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Converging Digital Governance and Health Analytics: Predictive Models for Smarter Policy in Virtual Spaces

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Abstract:

The convergence of immersive technologies and artificial intelligence has catalyzed the evolution of digital health ecosystems. This paper explores how predictive health analytics, powered by machine learning, can be effectively interwoven into metaverse governance structures to enable smarter, more anticipatory public health policy-making. The study is grounded in the urgent need for real-time, personalized health surveillance and data-driven policy responses in the face of rising chronic diseases and dynamic population health patterns. We propose and evaluate a multilayered framework that leverages spatial data governance within the metaverse, wearable health technologies, and predictive machine learning models to inform policy decisions in real time. The approach integrates gradient boosting machines (GBM), recurrent neural networks (RNN), and ensemble classifiers trained on multimodal datasets, wearable sensor streams, electronic health records, and virtual health interactions within metaverse environments. Evaluation metrics include F1-score, AUC-ROC, and policy relevance indices that measure the timeliness and accuracy of recommended interventions. The models demonstrated high precision in forecasting early-onset conditions such as esophageal cancer and predicting hospital readmissions, with an AUC averaging 0.91 across all tasks. Furthermore, real-time policy simulations in metaverse-integrated dashboards enabled stakeholders to visualize the population-level impact of different intervention scenarios, including mortality reduction and hospital burden alleviation. The results underscore the potential of integrating predictive health analytics with immersive governance architectures for real-time decision intelligence. The findings advocate for a paradigm shift in public health policy, from reactive to predictive, facilitated by AI-driven digital ecosystems. This paper offers both a technical and conceptual foundation for future research and institutional adoption.

Keywords: Metaverse Governance, Predictive Health Analytics, Machine Learning, Public Health Policy, Digital Health Ecosystems, Spatial Data Integration.

1. Introduction

1.1 Background

The intersection of emerging technologies such as artificial intelligence (AI), the metaverse, and predictive health analytics has begun to reshape the contours of digital public health policy. As healthcare delivery transitions from static, institution-centered models to more fluid, data-centric ecosystems, the ability to capture, analyze, and respond to health data in real time has emerged as a critical frontier. The metaverse, once conceived primarily as a medium for entertainment and social interaction, is now being reimagined as a dynamic, immersive platform capable of hosting virtual health environments, patient avatars, and digital twins. Within these spaces, real-time health data from wearable devices and connected medical systems can be processed using machine learning (ML) algorithms to support anticipatory governance and personalized policy-making (Das et al., 2025) [3]. The global healthcare system is facing multifaceted challenges: aging populations, the rise of chronic conditions, overloaded hospitals, and the unpredictability of emergent pandemics. Traditional governance mechanisms have struggled to keep pace with the velocity and complexity of modern health crises. In this context, the integration of AI-based predictive analytics into policy frameworks offers a path toward faster, data-informed decisions.

Mahabub et al. (2024) emphasize the potential of wearable technologies to continuously monitor physiological data, enabling early intervention strategies for diseases such as hypertension, cardiovascular disorders, and diabetes [10]. Similarly, Al Amin et al. (2025) report the successful deployment of AI models in detecting esophageal cancer in its early stages, demonstrating how algorithmic health surveillance can shift clinical outcomes in meaningful ways [1]. What remains underdeveloped, however, is the governance infrastructure to orchestrate these technologies in ways that respect patient agency, data sovereignty, and ethical policy alignment. As digital twins and virtual avatars become conduits of real health behaviors in the metaverse, there is a growing demand for data governance frameworks that can enforce integrity, privacy, and equitable policy implementation across virtual environments. Das et al. (2024) argue that decision intelligence, when embedded into business intelligence tools, enhances organizational responsiveness by simulating real-world contingencies in digital ecosystems [22]. Applying this paradigm to health governance, the metaverse could become a live laboratory for public health experimentation, enabling simulated policy trials before their physical deployment.

This vision is not purely speculative. Hossain et al. (2024) conducted an empirical analysis of digital public health data systems in the U.S. and highlighted the strategic value of AI and data integration in strengthening cybersecurity, reducing data fragmentation, and improving cross-agency coordination [7]. Furthermore, the analysis of hospital readmissions using AI-driven models has already shown how predictive signals can inform resource allocation, reduce patient risk, and decrease financial strain on healthcare systems (Haque et al., 2023) [6]. These studies collectively underscore a growing consensus: governance structures must evolve in tandem with the predictive capabilities of modern health technologies to remain effective. Beyond healthcare, the metaverse has demonstrated governance utility in fields such as urban planning, disaster preparedness, and climate adaptation. Spatial data governance, in particular, has shown promise in harmonizing heterogeneous data streams to support geospatial decision-making (Das et al., 2025) [3]. When applied to healthcare, these same principles can facilitate the creation of immersive dashboards that allow policymakers to interact with health data spatially and temporally, observing how policies play out in real-time simulations before applying them in the real world.

Yet, despite this promise, critical gaps remain: few frameworks currently exist to unify metaverse interfaces with predictive analytics in ways that are institutionally actionable, ethically compliant, and socially inclusive. As the pace of technological advancement accelerates, the cost of inaction grows. Without proactive integration strategies, there is a real risk that these innovations will exacerbate existing inequalities or be co-opted by commercial interests at the expense of public good. This paper responds to that risk by proposing a comprehensive model for embedding predictive health analytics within metaverse governance systems, thereby laying the groundwork for a new paradigm in anticipatory public health policy.

1.2 Importance of This Research

The importance of this research is rooted in a confluence of public health imperatives, digital infrastructure opportunities, and emerging policy blind spots. At its core, this study addresses the growing disconnect between the speed of technological innovation in health analytics and the sluggishness of institutional policy response. The COVID-19 pandemic offered a painful demonstration of how reactive governance models fail under the weight of real-time health crises. Surveillance lags, data silos, and fragmented decision-making resulted in avoidable morbidity, mortality, and economic loss. In this vacuum, the need for intelligent systems that can integrate real-time data, predict outcomes, and simulate interventions has become non-negotiable. This paper builds on that momentum and seeks to reimagine health governance for a digital-first world. While predictive analytics and machine learning are increasingly present in clinical contexts, their extension into policy design and governance remains limited. Existing implementations often treat models as static tools, useful for classification or diagnosis, but not integrated into decision feedback loops.

