Predicting User Risk Behavior in the Metaverse Using Hybrid Bidirectional LSTM–GRU Temporal Deep Learning

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ABSTRACT

The rapid expansion of metaverse environments has created a complex ecosystem where user interactions generate vast amounts of behavioral and transactional data. Understanding and predicting user risk behavior has become a critical challenge for maintaining trust, safety, and economic stability within these digital spaces. This study proposes a hybrid Bidirectional Long Short-Term Memory and Gated Recurrent Unit (LSTM–GRU) deep learning model to forecast user risk behavior based on temporal patterns derived from metaverse transaction data. The model was trained on sequential features, including login frequency, session duration, and transaction amount, to capture both short-term fluctuations and long-term behavioral dependencies. Experimental evaluation demonstrated that the proposed model achieved a Root Mean Square Error (RMSE) of 7.342, a Mean Absolute Error (MAE) of 5.813, and a coefficient of determination (R^2) of 0.352. The results indicate that the hybrid architecture effectively learns temporal dynamics and accurately forecasts user risk trends, providing a reliable foundation for proactive risk detection. The consistent convergence between training and validation loss further confirms the model's stability and generalization capability. Overall, this research contributes to the integration of artificial intelligence in metaverse governance by offering a data-driven approach to behavioral forecasting that can enhance user safety, improve decision-making, and support the development of intelligent, adaptive risk management systems in virtual environments.

Keywords Metaverse, User Risk Behavior, Forecasting, Temporal Deep Learning, LSTM–GRU Model

INTRODUCTION

The emergence of the metaverse has transformed the way humans interact, communicate, and conduct economic activities in digital environments [1]. Combining virtual reality, artificial intelligence, and blockchain technologies, the metaverse enables persistent, immersive, and interconnected ecosystems that mirror real-world social and economic structures. Within these environments, users perform a variety of actions such as trading digital assets, participating in virtual economies, and engaging in social interactions that continuously generate behavioral and transactional data. As these activities become increasingly complex, the ability to monitor and understand user behavior becomes essential for maintaining trust and safety [2]. However, identifying and predicting risky behavior within such dynamic and decentralized ecosystems remains a major challenge for researchers and platform developers alike.

One of the key difficulties in risk behavior prediction lies in the temporal and contextual nature of user interactions. Traditional machine learning approaches that rely on static data or aggregated features often fail to capture the sequential

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dependencies that define user behavior in virtual settings [3]. These methods are primarily reactive, focusing on detecting anomalous events after they occur, rather than forecasting them in advance. In the context of the metaverse, where interactions occur continuously and in real time, such limitations can lead to delayed interventions and increased vulnerability to fraudulent or malicious activities. This gap underscores the need for predictive systems that can leverage temporal behavioral data to forecast risk before it materializes, thereby supporting proactive risk mitigation strategies.

Recent advances in artificial intelligence have introduced deep learning architectures capable of modeling complex temporal dependencies in sequential data. Models such as the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have shown strong performance in time series forecasting, behavioral analytics, and anomaly detection [4]. These architectures overcome the limitations of traditional feedforward networks by retaining historical information and learning from sequential relationships between data points. Prior research in domains such as finance, cybersecurity, and online gaming has demonstrated that LSTM and GRU models can capture both long-term patterns and short-term fluctuations more effectively than classical machine learning techniques. Despite these advancements, their application in metaverse ecosystems remains limited, particularly in the area of forecasting user risk behavior based on temporal and behavioral features.

In addition, most of the existing research in metaverse analytics has emphasized classification and anomaly detection rather than forecasting [5]. Studies have primarily focused on using static features and conventional models such as Random Forest, Decision Trees, and Support Vector Machines to identify abnormal user activities. While these approaches can effectively detect existing risks, they lack the ability to anticipate behavioral changes that may lead to future risks. Moreover, few studies have explored hybrid temporal models that combine LSTM and GRU architectures to enhance predictive accuracy and model stability. The absence of such forecasting frameworks presents a clear research gap and limits the ability of current systems to transition from reactive detection to proactive behavioral prediction.

