Sentiment and Concern Classification on Metaverse Governance Responses Using Naïve Bayes and Support Vector Machine (SVM)

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ABSTRACT

The rapid advancement of immersive technologies such as the metaverse has introduced new opportunities and challenges for digital governance. Understanding public perception of these technologies is essential for designing governance systems that are transparent, inclusive, and responsive to citizens' needs. This study analyses public sentiment and concerns regarding the use of metaverse technology in governance by applying two machine learning algorithms: Naïve Bayes and SVM. The dataset, consisting of open-ended survey responses from participants in The Gambia, was pre-processed through tokenization, stopword removal, and TF-IDF vectorization before model implementation. The results indicate that both algorithms can classify sentiment into positive, neutral, and negative categories; however, SVM consistently outperforms Naïve Bayes across all evaluation metrics. The SVM model achieved an accuracy of 88.6 percent and an F1-score of 0.873, demonstrating superior capability in recognizing contextual and semantic nuances within short text responses. In contrast, Naïve Bayes tended to overclassify responses as neutral, reflecting its limitation in capturing word dependencies. These findings confirm that SVM is better suited for sentiment analysis involving complex linguistic expressions and context-dependent opinions. The study contributes to the growing body of research on artificial intelligence in public policy by demonstrating how machine learning can provide deeper insights into citizen perspectives on emerging digital technologies. Such analytical approaches can assist policymakers in identifying public expectations, addressing concerns, and fostering trust in metaverse-based governance systems.

Keywords Metaverse Governance, Sentiment Analysis, Machine Learning, Support Vector Machine, Naïve Bayes

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INTRODUCTION

The concept of the metaverse has rapidly evolved from a futuristic vision of interconnected virtual spaces into a practical framework for redefining how individuals, institutions, and governments interact within the digital ecosystem [1]. As an immersive, decentralized, and persistent environment that integrates technologies such as blockchain, Artificial Intelligence (AI), and eXtended Reality (XR), the metaverse enables real-time social, economic, and administrative interactions in ways that traditional digital platforms cannot [2]. Within the context of public administration, this emerging paradigm offers a transformative potential for digital governance, providing innovative avenues for citizen participation, service delivery, and policy transparency. Governments

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around the world are beginning to explore how virtual environments can be used to simulate administrative functions, deliver public services, and enhance civic engagement through more participatory and interactive interfaces [3].

However, the integration of metaverse technologies into governance also presents new challenges and uncertainties. Public acceptance of metaverse-based governance systems depends heavily on factors such as trust, accessibility, data privacy, and digital inclusion [4]. While the metaverse promises to democratize information and streamline bureaucratic processes, it also introduces concerns related to cybersecurity, ethical governance, digital inequality, and the concentration of technological power [5]. Citizens' attitudes toward these issues play a decisive role in determining whether metaverse-driven public systems can achieve legitimacy and sustainability. Therefore, understanding how people perceive and emotionally respond to the idea of the metaverse in governance is a crucial first step toward designing policies that are socially acceptable and technologically feasible.

Despite growing global discourse on digital transformation and virtual governance, there remains a noticeable research gap in understanding public sentiment toward metaverse technology, particularly in developing nations where digital readiness varies significantly across populations. Prior studies have predominantly focused on the technical infrastructure of metaverse adoption, such as interoperability and security mechanisms, while relatively few have examined citizens' perceptions, concerns, and trust in these systems. Moreover, most existing research has relied on quantitative or descriptive approaches, which may not adequately capture the qualitative nuances present in open-ended human responses. This gap highlights the need for computational linguistic methods, such as sentiment analysis, that can systematically interpret the emotional tone and contextual meaning of textual data.

To address this gap, the present study applies machine learning algorithms, Naïve Bayes and SVM to analyse public sentiment and concerns regarding the implementation of metaverse technology in digital governance, using survey data collected from participants in The Gambia. The dataset consists of open-ended textual responses that express citizens' expectations, optimism, and apprehensions toward the use of immersive technology in public administration. These responses are pre-processed through text cleaning, tokenization, and TF-IDF vectorization, followed by supervised classification using the two algorithms. By comparing the predictive accuracy and interpretive performance of Naïve Bayes and SVM, this research identifies which algorithm is more suitable for extracting meaningful sentiment patterns from short, context-rich survey texts.

