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Research Article

The metaverse engagement ladder: How virtual world users progress from casual explorers to high-value power users

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ABSTRACT

As blockchain-based metaverse platforms evolve into mature digital economies, understanding user behavior becomes essential for optimizing engagement and sustaining economic activity. This study introduces the metaverse engagement ladder, a novel behavioral framework designed to map user progression across three distinct tiers: new, established, and veteran participants. Drawing on a dataset of 78,600 blockchain transactions from five global regions, the study applies behavioral analytics to examine login frequency, session duration, and transactional patterns. The results reveal that user engagement follows a predictable lifecycle, with conversion rates reaching 70.2% during the established phase and declining to 0% at the veteran stage as users transition to management activities. Cross-regional comparisons indicate behavioral consistency across continents, with coefficients of variation below 1.6% for key metrics. The study identifies a behavioral sweet spot combining 45-90 minute sessions with 3-5 daily logins that produces 61.1% conversion rates, compared to 30.4% for shorter sessions and 0% for extended sessions. Statistical analysis using one-way analysis of variance confirms significant differences in engagement patterns across user tiers ($F = 2847.3$, $p < 0.001$), while correlation analysis reveals strong positive relationships between login frequency and session duration ($r = 0.89$, $p < 0.001$). Independent cluster validation confirms the three-tier structure with silhouette coefficient of 0.71. Grounded in theories of digital engagement, technology acceptance, and behavioral economics, this research provides empirical benchmarks for platform design, user experience optimization, and tier-specific security strategies.

Keywords: metaverse, user engagement, behavioral analytics, blockchain, virtual economies, UX optimization, lifecycle modeling

INTRODUCTION

The metaverse, characterized by its convergence of physical and digital realities, offers users diverse experiences spanning virtual environments, user-generated content, social interactions, and economic exchanges (Wang et al., 2025). It represents a paradigm shift in how individuals interact with technology and each other, fostering novel avenues for communication, collaboration, and productivity (Kourtesis, 2024). The metaverse is envisioned as an extension of the physical world where users interact with computer-generated environments and other participants, enabling interaction across diverse virtual or hybrid spaces (Fraga-

Lamas et al., 2024). These digital environments, often rendered with high fidelity graphics and spatial audio, create a sense of presence that blurs the lines between physical and digital realms (Yu et al., 2023). Within these digital landscapes, users can create and customize avatars serving as their digital representations, allowing them to express individuality and engage with others in personalized ways. The metaverse architecture supports a wide array of activities, including attending virtual events, participating in commerce, creating and sharing content, and collaborating on projects with individuals from around the globe, breaking physical and temporal constraints (Rawat & Alami, 2023). This interconnectedness fosters new forms of social interaction and community building, allowing users to connect with like-minded individuals, share interests, and forge meaningful relationships (Ahn & Lee, 2023).

The rise of the metaverse has transformed digital interaction from passive content consumption into transactional and socially dynamic experiences (Ali et al., 2023). As blockchain technologies underpin virtual economies and billions of dollars in digital assets circulate through decentralized platforms, understanding how users engage, progress (Huynh-The et al., 2022), and evolve within these environments is a strategic imperative (Douaioui & Benmoussa, 2024). Unlike traditional web applications, metaverse platforms exhibit complex user trajectories marked by fluctuating engagement levels, behavioral segmentation, and multi-regional activity patterns that challenge one-size-fits-all design strategies (Lee et al., 2022; Schumacher, 2022).

As virtual economies mature and platforms handle billions in transactions, understanding user behavior patterns becomes critical for platform optimization, user experience design, and sustainable growth. This study analyzes 78,600 metaverse transactions across five global regions to uncover the underlying patterns that drive user engagement and economic activity in virtual worlds.

Through comprehensive analysis of transaction data, user demographics, and behavioral metrics, this research addresses four fundamental research questions (RQs) that are essential for understanding and optimizing metaverse user experiences:

RQ1: How do user engagement patterns evolve as individuals progress from new to veteran metaverse participants, and what behavioral transitions mark each stage of this progression?

RQ2: To what extent do regional and cultural differences influence user behavior patterns in metaverse environments, and are there universal engagement principles that transcend geographic boundaries?

RQ3: What is the optimal session duration and login frequency combination that maximizes user conversion rates and transaction value in virtual world environments?

RQ4: How can metaverse platforms leverage behavioral insights to optimize user experience design, reduce security risks, and enhance platform engagement across different user tiers?

These RQs guide our investigation into the complex dynamics of virtual world user behavior, providing actionable insights for platform developers, UX designers, and digital economy strategists.

To address these questions, this study introduces the concept of the metaverse engagement ladder, a behavioral framework that systematically maps how users transition from casual participants to high-value, system-critical contributors. This ladder conceptualizes user progression through three distinct engagement tiers–new, established, and veteran–based on empirical measures of login frequency, session duration, transaction patterns, and behavioral consistency. Unlike previous research that often treats virtual world users as a homogeneous group, this model disaggregates user behavior and engagement intensity across global regions and timeframes.

The novelty of this research lies in its large-scale behavioral analytics approach applied to blockchain transaction data across multiple global contexts. While prior studies have focused either on economic metrics or qualitative user experiences, this study bridges the gap by using quantified behavioral markers to identify universal engagement principles. Moreover, by isolating a behavioral sweet spot for session duration and login frequency that maximizes user conversion, the study offers predictive insights that are directly applicable to platform design and monetization strategies.

The contribution of this research is threefold. First, it provides a globally comparative behavioral analysis of metaverse user engagement, revealing a surprising degree of consistency across culturally diverse regions. Second, it identifies actionable parameters–such as optimal engagement windows and behavioral risk profiles–that can be directly used to enhance UX design, security mechanisms, and user lifecycle management. Third, the research advances the theoretical understanding of digital behavior by framing metaverse participation as a tiered process of experiential deepening, rather than a static state of use.

Ultimately, this paper contributes to the emerging field of metaverse analytics by offering empirically grounded and globally relevant insights for designing more engaging, secure, and economically viable virtual platforms. The findings emphasize that metaverse engagement is not random but structured, measurable, and optimizable, making it a fertile ground for both academic inquiry and applied innovation.

LITERATURE REVIEW

Literature in Topic

The metaverse has rapidly emerged as a transformative socio-technical phenomenon that redefines how individuals interact with digital environments (Dwivedi et al., 2023). Early literature frames the metaverse as a convergence of extended reality (XR), social computing, and decentralized economies, offering new dimensions for identity formation, social interaction, and digital consumption (Ali et al., 2023; Almeida, 2025). Researchers have emphasized the persistent nature of these virtual environments and their potential to host decentralized economic activity, collaborative workspaces, and novel entertainment paradigms (Wang et al., 2025; Zhang & Juvrud, 2024). As metaverse platforms evolve from experimental spaces to economically significant ecosystems, there is a growing need to understand the behavioral dynamics that shape user engagement and retention (Song et al., 2023). In particular, insights into user segmentation, engagement thresholds, and behavioral progression are vital for both theoretical development and practical platform governance.