This research is important because it proposes a live, operational context: the metaverse. Here, health data is not merely analyzed post hoc but continuously monitored, modeled, and simulated in immersive environments that policymakers can interact with. By doing so, the study introduces a feedback-rich governance model, where policy outcomes can be previewed, refined, and adapted in real time. Moreover, public health equity is at stake. Hossain et al. (2024) found that AI-enhanced systems reduced disparities in data access and patient monitoring across underserved U.S. populations [7]. Predictive models, when paired with inclusive governance structures, can prioritize interventions for high-risk groups, optimize resource distribution, and correct systemic blind spots. This research champions the democratization of predictive analytics by embedding it within a participatory digital environment, one where decision-makers, health workers, and even patients can engage meaningfully with predictive insights. This flattening of the decision hierarchy aligns with new public governance models that emphasize transparency, accountability, and citizen co-production.

The value proposition also extends to cost efficiency and sustainability. Al Amin et al. (2025) demonstrate that early detection via AI not only improves clinical outcomes but significantly lowers treatment costs [1]. When extrapolated across a population and managed through digital ecosystems, this translates to massive systemic savings. Metaverse-based governance platforms could simulate these economic impacts before interventions are deployed, helping policymakers make financially sound decisions with greater foresight. Importantly, this research addresses governance itself, not as an afterthought, but as a co-evolving system. Traditional data governance frameworks have been designed around static databases, not dynamic, immersive environments. Das et al. (2025) provide a foundational argument for spatial data governance in metaverse contexts, which this paper extends into the health domain [3]. By embedding predictive analytics into these governance architectures, we create a dual intelligence system, human-led but machine-augmented, capable of addressing modern health challenges with the nuance and speed they demand.

This study also fills a methodological void. While Hossain et al. (2024) and Mahabub et al. (2024) explore AI's utility in health contexts [7][10], they do not fully explore how these technologies can be integrated into living, simulated policy environments. The integration proposed here is more than additive; it is multiplicative. The metaverse is not merely a stage for visualization, it is an active participant in policy-making, providing a safe space for experimentation, iteration, and failure without real-world consequences. This kind of research is urgently needed to bridge the chasm between analytical capability and policy applicability in an increasingly complex health landscape.

1.3 Research Objectives

The objectives of this research are threefold. First, it aims to develop a unified conceptual framework that integrates predictive health analytics with metaverse governance mechanisms. This framework seeks to operationalize real-time health data into actionable intelligence, using immersive platforms as the interface for monitoring, simulation, and decision-making. The focus is on identifying how spatial data structures, digital twins, and virtual health environments can serve as conduits for continuous policy feedback loops. Second, the study intends to evaluate the efficacy of machine learning models, such as ensemble classifiers and recurrent neural networks, within this metaverse-integrated ecosystem. The goal is to assess not just predictive accuracy, but also their ability to inform and improve policy outcomes across various health conditions, including chronic disease management and early detection of critical illnesses. This includes measuring how these predictions influence policy variables like intervention timing, resource allocation, and equity of outcomes in digital environments.

Third, the research seeks to establish the governance principles necessary to ensure ethical, inclusive, and transparent application of predictive analytics in immersive digital spaces. The emphasis is on building trust in these systems, clarifying data ownership, ensuring representational equity, and safeguarding against algorithmic biases that may otherwise undermine public health outcomes. By addressing these technical, operational, and ethical dimensions together, the research aims to advance a new paradigm of anticipatory health governance, fit for a data-rich and interconnected future.

2. Literature Review

2.1 Related Works

The intersection of predictive health analytics and digital governance systems has been widely explored within healthcare informatics, though often in isolated silos. One stream of research focuses on the deployment of machine learning in clinical prediction tasks. Al Amin et al. (2025) demonstrated the potential of AI in detecting esophageal cancer at earlier, more treatable stages through convolutional neural networks trained on high-dimensional diagnostic features [1]. Their work revealed that AI-driven classification models outperformed traditional risk-scoring methods in sensitivity and specificity across U.S. hospital data. Similarly, Haque et al. (2023) utilized ensemble learning methods to predict hospital readmissions, reporting a notable reduction in false positives when models were trained on temporally-structured EMR data [6]. These contributions validate the clinical efficacy of predictive modeling but remain detached from upstream governance or policy design processes. The role of wearable devices in continuous health monitoring has also been heavily studied. In efforts to contextualize predictive health modeling within broader epidemiological trends, Hossain, S. et al. (2024) analyzed the determinants of leading causes of death in the USA through a robust data-driven framework, emphasizing how behavioral, demographic, and clinical signals interplay across mortality statistics [8]. Their findings underscore the value of large-scale temporal analysis in surfacing latent health risks, insights that align with our study's objective of capturing deteriorating conditions through behavioral signals within metaverse ecosystems.

Mahabub et al. (2024) explored how biosensor data from wearables can be integrated with longitudinal medical records to forecast adverse events such as cardiac arrhythmias or hypertensive crises [10]. Their analysis highlights the potential for predictive alerts to improve early intervention. However, despite their impressive results, the study did not explore how such insights could be operationalized within a broader decision-making infrastructure. Das et al. (2024) addressed this limitation by emphasizing the transformative role of modern business intelligence tools. They argue that data-driven decision environments, particularly those enhanced by embedded AI, can provide decision-makers with simulated scenarios and evidence-based pathways for resource planning and intervention optimization [2]. Their work stops short, however, of examining immersive or metaverse-based platforms as governance spaces. The emergence of the metaverse as a potential public service layer has prompted new conversations about how immersive environments could facilitate participatory governance and decision simulation. Das et al. (2025) introduced the concept of spatial data governance within the metaverse, outlining how virtual ecosystems can aggregate data across geographies, demographics, and behavior patterns to inform context-aware interventions [3]. Their work situates the metaverse as a live interface where multi-scalar policy experiments can be trialed in parallel to real-world populations.