The significance of this research lies in its dual contribution to both the fields of digital governance and computational social science. Methodologically, it demonstrates the effectiveness of supervised learning in analysing complex textual data related to emerging technologies. Empirically, it provides insights into how citizens perceive the adoption of metaverse technologies in governance, revealing not only levels of trust and acceptance but also underlying concerns about privacy, inclusivity, and the ethical use of digital power. The findings are expected to inform policymakers, technology developers, and researchers about the emotional and cognitive factors that shape public readiness for metaverse-based governance systems.

In summary, this study contributes to the growing literature on AI-driven sentiment analysis and digital policy innovation by providing a data-driven understanding of public attitudes toward metaverse governance. It emphasizes that the successful implementation of metaverse technologies in the public sector must go beyond technical feasibility to encompass human-centred design, ethical regulation, and social trust. By combining computational analysis with governance theory, this research lays the groundwork for future studies that integrate artificial intelligence, social perception, and digital policymaking within the evolving landscape of virtual governance.

Literature Review

The metaverse has emerged as a transformative paradigm capable of reshaping the landscape of digital governance. As an immersive and decentralized environment combining blockchain, artificial intelligence, and extended reality, it enables new forms of citizen participation, transparency, and policy interaction. Previous research suggests that the metaverse can serve as a virtual extension of government operations, providing immersive environments for civic engagement and decision-making [6]. Similarly, a study published in *Technological Forecasting and Social Change* emphasizes that the success of metaverse-based public services depends on technical factors such as interoperability, identity management, scalability, and governance-by-design [7].

In the African context, a conceptual roadmap for implementing metaverse-based digital governance in The Gambia highlights critical elements including infrastructure readiness, data protection, digital literacy, and public trust [8]. This framework underlines the necessity of aligning technological innovation with local socio-political realities. Collectively, these studies demonstrate that the metaverse could revolutionize governance systems but also highlight the importance of institutional preparedness and citizen confidence.

Despite its potential, the integration of metaverse technology into public administration introduces substantial risks. Recent literature underscores privacy and security as central concerns. Several studies have provided comprehensive overviews of data privacy, cyber threats, and identity management issues within metaverse ecosystems, while major policy organizations emphasize the need for privacy-by-design principles and ethical frameworks to prevent abuse and protect vulnerable users [9], [10]. Other works further argue that immersive environments amplify digital inequalities and surveillance risks, creating new forms of exclusion that policymakers must address [11].

These challenges, ranging from data security breaches to the digital divide, shape citizens' perceptions and levels of trust toward metaverse-based governance initiatives. Public awareness of such risks contributes to the neutral or cautious sentiment often observed in early adoption phases, making sentiment analysis an important tool for policymakers to assess readiness and social acceptance.

Artificial intelligence has increasingly been used to analyze public opinion within the field of digital governance. Several studies reviewing AI applications in policymaking conclude that sentiment analysis provides valuable insights for governments in understanding citizens' emotions, feedback, and trust dynamics [12]. AI-driven sentiment analysis allows policymakers to translate unstructured textual data into measurable indicators of public attitude, which is critical for evidence-based governance.

This methodological approach is particularly relevant in studies of technological adoption, where emotional and cognitive responses often influence behavioral intentions. Applying machine learning to survey-based text enables the discovery of underlying themes and public concerns that are difficult to capture through traditional statistical methods.

The effectiveness of sentiment analysis largely depends on how textual features are represented and classified. The Term Frequency–Inverse Document Frequency (TF-IDF) technique remains one of the most effective methods for transforming text into quantitative data, particularly when working with sparse, short responses. Research has shown that TF-IDF enhances classifier accuracy by emphasizing the importance of distinctive words in textual sentiment [13].