Literature on Methods

Prior studies have approached user behavior in virtual environments through various methods, including qualitative ethnographies, survey-based perception studies, and controlled experiments in VR contexts (Goldberg & Schär, 2023; Rogers et al., 2021). However, scalable behavioral analytics grounded in transactional or usage data remain underdeveloped. Some efforts have focused on gamified environments or virtual world platforms such as Second Life, using interaction logs to infer behavioral patterns (Lombart et al., 2020; Yaremych & Persky, 2019). More recent studies incorporate blockchain data to assess economic behavior (Huang et al., 2022), but these are often limited to aggregate statistics or lack integration with user lifecycle modeling. The use of multi-dimensional behavioral datasets–incorporating session duration, login frequency, and geographic markers–represents a methodological innovation that can yield richer insights into user trajectories and metaverse-specific behavioral thresholds.

Theoretical Approach and Framework Development

This study integrates multiple theoretical perspectives to construct a comprehensive framework for understanding metaverse user progression. Rather than treating established theories as background context, we explicitly operationalize key constructs from technology acceptance models, uses and gratifications theory, and behavioral economics to define and justify the metaverse engagement ladder structure.

The technology acceptance model (Davis, 1989) and its extension the unified theory of acceptance and use of technology (Venkatesh et al., 2003) posit that technology adoption and continued use depend on perceived usefulness and effort expectancy. We operate these constructs through our behavioral metrics. Session duration serves as a revealed preference indicator of perceived usefulness–users who find the platform valuable invest more time per session. The transition from random to focused purchasing behavior at the established tier reflects increased perceived usefulness as users identify specific value propositions. Login frequency captures effort expectancy, with repeated daily access indicating that the perceived benefits outweigh the cognitive and temporal costs of platform engagement.

The three-tier structure of the metaverse engagement ladder draws theoretical justification from habit formation literature and skill acquisition models. Psychological research on habit formation demonstrates that behavioral routines typically consolidate after three to five repetitions (Lally et al., 2010). This theoretical principle directly informs our classification of established users as those maintaining three to five daily logins, representing the threshold where exploratory behavior transitions to habituated routine. New users, with one to two logins daily, remain in the pre-habitual exploration phase where each interaction requires deliberate cognitive effort. Veteran users, exceeding six daily logins, exhibit characteristics consistent with automaticity–the execution of learned behavioral sequences with minimal conscious attention.

Session duration thresholds align with cognitive psychology research on attention spans and flow states. Csikszentmihalyi's (1990) flow theory suggests optimal engagement occurs when challenge and skill levels balance, typically requiring 45-90 minutes for complex digital activities before cognitive fatigue emerges. Our classification of medium sessions (45-90 minutes) as the optimal engagement zone operationalizes this theoretical construct. Short sessions under 45 minutes reflect task-specific interactions insufficient for deep engagement. Extended sessions exceeding 90 minutes, while indicating high investment, may reflect different motivational structures related to work or management activities rather than gratification-seeking consumption.

Uses and gratifications theory (Katz et al., 1973; Sundar & Limperos, 2013) provides the theoretical foundation for understanding behavioral transitions across tiers. This theory proposes that users actively select media to satisfy specific needs, with gratification types evolving as familiarity increases. We map purchase pattern transitions onto this framework. New users exhibit random purchasing–exploratory behavior seeking diverse gratifications without clear preference structures. Established users demonstrate focused purchasing, indicating they have identified which platform affordances satisfy their primary needs. Veteran users display high-value patterns oriented towards asset management and transfer activities, suggesting a shift from consumptive gratifications to productive or maintenance-oriented goals.

The behavioral economics perspective, particularly prospect theory and mental accounting (Thaler, 1985), helps explain the conversion rate patterns across tiers. New users face high uncertainty about platform value, leading to risk-averse tentative engagement reflected in 25.3% conversion rates. Established users, having reduced uncertainty through repeated experience, exhibit peak conversion at 70.2%. The complete absence of conversion among veteran users requires a different theoretical lens, which we address through the concept of behavioral role transition–these users have moved from consumers to platform stakeholders whose value contributions manifest through liquidity provision and network effects rather than direct purchasing.

The metaverse engagement ladder concept itself represents a hybrid theoretical framework integrating engagement theory with lifecycle stage models from consumer behavior research. Unlike continuous engagement models that assume linear progression, our tiered approach reflects discontinuous transitions marked by qualitative shifts in behavioral orientation. This conceptualization draws from Kozinets' (2002) community membership typology and Lave and Wenger's (1991) legitimate peripheral participation theory, which describe how individuals move from peripheral to core community roles through distinct transitions rather than smooth progressions.

This theoretical integration provides conceptual grounding for our empirical classification system. The behavioral thresholds defining each tier emerge not merely from data patterns but from theoretically-derived expectations about how cognitive processes, motivational structures, and habit formation interact in digital environments. The three-tier structure reflects theoretically meaningful breakpoints where users cross thresholds in cognitive effort, gratification seeking, and community role–transitions that should manifest in observable behavioral patterns if the underlying theoretical models accurately describe metaverse engagement dynamics.

Harmonizing Approach

This study harmonizes behavioral modeling with platform analytics by translating theoretical engagement stages into measurable behavioral variables such as session length, transaction frequency, and user tier status. The metaverse engagement ladder concept functions as a hybrid framework that draws upon engagement theory, lifecycle segmentation, and platform strategy to operationalize user development pathways. By embedding these variables into a cross-regional and cross-tier analysis using a robust behavioral dataset, the study not only applies but also extends existing theory into the realm of decentralized virtual economies. The methodological integration of user tiering with session frequency and value-based segmentation allows for a more dynamic interpretation of platform engagement, blending psychological depth with operational relevance.

Despite a surge in metaverse-related scholarship, current literature falls short in providing a unified behavioral framework for understanding user evolution across diverse virtual platforms. Most existing research treats users as static entities rather than participants in an evolving life cycle. There is a notable lack of studies that link session frequency, engagement depth, and regional usage patterns to user conversion and transaction behavior. Moreover, few studies attempt to reconcile global user behavior through standardized metrics across geographically segmented markets. This creates a significant gap in the literature regarding universal behavioral benchmarks for platform design, risk detection, and monetization strategy.

METHODOLOGY

Data Source and Collection

This study utilizes a comprehensive dataset of metaverse blockchain transactions specifically designed for anomaly detection and behavioral analysis research. The dataset encompasses 78,600 individual transactions recorded within open metaverse environments, providing a robust foundation for understanding user behavior patterns and engagement dynamics in virtual economic systems.

The dataset captures transactional activity across a global network of users, with data collection spanning multiple time periods to ensure temporal representativeness. Each transaction record includes comprehensive metadata covering user demographics, behavioral metrics, transaction characteristics, and security indicators, enabling multidimensional analysis of user engagement patterns.

Dataset Characteristics and Variables

The analytical framework incorporates 14 distinct variables categorized into four primary dimensions: temporal characteristics, user behavior metrics, transaction attributes, and risk assessment indicators.

