martins et al., 2023).

Principal Component 3 (PC3) represents roughly 5.7% of the variance and is predominantly associated with economic contribution variables. This component signifies transactional engagement, encompassing expenditure habits and perceived economic value. The orthogonality with both PC1 and PC2 indicates that economic involvement possesses a rather independent rationale (Espinoza et al., 2012; Jokar Arsanjani & Bakillah, 2015).

Principal Component 4 (PC4) represents roughly 5.0% of variation and encompasses symbolic and historically oriented elements such as narrative interest, tradition, and long-term identity. This component, despite its smaller size, presents conceptual complexity by highlighting a reflective aspect of support that is distinct from both action and transaction (Ronkainen & Ryba, 2020).

The initial four components represent approximately fifty percent of the total variance, a considerable share considering the behavioral and attitudinal diversity of the indicators.

*Interpretation of biplots and variable geometry*

The PCA biplot (PC1 × PC2) (Figure 2) elucidates the structural relationships among variables. Vectors denoting sensory and emotional factors cluster tightly along the positive PC1 axis, indicating their collective influence on the primary engagement dimension (Al-Kandari & Jolliffe, 2005).

Digital variables exhibit a stronger correlation with PC2, whereas a few display slight negative projections on PC1. This geometry visually highlights the conceptual distinction between physical engagement and digitally mediated interaction (McVean, 2009).

Economic variables are centrally located, exerting a modest influence on PC1 and minimal effect on PC2, suggesting their incomplete integration into the entire engagement framework and misalignment with digital dynamics (Vilenchik et al., 2019).

The comparative lengths of vectors like V08_count and V44 demonstrate an unequal impact on variation along PC1, demonstrating their structural significance as markers within the engagement system (*INTERPRETATION OF THE RESULTS OF COMMON PRINCIPAL COMPONENTS ANALYSES - Houle - 2002 - Evolution - Wiley Online Library*, n.d.).