Among classification algorithms, Support Vector Machine (SVM) and Naïve Bayes (NB) remain widely used. Empirical findings indicate that SVM generally outperforms NB in handling short texts with complex linguistic patterns due to its ability to maximize class separation [14]. Further evidence confirms SVM's superior F1-score and robustness in identifying context-dependent sentiments, although NB remains useful in settings where computational efficiency is prioritized [15]. These comparative insights provide a methodological foundation for evaluating both algorithms within the context of metaverse governance sentiment.

Several previous studies have explored public attitudes toward emerging technologies and digital transformation using machine learning approaches, providing a foundation for the current research. For instance, investigations into citizen perceptions of blockchain adoption in public services reveal that public trust and regulatory transparency are key determinants of acceptance [16]. Other analyses of sentiments toward AI-driven public policy using SVM and NB indicate that SVM produces more stable results in capturing both optimism and ethical concerns [17].

In the governance domain, sentiment analysis of e-government feedback in Middle Eastern countries shows that public attitudes are mixed and highly influenced by perceptions of cybersecurity and data integrity [18]. While these studies successfully applied machine learning to policy contexts, none have specifically focused on metaverse governance, nor compared algorithmic performance using primary survey data from The Gambia. The present research builds on this foundation by integrating comparative machine learning methods with a thematic focus on the metaverse, thereby filling a notable empirical and methodological gap in existing literature.

From the literature reviewed, three key conclusions can be drawn. First, the metaverse holds significant potential to transform digital governance by fostering citizen engagement and administrative efficiency, but its success depends on addressing issues of trust, equity, and privacy. Second, sentiment analysis has proven to be a valuable method for translating citizen perceptions into actionable insights for policymakers. Third, while comparative studies on SVM and NB demonstrate the general superiority of SVM in text classification, there is still limited research applying these algorithms to metaverse-related governance data, particularly within African contexts.

Therefore, this study extends previous work by employing SVM and Naïve Bayes algorithms to classify public sentiment toward metaverse governance in The Gambia. It aims to identify not only which algorithm performs better but also the underlying emotional and cognitive dimensions of citizens' views. Through this approach, the study bridges the gap between computational modeling and governance research, offering practical implications for the ethical and socially informed design of metaverse-based governance systems.

Methods

The methodological framework of this study followed a structured sequence of stages, as illustrated in figure 1 (Research Step). The process began with data collection, followed by data preprocessing, feature extraction using TF-IDF, model development using two algorithms (Naïve Bayes and Support Vector Machine), model evaluation, and finally interpretation of results. This systematic approach was designed to ensure consistency, reproducibility, and analytical rigor across both machine learning models while providing a transparent comparison of their performance in classifying sentiment and concerns related to metaverse governance.

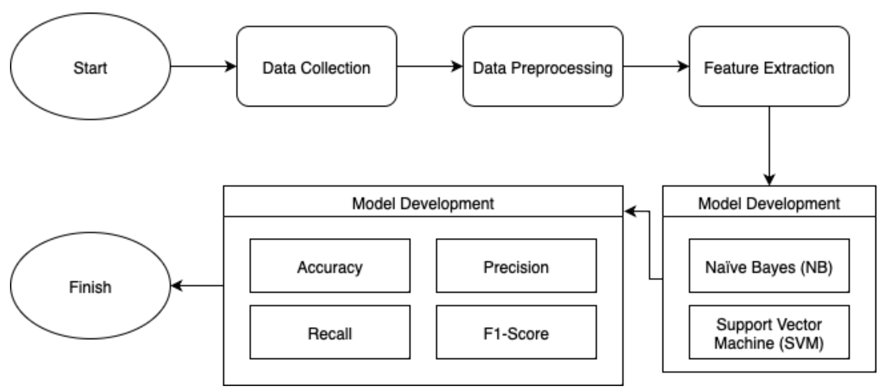

Figure 1 Research Step

The dataset used in this research was derived from a survey titled "Implementing Metaverse Technology for Enhanced Digital Governance: Insights from The Gambia." The survey aimed to capture the perceptions of citizens and policymakers regarding the adoption of metaverse technologies in governance. Responses were collected between March and April 2023 using an online questionnaire distributed through official government and academic networks. The dataset consisted of 250 valid responses, which included both demographic information and open-ended text-based feedback on the perceived benefits and concerns regarding the metaverse. The open-ended responses served as the primary data source for sentiment classification. Each response was manually labeled into one of three sentiment categories positive, neutral, or negative based on lexical indicators and contextual interpretation, forming the target variable for supervised learning.