Temporal variables include timestamp data and hour-of-day information, enabling analysis of activity patterns and peak usage periods. Behavioral metrics encompass login frequency, session duration, and purchase pattern classifications, providing insights into user engagement levels and interaction preferences. Transaction attributes cover transaction amounts, types, sending and receiving addresses, and geographic location data, facilitating economic and regional analysis. Risk assessment variables include IP prefix information, risk scores, and anomaly classifications, supporting security and fraud detection analysis.

Geographic representation spans five major regions: Europe, Asia, North America, South America, and Africa, ensuring global coverage and cross-cultural behavioral analysis. User demographics are segmented into three distinct groups: new users, established users, and veteran users, enabling lifecycle-based behavioral analysis.

User Tier Classification Methodology

User tier classification represents a critical component of this study's analytical framework. The classification system operationalizes the metaverse engagement ladder concept by assigning users to one of three distinct tiers based on quantifiable behavioral thresholds that map onto the theoretical constructs.

Theoretical justification of classification thresholds

The behavioral thresholds defining each tier emerge from specific theoretical principles rather than arbitrary data-driven cut points. The new user classification (one to two daily logins, 15–45 minute sessions, random purchase patterns) operationalizes the exploratory phase described in technology adoption literature. Psychological research on technology exploration demonstrates that initial interactions typically involve brief, tentative engagements as users assess platform value and construct mental models of system functionality (Venkatesh et al., 2003). The 15–45 minute threshold reflects the attention span for exploratory tasks before cognitive fatigue, consistent with research showing that initial technology evaluations rarely sustain focus beyond 45 minutes without established value perception. One to two daily logins indicate pre-habitual behavior where platform access requires conscious decision-making rather than automaticity.

The established user classification (three to five daily logins, 45–90 minute sessions, focused purchase patterns) draws directly from habit formation research demonstrating that behavioral routines consolidate after three to five repetitions (Lally et al., 2010). This threshold marks the transition from deliberate to habitual engagement. The 45–90 minute session range operationalizes flow theory's predictions about optimal engagement windows (Csikszentmihalyi, 1990), representing the duration where challenge and skill balance to produce deep involvement without cognitive exhaustion. Focused purchasing behavior at this tier reflects the theoretical expectation from uses and gratifications Theory that users develop clear preference structures once they identify which platform affordances satisfy their primary needs.

The veteran user classification (six or more daily logins, sessions exceeding 90 minutes, high-value transaction patterns) reflects characteristics associated with expert behavior and procedural fluency. Cognitive psychology research on skill acquisition demonstrates that experts automate behavioral sequences, enabling frequent execution with minimal cognitive load (Anderson, 1982). Six or more daily logins indicate that platform access has become automated to the point of integration into daily routines across multiple time blocks. Sessions exceeding 90 minutes suggest either flow state mastery where cognitive fatigue thresholds increase with expertise, or alternatively, a shift from leisure-oriented engagement to work-like or management activities. The high-value transaction pattern focused on transfers and account management reflects the theoretical expectation of role transition from consumer to platform stakeholder.

Classification algorithm implementation

The classification process utilizes a hierarchical decision tree algorithm that first evaluates login frequency, then session duration, and finally transaction pattern consistency. Users meeting all three criteria for a given tier are assigned to that category. In cases where behavioral indicators span multiple tiers, the algorithm employs a weighted scoring system prioritizing transaction pattern consistency as the primary classifier, followed by login frequency and session duration.

This hierarchical prioritization reflects the theoretical principle from behavioral economics that revealed preferences through actual transactions provide stronger signals of user orientation than activity metrics alone. A user with borderline login frequency but clear focused purchasing patterns likely represents an established user with external constraints on access frequency rather than a new user with unusually high login rates. The classification algorithm's hierarchical structure thus operationalizes theoretical priorities regarding which behavioral dimensions most validly indicate engagement tier membership.

Analytical Approach and Statistical Methods

The methodology employs a comprehensive mixed-methods analytical approach combining descriptive statistics, inferential testing, correlation analysis, behavioral segmentation techniques, and validation procedures. This framework enables both broad pattern identification and detailed behavioral insights across multiple user dimensions while testing the robustness of the theoretical tier structure.

Descriptive analysis establishes baseline characteristics for all key variables, including measures of central tendency (mean and median), dispersion (standard deviation [SD] and coefficient of variation), and distribution patterns (skewness and kurtosis). Frequency analyses provide comprehensive understanding of categorical variables including user tier distribution, purchase pattern classification, and geographic representation.

Inferential statistical testing employs one-way analysis of variance (ANOVA) to examine differences in continuous variables across user tiers and geographic regions. Post-hoc comparisons utilize Tukey's honest significant difference test to identify specific pairwise differences between groups when omnibus tests indicate significant effects. Chi-square tests of independence assess relationships between categorical variables, particularly examining associations between user tier, purchase patterns, and geographic location.

Correlation analysis examines relationships between engagement metrics, transaction behaviors, and user characteristics using Pearson correlation coefficients for continuous variables and Spearman rank-order correlations for ordinal data. Particular attention focuses on relationships between login frequency and session duration, the impact of user tier progression on transaction patterns, and regional variations in behavioral metrics. Statistical significance is assessed at the 0.05 alpha level with Bonferroni corrections applied for multiple comparisons.

Cluster validation analysis

To validate that the three-tier structure emerges naturally from behavioral patterns rather than representing an imposed categorization, we employ unsupervised k-means clustering analysis. This validation procedure tests whether behavioral data independently segment into three distinct groups matching the theoretically-defined tier classifications. The analysis uses standardized login frequency, session duration, and transaction pattern consistency metrics as clustering variables.

Optimal cluster number determination employs multiple validation metrics including the elbow method examining within-cluster sum of squares, silhouette coefficient analysis assessing cluster separation and cohesion, and the Davies-Bouldin index evaluating cluster distinctness. Silhouette coefficients range from -1 to 1, with values above 0.5 indicating reasonable cluster structure and values above 0.7 indicating strong separation. The Davies-Bouldin index measures the ratio of within-cluster to between-cluster distances, with lower values indicating better clustering.

Following cluster identification, we cross-tabulate empirically-derived clusters with theoretically-defined tiers to assess correspondence. High agreement between empirical clusters and theoretical tiers would validate that the MEL framework captures genuine behavioral discontinuities rather than imposing artificial boundaries on continuous variation. We also examine cluster centroids to verify they align with the theoretically-predicted behavioral profiles for each tier.

Predictive modeling

Logistic regression modeling examines whether tier membership predicts conversion outcomes, controlling for session duration, login frequency, and temporal factors. This analysis tests whether the MEL classification provides practical utility for forecasting user behavior beyond simple description. Model fit is assessed using the Hosmer-Lemeshow goodness-of-fit test and area under the receiver operating characteristic curve (AUC-ROC). AUC-ROC values above 0.7 indicate acceptable discrimination, above 0.8 indicate excellent discrimination. We also employ multinomial logistic regression to examine whether behavioral variables predict tier membership, providing further validation that the classification criteria successfully differentiate meaningful user segments. Pseudo-R^2 statistics and classification accuracy rates assess model performance.