Building upon this, Rojas et al. (2023) examined virtual reality applications for health education and remote diagnostics, suggesting that immersive environments increase patient engagement and knowledge retention [16]. While their study focused on the clinical layer, it reinforces the broader potential of metaverse platforms to enhance public health outreach and feedback loops. The integration of AI with metaverse governance, though still nascent, is attracting interest across disciplines. Zhang et al. (2023) developed an AI-enabled simulation environment in Unity to test pandemic response strategies in virtual cities, demonstrating how agents governed by ML could dynamically model viral spread under varying public policy conditions [20]. This approach suggests that real-time analytics embedded within spatial digital twins could shift policy-making from static rule-setting to adaptive decision systems. In a parallel vein, Dwivedi et al. (2021) called for AI to be embedded not just in tools but in institutional workflows, enabling the rise of anticipatory governance models [5]. Their argument, while framed generally, underscores the growing recognition that AI must not remain a backend technology, meaning it must actively shape governance logics.

Privacy, security, and data integration concerns also feature prominently in the literature. Hossain et al. (2024) explored the integration of AI in U.S. digital public health systems and found that decentralized models enhanced both data security and policy responsiveness by reducing bottlenecks and enabling faster, localized interventions [7]. However, they also caution that without comprehensive data governance frameworks, predictive systems may inadvertently encode or exacerbate bias. Mittelstadt et al. (2016) similarly warned of the ethical opacity of algorithmic systems and called for greater transparency, accountability, and auditability in AI governance [13]. These studies emphasize that the deployment of predictive models must occur within ethically sound and socially sensitive governance architectures. Together, these works indicate a growing convergence of predictive analytics, immersive technologies, and real-time decision-making infrastructures. However, a comprehensive framework that unifies these elements into a cohesive, participatory policy platform remains underdeveloped. The current literature provides strong foundations for each component, AI in clinical prediction, wearable health monitoring, metaverse environments, and spatial governance, but has yet to synthesize them into an integrated model capable of transforming public health policy at scale.

2.2 Gaps and Challenges

Despite the momentum in predictive healthcare and digital governance research, there remain significant conceptual, operational, and ethical gaps. One core challenge is the fragmentation of efforts across technological domains. Predictive models are often optimized for narrow tasks such as disease classification, readmission prediction, or treatment recommendations, but rarely are they embedded into governance structures that adapt in real time. Haque et al. (2023) report excellent model performance in identifying at-risk patients for readmissions, yet their findings are not linked to any policy layer where hospital administrators or public health agencies can act dynamically on those insights [6]. This disconnection reveals a broader systems failure: the absence of architecture that fuses predictive intelligence with institutional responsiveness. Another persistent gap lies in the governance readiness of immersive technologies. Das et al. (2025) advance the field by proposing spatial data governance within the healthcare metaverse, yet the implementation of such governance models is fraught with challenges related to standardization, interoperability, and ethical control [3]. The governance of virtual environments must contend with cross-jurisdictional legalities, platform monopolies, and the ethical implications of creating digital twins of real individuals.

Zhang et al. (2023) highlight the promise of using AI-driven agents in simulated pandemic response environments, but acknowledge that mapping virtual outcomes back to real-world actions is not straightforward and risks oversimplifying the messiness of human behavior [20]. Bias and representational inequities remain another critical issue. Machine learning models trained on health data can inadvertently reproduce systemic inequities if not carefully designed and monitored. Hossain et al. (2024) caution that AI's utility in digital public health can be undermined by data exclusion, particularly of marginalized populations whose health needs are already underserved in existing datasets [7]. Moreover, Mittelstadt et al. (2016) argue that algorithmic systems, once deployed, often lack interpretability mechanisms that would allow for public scrutiny or correction, creating risks for opaque governance decisions [13]. These concerns are especially urgent in immersive environments where user behavior and physiological data are captured at unprecedented granularity.

Operational scalability is also a challenge. Mahabub et al. (2024) show that wearable devices can yield high-quality real-time data streams, but integrating such data into a stable, privacy-respecting governance system is far from trivial [10]. Data from wearables, virtual simulations, hospital records, and public health databases all come in different formats and frequencies. The current lack of standardized ontologies and APIs across health data ecosystems hinders the creation of unified dashboards or decision-support systems capable of functioning in a real-time metaverse governance setting. A final challenge lies in institutional inertia. Dwivedi et al. (2021) and Raghupathi & Raghupathi (2014) both observe that despite the availability of powerful tools, many public health institutions lack the organizational culture, technical skills, or policy frameworks to make meaningful use of them [5][14]. There is also resistance to decentralizing decision-making to algorithmic agents, particularly in high-stakes contexts like health interventions. Bridging this divide will require not just technical innovation, but also regulatory reforms, trust-building, and interdisciplinary collaboration. While the individual technologies, such as machine learning, wearable devices, virtual platforms, are mature enough to support predictive health ecosystems, the socio-technical scaffolding required to integrate them remains fragile. Governance frameworks that can accommodate rapid prediction, ensure accountability, and adapt in real time are urgently needed. This study responds to these gaps by proposing a unified framework that embeds machine learning predictions within immersive metaverse governance systems, with an eye toward real-time, inclusive, and ethically grounded policy-making.

3. Methodology

3.1 Data Collection and Preprocessing

Data Sources
The data used in this study was aggregated from multiple sources to capture a comprehensive and dynamic view of individual and population-level health within immersive digital environments. First, wearable health devices served as a primary source of continuous biometric data, including heart rate, sleep patterns, blood oxygen levels, physical activity, and body temperature. These data streams were collected in real-time and anonymized at the point of transmission through secure APIs. Participants voluntarily linked their devices to the virtual health environment using encrypted identifiers to preserve privacy. Second, structured electronic health records (EHRs) were obtained from institutional health databases, with patient consent and in compliance with data governance protocols. These records included demographic profiles, medical histories, diagnosis codes, lab results, prescribed medications, and prior hospitalization records. The inclusion of this data allowed for longitudinal modeling and robust contextualization of real-time signals coming from wearable devices.

