World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(REVIEW ARTICLE)

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Privacy-Preserving Zero Trust: Federated Learning for Behavioral Biometrics in Regulated Industries

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World Journal of Advanced Research and Reviews, 2023, 20(02), 1610-1643

Publication history: Received on 21 September 2023; revised on 21 November 2023; accepted on 28 November 2023

Article DOI: https://doi.org/10.30574/wjarr.2023.20.2.2219

Abstract

Zero Trust Architecture (ZTA) integration with Federated Learning (FL) is a game changer in authentication systems of controlled industries. This study hypothesizes the privacy saving model based on a framework that integrates behavioral biometrics with decentralized machine learning to allow continuous user authentication without accessing sensitive data. The suggested system will utilize hybrid Convolutional Neural Network-Recurrent Neural Network (CNN-RNN) models in a federated learning setup to involve spatio-temporal trends in user behavior whilst data localization on edge devices. The outcomes of the experiment show that the accuracy rates are over 92% when it comes to identifying a user in a variety of behavioral modalities, such as the keystroke dynamics and the patterns of mouse movement. The framework is used to eliminate centralized data storage vulnerabilities that can lead to critical privacy requirements in the healthcare, financial services, and government sectors. Differential privacy mechanisms both guarantee that sensitive information is not leaked when updating the model and also guard against inference attacks with the help of secure aggregation protocols. The overhead reduction in performance measures is found to be 27% versus the traditional centralized methods. The Zero Trust model confirms user identity by behavioral signature continually giving adaptive risk scoring to access control decisions. This piece of work adds new elements of architecture combining policy enforcement points with federated aggregators and blockchain-generated audit trails. The system ensures compliance with the General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) by implementing the principle of data minimum and clear processing. The viability of the framework to be deployed in the production with latency under 150ms to make authentication decisions is validated empirically in three regulated industry settings.

Keywords: Zero Trust Architecture; Federated Learning; Behavioral Biometrics; Privacy Preservation; Continuous Authentication; Hybrid Neural Networks; Differential Privacy; Edge Computing; Decentralized Machine Learning

1. Introduction

1.1. Privacy-Preserving Authentication Systems in Contemporary Digital Ecosystems

The spread of the digital transformation programs in regulated sectors has literally transformed the security environment, which requires the use of authentication systems that offer a compromise between the strict access control and the maintenance of the privacy (Mothukuri et al., 2021). The conventional frameworks of perimeter-based security are no longer effective against advanced cyber threat groups, insider attackers, and the decentralization of the current computing environment (Wang et al., 2020). Behavioural biometrics is also converging with Zero Trust Architecture (ZTA), which is an exciting avenue of solution but an aspect that has been limited to regulated areas is the issue of privacy and the needs of compliance. Behavioural biometrics also provides real-time authentication because user interaction patterns, such as keystroke dynamics and mouse gestures and touchscreen gestures, can be analyzed,

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as a non-invasive alternative to the traditional authentication credentials. Nevertheless, the storage and analysis of behavioral data on centralized servers poses significant privacy opportunities, providing attractive targets to adversaries and potentially going against the laws of information protection including General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) (Abadi et al., 2016).

The key concept of Zero Trust Architecture is to redefine security by removing the implicit trust beliefs and make the user identity and device posture continuously checked (Wei et al., 2020). This type of architecture is in line with regulatory demands in having rigid access controls and audit capabilities and in enabling adaptable risk evaluation based on contextual variables. With Federated Learning (FL) integrated into Zero Trust systems, it is possible to train models in privacy-preserving manners, with behavioral biometric information being locally stored on client devices, and only encrypted model updates are sent to central aggregators. The latter decentralized paradigm implies dealing with fundamental privacy issues because sensitive behavioral patterns cannot be transferred to any other device, which greatly limits exposure to data breaches and unauthorized security (Kairouz et al., 2021). In addition, FL is inherently designed to support the heterogeneous data distributions of behavioral biometrics, where the patterns of individual users differ significantly across the populations.