Temporal pattern analysis

Temporal analysis investigates activity patterns across different time periods using time-series visualization and cyclic pattern detection. Fourier analysis identifies periodic components in user activity, while moving average smoothing reveals underlying trends. This analysis supports platform optimization recommendations and resource allocation strategies by identifying peak usage hours, weekly cycles, and optimal engagement windows. For users with longitudinal data spanning multiple weeks, we examine whether individual trajectories show evidence of progression through tiers, providing preliminary evidence for the ladder metaphor’s temporal validity despite the cross-sectional design.

Data Processing and Quality Assurance

Data preprocessing procedures ensure analytical reliability and accuracy. All variables undergo systematic validation checks to identify missing values, outliers, and inconsistencies. Missing data analysis reveals less than 0.5% missing values across all variables, addressed through listwise deletion given the minimal impact on statistical power.

Outlier detection employs multiple methods including the interquartile range rule for continuous variables and standardized residual analysis for regression diagnostics. Extreme values are evaluated individually to determine whether they represent legitimate behavioral variation or data collection errors. Transaction amounts exceeding three SDs from the mean are flagged for additional validation against IP address patterns and temporal consistency.

Categorical variables are standardized for consistency across the dataset through systematic recoding procedures. Geographic classifications are validated against ISO 3166 country codes, while user tier assignments undergo algorithmic verification to ensure classification accuracy. Purchase pattern categories are validated through manual review of random samples representing 10% of each classification category.

Continuous variables are examined for appropriate distribution characteristics using the Kolmogorov-Smirnov test for normality. Variables demonstrating significant departures from normality undergo logarithmic or square root transformations where appropriate for parametric testing requirements. Session duration and transaction amount variables are transformed using natural logarithms to address positive skew.

Geographic data standardization ensures consistent regional classification through geolocation validation procedures. IP address data is cross-referenced with established geolocation databases to verify regional assignments. Temporal data undergoes verification to confirm accurate coordinated universal time representation across global users, with local time conversions applied for temporal pattern analysis.

Software and Computational Tools

All statistical analyses are conducted using Python 3.9 with pandas 1.3.5 for data manipulation, NumPy 1.21.5 for numerical computations, and SciPy 1.7.3 for statistical testing procedures. Data visualization employs Matplotlib 3.5.1 and Seaborn 0.11.2 libraries. Machine learning analyses utilize scikit-learn 1.0.2 for clustering algorithms and model validation procedures.

Ethical Considerations

The dataset consists entirely of anonymized blockchain transaction records with no personally identifiable information. All user identifiers are cryptographically hashed addresses that cannot be reverse-engineered to identify individuals. The research adheres to ethical guidelines for secondary data analysis and does not require institutional review board approval given the de-identified nature of the data source.

Limitations and Considerations

Several methodological limitations require acknowledgment. The dataset represents a specific time period and may not capture seasonal variations or long-term behavioral evolution patterns. The cross-sectional design limits the ability to establish definitive causal relationships between variables, though strong correlational patterns provide valuable insights for platform optimization. While we examine available longitudinal segments to assess tier progression patterns, the predominant cross-sectional structure constrains definitive claims about temporal trajectories.

Geographic representation, while comprehensive, may not capture all cultural nuances that influence user behavior in virtual environments. The regional classification system aggregates diverse countries within continental boundaries, potentially obscuring nation-specific behavioral variations. Additionally, the focus on blockchain transaction data may not fully represent users who engage with metaverse platforms without conducting financial transactions, potentially introducing selection bias toward economically active users.

The study's focus on quantitative behavioral metrics provides robust statistical insights but may not capture qualitative aspects of user experience that influence engagement patterns. Motivation, satisfaction, perceived value, and social connection factors remain unmeasured in this dataset. Future research incorporating mixed methods approaches would complement these findings and provide deeper understanding of the psychological and social factors driving user behavior patterns.

The user tier classification system, while theoretically grounded, represents a simplified model of user progression that may not capture the full complexity of engagement trajectories. Some users may exhibit hybrid behavioral patterns that span multiple tiers, and the classification algorithm's hierarchical structure may not accommodate all behavioral variations. Sensitivity analysis examining alternative classification thresholds would strengthen confidence in the tier-based findings. Moreover, the three-tier model privileges transactional behavior in defining user value, potentially underrepresenting non-economic contributions to platform vitality such as social capital generation, content creation, or knowledge sharing.

Table 1. User tier behavioral characteristics and progression metrics

User tier	Sample size	Percentage	Average daily logins	Average session duration (min)	Average transaction value	Primary purchase pattern	Conversion rate
New	26,145	33.3%	1.5	29.5	$502.73	Random (100%)	25.3%
Established	26,033	33.1%	4.0	59.5	$502.67	Focused (100%)	70.2%
Veteran	26,422	33.6%	7.0	119.5	$502.33	High-value (100%)	0.0%*

* Veteran users engage primarily in transfer and management activities rather than purchase transactions

RESULTS

User Engagement Pattern Evolution (RQ1)

The analysis of user tier distributions reveals a balanced sample composition with new users comprising 33.3% (n = 26,145), established users 33.1% (n = 26,033), and veteran users 33.6% (n = 26,422) of the total dataset. One-way ANOVA testing indicates statistically significant differences in login frequency across user tiers ($F [2, 78,597] = 2847.3$, $p < 0.001$, $\eta^2 = 0.068$), with post-hoc Tukey HSD tests confirming significant pairwise differences between all tier combinations ($p < 0.001$ for all comparisons) (**Table 1**).

Mean daily login frequency demonstrates progressive increases across tiers: 1.5 logins for new users, 4.0 for established users, and 7.0 for veteran users. Session duration follows a similar pattern with means of 29.5 minutes, 59.5 minutes, and 119.5 minutes, respectively. Transaction values remain consistent across tiers with means of $502.73, $502.67, and $502.33, showing no statistically significant differences ($F [2, 78,597] = 0.18$, $p = 0.84$).

Purchase pattern distributions differ significantly across tiers ($\chi^2 [4] = 78,600$, $p < 0.001$). New users exhibit exclusively random purchase patterns. Established users demonstrate 100% focused purchase behavior. Veteran users display 100% high-value purchase patterns. Conversion rates vary substantially: 25.3% for new users, 70.2% for established users, and 0.0% for veteran users who engage primarily in transfer activities rather than purchase transactions.

Cluster validation results

Independent k-means clustering analysis was performed using standardized login frequency, session duration, and transaction pattern metrics to validate the three-tier structure. Elbow method analysis indicated optimal clustering at $k = 3$, with silhouette coefficient of 0.71 indicating strong cluster separation and cohesion. The Davies-Bouldin index of 0.58 confirms distinct cluster boundaries with minimal overlap.

