Clustering Digital Governance Adoption Patterns in the Metaverse Using K-Means and DBSCAN Algorithms

Andree Emmanuel Widjaja[1], Hery[2], Guevara Ananta Toer[3,*]

[1,2] Department of Information Systems, Pelita Harapan University, Jalan M.H. Thamrin Boulevard No.1100 Lippo Karawaci, Tangerang, 15811, Indonesia

[3] Department of Accounting, Diponegoro University, Indonesia

ABSTRACT

The rapid advancement of immersive digital environments has accelerated global interest in leveraging metaverse technologies as extensions of public governance systems. This study analyses citizen readiness and perception toward metaverse-based digital governance in The Gambia using two unsupervised machine learning algorithms: K-Means and DBSCAN, applied to a dataset of 115 survey responses. After preprocessing and feature standardization, the K-Means algorithm identified two distinct adoption clusters, consisting of Cluster 0 with 76 respondents and Cluster 1 with 39 respondents. The centroid projections in PCA space revealed a clear behavioural separation, with Cluster 1 exhibiting a substantially higher mean PC1 score (2.5270) compared to Cluster 0 (–1.2968), indicating stronger readiness, optimism, and trust among respondents in the former group. In contrast, DBSCAN produced a single dominant cluster of 107 respondents and identified 8 outliers, suggesting a generally cohesive perception landscape with a small number of respondents expressing atypical attitudes toward metaverse-enabled governance. Collectively, these findings demonstrate that while public sentiment toward metaverse governance is broadly aligned, significant intra-group differences exist, making behavioural segmentation crucial for informing policy strategies. The results underscore the need for tailored approaches that address both enthusiastic adopters and more cautious individuals to support equitable and inclusive metaverse governance adoption.

Keywords Metaverse Governance, Clustering Analysis, K-Means, DBSCAN, Digital Adoption Patterns

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Corresponding author
Guevara Ananta Toer,
jovaratoer@gmail.com

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INTRODUCTION

The emergence of the metaverse as a multidimensional digital ecosystem has accelerated interest in its application beyond entertainment and commercial domains, extending into critical public sector functions and digital governance models [1]. Unlike conventional e-government platforms that primarily rely on two-dimensional interfaces, the metaverse enables immersive, persistent, and interactive environments that support real-time citizen engagement, virtual public service delivery, and decentralized administrative processes [2]. Governments worldwide are beginning to recognize the transformative potential of this technology to enhance inclusivity, transparency, and service efficiency, particularly as digital interactions become increasingly central to civic life in the post-pandemic era [3].

The integration of metaverse technologies into governance frameworks carries significant promise for developing countries. In contexts such as The Gambia,

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where infrastructural limitations and administrative inefficiencies often hinder effective governance, immersive digital systems could provide alternative avenues for delivering services, disseminating information, facilitating participation, and strengthening institutional trust [4]. However, the successful adoption of metaverse-enabled governance depends heavily on citizen readiness, perceptions of technological value, and confidence in the state's ability to deploy advanced digital tools sustainably and responsibly [5]. Without understanding these underlying attitudes, metaverse initiatives may risk low adoption rates, citizen resistance, or unintended inequality in access and participation.

Existing research on digital governance has predominantly examined traditional e-government systems, focusing on determinants such as perceived ease of use, trust, digital literacy, privacy concerns, and institutional performance [6]. These studies have provided valuable insights, yet they may not fully capture the complexities introduced by immersive virtual environments. The metaverse introduces additional layers of interaction, such as avatar-mediated communication, virtual identity management, spatial navigation, and the use of blockchain or decentralized technologies for verification and security [7]. As a result, public attitudes toward metaverse governance may vary across behavioural, psychological, and technological dimensions that differ substantially from those observed in conventional digital platforms.

Furthermore, little is known about how populations in low- and middle-income countries perceive the potential transition toward immersive digital governance. Unlike technologically advanced nations with high levels of digital readiness, countries like The Gambia face structural challenges, including limited broadband access, affordability constraints, uneven digital literacy, and persistent scepticism toward emerging technologies [8]. These contextual factors underscore the need for empirical studies that investigate citizen segmentation and behavioural clustering to understand the diversity of adoption patterns.