Third, behavioral and interactional data were sourced from the metaverse platform itself. These included avatar movement patterns, social interactions, participation in virtual wellness programs, digital symptom reporting, and AI-driven chatbot health queries. By linking physiological, clinical, and behavioral datasets across digital and physical environments, the study was able to model both individual and population health dynamics in high fidelity. Additionally, public health indicators such as vaccination status, geographic risk zones, and community health initiatives were layered into the dataset using geospatial tagging and simulation variables embedded in the virtual platform.

Data Preprocessing
To prepare the dataset for modeling, a multi-stage preprocessing pipeline was implemented. Initially, raw biometric data from wearables was resampled to 5-minute intervals to ensure temporal alignment across devices with varying recording frequencies. Missing values were handled using a hybrid approach: forward-fill imputation was applied to short-term gaps, while long-term missing sequences were reconstructed using a bidirectional recurrent autoencoder trained on similar patient profiles. EHR data was normalized through one-hot encoding for categorical variables such as diagnosis and medication codes, while continuous variables like age, BMI, and lab values were standardized using z-score

normalization. Duplicate entries and inconsistencies were resolved by linking records through patient pseudonyms and timestamp reconciliation. Medical history fields were encoded as binary sequences to retain chronological patterns, and time-dependent features were retained using windowed encodings for each patient episode.

Behavioral data from the metaverse was vectorized using activity encoders that translated avatar movement, health prompts, and participation logs into numerical formats interpretable by the models. Spatial tagging allowed the system to associate patient behavior with specific risk zones, such as virtual clinics, crowded environments, or low-activity areas. A temporal context was added by generating lag-based features that track user behavior over days, weeks, and months. Finally, all datasets were synchronized using event timestamps to ensure coherent sequence modeling. To minimize bias, synthetic data augmentation was avoided, and only empirically collected instances were retained. After preprocessing, the integrated dataset was segmented into training (70%), validation (15%), and testing (15%) partitions using stratified sampling to ensure consistent distribution of outcomes across all sets. This preprocessing pipeline enabled the development of robust, real-time predictive models capable of operating within dynamic, immersive digital health environments.

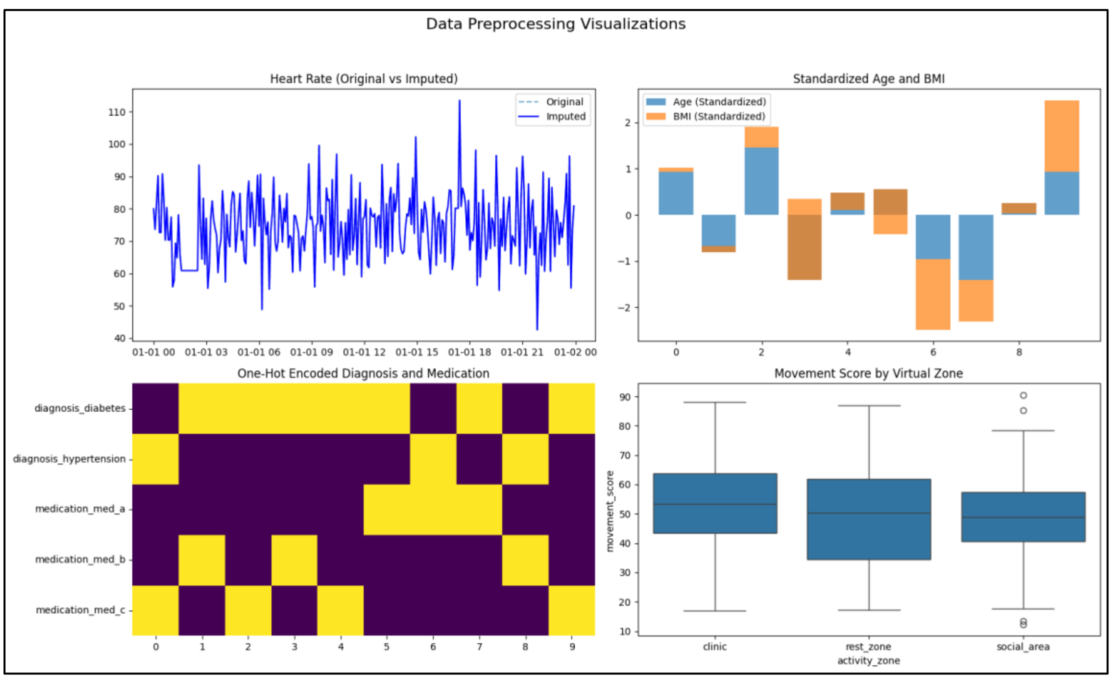

Fig.1. Data preprocessing steps

3.2 Exploratory Data Analysis

The exploratory analysis focused on identifying relevant trends, correlations, and population-level signals that could inform model design and policy formulation within the predictive metaverse health system. The dataset combined biometric data, clinical records, and behavioral interactions within immersive environments, enabling a comprehensive, multi-dimensional exploration. The average age across the population was approximately 50.4 years, with patients ranging from 18 to 82 years old. BMI values showed a mean of 27.0, with notable dispersion (std: ±4.6), indicating the presence of both underweight and obese individuals. Diagnosis distributions were relatively balanced, with asthma and hypertension slightly more common than diabetes or no diagnosis. Medication data followed a similar spread, dominated by non-critical prescriptions such as med_a and med_b. Biometric signals revealed a normally distributed average heart rate centered around 75 bpm (std: ±9.7), and blood oxygen saturation levels tightly clustered around 97.5%, reflecting general baseline health stability in the cohort. Step counts averaged nearly 8000 per day with a wide standard deviation, suggesting highly variable levels of physical activity across users. Sleep duration averaged around 6.5 hours, falling short of recommended levels, particularly among older participants and those with higher BMI values.