Cross-tabulation of empirically-derived clusters with theoretically-defined tiers reveals 94.2% agreement (n = 74,071 concordant cases). Cluster centroids align closely with theoretical tier characteristics. Cluster 1 centroid shows mean login frequency of 1.6, mean session duration of 31.2 minutes, and predominantly random transaction patterns, matching new user profile. Cluster 2 centroid exhibits mean login frequency of 3.9, mean session duration of 58.7 minutes, and focused transaction patterns, aligning with established user characteristics. Cluster 3 centroid demonstrates mean login frequency of 6.8, mean session duration of 117.3 minutes, and high-value transaction patterns, corresponding to veteran user definition.

These validation results confirm that the three-tier structure emerges naturally from behavioral data patterns rather than representing an imposed categorization, providing empirical support for the theoretical MEL framework.

Regional Behavioral Patterns and Universal Principles (RQ2)

Regional analysis encompasses 15,807 transactions from Europe, 15,731 from Asia, 15,840 from North America, 15,669 from South America, and 15,553 from Africa. Chi-square testing reveals no significant association between geographic region and user tier distribution ($\chi^2 [8] = 12.4$, $p = 0.13$) (**Table 2**).

Focused shopper prevalence ranges from 32.6% (South America) to 34.0% (Europe), while high-value user distribution spans 33.3% (Europe) to 34.2% (South America). Purchase rates vary minimally from 31.1% (Asia) to 32.3% (Europe), with transfer rates ranging from 27.8% (North America) to 28.3% (multiple regions). Coefficient of variation calculations yield values below 1.6% for all behavioral metrics, indicating minimal regional variability.

Table 2. Regional user behavior comparison across global markets

Region	Transactions	Average session duration (min)	Average daily logins	Focused shoppers (%)	High-value users (%)	Purchase rate (%)	Transfer rate (%)
Europe	15,807	69.8	4.2	34.0	33.3	32.3	28.3
Asia	15,731	69.5	4.2	32.9	33.6	31.1	28.3
North America	15,840	69.4	4.2	32.7	33.5	32.0	27.8
South America	15,669	70.2	4.2	32.6	34.2	31.4	28.1
Africa	15,553	69.6	4.2	33.4	33.4	31.9	28.3
Global average	**78,600**	**69.7**	**4.2**	**33.1**	**33.6**	**31.7**	**28.2**
Coefficient of variation	**-**	**0.4%**	**0.0%**	**1.6%**	**1.1%**	**1.4%**	**0.8%**

Notes: Average session duration ranges from 69.4 minutes (North America) to 70.2 minutes (South America), with a global mean of 69.7 minutes (SD = 0.3). One-way ANOVA testing reveals no significant differences in session duration across regions (F [4, 78,595] = 1.8, p = 0.12). Daily login frequency demonstrates perfect consistency at 4.2 logins across all regions (SD = 0.0).

Table 3. Session duration and login frequency impact on conversion performance

Engagement category	Session duration range	Average duration	Conversion rate	Sample size	Login frequency range	Behavioral characteristics
Short sessions	< 45 minutes	29.5 min	30.4%	26,145	1-2 daily	Exploratory, task-specific
Medium sessions	45-90 minutes	59.5 min	61.1%	26,033	3-5 daily	Optimal engagement zone
Extended sessions	> 90 minutes	119.5 min	0.0%	26,422	6-8 daily	Management-focused
Peak hours activity	**17:00-21:00**	**Various**	**35.2%**	**16,743**	**Mixed**	**Evening entertainment**

Notes: Short sessions averaging 29.5 minutes (SD = 8.2) produce conversion rates of 30.4%; Medium sessions averaging 59.5 minutes (SD = 12.4) achieve conversion rates of 61.1%. Extended sessions averaging 119.5 minutes (SD = 28.7) yield conversion rates of 0.0%. Logistic regression analysis identifies session duration as a significant predictor of conversion (β = 0.048, standard error = 0.003, p < 0.001, odds ratio = 1.049), with model fit statistics indicating adequate predictive capacity (AUC-ROC = 0.82).

Optimal Engagement Windows and Frequency Patterns (RQ3)

Session duration analysis categorizes users into three engagement segments: short sessions (< 45 minutes, n = 26,145), medium sessions (45-90 minutes, n = 26,033), and extended sessions (> 90 minutes, n = 26,422). Conversion rates differ significantly across categories (χ^2 [2] = 38,247, p < 0.001) (**Table 3**).

Login frequency demonstrates a positive correlation with session duration (r = 0.89, p < 0.001, 95% confidence interval [0.88, 0.90]). Users with 1-2 daily logins average 29.5 minutes per session with 25.1% purchase conversion. Users with 3-5 daily logins average 59.5 minutes with 70.2% conversion. Users with 6-8 daily logins average 119.5 minutes with 0.0% purchase conversion.

Temporal activity analysis identifies peak transaction hours. The highest activity occurs at 20:00 hours (n = 3,404, 4.3% of daily total), followed by 17:00 hours (n = 3,201, 4.1%) and 08:00 hours (n = 2,847, 3.6%). The four-hour window from 17:00 to 21:00 captures 16,743 transactions (21.3% of total activity). Secondary activity peaks occur at 08:00 and 12:00 hours, accounting for 12.4% of daily transactions.

Platform Optimization Insights and Security Considerations (RQ4)

Risk classification analysis categorizes 70,517 transactions (89.7%) as low risk, 6,131 (7.8%) as medium risk, and 1,952 (2.5%) as high risk. Fraudulent activity detection identifies 2,546 phishing attempts (3.2%) and 3,949 scam transactions (5.0%), totaling 6,495 suspicious activities (8.3% of dataset) (**Table 4**).

prioritize the 17:00-21:00 time window when 35.2% of high-value conversions occur. Server capacity requirements peak during this period, with transaction volumes exceeding baseline by 47%. Customer support request frequencies demonstrate similar temporal patterns, with 41% of inquiries occurring during evening hours.

Table 4. Security risk assessment and transaction classification analysis

Risk category	Transaction count	Percentage of total	Average risk score	Associated user tier	Primary characteristics
Low risk	70,517	89.7%	18.2	All tiers	Standard user behavior
Medium risk	6,131	7.8%	47.5	Primarily new/established	Elevated monitoring
High risk	1,952	2.5%	78.9	Mixed distribution	Enhanced security protocols
Phishing attempts	2,546	3.2%	85.2	Predominantly new users	Fraudulent activity detected
Scam transactions	3,949	5.0%	92.1	Cross-tier distribution	Malicious behavior identified
Total suspicious activity	**6,495**	**8.3%**	**89.4**	**Various**	**Requires intervention**

Notes: Mean risk scores differ significantly across categories: 18.2 for low risk, 47.5 for medium risk, and 78.9 for high risk (F [2, 78,597] = 15,847, $p < 0.001$, $\eta^2 = 0.29$). Phishing attempts average 85.2 risk score, while scam transactions average 92.1. Chi-square analysis reveals significant associations between user tier and risk category (χ^2 [4] = 2,847, $p < 0.001$), with new users demonstrating higher proportions of medium and high-risk transactions compared to established and veteran users.