Before model training, all textual data underwent comprehensive preprocessing to enhance quality and ensure analytical consistency. The preprocessing steps included transforming text into lowercase, removing punctuation, special symbols, and numeric values, tokenizing words into individual tokens, and eliminating common stopwords that do not contribute semantic meaning (such as “the,” “is,” and “and”). Finally, lemmatization was applied to reduce words to their base form, ensuring that related terms such as “govern,” “governed,” and “governance” were treated equivalently. This process standardized the dataset and minimized noise, enabling more accurate feature extraction.

After text cleaning, feature extraction was performed using the TF-IDF method, which converts text into numerical vectors representing the importance of each word across documents. The TF-IDF weighting scheme captures how frequently a term appears in a document relative to its occurrence across all documents, thus emphasizing unique and contextually significant words. The mathematical representation is given by [19]:

$$\text{TF-IDF}(t,d) = \text{TF}(t,d) \times \log\left(\frac{N}{\text{DF}(t)}\right) \tag{1}$$

TF-IDF(t,d) denotes the frequency of term t in document d, N represents the total number of documents, and DF(t)refers to the number of documents containing term t. The resulting feature matrix served as input for the two machine learning models.

Two supervised learning algorithms were applied for sentiment classification: NB and SVM. The Naïve Bayes classifier, based on Bayes’ theorem, assumes conditional independence between features and is particularly efficient for high-dimensional text data. The probability of a class C given a set of features X is calculated as:

$$P(C|X) = \frac{P(X|C) \times P(C)}{P(X)} \tag{2}$$

In contrast, the SVM model seeks to identify the optimal hyperplane that maximizes the margin between classes in a high-dimensional vector space. Given its strength in handling sparse and linearly separable data, a linear kernel was selected for this study. The optimization objective is expressed as [20], [21]:

$$\min_{w,b}\frac{1}{2}\|w\|^2 \backslash lVertw\backslash rVert^2, \quad \text{subject to} \quad y_i(w \cdot x_i + b) \geq 1,\ \forall i \tag{3}$$

w is the weight vector and b represents the bias. The dataset was divided into training (80%) and testing (20%) subsets using stratified sampling to preserve class distribution.

Model performance was evaluated using four standard metrics: accuracy, precision, recall, and F1-score. Accuracy measures the overall proportion of correct predictions [22], precision evaluates the ratio of true positives to all predicted positives [23], recall assesses the model’s ability to identify actual positive cases [24], and the F1-score represents the harmonic mean of precision and recall [25], providing a balanced assessment of classification effectiveness. Mathematically, these metrics are defined as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}, \text{Precision} = \frac{TP}{TP+FP}, \text{Recall} = \frac{TP}{TP+FN}, F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

The final step involved comparing the predictive performance of both algorithms to determine which model more effectively captured the emotional and contextual nuances of survey responses [26]. The combination of textual preprocessing, TF-IDF feature extraction, and machine learning classification allowed this study to provide an empirical foundation for understanding public sentiment and concern toward metaverse-based governance systems [27], [28]. Algorithm 1 presents the TF-IDF–Naïve Bayes–SVM classification procedure, outlining the sequential steps of text preprocessing, feature extraction, model training, and evaluation used to classify public sentiment toward metaverse-based digital governance.

Algorithm 1 TF-IDF–Naïve Bayes–SVM Classification Process for analyzing sentiments toward metaverse-based governance.