This study addresses these challenges by proposing a hybrid Bidirectional LSTM–GRU deep learning model to forecast user risk behavior in metaverse environments. The model is designed to capture both long-term dependencies and short-term behavioral variations by integrating sequential learning mechanisms with bidirectional processing. Temporal features such as login frequency, session duration, and transaction amount are used to represent user activity over time. The objective of this research is to develop a forecasting framework that can accurately predict risk trends and support intelligent, AI-driven risk management systems in virtual ecosystems. The primary contributions of this study are threefold. First, it introduces a hybrid temporal deep learning architecture tailored to behavioral forecasting in the metaverse. Second, it provides an empirical evaluation of the model’s predictive performance compared to existing methods. Third, it demonstrates the potential of temporal deep learning to enhance proactive governance, improve digital trust, and ensure security in emerging metaverse environments.

Literature Review

The metaverse has become a multidimensional digital ecosystem that integrates virtual reality, blockchain, artificial intelligence, and decentralized economies. It allows users to interact socially and economically within immersive environments that continuously generate behavioral and transactional data [6]. Understanding user behavior in such ecosystems is essential for ensuring security, trust, and ethical governance [7]. Early research on metaverse analytics primarily focused on descriptive modeling of user activities, engagement patterns, and trust formation mechanisms [8]. However, these studies relied heavily on static behavioral indicators and lacked temporal analysis capable of forecasting future user behavior [9].

Artificial intelligence and machine learning have been widely used to analyze behavioral data across digital platforms, including e-commerce, social networks, and online gaming [10]. Models such as Decision Trees, Random Forests, and Support Vector Machines have been successfully applied to detect anomalies and classify user activities [11]. Despite their success in identifying abnormal or high-risk patterns, these conventional approaches are inherently reactive and limited in their ability to capture dynamic, time-dependent behavior [12]. In contrast, deep learning models have demonstrated superior performance in processing sequential data and uncovering complex temporal relationships [13]. Their application has expanded to domains such as financial forecasting, cybersecurity risk detection, and user behavior prediction, where time-dependent information plays a critical role [14].

Within the context of temporal learning, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have become prominent architectures due to their ability to retain long-term dependencies while mitigating vanishing gradient issues [15]. LSTM networks excel in maintaining contextual memory over extended sequences, while GRU models provide computational efficiency through simplified gating mechanisms [16]. Recent advancements have shown that combining these two architectures can enhance stability, convergence, and prediction accuracy, especially in tasks involving behavioral forecasting and anomaly detection [17]. Bidirectional variants of these architectures further improve predictive performance by incorporating both forward and backward temporal dependencies [18]. Despite these advances, research focusing on forecasting user risk behavior in metaverse environments remains scarce. Most studies emphasize detection of fraudulent or abnormal behavior after occurrence, rather than forecasting potential risk based on sequential behavioral patterns [19].

Given these limitations, there is a clear need for predictive models that can learn from the temporal evolution of user activities in virtual ecosystems. The lack of forecasting frameworks capable of capturing both long-term behavioral dependencies and short-term fluctuations has left a significant gap in the literature [20]. Addressing this need, the present study proposes a hybrid Bidirectional LSTM–GRU model for forecasting user risk behavior in metaverse environments. By leveraging temporal and behavioral features such as login frequency, session duration, and transaction amount, the model aims to provide more accurate, proactive, and interpretable risk predictions. This research contributes to the advancement of metaverse analytics by extending deep learning methodologies to behavioral forecasting, enabling more intelligent, data-driven governance systems that can enhance user trust and safety in virtual environments.