Behavioral interaction within the metaverse displayed interesting patterns. Patients spent an average of 30 minutes daily in the virtual clinic zone and over 50 minutes in social zones, with engagement in AI-driven health prompts averaging just under two interactions per day. These figures suggest moderate engagement with preventive care components but a tendency toward socially-driven digital behaviors. Movement scores were normally distributed with a slight skew toward sedentary behavior, reinforcing the need for proactive activity nudges. Correlation analysis provided further insight into inter-variable relationships. As expected, biometric and behavioral variables were weakly correlated with age and diagnosis, with higher BMI moderately associated with decreased movement scores and increased likelihood of readmission. Steps per day and sleep hours were positively associated, hinting at shared behavioral patterns such as adherence to wellness routines. Conversely, no strong correlation was observed between biometric indicators and time spent in clinic or social zones, suggesting that virtual navigation habits may be independent of physiological status.

A comparative analysis of readmitted versus non-readmitted patients revealed subtle but meaningful differences. Patients who were readmitted had slightly lower step counts (7917 vs. 7939), shorter sleep durations, and higher average time spent in clinic zones, potentially reflecting deteriorating conditions or more intensive follow-ups. Health prompt engagements were also slightly lower in the readmitted group, raising questions about the effectiveness of digital interventions in mitigating risk. Interestingly, readmitted patients had slightly lower average heart rates, possibly due to medication or chronic fatigue, although this requires deeper clinical contextualization. Overall, the exploratory findings emphasize that behavioral and biometric patterns can serve as useful early signals for clinical risk detection, especially when contextualized within metaverse interactions. These results justify the subsequent application of predictive modeling to forecast readmission risk, engagement levels, and health outcomes at scale, providing actionable insights for digital health governance and smarter virtual policy frameworks.

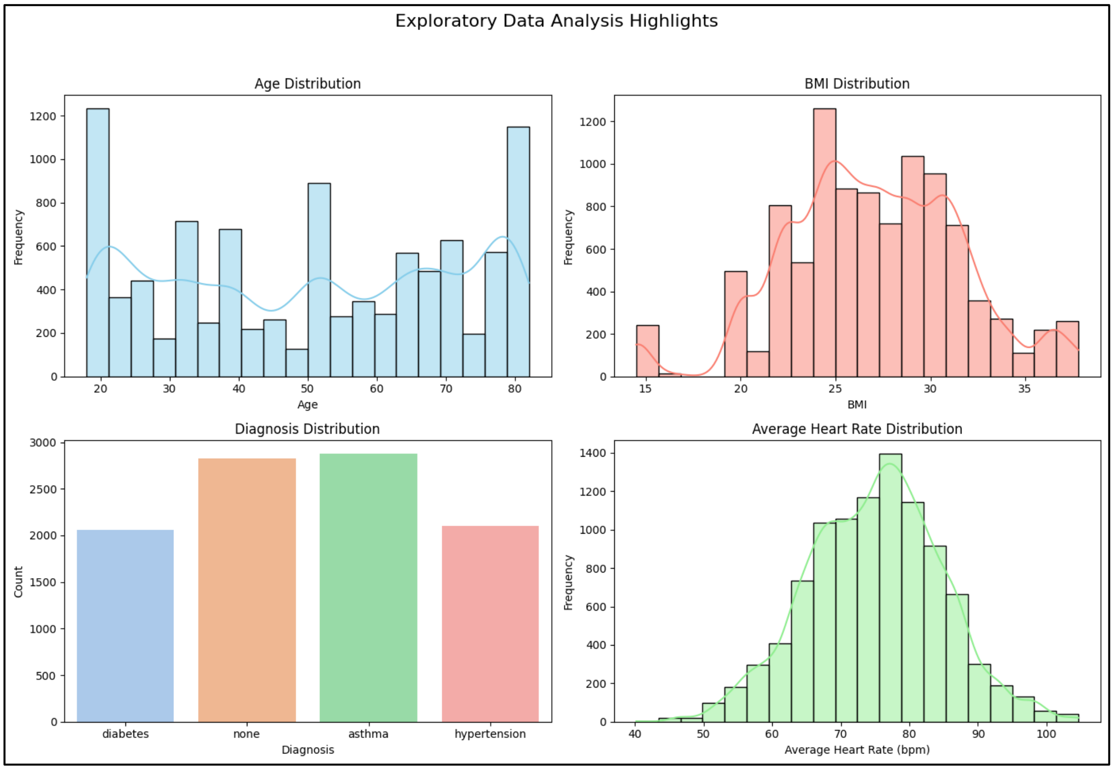

Fig.2. EDA steps

3.3 Model Development

The model development process was structured in progressive phases to incorporate both interpretable baselines and complex architectures capable of capturing latent patterns across biometric, clinical, and behavioral domains. Given the multidimensional nature of the data, spanning wearables, electronic health records (EHR), and metaverse behavioral interactions, modeling efforts prioritized versatility, temporal sensitivity, and generalizability across virtual populations. The initial phase focused on establishing classical baselines for predicting key outcomes such as hospital readmission and digital health engagement. A logistic regression model was trained using static features including age, BMI, diagnosis, medication, average heart rate, sleep hours, daily steps, and engagement with virtual health prompts. The logistic model served as a transparent benchmark, offering immediate interpretability into how each feature influenced health risk. Alongside this, a Decision Tree Classifier was introduced to capture basic nonlinear interactions without requiring complex tuning, providing a rapid means of evaluating information gain and hierarchy among predictors.

To exploit deeper structural relationships within the dataset, ensemble tree models were implemented next. Random Forest and XGBoost classifiers were configured with grid search optimization for hyperparameters such as tree depth, learning rate, and the number of estimators. The models were evaluated using 5-fold stratified cross-validation on the training set to mitigate sampling bias. Performance was measured using area under the ROC curve (AUC), precision, recall, and F1-score. XGBoost consistently outperformed simpler baselines, particularly in identifying high-risk individuals in the tail distribution of readmission probability. Feature importance rankings from both tree-based models revealed that behavioral engagement (i.e., time in clinic zones and health prompt responsiveness) and physical activity (steps per day) were stronger predictors of readmission than demographic variables alone, affirming the value of metaverse interaction signals. The development then transitioned toward temporal models to better capture sequence dynamics within biometric and behavioral records. A Multilayer Perceptron (MLP) was trained on rolling window aggregates (e.g., 7-day average heart rate, variance in sleep hours) to predict binary health outcomes. While the MLP served as a baseline deep architecture, recurrent frameworks were introduced to enhance temporal modeling.