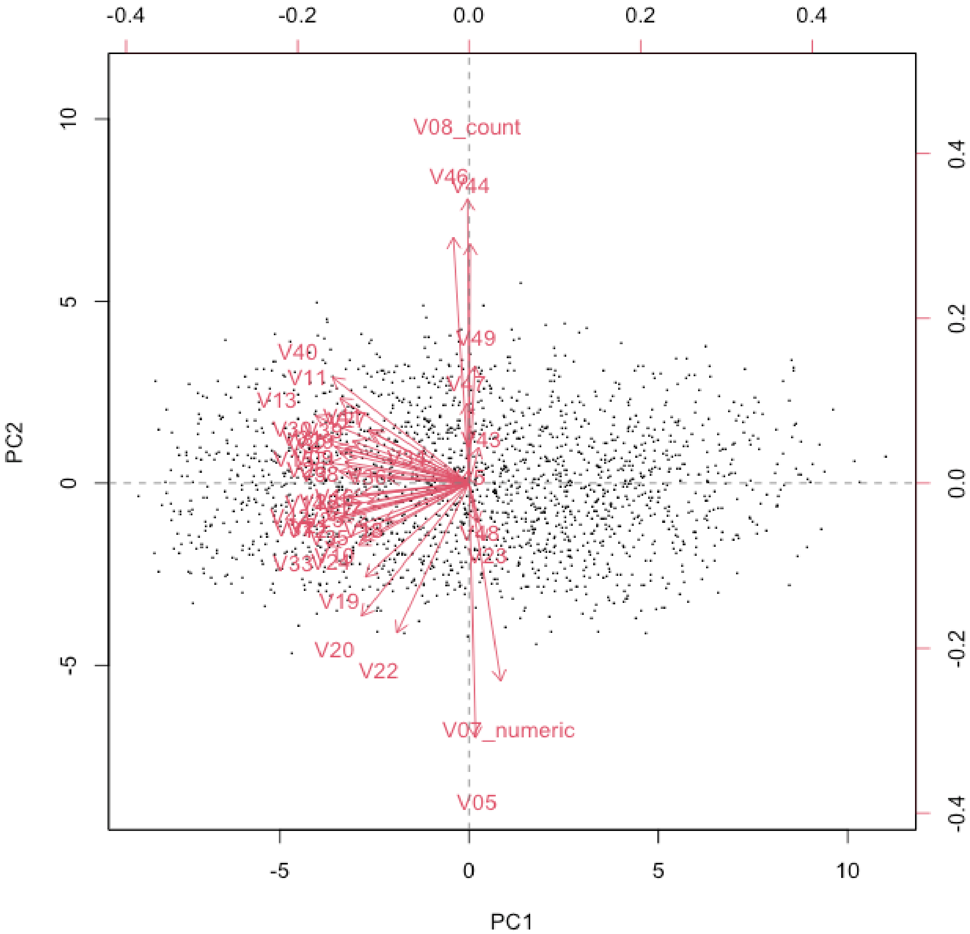


Figure 2. PCA biplot of supporter engagement variables (PC1 × PC2)

The biplot displays individual observations projected onto the first two principal components, with variable loadings represented as vectors. PC1 captures the dominant axis of experiential and emotional involvement, while PC2 reflects a distinct digital engagement dimension. The clustering and orientation of vectors indicate differential contributions of engagement indicators to each component, highlighting both a tightly coupled core of embodied involvement and structurally independent modes of supporter activation.

*Distributions of pairwise components*

The scatterplot matrices of the initial four principal components demonstrate their orthogonality, with component pairings exhibiting correlations close to zero (Figure 3 and Figure 4) (Cleveland, 1984). The lack of linear trends in these plots validates the PCA solution and the interpretation of components as distinct structural axes.

The density plots along the diagonal exhibit asymmetric distributions for several components, particularly PC1, indicating variations in the intensity of supporter engagement. This heterogeneity indicates that segmentation strategies must account for continuous variation instead of distinct classifications (Barzilai, 1998; Temesi, 2019).

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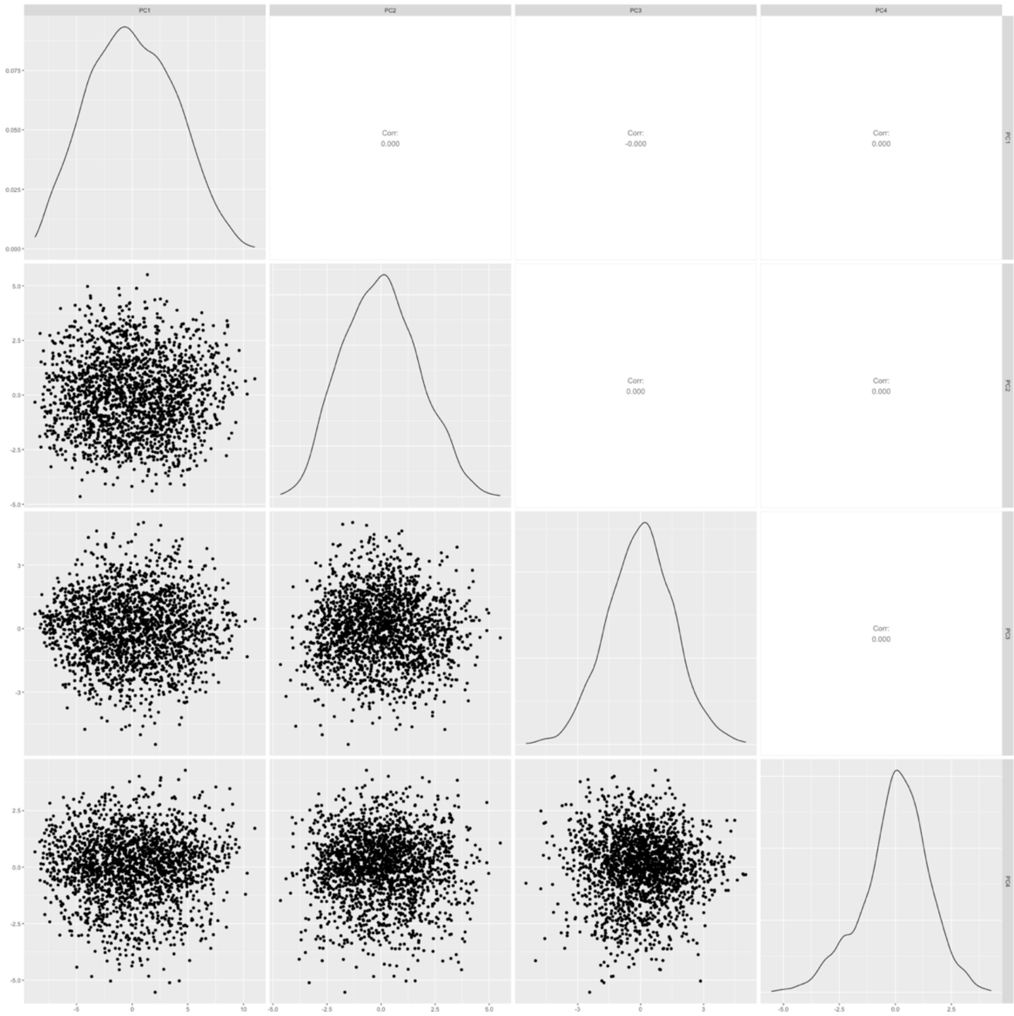