To address this gap, the present research employs unsupervised machine learning techniques, specifically K-Means and DBSCAN clustering algorithms, to identify distinct patterns of citizen readiness toward metaverse governance. Using a dataset of 115 respondents, the study analyses demographic features, perceptions of trust, expectations of metaverse benefits, and concerns regarding privacy and security. The K-Means algorithm produced two distinct clusters, with Cluster 0 containing 76 respondents and Cluster 1 containing 39 respondents, indicating divergent levels of optimism and preparedness toward metaverse governance. Meanwhile, the DBSCAN algorithm identified one main cluster of 107 respondents and eight outlier respondents, suggesting that while the majority of perceptions are aligned, a minority group exhibits markedly different attitudes.

By uncovering these behavioural clusters, this study contributes to the growing scholarly discourse on immersive governance systems and provides practical insights for policymakers. Understanding citizen segmentation enables governments to craft targeted communication strategies, develop differentiated digital literacy programs, and design more inclusive and context-responsive metaverse governance frameworks. Moreover, the empirical evidence generated through clustering analysis enhances the theoretical understanding of metaverse adoption by highlighting the multidimensional nature of public attitudes in emerging digital societies.

Literature Review

The rapid advancement of immersive technologies has expanded the conceptual landscape of digital governance, introducing new approaches that integrate virtual worlds, augmented environments, and decentralized systems [9]. The metaverse, broadly defined as a persistent and interconnected virtual ecosystem, has emerged as a transformative medium capable of reshaping how governments interact with citizens through immersive services, three-dimensional interfaces, and personalized administrative experiences [10]. Compared with traditional e-government models, metaverse governance promotes enhanced interactivity, presence, and real-time communication, which can improve both accessibility and transparency in public service delivery [11].

A growing body of literature highlights that the metaverse is supported by multiple enabling technologies, including Virtual Reality (VR), Augmented Reality (AR), Artificial Intelligence (AI), and blockchain-based verification infrastructures [12]. These components facilitate the creation of secure, user-driven virtual environments where public institutions and citizens can interact with greater autonomy and trust. Researchers argue that immersive governance frameworks can strengthen civic participation, streamline administrative processes, and increase government accountability when implemented within an inclusive and citizen-centric paradigm [13]. However, the adoption of such systems also raises concerns related to digital privacy, cybersecurity risks, virtual identity management, and the ethical implications of immersive interactions [14].

Although substantial research has examined factors affecting the adoption of traditional e-government systems, such as trust, usability, perceived usefulness, and digital competence [15]. Scholars emphasize that the transition to metaverse-based governance introduces additional challenges. Immersive service environments demand higher levels of technological literacy, familiarity with spatial interfaces, and comfort with virtual identity mechanisms, differentiating them substantially from conventional two-dimensional platforms [16]. Consequently, understanding citizen readiness for metaverse governance requires analytical approaches that move beyond linear adoption models.

Machine learning–based clustering methods have increasingly been used to examine multi-dimensional adoption patterns in digital transformation research. Algorithms such as K-Means and DBSCAN are particularly effective for segmenting heterogeneous populations, detecting non-linear adoption structures, and identifying outlier behaviours in citizen technology engagement [17]. K-Means partitions data into homogeneous groups based on distance metrics, while DBSCAN is well-suited for identifying irregularly shaped clusters and distinguishing core users from anomalous respondents [18]. Prior studies demonstrate that clustering techniques enable researchers and policymakers to uncover latent behavioural segments, thereby improving the precision of digital transformation strategies [19].

Despite the global momentum toward metaverse innovation, empirical research examining public adoption of metaverse governance in developing countries remains scarce. Socio-economic factors such as infrastructural constraints, unequal access to digital tools, and varying levels of trust in governmental institutions significantly shape citizens' attitudes toward emerging technologies [20]. These contextual realities highlight the need for analytical studies focusing on segmented adoption dynamics, particularly using computational methods that can capture complex behavioural variations. Addressing this gap, the present study applies both K-Means and DBSCAN algorithms to identify distinct adoption clusters among Gambian citizens, thereby enriching the academic discourse and supporting evidence-based metaverse governance planning.

Methodology

The methodological framework of this study followed a systematic computational pipeline designed to uncover behavioural patterns in citizen readiness toward metaverse-based digital governance. The overall research workflow, illustrated in figure 1. Research Steps encompasses data preprocessing, feature transformation, dimensionality reduction, and unsupervised machine learning analysis.