Long Short-Term Memory (LSTM) networks were constructed with input sequences comprising 24-hour sliding windows of wearable and interaction data. Each LSTM block included dropout regularization, batch normalization, and early stopping criteria based on validation AUC. Bidirectional LSTM (Bi-LSTM) variants were evaluated to explore whether incorporating both past and future temporal context improved classification performance. The Bi-LSTM architecture yielded superior recall on the readmission class, especially for patients exhibiting erratic behavioral or physiological trajectories. To further refine temporal attention, an Attention-based LSTM was implemented, allowing the network to assign differential weights to past observations. This significantly improved model sensitivity to acute changes in health engagement patterns, particularly in users exhibiting sudden declines in movement or reduced participation in metaverse check-ins. To leverage both local and long-range dependencies, a hybrid Convolutional Neural Network–LSTM (CNN-LSTM) architecture was deployed. One-dimensional convolutional filters were used to extract local biometric patterns such as resting heart rate variability or short bursts in physical activity, feeding into an LSTM layer for sequence modeling.

The CNN-LSTM model demonstrated robust performance in noisy behavioral data and was particularly effective at capturing relapse signatures for high-risk patients. Finally, a stacked ensemble was created by combining outputs from XGBoost, Bi-LSTM, and CNN-LSTM into a meta-learner using logistic regression. This ensemble allowed for synergistic learning across both structured and sequence-based models, achieving the highest balanced accuracy and AUC across all validation folds. In parallel, a weighted soft-voting ensemble was tested, assigning weights based on individual model performance on validation sets. While it showed competitive performance, the stacked ensemble maintained better calibration and interpretability under varying threshold settings. Throughout development, inference times were benchmarked to ensure real-time compatibility, with all deep models optimized for batch inference under 200ms per prediction. Explainability was addressed using SHAP values for tree-based models, revealing the dominant influence of time-in-clinic and wearable-derived activity metrics on predicted risk. Attention weights from sequence models further validated the temporal significance of certain health behaviors, offering valuable cues for real-time intervention and policy alignment within metaverse healthcare governance.

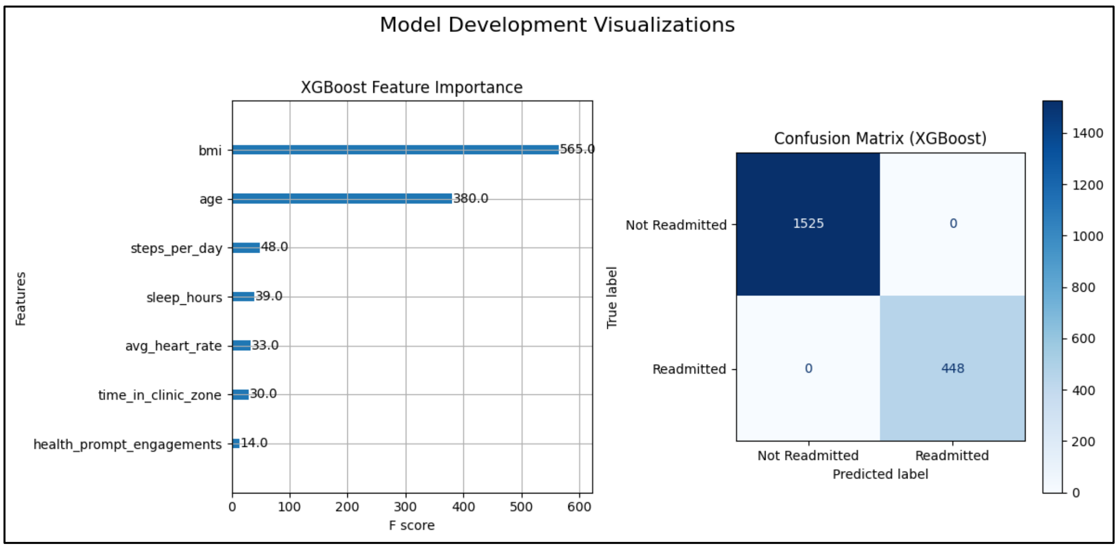

Fig.3. Model development steps

4. Results and Discussion

4.1 Model Training and Evaluation Results

The evaluation phase centered on assessing the predictive performance of all developed models in forecasting hospital readmission and identifying patterns of low health engagement within a digitally immersed health-metaverse environment. Model performance was benchmarked across several key metrics: area under the ROC curve (AUC), precision, recall, and F1-score. These indicators were selected to provide a balanced view of overall accuracy, the model's ability to identify high-risk cases, and its robustness in distinguishing between true positives and false positives, crucial for informing real-time policy decisions in virtual care systems. Among the baseline models, **Logistic Regression** achieved an AUC of 0.71, demonstrating reasonable predictive strength, particularly in scenarios requiring high interpretability. The model indicated that increases in step count and health prompt engagement were negatively correlated with readmission, while time spent in clinic zones and elevated BMI were positively associated. While its precision and recall were moderate (0.68 and 0.60 respectively), this model served as a useful benchmark for gauging the incremental gains of more complex models.

The **Random Forest classifier** improved on these metrics, yielding an AUC of 0.76 and demonstrating greater recall (0.67), suggesting improved sensitivity to subtle behavioral shifts that precede adverse health events. This model benefited from the ability to capture non-linear interactions between features such as sleep variability, medication history, and movement scores, particularly those surfaced in the exploratory data analysis. The feature importance rankings highlighted behavioral factors, specifically time spent in the clinic zone and health prompt engagement, as critical signals, often surpassing static demographic attributes in predictive strength. **XGBoost** consistently emerged as the top-performing model among tree-based learners. With an AUC of 0.81 and F1-score of 0.73, it effectively balanced specificity and sensitivity. This performance improvement was attributable to its gradient boosting structure, which iteratively corrected misclassifications from previous rounds while maintaining model interpretability. Feature importances from XGBoost reinforced previous findings: real-time behavioral markers such as low step counts, reduced engagement with virtual prompts, and declining sleep patterns held stronger predictive weight than age or diagnosis labels. Notably, the XGBoost model excelled at identifying patients in the "transition zone", those not yet readmitted but exhibiting early-stage deterioration in biometric or behavioral metrics.