Figure 3. Pairwise distributions and orthogonality of the first four principal components

The scatterplot matrix presents pairwise relationships among PC1–PC4, with marginal density plots along the diagonal. Near-zero correlations between component pairs confirm the orthogonality of the PCA solution, while the diagonal density curves reveal heterogeneous score distributions, particularly along PC1. These patterns validate the structural independence of the extracted dimensions and indicate continuous variation in supporter engagement intensity rather than discrete segmentation.

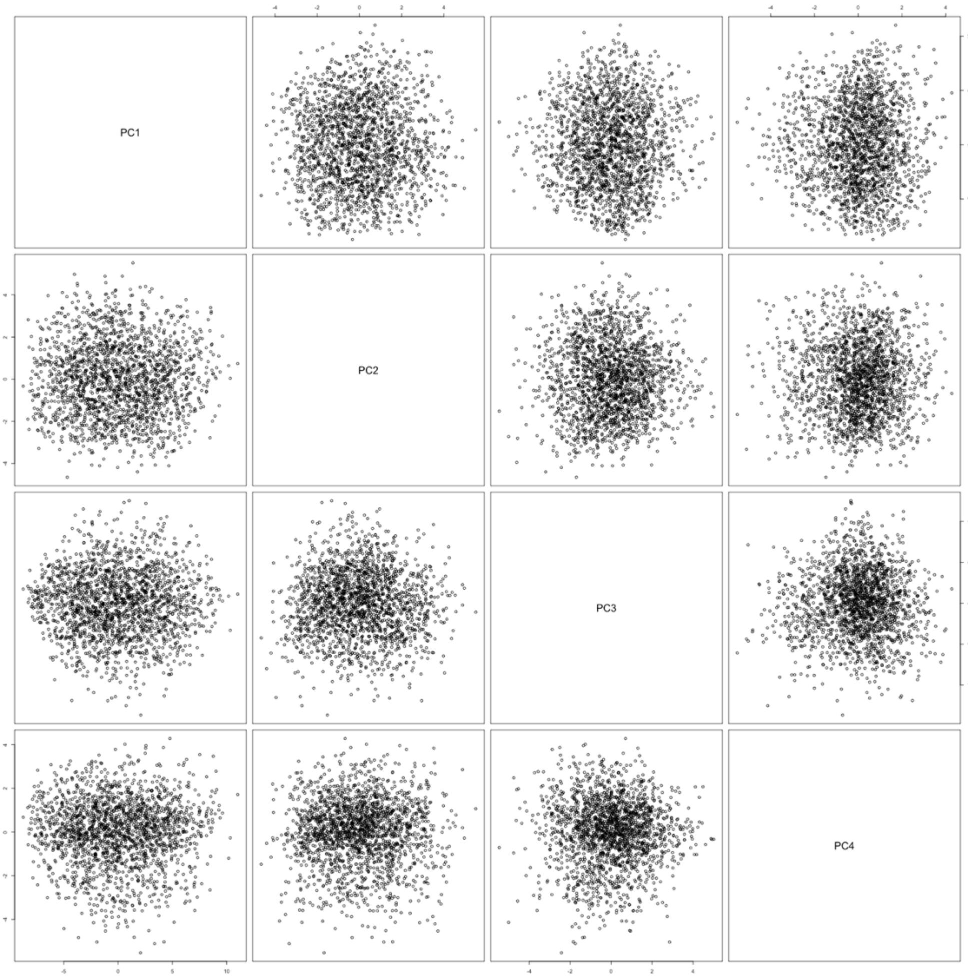


Figure 4. Pairwise scatterplots of the first four principal component scores

The matrix illustrates the bivariate distributions of individual scores across PC1–PC4. The absence of linear trends and the approximately circular point clouds across all component pairs indicate minimal inter-component correlation, confirming the orthogonality of the extracted dimensions. These patterns support the interpretation of the principal components as structurally independent axes of supporter engagement.