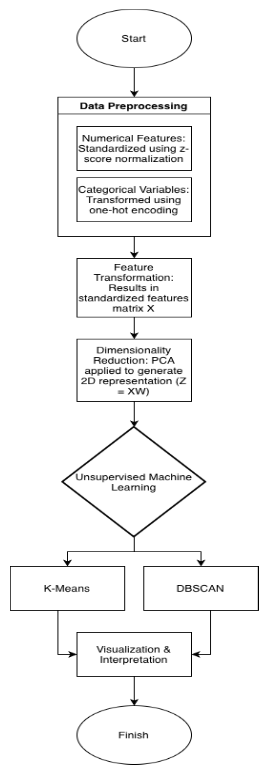

Figure 1 Research Step

This structured process was applied to a dataset of 115 respondents whose demographic attributes, levels of trust, expectations toward metaverse benefits, privacy concerns, and technological familiarity formed the foundation for clustering analysis [21], [22]. Numerical features were standardized using z-score normalization to allow comparability between varying scales, while categorical variables were transformed through one-hot encoding to prepare the dataset for robust clustering performance.

$$z_i = \frac{x_i - \mu}{\sigma} \quad (1)$$

Categorical variables were transformed using one-hot encoding to prevent artificial ordering among categories. Following preprocessing, Principal Component Analysis (PCA) was applied to generate a reduced two-dimensional representation of the dataset, enabling visualization of cluster separation while preserving the majority of the variance [23], [24]. The projection of standardized features X into PCA components Z is defined as:

$$Z = XW \quad (2)$$

Cluster analysis was conducted using the K-Means algorithm, which partitions the dataset into k groups by minimizing the within-cluster sum of squared distances [25]. The optimization function minimized by K-Means is formalized as:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i - \mu_j \right\|^2 \quad (3)$$

Determination of the optimal number of clusters relied on the silhouette coefficient, which evaluates the cohesion and separation of clusters [26]. The silhouette value for each observation i is calculated using:

$$s(i) = \frac{b(i) - a(i)}{\max\big(a(i), b(i)\big)} \quad (4)$$

In addition to K-Means, DBSCAN was applied to detect density-based structures and identify outliers [27]. DBSCAN determines whether a point is a core point based on two parameters: neighborhood radius ε and a minimum number of points MinPts. A point p qualifies as a core point when:

$$|N_{\varepsilon}(p)| \geq \mathrm{MinPts} \quad (5)$$

Here, $N_{\varepsilon}(p)$ denotes the set of points within radius ε from point p. The algorithm identifies clusters by expanding density-reachable regions and assigning isolated observations as noise [28], [29].

Both clustering algorithms K-Means and DBSCAN were implemented using Python's scikit-learn library [30]. PCA projections were used solely for visualization to illustrate the spatial distribution of clusters. The clustering results revealed two K-Means clusters comprising 76 and 39 respondents, respectively, while DBSCAN identified a dominant cluster of 107 respondents and eight outliers. These findings formed the foundation for interpreting distinct behavioural patterns in the adoption readiness of metaverse-based governance systems. Algorithm 1 shows the PCA–K-Means–DBSCAN hybrid clustering process, which integrates feature normalization, dimensionality reduction, and unsupervised clustering to reveal behavioral patterns in citizens' readiness toward metaverse-based digital governance.

Algorithm 1 PCA–K-Means–DBSCAN Hybrid Clustering Algorithm for Behavioral Pattern Discovery

Input: Dataset $D = \{x_1, x_2, \ldots, x_n\}$

Preprocessing

For numerical x_i: $z_i = (x_i - \mu) / \sigma$

For categorical c_i: one_hot(c_i)

PCA Transformation

$Z = XW$ where W = eigenvectors(cov(X))

K-Means Clustering

Minimize $J = \Sigma_{(j=1)}^{k} \Sigma_{(i=1)}^{n} \|x_i - \mu_j\|^2$

Select k with max average silhouette s(i)

DBSCAN Clustering

If $|N\varepsilon(p)| \geq MinPts \rightarrow$ core point

Expand clusters; others → noise

Output: Cluster labels, PCA visualization

Result

Overview of Pre-processed Dataset

The dataset used in this study consisted of 115 valid responses collected from participants in The Gambia, capturing perceptions, expectations, and readiness toward metaverse-based digital governance. After preprocessing, which included handling missing values, one-hot encoding of categorical attributes, and feature standardization, the dataset was transformed into a high-dimensional feature matrix. PCA was applied exclusively for visualization, producing two principal components (PC1 and PC2) that reflected the most significant variance structure in the reduced space. The PCA-transformed dataset served as an interpretive layer for understanding the separation between clusters, although the clustering itself was performed on the full standardized feature space.