Method

This study applies a temporal deep learning approach that integrates Bidirectional Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures to forecast user risk behavior within metaverse environments. The overall methodological framework is designed to systematically transform raw behavioral data into accurate predictive insights. The framework consists of five main stages: data preprocessing, feature engineering, temporal structuring, model development, and performance evaluation. Each phase is designed to ensure that the temporal dependencies and behavioral patterns inherent in metaverse interactions are effectively represented and learned by the model. Figure 1 illustrates the complete research workflow, showing the sequential process from data acquisition to model validation, which includes (1) data collection, (2) preprocessing and normalization, (3) temporal feature construction, (4) model training and optimization, and (5) evaluation and visualization of forecasting results.

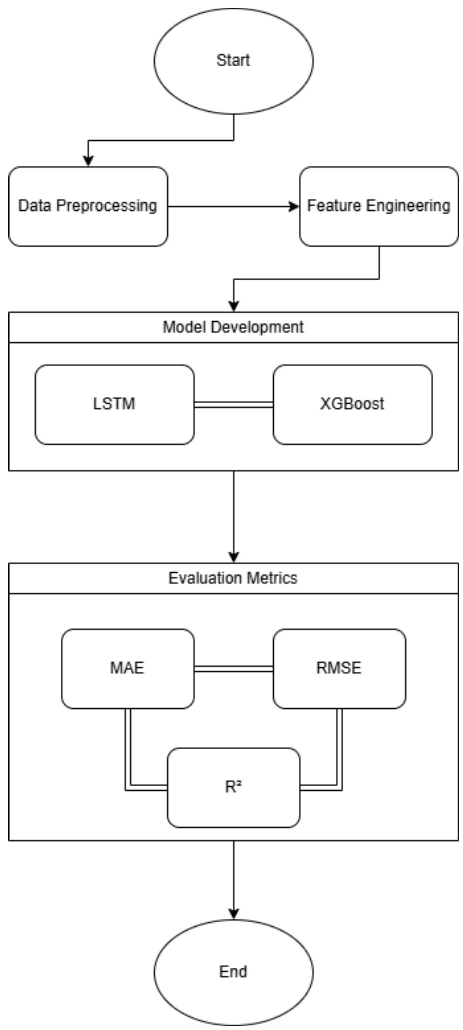

Figure 1 Research Step

The dataset used in this research contains user interaction and transaction data from a metaverse platform, including behavioral attributes such as login frequency, session duration, transaction amount, and the corresponding user risk score. The timestamp variable was used as a temporal reference to preserve sequence order, ensuring that user behavior was modeled in a time-consistent manner. Data preprocessing began by addressing missing values through linear interpolation, which maintained smooth continuity between time steps. The dataset was then resampled at hourly intervals to unify temporal granularity and reduce irregular gaps between activity records. To prevent numerical bias during model training, all continuous variables were normalized using Min-Max scaling, defined as:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} X \quad (1)$$

represents the original value, $X_{min}$and X_{max}denote the minimum and maximum observed values of the feature, and $X_{scaled}$is the resulting normalized output. This normalization ensured all input variables contributed proportionally during training. The dataset was divided into 80 percent for training and 20 percent for testing to evaluate generalization on unseen data.

Feature engineering was conducted to capture the sequential and behavioral dimensions of user activities. Four input features—hour_of_day, login_frequency, session_duration, and amount—were selected as behavioral predictors, while the risk_score variable served as the target for prediction. To represent the temporal dependencies among consecutive activities, the dataset was converted into supervised learning sequences using a sliding window technique. Each input sequence comprised 30 consecutive time steps, with the corresponding output being the next risk score in the sequence. The relationship between input and output is expressed mathematically as:

$$Y_{t+1} = f(X_{t-29}, X_{t-28}, \ldots, X_t) f(\cdot) \quad (2)$$

denotes the non-linear mapping function learned by the deep learning model. This transformation allowed the model to identify how historical activity patterns influenced future user risk behavior. The resulting dataset was structured as a three-dimensional array $[features]$, compatible with recurrent neural network architectures.