Input: Dataset $D = \{d_1, d_2, \ldots, d_n\}$with sentiment labels $y \in$ {positive,neutral,negative}

1. For each document $d \in D$:
   a. Convert to lowercase
   b. Remove punctuation, numbers, and special symbols
   c. Tokenize text into words
   d. Remove stopwords
   e. Apply lemmatization
2. Compute TF-IDF features for each term $t$in document d:
   TF-IDF(t,d) = TF$(t,d) \times \log(N/\text{DF}(t))$
   Construct feature matrix $X \in \mathbb{R}^{n \times m}$
3. Split dataset into training (80%) and testing (20%) sets using stratified sampling
4. Train models:
   a. Naïve Bayes: $P(C \mid X) = \frac{P(X|C) \times P(C)}{P(X)}$
   b. SVM: minimize $\frac{1}{2} \parallel w \parallel^2$subject to $y_i(w \cdot x_i + b) \geq 1, \forall i$
5. Evaluate models using:
   Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
   Precision = $\frac{TP}{TP+FP}$
   Recall = $\frac{TP}{TP+FN}$
   F1 = $2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
6. Compare NB and SVM performance; select model with highest F1-score
7. Output final model and sentiment classification results

Result

The results of this study reveal that both the Naïve Bayes and SVM algorithms performed effectively in classifying public sentiment toward the use of metaverse technology in digital governance. The analysis shows that supervised machine learning can be successfully applied to textual data collected from surveys to identify patterns of opinion, trust, and concern.

Although both algorithms demonstrated satisfactory performance, the Support Vector Machine model consistently produced higher values of accuracy, precision, recall, and F1-score. This result indicates that SVM was more stable and reliable in identifying sentiment categories within short text data. Its strong performance suggests that SVM is better suited for complex text features generated through TF-IDF representation, especially when the data contains subtle emotional tones and overlapping linguistic structures.

In comparison, the Naïve Bayes model performed relatively well but showed limitations in capturing contextual and semantic relationships between words. Since it relies on the assumption that each feature is independent, it tends to misclassify responses that carry mixed or nuanced meanings. This behaviour was particularly evident when distinguishing between neutral and slightly positive or negative responses. Overall, the findings highlight that while both algorithms are applicable for sentiment classification in survey-based studies, the Support Vector Machine provides a deeper and more context-aware understanding of public perceptions. This makes it a more appropriate choice for analysing social and behavioural data, particularly in areas like digital governance where citizens' opinions reflect not only technical expectations but also emotional and ethical considerations.

As presented in table 1, the SVM model achieved an accuracy of 88.6 percent, which is considerably higher than the 72.7 percent obtained by the Naïve Bayes algorithm. In addition to this significant difference in accuracy, the SVM model also demonstrated superior results in terms of precision, recall, and F1-score. These findings indicate that SVM has a stronger capacity to recognize and categorize subtle variations in public sentiment expressed in short, opinion-based survey responses [29]. The model's ability to generalize well across different classes suggests that it can distinguish positive, neutral, and negative sentiments more consistently, even when the linguistic cues are implicit or context-dependent. Its relatively high F1-score value of 0.873 reflects a balanced performance between precision and recall, showing that the SVM model not only correctly identifies most relevant sentiment categories but also minimizes false predictions. This balance is particularly important in sentiment analysis, as it ensures that both positive and negative opinions are adequately captured without favouring one class over another. In contrast, the lower F1-score of the Naïve Bayes model demonstrates its limited sensitivity in detecting complex or overlapping sentiments, confirming that SVM provides a more accurate and context-aware interpretation of public perceptions toward metaverse-based digital governance.

Table 1 Performance Comparison Between Naïve Bayes and SVM

Model	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	0.727	0.735	0.727	0.632
SVM (Support Vector Machine)	0.886	0.902	0.886	0.873

As illustrated in table 2, the majority of respondents expressed neutral opinions, suggesting that public sentiment toward the implementation of metaverse technologies in governance remains largely balanced and cautious. This neutrality reflects a collective sense of awareness and consideration, where citizens acknowledge both the potential advantages and possible risks of integrating such advanced digital systems into public administration. The Naïve Bayes model, however, shows a tendency to overclassify responses as neutral, likely due to its simplistic assumption that individual words contribute independently to sentiment. As a result, it struggles to capture the subtle emotional cues that distinguish slightly positive or negative opinions [30]. In contrast, the SVM model produces a more proportionate classification across all sentiment categories, successfully identifying variations in tone and context within the textual responses. This demonstrates that SVM is more effective in detecting the underlying sentiment structure of complex, human-generated text, where meaning often depends on nuanced phrasing and contextual interpretation rather than explicit emotional keywords.