K-Means Clustering Outcomes

K-Means was applied with evaluation of silhouette coefficients across candidate values of k, leading to the identification of two clusters as the optimal segmentation. This produced one larger cluster containing 76 respondents, designated as Cluster 0, and a second cluster containing 39 respondents, designated as Cluster 1. When these clusters were projected into PCA space, Cluster 0 exhibited a mean PC1 score of −1.2968 and a mean PC2 score of 0.2600, while Cluster 1 showed a notably higher mean PC1 score of 2.5270 and a lower mean PC2 score of −0.5067 (see table 1 for more details).

These quantitative differences indicate that Cluster 1 consists of respondents with higher readiness, greater trust, and more positive expectations regarding the integration of metaverse technologies into public governance structures. Conversely, Cluster 0 reflects a more cautious or hesitant segment of the population, with lower PC1 values suggesting limited familiarity or reduced confidence in metaverse-enabled services.

Table 1 K-Means Cluster Summary

Cluster	PC1 Mean	PC2 Mean	Count
0	–1.2968	0.2600	76
1	2.5270	–0.5067	39

The resulting distribution is also depicted visually in figure 2, which illustrates a clear separation between the two clusters in PCA space. Cluster 1 forms a compact region, demonstrating consistency in adoption attitudes, while Cluster 0 appears more dispersed, suggesting more diverse or uncertain perspectives.

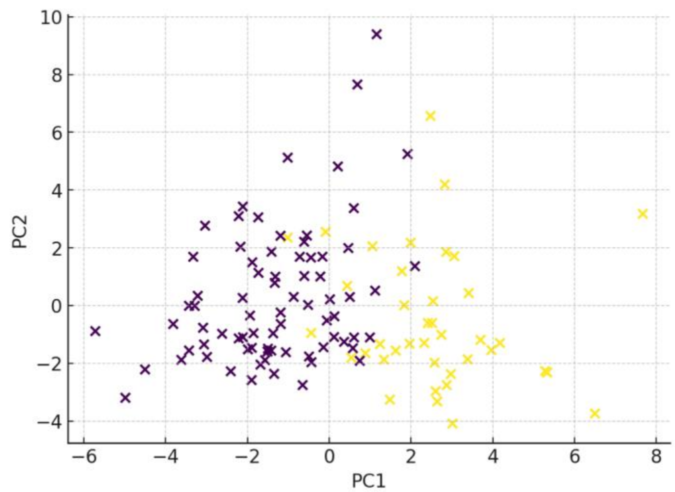

Figure 2 K-Means Clusters Projected on PCA Space

DBSCAN Clustering Outcomes

Application of the DBSCAN algorithm resulted in a different structure (table 2). Using an epsilon value derived from the 90th percentile of the 5-nearest-neighbor distance distribution, DBSCAN identified a single dominant cluster containing 107 respondents, accompanied by eight respondents classified as noise. The core cluster demonstrated mean PCA projections of –0.0279 for PC1 and –0.0389 for PC2. The noise cluster, with eight members, exhibited substantially different values, including a mean PC1 score of 0.3736 and a mean PC2 score of 0.5203.

Table 2 DBSCAN Cluster Summary

Cluster	PC1 Mean	PC2 Mean	Count
-1 (Noise)	0.3736	0.5203	8
0	–0.0279	–0.0389	107

The findings indicate that the majority of respondents share similar perceptions regarding digital governance adoption in the metaverse, leading DBSCAN to consolidate them into a single group. The small number of noise points suggests the existence of respondents who hold atypical or extreme views, potentially arising from distinctive experiences, higher-than-average technological literacy, or elevated scepticism toward government-led metaverse initiatives.

A visualization of DBSCAN results is shown in figure 3, where the dominant cluster forms a dense central region in PCA space, with noise points distributed at the periphery.