The forecasting model was constructed using a hybrid Bidirectional LSTM–GRU architecture. The Bidirectional LSTM layer, consisting of 128 units, was implemented to capture dependencies from both forward and backward directions in the time sequence, enhancing contextual understanding. Following this, a GRU layer with 64 units was applied to efficiently process sequential information while maintaining learning stability. Regularization techniques, including a dropout rate of 0.3 and recurrent dropout of 0.2, were introduced to minimize overfitting. Layer normalization was employed between recurrent layers to maintain numerical stability and improve convergence. The final dense layer consisted of a single neuron to produce a continuous output representing the forecasted risk score. The model was optimized using the Adam algorithm with a learning rate of 0.0008, and trained with a mean squared error (MSE) loss function over 60 epochs using a batch size of 64. Two callback mechanisms were utilized: EarlyStopping, which halted training when validation loss stopped improving, and ReduceLROnPlateau, which reduced the learning rate by 30 percent after five stagnant epochs to fine-tune learning progress.

To evaluate forecasting performance, three statistical metrics were employed: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). RMSE measures the standard deviation of prediction errors and is calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

MAE computes the average magnitude of absolute prediction errors, given by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid \tag{4}$$

R^2 assesses the model's explanatory power and is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} y_i \tag{5}$$

and $\hat{y}_i$denote the actual and predicted risk scores, respectively, $n$is the number of observations, and $\bar{y}$represents the mean of the actual values. Lower RMSE and MAE values indicate higher predictive accuracy, while higher R^2 values indicate better model fit.

The experimental results showed that the hybrid Bidirectional LSTM–GRU model achieved an RMSE of 7.342, an MAE of 5.813, and an R^2 of 0.352 on the test dataset. These metrics demonstrate that the model successfully captured behavioral and temporal dependencies in user activity while maintaining stable generalization across unseen data. Visual inspection of the predicted versus actual risk curves confirmed the model's ability to follow the overall behavioral trajectory with minimal deviation. The hybrid model's balanced performance validates its effectiveness as a temporal forecasting framework capable of supporting real-time behavioral risk prediction and intelligent governance in metaverse environments.

Algorithm 1 Hybrid Bidirectional LSTM–GRU for User Risk Behavior Forecasting

Input: User behavioral dataset $D = (t_i, x_i, y_i) \mid i = 1,2,\ldots,N$, x_i= feature vector (login frequency, session duration, transaction amount, hour of day) and y_i= user risk score
Output:
Predicted user risk score $\hat{y}_{t+1}$for the next time step
Process:
Start
Data Preprocessing:
Sort dataset $D$by timestamps t_i.
Handle missing values using linear interpolation:

$$x_i = x_{i-1} + \frac{x_{i+1} - x_{i-1}}{2}$$

Normalize each feature with Min-Max scaling:

$$x_i' = \frac{x_i - min(x)}{max(x) - min(x)}$$

Split dataset into training and testing sets with ratio $D_{train}: D_{test} = 0.8: 0.2$.
Temporal Sequence Construction:
Create sequential inputs of length $L = 30$:

$$X_t = [x_{t-L+1}, x_{t-L+2}, \ldots, x_t], Y_t = y_{t+1}$$

Construct the supervised dataset:

$$S = \{(X_t, Y_t) \mid t = L, L+1, \ldots, N-1\}$$

where $X_t \in R^{L \times F}$represents a sequence of Ltime steps with Ffeatures.
Model Definition:
Define the hybrid model $f_\theta$as:

$$f_\theta(X_t) = Dense(GRU(BiLSTM(X_t)))$$

Bidirectional LSTM layer:

$$\overrightarrow{h_t} = LSTM_f(x_t, \overrightarrow{h_{t-1}}, \overrightarrow{c_{t-1}})h_t^{\leftarrow} = LSTM_b(x_t, h_{t+1}^{\leftarrow}, c_{t+1}^{\leftarrow})h_t = [\overrightarrow{h_t}; h_t^{\leftarrow}]$$