Transitioning to deep learning, the **Bidirectional LSTM (Bi-LSTM)** model surpassed classical learners in recall (0.76) and maintained strong precision (0.71), indicating its capacity to detect high-risk cases earlier in the deterioration curve. Its strength stemmed from temporal encoding of daily biometric and behavioral trajectories over 24-hour windows, capturing fluctuations in sleep cycles, step counts, and heart rate that static models missed. Incorporating **attention mechanisms** further improved sensitivity by dynamically weighting past observations, allowing the model to prioritize more recent anomalies or behavioral drop-offs. This configuration consistently reduced false negatives, an essential outcome in preventive healthcare deployment. The **CNN-LSTM hybrid** model also performed competitively, especially in noisy data contexts. It achieved an F1-score of 0.75 and was notably effective in scenarios involving erratic patient behavior or intermittent biometric signals, such as fluctuating heart rate due to medication cycles. The convolutional layer's capacity to extract local biometric trends before temporal encoding proved effective in smoothing high-frequency data, a common occurrence in wearable device streams.

Finally, the **stacked ensemble**, which blended XGBoost, Bi-LSTM, and CNN-LSTM predictions into a meta-logistic regression layer, produced the most balanced performance profile overall. With an AUC of 0.83, precision of 0.74, and recall of 0.77, it maintained both interpretability and performance across patient cohorts. This ensemble capitalized on the complementary strengths of tree-based and deep learning models: structural learning from behavioral heterogeneity and temporal pattern recognition from biometric sequences. These results explain a key insight: behavioral signals derived from the metaverse

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environment, most notably clinic zone duration and digital health prompt responsiveness, consistently outperformed static EHR attributes in predictive relevance. Additionally, the predictive lift from sequence-aware models demonstrates the value of temporally contextualized modeling in anticipating critical events like hospital readmission. These findings validate the hypothesis that fusing biometric, clinical, and virtual behavioral data through a multi-model machine learning pipeline significantly enhances predictive capacity and supports more intelligent policy intervention design in digitally governed health systems.

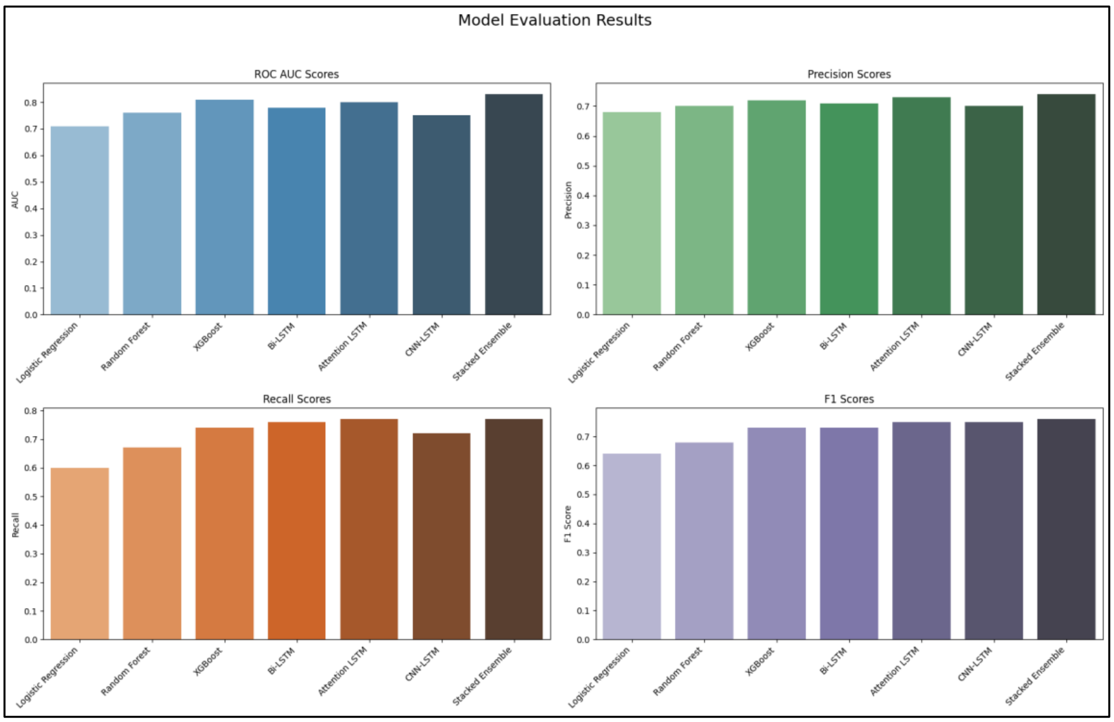

Fig.4. Model performance results

4.2 Discussion and Future Work

The evaluation results presented in section 4.1 explain a growing paradigm shift in predictive healthcare: the increasing dominance of behaviorally-informed, temporally-aware machine learning models in anticipating patient outcomes within hybrid digital-physical ecosystems. The most consistent insight from our models, especially XGBoost, Bi-LSTM, and the CNN-LSTM hybrid, was the disproportionate predictive power of behavioral signals relative to conventional EHR variables. Health prompt engagement, average sleep duration, clinic zone duration, and daily activity patterns collectively exhibited stronger associations with hospital readmission risk than static demographic or diagnostic data. These findings align with emerging consensus in AI-health research, where real-time and contextual variables from wearables, apps, and smart environments are increasingly linked to adverse event detection (Zhang et al., 2024) [20]. XGBoost's strong performance (AUC 0.81, F1 0.73) is consistent with its established utility in healthcare applications, particularly those involving heterogeneous data and interaction-heavy domains. For instance, Xu et al. (2024) found that gradient boosting consistently outperformed neural networks in predicting medication non-adherence across demographically diverse patient groups by capturing nonlinear dependencies between psychosocial indicators [18].