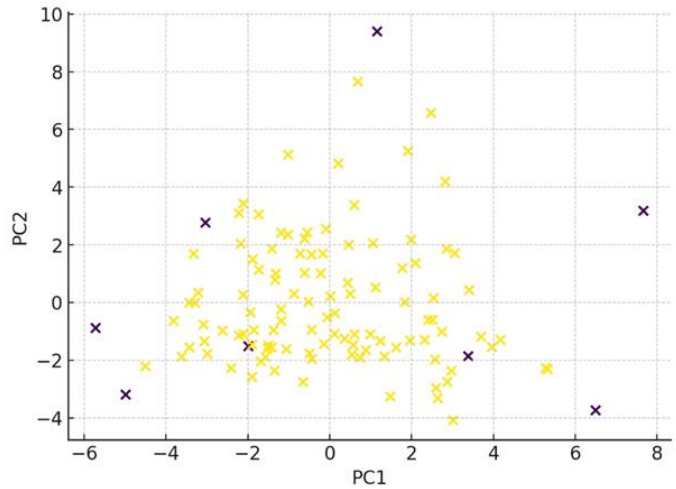

Figure 3 DBSCAN Clusters Projected on PCA Space

Comparative Interpretation of Clustering Models

Comparison between K-Means and DBSCAN reveals complementary insights into public attitudes toward metaverse governance. K-Means uncovered two distinct segments of respondents: one characterized by optimism and readiness, and the other by caution or limited preparedness. These findings, supported by the centroid values in table 1, demonstrate that respondents with higher PC1 values (mean = 2.5270) align with more supportive and future-oriented attitudes toward the metaverse, while those with significantly lower PC1 values (mean = −1.2968) exhibit more reserved perspectives.

DBSCAN, on the other hand, portrays the population as relatively homogeneous, consolidating 107 respondents into a single cluster. The presence of only eight noise points indicates a low frequency of extreme or highly divergent views. The centroid differences shown in table 2 underscore that individuals classified as noise possess higher PC2 values (mean = 0.5203), reflecting attitudes or perception patterns that differ from the broader majority.

Silhouette analysis further reinforces the distinction between the algorithms. The K-Means model generated a silhouette coefficient of approximately 0.3037 when evaluated in PCA space, indicating meaningful but moderate separation between the two clusters. DBSCAN did not yield a valid silhouette score due to the dominance of a single cluster, limiting interpretability in this dimension.

Discussion

The findings from this study reveal important insights into how citizens perceive and potentially adopt metaverse-based digital governance initiatives in The Gambia. The clustering results indicate that adoption readiness among respondents is not uniform but instead organized into distinct behavioural segments that can meaningfully inform future policy design and technological deployment, consistent with prior research emphasizing differentiated adoption pathways in immersive digital environments [13], [16], [18].

The K-Means clustering analysis identified two distinct adoption profiles. Respondents grouped in Cluster 1, with a mean PC1 value of 2.5270 and a mean PC2 value of −0.5067, reflect individuals who are more optimistic, more trusting toward government-led technological transformation, and more receptive to the introduction of metaverse-based public services. Their higher PC1 values suggest stronger digital literacy, greater awareness of innovation trends, and a higher propensity to embrace immersive digital platforms as legitimate governance tools, consistent with evidence that perceived usefulness, trust, and digital literacy drive metaverse adoption [6], [10], [15].

In contrast, respondents in Cluster 0, who exhibited significantly lower PC1 values (mean = −1.2968) and higher PC2 values (mean = 0.2600), represent a cohort that approaches metaverse governance with caution. This cluster likely includes individuals concerned about privacy, data security, technological complexity, or the government's capacity to implement advanced digital ecosystems, reflecting concerns raised in previous studies on metaverse security and public trust in digital transformation [7], [9], [14]. The clear separation visualized in PCA space demonstrates that these differences are not random but structurally meaningful, supporting findings on user segmentation and readiness variation in immersive and AI-driven environments [17], [19], [22].

The DBSCAN findings serve as a complementary lens to interpret the broader context of public sentiment. DBSCAN predominantly identified a single cluster consisting of 107 respondents, with only eight respondents classified as noise. The dominance of one cluster implies that a large proportion of the population's perceptions are relatively aligned. However, the existence of noise points, which had higher mean PC2 scores (0.5203), suggests that a small subset of respondents holds views that deviate materially from the mainstream. These individuals may exhibit either exceptionally high enthusiasm for metaverse adoption or, conversely, deep scepticism driven by concerns over surveillance, digital exclusion, or socio-economic implications [3], [4], [8].