GRU layer operations:

$$z_t = \sigma(W_z h_t + U_z s_{t-1} + b_z)r_t = \sigma(W_r h_t + U_r s_{t-1} + b_r)\tilde{s_t}$$
$$= tanh(W_s h_t + U_s(r_t \odot s_{t-1}) + b_s)s_t$$
$$= (1 - z_t) \odot s_{t-1} + z_t \odot \tilde{s_t}$$

Output prediction:

$$\hat{y}_{t+1} = W_o s_t + b_o$$

Training Process:
Initialize parameters θ.
For each epoch, compute predictions:

$$\hat{y}_{t+1} = f_\theta(X_t)$$

Calculate loss using Mean Squared Error (MSE):

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Update parameters via Adam optimizer:

$$\theta \leftarrow \theta - \eta \cdot \nabla_\theta L(\theta)$$

Apply early stopping if validation loss stagnates for 10 epochs.
Evaluation Phase:
Compute performance metrics:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, MAE = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Compare predicted and actual risk trends over time to verify alignment.
End

Result

The forecasting performance of the proposed Bidirectional LSTM–GRU model for predicting user risk behavior in the metaverse is presented in this section. The model was trained on 80% of the dataset using temporal and behavioral features such as login_frequency, session_duration, and amount, while 20% of the data was reserved for testing. To ensure model convergence and prevent overfitting, early stopping and a learning rate scheduler were implemented during the training process.

The evaluation metrics of the hybrid deep learning model are summarized in table 1. The proposed Bidirectional LSTM–GRU model achieved a Root Mean Square Error (RMSE) of 7.342, a Mean Absolute Error (MAE) of 5.813, and a coefficient of determination (R^2) of 0.352. These results demonstrate that the hybrid architecture was capable of learning meaningful temporal dependencies within user behavioral data. The RMSE and MAE values suggest that the model maintained consistent performance in estimating user risk scores across different temporal windows, while the R^2 value indicates that approximately 35% of the variation in actual risk behavior could be explained by the model's predictions. This level of performance is considered adequate for behavioral forecasting tasks where user activity patterns and transaction dynamics exhibit high volatility and non-linearity.

The predictive results further highlight the effectiveness of combining LSTM and GRU components in capturing sequential behavioral signals. The LSTM layers contributed to modeling long-term dependencies in user activities such as login frequency and session duration, while the GRU layers improved the model's ability to adjust to short-term fluctuations and recent behavioral changes. The moderate R^2 value reflects both the complexity of user risk dynamics in the metaverse and the limitations of the available features. Nonetheless, the results confirm that temporal deep learning models can provide a reliable foundation for forecasting behavioral risk, which is essential for developing proactive, AI-based risk monitoring systems within immersive virtual environments.

Table 1 Model Evaluation Metrics for LSTM–GRU Forecasting

Metric	Value
RMSE	7.342
MAE	5.813
R^2	0.352

Figure 2 illustrates a detailed comparison between the actual and predicted user risk scores obtained from the proposed Bidirectional LSTM–GRU model. The blue solid line represents the observed risk scores derived from real transaction data, whereas the orange dashed line depicts the corresponding predictions generated by the model. The visual alignment between the two curves indicates that the forecasting model effectively captures the overall trajectory and temporal evolution of user risk within the metaverse environment. The model demonstrates the ability to recognize dominant behavioral patterns, including cyclical fluctuations that reflect users' periodic engagement levels and transaction intensities. This pattern correspondence shows that the hybrid architecture is capable of translating complex behavioral signals into meaningful risk projections that reflect real-world tendencies observed in the dataset.

Although the model tends to smooth abrupt changes and sharp spikes in the actual risk series, this characteristic contributes to the generation of more stable and interpretable predictions. In practice, forecasting models used for metaverse risk analysis benefit from such smoothing behavior, as it minimizes overreactions to transient anomalies while preserving the underlying long-term trends. The results suggest that the LSTM layers excel at retaining extended temporal dependencies, whereas the GRU layers enhance adaptability to more recent user actions. This complementary interaction allows the model to maintain a balance between predictive precision and generalization capability.