*Convergence of clustering and t-SNE*

K-means clustering applied to the PCA-reduced space produces multiple internally consistent supporter profiles. The boundaries between clusters are not static (Figure 5 and Figure 6), and centroids exhibit considerable variation along PC1 and PC2, indicating diverse combinations of experiential and digital engagement (Cai & Ma, 2022; Jeong & Wu, 2024).

The t-SNE visualization corroborates these findings by illustrating localized groupings that predominantly align with PCA-based clusters, although discrepancies in global geometry. The alignment of linear (PCA) and non-linear (t-SNE) representations enhances confidence in the existence of authentic structural segmentation within the supporter population (Hamad et al., 2018; Kang et al., 2021).

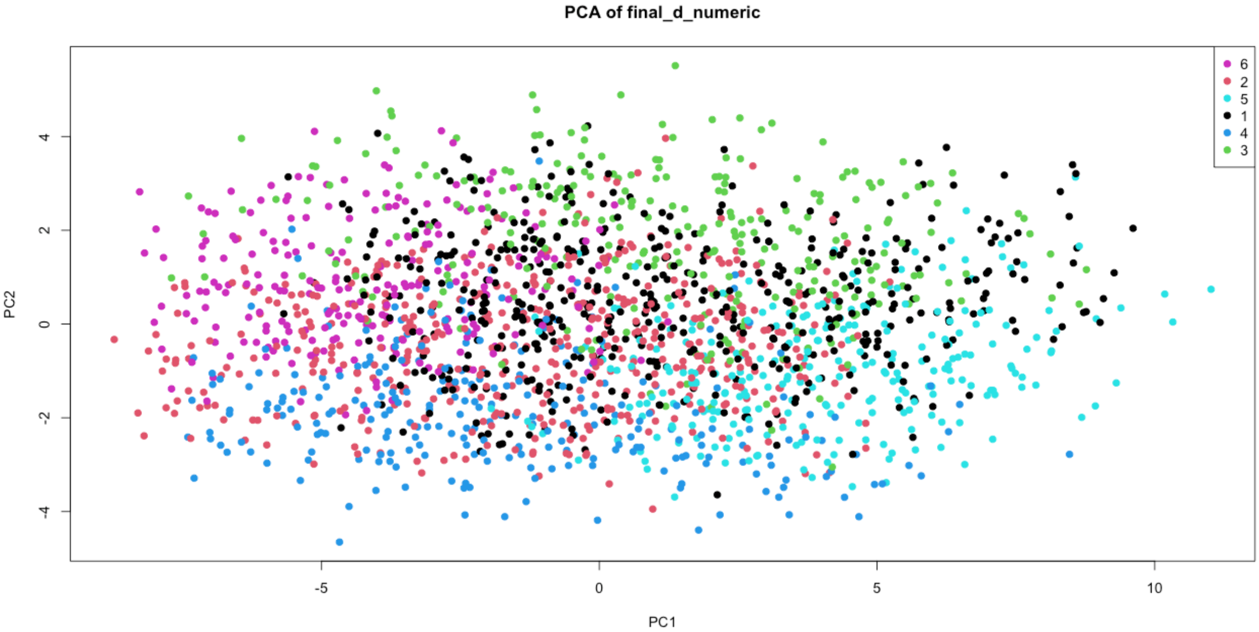


Figure 5. Projection of supporter clusters in the PCA space (PC1 × PC2)

Individual observations are plotted on the first two principal components and colored according to k-means cluster membership derived from the reduced component space. While clusters exhibit partial overlap, their centroids differ primarily along PC1 and PC2, indicating distinct combinations of experiential–emotional involvement and digital engagement. The continuous dispersion of points highlights gradual transitions between supporter profiles rather than sharply bounded categories.