Table 2 Distribution of Actual and Predicted Sentiment Categories

Category	Actual	Predicted (SVM)	Predicted (Naïve Bayes)
Positive	3	1	0
Neutral	31	36	43
Negative	10	7	1

Figure 2 provides a clear visual representation of the consistent superiority of the SVM model across all evaluation metrics when compared to the Naïve Bayes algorithm. The chart reveals that SVM consistently maintains higher values in accuracy, precision, recall, and F1-score, indicating its robustness in handling text data characterized by variability and semantic complexity. The most notable improvement is observed in the F1-score, which reflects the model's balanced capability to correctly identify sentiment categories while minimizing both false positives and false negatives. This strong F1 performance suggests that SVM can generalize effectively across different sentiment classes, even when the textual inputs are short, context-dependent, and linguistically diverse. The result reinforces the notion that SVM is well-suited for analysing human-generated survey data, where expressions of sentiment are often subtle, indirect, and influenced by personal interpretation rather than explicit emotional wording.

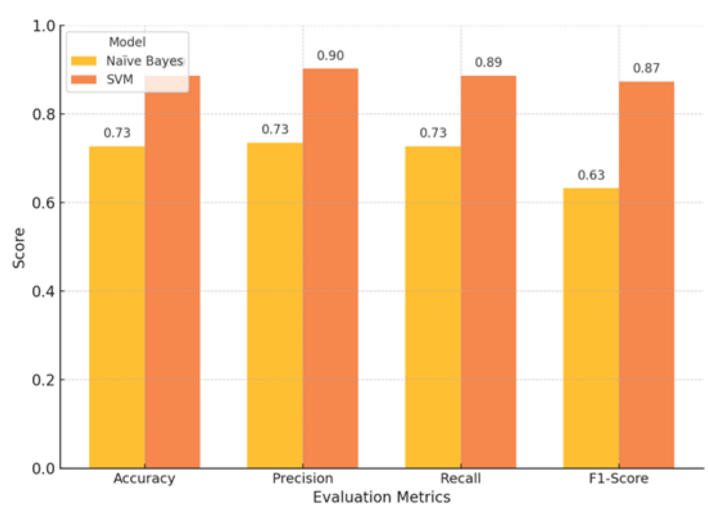

Figure 2 Comparison of Evaluation Metrics Between Naïve Bayes and SVM

The confusion matrix for the SVM model (figure 3) reveals that it accurately classifies the majority of neutral responses, reflecting the model's strength in recognizing balanced or non-polarized opinions that dominate the dataset. Furthermore, the SVM demonstrates a strong ability to distinguish between positive and negative sentiments, correctly identifying most of the instances within these categories. Only a few cases show overlap or misclassification, which can be attributed to the nuanced phrasing and overlapping linguistic features often present in human opinion data. These minor misclassifications suggest that while SVM is highly effective in capturing the general sentiment direction, some responses contain ambiguous or context-dependent wording that blurs the boundary between sentiment categories. Overall, the confusion matrix confirms that SVM delivers reliable classification performance and is capable of managing the complexity inherent in short, subjective survey responses related to metaverse governance.