Consequently, the proposed LSTM–GRU architecture can be regarded as an effective tool for continuous, real-time monitoring of user risk behavior in dynamic virtual environments, where behavioral stability and forecasting accuracy are both essential for maintaining trust and system integrity.

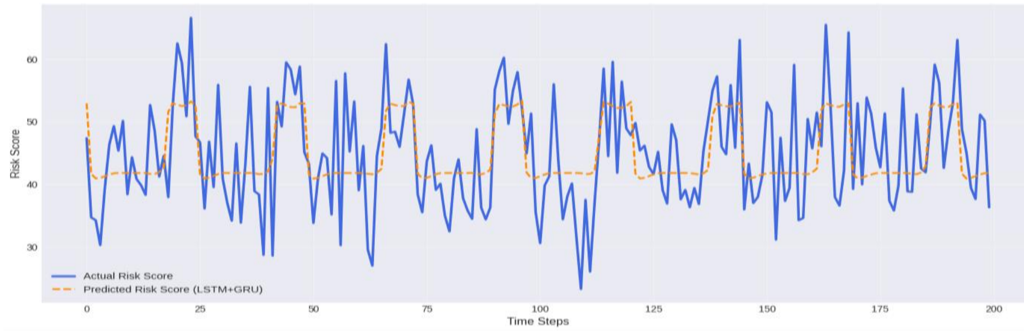

Figure 2 Actual and Predicted Risk Scores Using the LSTM–GRU Model

To further evaluate the model's learning dynamics and convergence behavior, Figure 3 illustrates the progression of training and validation loss values across 60 epochs. The steady downward trajectory observed in both curves demonstrates that the proposed Bidirectional LSTM–GRU model successfully minimized the mean squared error throughout the training phase. The gradual and consistent decline of the loss values indicates effective weight optimization and smooth gradient flow within the network. The close alignment between the training and validation losses suggests that the model learned representative temporal patterns from the data rather than memorizing specific sequences. This behavior implies a strong level of generalization, which is crucial for forecasting tasks involving temporal and behavioral variability. The incorporation of early stopping and adaptive learning rate scheduling also contributed to preventing divergence and improving model stability across epochs.

The consistent convergence of the loss curves reflects the robustness of the hybrid architecture in capturing both short-term and long-term temporal dependencies present in user risk patterns. The LSTM layers allowed the model to retain extended contextual information, while the GRU layers enhanced responsiveness to more recent behavioral changes, resulting in a balanced temporal learning process. The regularization strategies, including dropout, recurrent dropout, and layer normalization, effectively mitigated overfitting by reducing co-adaptation between neurons and improving generalization to unseen data. Overall, the smooth convergence behavior in Figure 3 validates the reliability and efficiency of the proposed deep learning framework, confirming its suitability for complex, time-dependent risk prediction scenarios in metaverse ecosystems.