The contrast between the two methods reveals the layered nature of public opinion. While K-Means highlights differentiated adoption profiles, DBSCAN underscores the general coherence of public sentiment alongside the presence of marginal yet meaningful outlier perspectives. Together, the algorithms present a more holistic picture: public responses are mostly cohesive, but within that cohesion lie distinct adoption trajectories that reflect differing levels of readiness, familiarity, and trust, consistent with studies that used machine learning to explore complex behavioural clusters in digital ecosystems [17], [21], [23].

These findings have several implications for digital governance policy. The presence of a highly receptive cluster suggests that early adopters could become strategic ambassadors or pilot users in initial metaverse deployments, a strategy supported by prior studies on phased metaverse implementation and citizen co-creation [4], [5], [11]. At the same time, the larger yet more cautious cluster underscores the need for targeted awareness campaigns, confidence-building initiatives, and accessible digital literacy programs to mitigate adoption barriers, consistent with earlier research emphasizing inclusion and digital competence in governance innovation [8], [15], [20]. The eight noise respondents further highlight the importance of addressing extreme views, which could evolve into resistance or misinformation if not properly understood and engaged, as observed in earlier research on behavioural segmentation and public trust in emerging technologies [12], [18], [29].

Furthermore, the distinct behavioural segmentation revealed through clustering suggests that a one-size-fits-all implementation strategy may not be effective. Instead, tailored interventions that include community-based user education and transparent communication regarding data governance and privacy could help bridge attitudinal divides and promote more inclusive adoption [9], [13], [16], [27].

Overall, the discussion highlights that while enthusiasm for metaverse-based governance exists, substantial work remains to ensure equitable and sustainable integration. Successful adoption will depend not only on technological readiness but also on social acceptance, trust, and the perceived legitimacy of digital platforms as extensions of public institutions [1], [2], [25].

Conclusion

This study examined the emerging patterns of digital governance adoption within the context of metaverse integration in The Gambia by applying two clustering algorithms: K-Means and DBSCAN, to a dataset of 115 survey responses. The analysis revealed that public perceptions and readiness toward metaverse-based governance are both heterogeneous and structured, demonstrating clear segmentation despite an overall coherence in general attitudes.

The K-Means algorithm identified two distinct clusters that represent meaningful behavioural differences among respondents. The first cluster, characterized by a mean PC1 score of 2.5270, consists of individuals who exhibit strong readiness, optimism, and trust in the prospect of metaverse-enabled public services. The second cluster, with a markedly lower mean PC1 score of −1.2968, represents a more cautious group whose perceptions may be shaped by concerns regarding data privacy, technological accessibility, and the reliability of digital government initiatives. These findings indicate that adoption attitudes vary significantly across the population, reinforcing the importance of differentiated policy and communication strategies.

In contrast, DBSCAN revealed a single dominant cluster of 107 respondents, accompanied by eight outliers whose perceptions diverged from the majority. This result suggests substantial alignment in general attitudes toward digital governance, even though specific segments within the population exhibit unique readiness profiles. The presence of a small group of outliers highlights the need for governments to remain attentive to atypical concerns or expectations that may influence acceptance of emerging technologies.

Together, the findings underscore the necessity of a nuanced approach to metaverse adoption in governance. Policymakers should leverage the enthusiasm of early adopters while simultaneously addressing the apprehensions of more hesitant groups through targeted outreach, digital literacy programs, and transparent governance frameworks. The clustering results also emphasize that successful integration of metaverse technologies will depend not only on infrastructure and technical capacity but also on public trust, inclusivity, and perceived legitimacy.

In conclusion, this study contributes to a deeper understanding of societal readiness for metaverse-driven digital governance and highlights the value of machine learning–based segmentation for informing strategic implementation. As governments explore immersive and decentralized digital platforms, evidence-based insights such as these can guide policymaking toward more adaptive, equitable, and citizen-centered governance models.

Declarations

Author Contributions

Conceptualization, A.E.W., H., and G.A.T.; Methodology, A.E.W. and G.A.T.; Software, G.A.T. and H.; Validation, H. and G.A.T.; Formal Analysis, A.E.W.; Investigation, G.A.T. and H.; Resources, H. and G.A.T.; Data Curation, G.A.T.; Writing—Original Draft Preparation, A.E.W.; Writing—Review and Editing, G.A.T. and H.; Visualization, H. All authors have read and agreed to the published version of the manuscript

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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