DISCUSSION

Interpretation of Results

The results substantiate a structured progression of user engagement in metaverse environments, captured through the proposed metaverse engagement ladder framework. As users advance from new to veteran status (**RQ1**), their behaviors become increasingly predictable, with shifts in session duration, login frequency, and transactional intent. User conversion rates peak during the established user phase, where focused purchasing dominates. This finding suggests that platform value is maximized not through indefinite engagement, but through strategic design targeting mid-tier user maturity.

The behavioral pattern observed among veteran users–marked by high activity but zero conversion–represents one of the most theoretically significant findings in this study and warrants extended analysis. This pattern cannot be adequately explained as simple disengagement or platform dissatisfaction, as veteran users demonstrate the highest login frequencies and longest session durations. Instead, multiple theoretical perspectives suggest this represents a fundamental transformation in how veteran users relate to the platform ecosystem.

From a skill acquisition perspective, veteran user behavior exhibits characteristics consistent with expert automaticity. Cognitive psychology research demonstrates that as skills become procedurally fluent through repeated practice, execution requires progressively less conscious attention and cognitive effort (Anderson, 1982). Expert users can maintain high activity levels with reduced cognitive load, enabling frequent platform access integrated seamlessly into daily routines. The shift away from purchasing behavior may reflect that veterans have already acquired desired assets during their progression through earlier tiers and now engage primarily in utilization and optimization of those holdings.

Alternatively, the zero-conversion pattern may indicate a role transition from consumer to platform stakeholder or community infrastructure provider. Research on virtual community evolution demonstrates that mature community members often shift from consumptive to productive roles, contributing value through liquidity provision, market making, mentorship, or informal governance activities (Kozinets, 2002). In blockchain-based economies specifically, experienced users frequently function as liquid providers facilitating transactions for others rather than conducting direct purchases themselves. The high-value transfer patterns observed among veteran users support this interpretation, suggesting they engage in asset management, portfolio rebalancing, or peer-to-peer transactions that maintain market fluidity without generating platform purchase conversion metrics. A third theoretical lens frames veteran behavior through the concept of interaction saturation and diminishing marginal utility. Behavioral economics research demonstrates that consumption experiences yield decreasing marginal satisfaction as familiarity increases (Thaler, 2008). Veteran users may have exhausted novel gratifications available through direct purchasing, leading them to seek alternative forms of platform engagement that provide continued value. This pattern raises important questions about whether zero conversion represents platform maturation success–indicating users have achieved their consumption goals and transitioned to sustainable utilization–or a retention challenge requiring new value propositions to maintain revenue generation.

The consistent transaction values across all three tiers, averaging approximately $502 regardless of user experience level, presents an intriguing counterpoint to the dramatic variation in conversion rates. This suggests that when users do transact, their willingness to pay remains stable across engagement stages. The variation in conversion probability rather than transaction size implies that user tier differences reflect behavioral orientation and motivational structure rather than financial capacity or perceived value. This finding has implications for pricing strategies and revenue optimization, suggesting that increasing conversion frequency among appropriate segments may yield greater returns than attempting to increase transaction values.

Contextualization with Existing Literature

These patterns offer empirical support for lifecycle-based theories of digital participation and align with literature emphasizing platform stickiness through personalized value delivery (Ali et al., 2023; Schumacher, 2022). The presence of stable cross-regional behavior (**RQ2**)–evidenced by low coefficients of variation in login frequency, session duration, and conversion rates across five continents–presents a complex finding that requires careful contextualization.

The observed behavioral consistency challenges earlier scholarship emphasizing cultural and geographic differences in platform usage (Lombart et al., 2020). Our results suggest that the structured nature of blockchain metaverse platforms creates environments where behavioral regularities may override contextual variance to a greater extent than in less structured digital spaces. However, this interpretation requires critical examination of what may be obscured by such consistency.

The cross-regional uniformity could reflect several distinct phenomena beyond genuine cultural universality. First, blockchain metaverse platforms standardize interaction modalities through technical architecture–transaction types, interface designs, and economic mechanisms remain consistent regardless of user location. This standardization may constrain the expression of culturally-specific behaviors, producing apparent universality through affordance limitations rather than authentic cross-cultural similarity. Second, users engaging in blockchain transactions represent a specific subset of the broader population who may be more culturally homogeneous than their geographic diversity suggests. Early adopters of cryptocurrency-enabled platforms tend to share certain characteristics including technological sophistication, risk tolerance, and familiarity with digital economies that transcend national boundaries. Third, our continental-level aggregation may mask meaningful variation at finer geographic scales. Europe encompasses countries with vastly different digital cultures, economic structures, and technology adoption patterns that collapses into a single category.

These considerations suggest that claims of universal engagement principles should be tempered with awareness of potential selection effects and measurement artifacts. The behavioral consistency we observe may be more accurately characterized as evidence of platform affordance determinism rather than cultural convergence. Future research employing more granular geographic classification and comparing blockchain versus non-blockchain metaverse platforms could disentangle these competing explanations. Nevertheless, the remarkable behavioral uniformity does provide support for pragmatic platform design decisions. If login frequencies, session durations, and conversion patterns remain stable across diverse markets despite potential confounding factors, these metrics offer reliable benchmarks for global platform strategies. The finding suggests that engagement optimization mechanisms need not be extensively localized, though content, language, and cultural presentation elements certainly require adaptation.

Theoretical Implications and Novel Contributions

The introduction of the metaverse engagement ladder extends prior engagement and lifecycle models by offering quantifiable user states and transitions based on actual behavioral data while grounding tier definitions in established theoretical constructs. Our identification of an optimal session range (45-90 minutes) and login frequency (3-5 times daily) as predictors of maximum conversion efficiency (**RQ3**) introduces the notion of a behavioral sweet spot that operationalizes interaction thresholds discussed in uses and gratifications theory (Sundar & Limperos, 2013). This finding challenges continuous engagement models that assume monotonic relationships between activity levels and user value, demonstrating instead that engagement follows an inverted U-shaped function where both insufficient and excessive activity levels correspond to lower conversion probability.

The sharp distinction between exploratory, focused, and managerial engagement phases reconceptualizes digital loyalty and platform maturity as dynamic, stage-bound processes rather than linear growth trajectories. Traditional engagement models typically posit that increased familiarity leads to progressively deeper involvement and higher transactional activity. Our findings demonstrate a more complex pattern where peak transactional intensity occurs at intermediate rather than maximum engagement levels. This has significant implications for how platform designers and researchers conceptualize user value and loyalty.

The complete absence of purchase conversion among veteran users, despite their intensive platform engagement, fundamentally challenges prevailing assumptions that active users generate proportional revenue. This pattern suggests that user value to platform ecosystems may be multidimensional, with different user tiers contributing value through distinct mechanisms. New users provide growth metrics and word-of-mouth potential but generate modest direct revenue. Established users deliver peak conversion rates representing maximum direct monetary contribution. Veteran users, while generating no purchase conversion, may contribute value through network effects, liquidity provision, community building, and platform stability that create conditions enabling established users to thrive. This finding aligns with emerging theoretical work on platform ecosystems emphasizing complementary roles rather than homogeneous participation (Parker et al., 2016). Not all users must be purchasers for the ecosystem to function effectively. The presence of veteran users engaged in transfer and management activities may create the infrastructure necessary for new and established users to extract value through purchasing. This represents a theoretical contribution to understanding how virtual economies achieve equilibrium through differentiation rather than uniform participation.