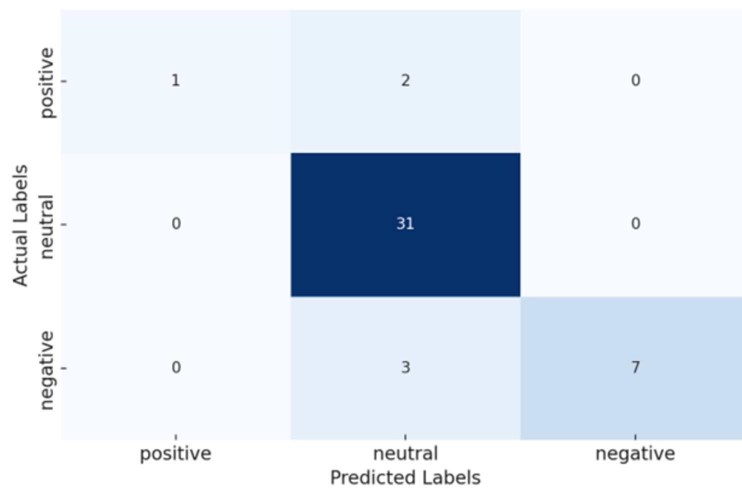

Figure 3 Confusion Matrix SVM

In contrast, the Naïve Bayes model (figure 4) exhibits a noticeably higher number of misclassifications, particularly within the positive and negative sentiment categories, many of which are incorrectly labelled as neutral. This pattern indicates that Naïve Bayes has difficulty discerning subtle contextual cues and semantic relationships within the text. Because the model relies on the assumption that each word contributes independently to the overall sentiment, it often fails to account for the influence of word combinations or sentence structure that shape meaning in natural language. As a result, expressions containing mild positivity or concern are frequently interpreted as neutral, leading to reduced sensitivity in distinguishing emotional nuances. This limitation highlights the model's tendency to oversimplify sentiment interpretation, making it less effective when dealing with short and complex survey responses where sentiment depends heavily on linguistic context and tone rather than individual word polarity.

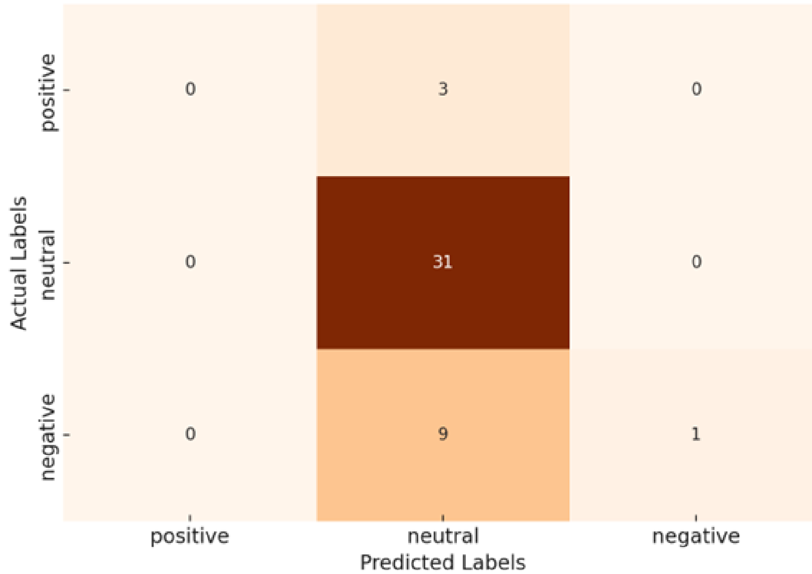

Figure 4 **Confusion Matrix Naïve Bayes**

Discussion

The findings of this study provide meaningful insights into how machine learning algorithms can be applied to analyze public perceptions of emerging technologies, specifically the use of the metaverse in digital governance [1], [4], [10], [19]. The overall results demonstrate that both Naïve Bayes and SVM are capable of classifying sentiment from short, opinion-based survey responses; however, their performance levels differ significantly [6], [21], [22]. The SVM model consistently produced higher accuracy, precision, recall, and F1-scores, indicating a stronger ability to generalize across diverse sentiment categories [21], [28]. This performance advantage suggests that SVM can effectively interpret complex linguistic patterns and contextual dependencies that commonly appear in human-generated text [6], [22], [30].