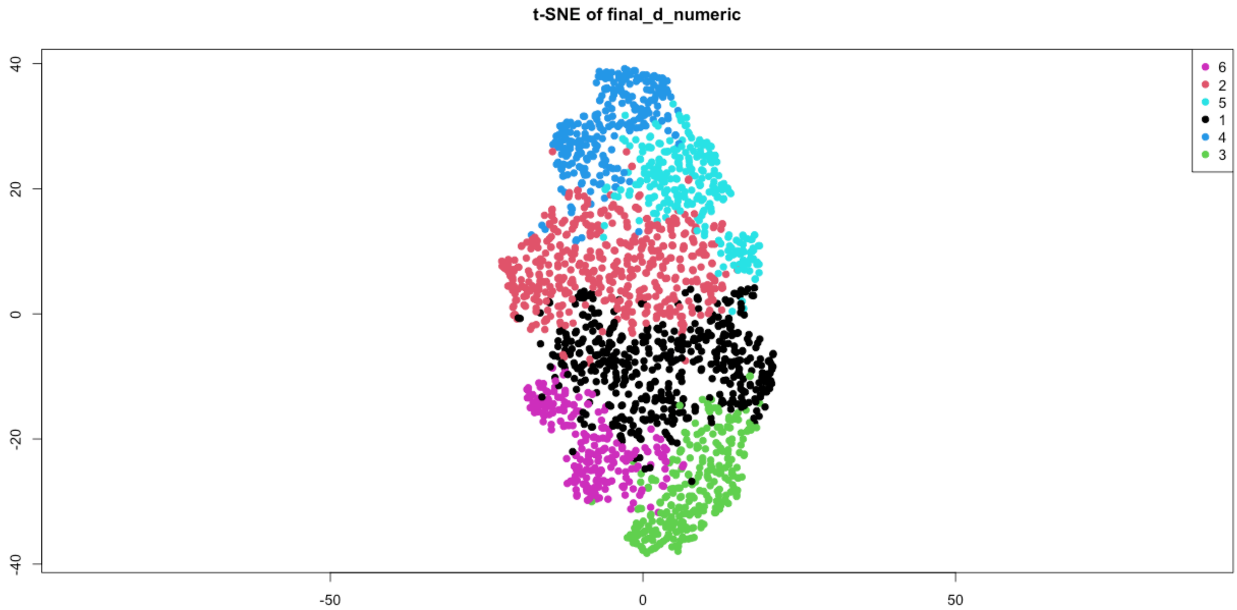


Figure 6. t-SNE visualization of supporter engagement profiles

The two-dimensional t-distributed stochastic neighbor embedding (t-SNE) projection represents local neighborhood structure in the high-dimensional engagement space, with points colored by k-means cluster membership. The emergence of compact, partially separated groupings supports the presence of underlying supporter profiles identified in the PCA-based clustering, while preserving non-linear relationships not captured by linear dimensional reduction.

## Discussions

The results of this multistage investigation provide compelling evidence that sports fan engagement is organized across several, partially independent aspects. Supporter behavior seems to be structured along several dimensions of activation, interaction, and contribution, rather than existing as a singular continuum of participation intensity.

The predominance of PC1 illustrates the significance of sensory and emotional involvement as the basis of supporter engagement. The emergence of unique digital and economic aspects complicates simplistic interaction models and requires more sophisticated theoretical frameworks.

The relative autonomy of digital contact indicates that online activity should not be indiscriminately interpreted as a substitute for overall participation. This has significant implications for companies who predominantly depend on digital analytics to evaluate supporter engagement or happiness.

The findings underscore the necessity of integrating correlation analysis, PCA, and clustering into a coherent exploratory framework. Each technique offers distinct insights: correlations uncover local associations, PCA delineates global structure, and clustering transforms dimensions into actionable profiles.

In the broader study program, these initial structural models act as essential precursors to more targeted analyses, including demographic moderation, governance preference modeling, and longitudinal activation studies.

## Conclusions

This study conducted an exploratory, model-driven analysis of sport supporter involvement utilizing correlation structure, principal component analysis, and clustering methods to develop first structural models of engagement and activation.

The results indicate that supporter involvement is multifaceted, encompassing experiential-emotional engagement, digital interaction, economic contribution, and symbolic identification. The dimensions are orthogonal, not hierarchical, highlighting the need for separate analytical and managerial approaches.

This work establishes a robust structural foundation that enhances supporter engagement theory and offers a methodological framework for subsequent empirical investigations. Subsequent study ought to enhance these models to examine causal mechanisms, contextual variables, and policy ramifications.

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