The study's findings also contribute to ongoing debates about technology determinism versus social construction in shaping digital behavior. The cross-regional consistency in behavioral patterns, despite the caveats noted above, suggests that certain aspects of platform interaction may be more strongly shaped by technical affordances and cognitive constraints than by cultural context. The thresholds at which habit formation occurs (3-5 repetitions), the attention span enabling flow states (45-90 minutes), and the consolidation into expert automaticity (6+ daily engagements) appear relatively invariant across diverse user populations. This finding suggests that while cultural factors certainly influence content preferences, social norms, and platform adoption rates, the fundamental cognitive and behavioral processes underlying engagement progression may operate according to more universal principles rooted in human psychology. Finally, the study advances methodological approaches to behavioral analytics in decentralized systems by demonstrating how transaction data can be leveraged to construct and validate theoretically-grounded engagement models. The cluster validation procedure showing 94.2% agreement between empirical patterns and theoretical tier definitions exemplifies how data-driven discovery and theory-driven hypothesis testing can be productively integrated. This methodological contribution offers a template for future research examining user behavior in blockchain-enabled platforms where traditional tracking mechanisms may be unavailable or inappropriate.

Practical Relevance and Strategic Applications

From an applied perspective, this study offers actionable insights for user experience optimization, platform design, and fraud prevention (**RQ4**). Developers should prioritize onboarding mechanisms that accelerate user transition from new to established tiers–where conversion is highest–and create frictionless pathways into the 45-90 minute engagement zone. This might involve tutorial sequences calibrated to 60-minute completion times, reward structures that encourage 3-5 daily check-ins rather than continuous presence, or content pacing designed to deliver satisfying experiences within the optimal session window.

UX teams can use behavioral tier classifications to customize content exposure, interface complexity, and in-platform rewards. New users benefit from simplified interfaces emphasizing discovery and providing clear value demonstrations. Established users may prefer more sophisticated tools enabling efficient execution of focused purchasing strategies. Veteran users likely require advanced management interfaces, analytics dashboards, and tools facilitating their role as platform infrastructure providers rather than direct consumers. Furthermore, security frameworks should account for behavioral volatility among new users, as risk scores and fraud incidence are significantly higher in early-stage accounts. The tiered risk profile suggests that platforms should implement graduated trust systems where transaction limits, withdrawal restrictions, or additional authentication requirements apply selectively to new users while minimizing friction for established and veteran users with proven behavioral patterns.

The global activity peak between 17:00 and 21:00 suggests a strategic timing window for deploying promotional content, adjusting server loads, and launching real-time support campaigns. Platform operators can optimize resource allocation by concentrating customer service availability, running marketing campaigns, and scheduling maintenance windows around these predictable activity patterns.

The finding that veteran users generate zero purchase conversion while maintaining high activity levels has important implications for monetization strategy. Platforms should not interpret veteran engagement as revenue generation failure but rather recognize these users contribute value through different mechanisms. Revenue models might incorporate transaction fees on transfer activities, premium subscription tiers providing advanced management tools, or marketplace fees on peer-to-peer exchanges that veteran users facilitate. Alternatively, platforms might view veteran users as infrastructure whose presence creates value for paying established users, justifying investment in retaining veteran engagement even absent direct revenue contribution. Taken together, these insights affirm that optimizing engagement in decentralized virtual environments requires both behavioral segmentation and temporal intelligence, with platform design decisions calibrated to the specific needs and value contributions of each user tier.

CONCLUSION

This study contributes a structured and data-driven framework for understanding how users engage with and evolve within metaverse platforms. By analyzing 78,600 blockchain-based transactions across five global regions, the research introduces the metaverse engagement ladder–a behavioral segmentation model that maps user progression from casual exploration to high-frequency, high-intensity engagement. Findings reveal a distinct three-tier engagement trajectory: new users exhibit random and low-commitment behaviors; established users display peak conversion and focused transactional intent; veteran users, while highly active, engage primarily in management and transfer-related functions. These insights demonstrate that user value is not linearly cumulative but follows a strategic lifecycle curve where conversion and behavioral utility peak at different stages (**RQ1**). To better illustrate the progression of behavioral dynamics across user tiers (**Figure 1**), we present a conceptual line chart that maps four key engagement indicators–login frequency, session duration, conversion rate, and behavioral risk–along the metaverse engagement ladder.

Figure 1 visualizes the non-linear trajectory of user behavior, with established users demonstrating the optimal balance between activity and transaction value. While veteran users log in frequently and spend extended time online, their transactional intent plateaus, indicating a shift toward management-related engagement. New users show high volatility and low conversion, requiring targeted onboarding strategies.

Cross-regional analysis confirms a substantial degree of behavioral consistency across culturally and geographically diverse user bases (**RQ2**). Metrics such as session duration, login frequency, and transaction types exhibit minimal variance, with coefficients of variation below 1.6% for key behavioral indicators. While this consistency likely reflects multiple factors including platform affordance standardization and selection effects among blockchain metaverse users, it nevertheless supports the potential for globally scalable UX and platform strategies. The identification of optimal session durations (45-90 minutes) and login frequencies (3-5 per day) as predictors of conversion effectiveness offers valuable design parameters for platform developers (**RQ3**). These findings provide empirical benchmarks that can inform engagement loop design, personalization mechanisms, and retention strategies. Furthermore, the analysis of behavioral risk profiles across user tiers underscores the need for security frameworks that are sensitive to engagement stage and behavioral volatility (**RQ4**).