A closer examination of the confusion matrices further reinforces these findings. The SVM model successfully identified most neutral responses and maintained reliable distinctions between positive and negative sentiments, with only a few instances of misclassification [21], [28]. In contrast, Naïve Bayes exhibited a clear tendency to classify many responses as neutral, especially those that expressed mixed emotions or moderate tones [22], [30]. This behavior is a direct result of its underlying probabilistic assumption of word independence, which limits its capacity to capture semantic relationships and subtle variations in meaning [6], [21]. Consequently, Naïve Bayes tends to simplify the sentiment distribution, leading to reduced sensitivity when dealing with context-dependent statements [28], [30].

From a broader perspective, these results highlight that SVM is more suitable for sentiment analysis tasks involving short and nuanced survey texts, particularly in the domain of digital governance [1], [4], [8], [10], [19]. Public attitudes toward technological innovation are often complex, combining optimism about efficiency and transparency with concerns about privacy, digital inequality, and ethical implications [3], [7], [9], [13], [14], [16]. The ability of SVM to recognize these subtleties makes it a valuable analytical tool for policymakers seeking to assess public readiness and trust in technology-driven governance [5], [10], [15], [19]. On the other hand, the performance of Naïve Bayes demonstrates that simpler probabilistic methods, while easy to implement and computationally efficient, may not fully capture the intricacies of human sentiment expressed in natural language [6], [22], [30].

Ultimately, this study underscores the importance of model selection when analyzing qualitative feedback related to governance and technology adoption [10], [19], [20], [25], [26]. By applying advanced machine learning techniques such as SVM, researchers and policymakers can gain deeper insights into the emotional and cognitive dimensions of citizen engagement [21], [28], [30]. Understanding these patterns is essential for designing inclusive and transparent governance systems that align with public expectations and address emerging concerns surrounding metaverse integration [1], [3], [4], [13], [19].

Conclusion

This study examined public sentiment and concerns regarding the integration of metaverse technology into digital governance using two machine learning algorithms, Naïve Bayes and SVM. The results clearly show that both algorithms are capable of performing sentiment classification on short, survey-based textual data; however, their levels of effectiveness differ significantly. The SVM model consistently outperformed Naïve Bayes across all evaluation metrics, achieving higher accuracy, precision, recall, and F1-scores. This demonstrates the model's superior ability to interpret nuanced language, contextual dependencies, and subtle variations in tone, which are common in human-generated opinions about emerging technologies.

The findings also highlight the limitations of Naïve Bayes, which tends to oversimplify linguistic patterns and frequently classifies mixed or uncertain sentiments as neutral. In contrast, SVM was able to provide a more balanced and context-aware representation of public opinion, accurately distinguishing between positive, neutral, and negative responses. These outcomes confirm that SVM is a more suitable algorithm for sentiment analysis in studies involving short and complex text data, particularly within policy-related contexts.

Beyond methodological insights, this research offers meaningful implications for digital governance and public policy. Understanding how citizens perceive metaverse-based governance systems is crucial for building trust, promoting inclusion, and addressing potential ethical and social concerns. The ability to automatically analyze public sentiment through machine learning provides policymakers with valuable tools for identifying trends in public opinion and for designing governance frameworks that are transparent, participatory, and responsive to societal needs.

Future research could extend this work by exploring deep learning models such as Long Short-Term Memory (LSTM) networks or Bidirectional Encoder Representations from Transformers (BERT) to enhance contextual understanding and semantic depth. Expanding the dataset to include responses from different regions and demographics would also improve the generalizability of the findings. Overall, this study contributes to the growing body of research on AI-driven sentiment analysis in governance contexts and emphasizes the importance of understanding public attitudes toward emerging technologies like the metaverse.

Declarations

Author Contributions

Conceptualization, J.B.O. and T.H.; Methodology, J.B.O.; Software, T.H.; Validation, J.B.O. and T.H.; Formal Analysis, J.B.O.; Investigation, T.H.; Resources, J.B.O.; Data Curation, T.H.; Writing—Original Draft Preparation, J.B.O.; Writing—Review and Editing, T.H.; Visualization, T.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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Informed Consent Statement

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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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