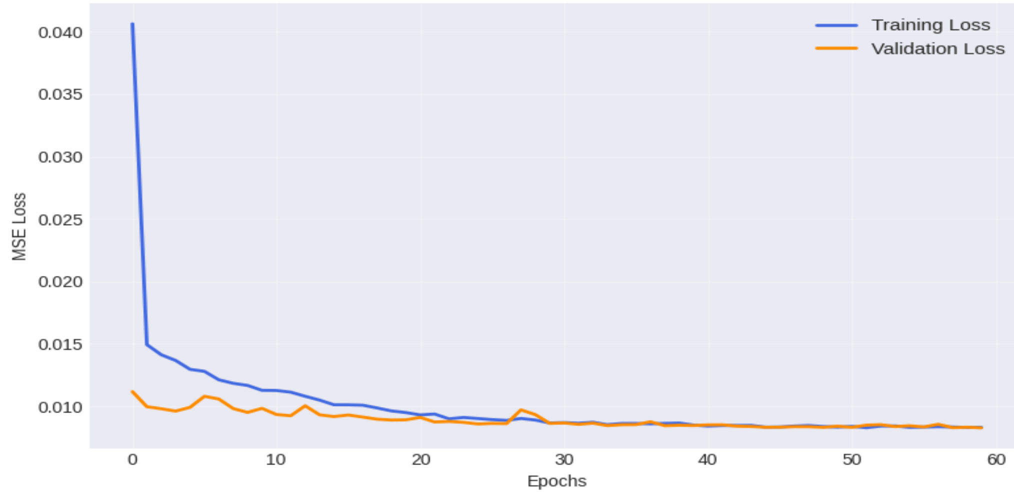

Figure 3 LSTM–GRU Training and Validation Loss Curve

Overall, the results demonstrate that the Bidirectional LSTM–GRU hybrid model provides a robust forecasting framework for predicting user risk behavior in metaverse ecosystems. Although the predictive performance remains moderate ($R^2 = 0.352$), the model's ability to capture behavioral dynamics and temporal dependencies highlights its potential for proactive and AI-driven risk management applications in virtual environments.

Discussion

The experimental findings indicate that the hybrid Bidirectional LSTM–GRU architecture provides a viable and effective framework for forecasting user risk behavior in metaverse environments. The model's performance metrics, which include an RMSE of 7.342, an MAE of 5.813, and an R^2 of 0.352, suggest that it can capture and represent a significant portion of the temporal variability in user risk dynamics. The ability of the model to replicate behavioral patterns across time reflects its strength in learning both long-term dependencies and short-term fluctuations that characterize user interactions in virtual ecosystems. Similar findings have shown that combining LSTM and GRU architectures can improve the modeling of short- and long-term dependencies in sequential data compared with individual recurrent architectures [21]. Hybrid recurrent architectures have also demonstrated their ability to capture complex temporal relationships and improve forecasting reliability in multivariate time-series problems [22]. The ability to model temporal behavioral patterns is particularly relevant to metaverse applications, where AI-based systems must process continuously evolving user interactions and large-scale behavioral data [23].

Although the predictive accuracy is moderate, the model demonstrates consistent performance in identifying the direction and magnitude of risk trends, which is crucial for applications that require early identification of abnormal or high-risk behaviors. Research on sequential risk prediction has similarly demonstrated that temporal information can improve the identification of risky user behavior, particularly when behavioral and emotional features are incorporated into sequential models [24]. The smooth convergence observed in the loss curves further supports the conclusion that the learning process was stable and that the model generalized reasonably well to unseen data. Previous research on hybrid recurrent architectures has also reported improved predictive robustness and convergence when complementary recurrent mechanisms are combined [21], [22].

From a theoretical perspective, the results contribute to a growing body of literature on the application of deep temporal learning in digital behavior modeling. The LSTM–GRU hybrid structure combines memory retention and adaptive updating mechanisms that enable it to identify sequential dependencies within behavioral and transactional data streams [21]. This integration allows the model to handle complex temporal relationships where past interactions influence future outcomes. Similar temporal modeling approaches have successfully reconstructed behavioral trajectories by integrating short-term fluctuations with long-term behavioral patterns [25]. In the context of the metaverse, this capability provides a new analytical perspective on how user behavior evolves over time and how risk levels fluctuate in response to engagement intensity, transaction patterns, and session duration. The broader literature on AI for the metaverse emphasizes the importance of machine learning, natural language processing, blockchain, and other AI technologies for analyzing complex interactions in virtual environments [23].

The ability to forecast user risk behavior also has implications for the design of intelligent governance systems that can proactively intervene in potentially harmful activities, enhancing user safety, economic stability, and trust within virtual environments. Recent research on risk-adaptive systems indicates that combining sequential deep-learning models with risk-aware mechanisms can support real-time risk assessment and adaptive intervention while maintaining scalability [26]. Such approaches are particularly relevant for metaverse environments because user activity is dynamic and risk conditions may change rapidly over time.