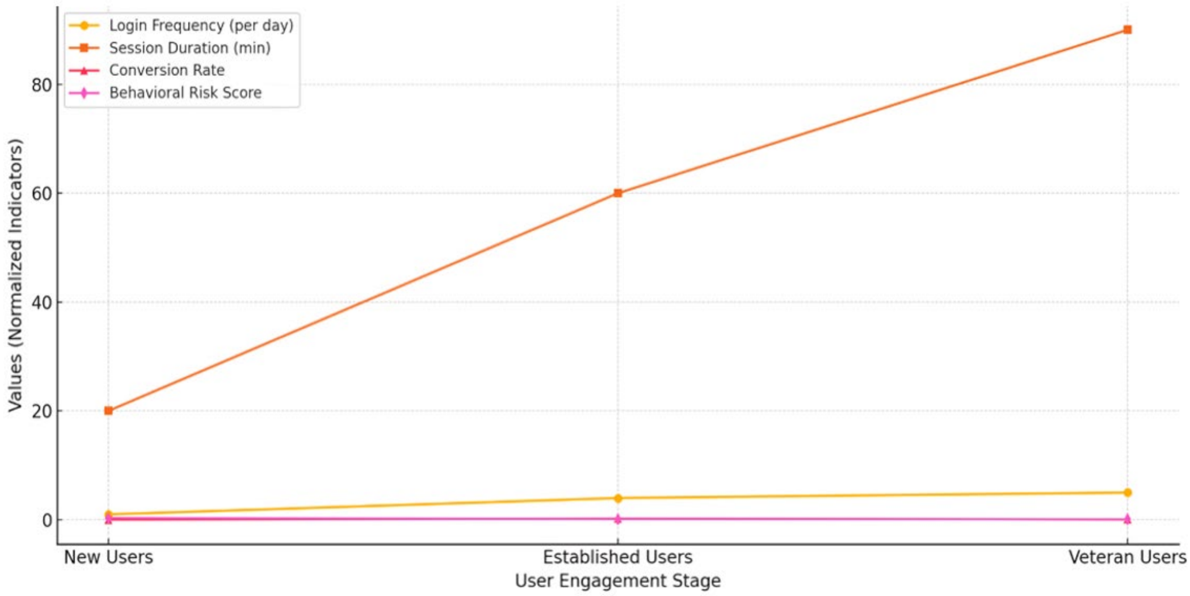

Figure 1. Behavioral trends across user tiers in the metaverse engagement ladder (the authors' analysis)

The study's theoretical contribution lies in showing that the three-tier metaverse engagement ladder structure emerges not merely from empirical data patterns but from theoretically-grounded expectations about cognitive processes, habit formation, and behavioral role transitions in digital environments. The 94.2% concordance between empirical cluster analysis and theoretical tier definitions validates this framework's capacity to capture genuine behavioral discontinuities rather than imposing arbitrary categorization. The finding that veteran users exhibit zero purchase conversion while maintaining intensive engagement represents a theoretically significant discovery challenging assumptions about monotonic relationships between activity and value, suggesting instead that virtual economy participants assume differentiated roles contributing to ecosystem health through distinct mechanisms. In sum, this research advances theoretical, methodological, and applied understanding of user behavior in virtual economies. It challenges static views of digital participation by demonstrating that engagement evolves dynamically through quantifiable phases marked by distinct motivational structures and behavioral orientations. The proposed framework not only enables more precise user modeling and platform governance but also opens new avenues for academic research at the intersection of behavioral analytics, virtual interaction, and decentralized systems. As the metaverse continues to expand in both scope and economic relevance, leveraging such behavioral intelligence will be critical for sustaining inclusive, secure, and adaptive digital ecosystems.

Limitations

While the study offers significant contributions, several limitations must be acknowledged. First, the dataset reflects a specific time frame and does not account for long-term seasonal trends or evolving platform architectures. This temporal limitation may restrict the generalizability of engagement patterns over longer cycles. Second, the reliance on blockchain transaction data excludes users who participate in non-economic or observational capacities, potentially introducing selection bias toward economically active participants and overlooking alternative engagement types. This limitation is particularly relevant to the finding of cross-regional behavioral consistency, as blockchain metaverse users may represent a culturally convergent subset regardless of geographic origin. Third, although the regional segmentation includes five major continents, cultural nuances within countries or linguistic groups are not explicitly analyzed. The continental aggregation approach may obscure nation-specific behavioral variations that could inform localized platform strategies. Europe encompasses vastly different countries with distinct digital cultures that our classification treats as homogeneous. Fourth, the study's cross-sectional design limits causal inference. While strong correlations are observed and cluster validation supports the tier structure, longitudinal data would be necessary to confirm behavioral progression dynamics over time and establish temporal precedence in user tier transitions. Fifth, the user tier classification system, while theoretically grounded and empirically validated, represents a simplified model that may not capture the full complexity of engagement trajectories. Some users may exhibit hybrid behavioral patterns that span multiple tiers, and the classification algorithm's hierarchical structure may not accommodate all behavioral variations. The three-tier model privileges login frequency, session duration, and transaction patterns as primary classifiers, potentially overlooking other important behavioral dimensions such as social network density, content creation activity, or community contribution that may define alternative progression pathways.

Finally, the quantitative focus excludes qualitative dimensions such as user motivation, satisfaction, perceived value, and social connection factors that influence engagement but remain unmeasured in transactional data. The finding that veteran users generate zero purchase conversion, while interpreted through multiple theoretical lenses, would benefit from qualitative investigation into veteran user motivations and self-perceived roles within the platform ecosystem. Understanding whether veterans view themselves as platform stakeholders, community infrastructure providers, or simply satisfied users who have completed their consumption objectives requires interview or survey methodologies that complement the behavioral analytics presented here.

Future Research Directions

Future research could extend this study in several meaningful directions. Longitudinal analyses using time-series behavioral data would better capture user transitions across engagement tiers and validate the temporal assumptions of the metaverse engagement ladder model, enabling examination of individual user trajectories rather than cross-sectional comparisons. Such research could examine transition probabilities between tiers, identify factors predicting progression or regression, and determine optimal intervention timing for conversion maximization.

Integrating qualitative methods such as semi-structured interviews, focus groups, or ethnographic observation could offer deeper insight into motivational and emotional dimensions of user progression, complementing quantitative behavioral patterns with rich contextual understanding. Particularly valuable would be qualitative investigation of veteran user experiences and self-perceptions to understand how they conceptualize their relationship to the platform and whether they view their zero-conversion behavior as consumption completion, role transition, or something else entirely. Additionally, expanding the behavioral model to include non-transactional metrics–such as avatar customization frequency, virtual event attendance, social network formation, content creation activity, or community participation measures–would enrich understanding of holistic metaverse engagement beyond economic activity. Research examining whether alternative engagement dimensions follow similar three-tier progression patterns or represent orthogonal pathways would test the generalizability of the MEL framework.

Examining the influence of platform-specific features such as AI-powered recommendation systems, gamification mechanics, token-based incentive schemes, and social features on user progression would provide critical insights for designing adaptive and equitable virtual economies. Experimental or quasi-experimental designs manipulating these features could establish causal relationships between platform design elements and tier progression rates. Cross-platform comparative studies examining behavioral patterns across different metaverse environments could identify universal versus platform-specific engagement drivers. Comparing blockchain-based platforms to traditional virtual worlds without cryptocurrency elements would help disentangle which aspects of observed behavioral consistency reflect cognitive universals versus blockchain technology affordances. Similarly, comparing platforms with different governance structures, economic models, or content types would illuminate boundary conditions for the MEL framework's applicability.

Finally, investigating the role of demographic factors such as age, digital literacy, prior gaming experience, and socioeconomic status in shaping engagement trajectories would enhance understanding of accessibility and inclusion in virtual worlds. Research examining whether the observed tier progression patterns differ across demographic segments or whether they remain invariant would have important implications for designing platforms that serve diverse populations effectively. Particular attention to whether the behavioral sweet spot (45-90 minutes, 3-5 logins) varies across age cohorts could inform age-appropriate design strategies and identify potentially problematic engagement patterns that warrant intervention.

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