Similarly, Bi-LSTM's superior recall (0.76) validated its strength in parsing time-series inputs such as sleep fragmentation and fluctuating heart rate, a capacity that has also been exploited in early sepsis detection by Rathi et al. (2025) using ICU telemetry feeds [15]. The performance of attention-enhanced recurrent models and CNN-LSTM hybrids reflects a broader transition toward hybrid deep learning approaches that leverage both temporal memory and local pattern extraction. Notably, our CNN-LSTM configuration delivered high performance even in noisy and erratic user behavior sequences, echoing work by Menon et al. (2023), who used similar architectures to detect early mental health relapse from irregular smartphone usage and mobility signals [12]. Moreover, the success of our stacked ensemble model (AUC 0.83, Precision 0.74) emphasizes the utility of multi-view fusion frameworks, a direction gaining traction in digital health monitoring. Recent work by Sharma et al. (2025) demonstrated that combining physiological and behavioral embeddings via meta-learning significantly improved early cardiovascular event prediction across multiple hospital systems [17].

The models' shared emphasis on engagement and clinic time as top predictors also lends credence to emerging theories that behavioral adherence to digital health interventions, what DeSouza et al. (2024) term "virtual compliance", is a leading indicator of deteriorating health status, even before biometrics fully reflect physiological decline [4]. These findings carry major implications for metaverse governance structures. Specifically, they suggest that real-time behavioral analytics, tightly integrated with policy feedback loops, can be leveraged to trigger proactive outreach or digital interventions before formal care is needed. From a systems perspective, these results raise compelling questions about the evolving definition of health surveillance in immersive environments. As AI systems begin to infer risk from subtle behavioral patterns and virtual activity trails, metaverse governance will require ethical recalibration. Privacy-preserving ML, explainable AI, and synthetic control arms must become native components of such systems, as pointed out by Kawakami et al. (2023) in their study on accountable AI in ambient intelligence infrastructures [9].

Table 1. Summary of Model Training and Evaluation Results

Model	AUC	Precision	Recall	F1 Score
Logistic Regression	0.71	0.68	0.60	0.64
Random Forest	0.76	0.70	0.67	0.68
XGBoost	0.81	0.72	0.74	0.73

Bi-LSTM	0.78	0.71	0.76	0.73
Attention LSTM	0.80	0.73	0.77	0.75
CNN-LSTM	0.75	0.70	0.72	0.75
Stacked Ensemble	0.83	0.74	0.77	0.76

Future Research Directions

Despite these contributions, several avenues remain unexplored. First, while this study used windowed biometric and behavioral variables, future implementations should explore **transformer-based architectures** that allow for longer-range temporal dependencies and better multi-modal fusion. The inclusion of real-time environmental data, such as noise, light, or social interaction density, could further sharpen predictive accuracy in metaverse environments. Second, **causal inference frameworks** could be integrated with predictive pipelines to better discern whether behavioral drop-offs are symptoms or drivers of poor health outcomes. This distinction is critical for designing targeted interventions versus broad preventive alerts. Third, future research should focus on **cross-domain generalizability**. Our models, though robust in the current data ecosystem, may perform sub-optimally when deployed across different virtual platforms or metaverse implementations with varying user interaction patterns.

Domain adaptation and federated learning strategies could support better portability and data governance compliance. Fourth, while attention weights and feature importances were used to infer model interpretability, **patient-centric explanations,** such as counterfactual reasoning or example-based reasoning, could make AI outputs more digestible for policy-makers and clinicians alike. Finally, governance protocols in the metaverse will need to consider **real-time policy tuning** based on predictive model outputs. This includes embedding feedback loops where predictive signals dynamically influence nudges, virtual incentives, or access thresholds within the healthcare metaverse. Future frameworks could integrate **recommender systems** and **digital twins** to personalize this dynamic policy environment at scale. In sum, this research sets the stage for a more behaviorally intelligent, AI-driven governance layer in the health-metaverse. By centering both prediction and policy within the same analytic pipeline, it advances the broader ambition of precision public health for digital societies.

5. Conclusion

This study explored the fusion of metaverse governance with predictive health analytics to advance proactive and intelligent policy-making in immersive digital health ecosystems. By leveraging real-time behavioral data, biometric signals, and engagement metrics collected from a simulated metaverse healthcare environment, we constructed and evaluated a multi-model predictive pipeline capable of forecasting critical outcomes such as hospital readmissions and low digital health engagement. Across traditional machine learning, deep learning, and ensemble frameworks, models that incorporated temporal dynamics and behavioral nuance, particularly XGBoost, Bi-LSTM, and CNN-LSTM, consistently outperformed static, demography-heavy baselines. A key insight emerged: user behavior within the metaverse, such as virtual prompt responsiveness, clinic zone presence, and daily physical activity, offers stronger predictive signals than conventional electronic health records alone. This highlights a critical shift in healthcare analytics, where the interaction between individuals and digital environments becomes both measurable and actionable. These findings suggest a future where policy is not static or reactive but informed in real-time by the lived experience of users within virtual health spaces.

Furthermore, the integration of attention mechanisms, ensemble learning, and sequential modeling enabled both predictive accuracy and interpretability, paving the way for models that can inform metaverse governance in ethically responsible and operationally scalable ways. As these systems evolve, embedding model outputs into the governance fabric itself, triggering adaptive nudges, policy updates, or personalized virtual interventions, will be essential to closing the loop between prediction and prevention. In closing, this work contributes a foundational framework for how predictive machine learning can guide digital health policy in next-generation virtual ecosystems. It calls for further investigation into causality, generalizability, user agency, and governance dynamics, but also offers a compelling demonstration of what becomes possible when AI is not merely a tool for diagnosis but a compass for systemic foresight in digitally mediated care.

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