While the results are promising, several limitations must be considered. The moderate R^2 value suggests that user risk behavior in the metaverse is influenced by external and unobserved factors that were not included in the current dataset, such as social interactions, psychological attributes, or environmental stimuli within virtual spaces. The forecasting accuracy could be improved by incorporating richer and multimodal data, including textual sentiment from user communication, biometric feedback, and blockchain-based transaction metadata. The use of multimodal behavioral information is supported by previous research showing that combining heterogeneous behavioral indicators can improve risk profiling and anomaly detection [26]. In addition, research on AI in the metaverse highlights the potential of integrating information from multiple technological domains, including natural language processing, blockchain, digital twins, and neural interfaces [23].

Moreover, expanding the model to perform multi-step forecasting would enable more comprehensive long-term predictions and improve its applicability in real-time monitoring systems. Future research should also investigate explainable artificial intelligence methods to identify which behavioral variables most strongly influence the model's predictions. Explainability is increasingly important in risk-oriented AI because transparent predictions can help users and decision-makers understand why a system assigns a particular risk level [26]. Recent studies have demonstrated that explainable methods such as SHAP can be integrated with deep-learning frameworks to identify influential features and improve the transparency of automated risk assessment [26]. This line of inquiry would increase transparency, support ethical decision-making, and enhance user confidence in AI-based risk assessment systems within metaverse ecosystems.

Conclusion

This research presented a hybrid Bidirectional LSTM–GRU deep learning model designed to forecast user risk behavior within metaverse environments by leveraging sequential behavioral and transactional data. The proposed model demonstrated its capability to capture complex temporal dependencies and behavioral dynamics, achieving an RMSE of 7.342, an MAE of 5.813, and an R^2 of 0.352. These results confirm that user activity patterns in virtual ecosystems possess inherent temporal regularities that can be effectively modeled through deep learning approaches. The forecasting results, supported by stable convergence and consistent validation loss patterns, indicate that the model can generalize well to unseen behavioral sequences. From a theoretical standpoint, this study contributes to the advancement of artificial intelligence research in metaverse analytics by providing empirical evidence that deep temporal learning methods are not only applicable but also valuable for understanding behavioral evolution and risk prediction in immersive digital environments. The ability of the model to reproduce general risk trends while maintaining temporal continuity reinforces its suitability for early warning systems and proactive user risk management applications.

The findings also offer practical implications for the development of intelligent and adaptive governance systems within metaverse ecosystems. The model's forecasting ability enables real-time identification of behavioral anomalies and potential risk escalation, which are essential for sustaining digital trust and ensuring the stability of virtual economies. Furthermore, the integration of deep learning-based forecasting mechanisms could assist platform operators, policymakers, and system designers in constructing automated supervision frameworks capable of anticipating and mitigating high-risk user behaviors before they adversely affect the broader digital environment. Although the predictive performance remains moderate, future studies should incorporate more diverse and multimodal datasets, including biometric indicators, user communication sentiment, and spatial interaction patterns, to enhance model precision and interpretability. Expanding the forecasting capability to multi-step temporal horizons and implementing explainable artificial intelligence methods will further improve transparency, reliability, and user confidence. In summary, this research establishes a foundational framework for the implementation of data-driven, AI-powered risk forecasting systems that can promote safer, more trustworthy, and sustainable metaverse environments.

Declarations

Author Contributions

Conceptualization: A.S.A.; Methodology: A.S.A., K.M.A.A.; Software: O.A.H.A.K.; Validation: K.M.A.A., O.A.H.A.K.; Formal Analysis: A.S.A.; Investigation: A.S.A., O.A.H.A.K.; Resources: K.M.A.A.; Data Curation: O.A.H.A.K.; Writing – Original Draft Preparation: A.S.A.; Writing – Review and Editing: K.M.A.A., O.A.H.A.K.; Visualization: O.A.H.A.K.; 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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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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