Hybrid neural networks based on the use of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in a federated setting represent both spatial and temporal aspects of behavioural biometric information (Zhang et al., 2021). CNNs are good at local feature extraction of raw input sequences, feature patterns in pressure profiles of keystroke or mouse trajectory curvature. RNNs add to this feature, as they can capture time-related relationships and sequential associations that constitute user-specific behavioural patterns (Rieke et al., 2020). These architectures synthesized into privacy preserving frameworks allow one to identify the users accurately without violating the data protection regulations. Controlled sectors such as the healthcare industry, financial services and government sectors have special authentication needs because of the sensitivity of the information processed, regulatory control and the impact of a security breach (Dwork and Roth, 2014). These industries cannot afford to implement generic authentication solutions and need to implement industry-specific solutions addressing industry-specific threat models, compliance requirements, and operational constraints.

1.2. Fundamental Principles of Zero Trust Security Architecture

Zero Trust Architecture is an extensive security model that is based on the idea that none of the entities, both within and outside the organizational perimeter, should be trusted per se (Zhao et al., 2018). This change of paradigm with the old models of perimeter defence presupposes constant authentication and authorization of all access requests irrespective of their origin (Li et al., 2020). The fundamental principles of Zero Trust are the explicit verification of the identity of users and devices, least privilege, and mentality of breach. Zero Trust implementation needs to divide its security controls into policy decision points that compare access requests to dynamic trust scores and policy enforcement points that execute authorization decisions (Hard et al., 2018). These elements must work in tandem to offer real time risk assessment capabilities that can evolve with the changing threat environments and user behavioural trends.

Behavioral biometrics use with the Zero Trust frameworks also improves continuous authentication abilities as it can validate user identity during active sessions as opposed to merely using initial credentials to access the network. The patterns of behaviors are unique and stable enough to be trusted as predictors of identity, yet on the other hand, they are not easy to imitate (or spoof by rivals) (Mo et al., 2021). The integration of various modalities of behavior such as typing rhythm, mouse dynamics, and navigation pattern produce a multidimensional behavioral profile that makes identification more accurate and prevents impersonation attacks stronger. Zero Trust systems should be capable of supporting the probabilistic behavioral biometric authentication environment, in which matching decisions are threshold-based comparisons to the learned user profiles as opposed to deterministic credential checking. This involves advanced risk scoring algorithms that combine behavioral similarity scores with feature context (where the access point is, what device is used, how sensitive the requested resource is) (Konečný et al., 2016).

In the case of regulated industries, privacy concerns take the lead of Zero Trust deployment, as the behavioral data processing should adhere to stringent data protection policies. The process of behavioral biometrics collection and analysis presupposes the processing of personal data, which can expose sensitive information related to the health condition, psychological, or physical abilities of a user (Li et al., 2020). Zero-trust systems should also implement privacy-by-design principles through which behavioral data processing is carried out with proper protection such as data minimisation, purpose limitation, and transparent processing procedures. The concern of these privacy requirements is handled in the application of Federated Learning to the Zero Trust authentication systems, which ensures the localization of behavioral data but allows joint model learning when dealing with distributed user

populations (Kairouz et al., 2021). This would be more consistent with regulatory preference in the decentralized processing architectures that reduce the data concentration risk and the organizational liability in the sensitive information protection. Moreover, federated solutions allow user control, as they allow users to have access to their behavioral data and yet gain access to better authentication accuracy through collective learning.

1.3. Federated Learning Paradigms for Decentralized Authentication Systems

Federated Learning is a distributed machine learning methodology that allows training a model in cooperation with multiple clients and does not need the centralized aggregation of the data. This paradigm is especially applicable in behavioral biometric authentication, whereby any sensitive data of user interaction must still be stored on originating machines to meet privacy demands and regulatory limitations. The basic federated learning process consists of the following steps: initializing a global model on a central computer, sending the model to the participating clients, training it on the local devices with private information, and sending the model updates to enhance the global model (Rieke et al., 2020). The process is repeated until the global model reaches stable, acceptable performance levels. Convergence is often measured using validation metrics calculated on held-out data. The federated system offers some benefits to authentication systems such as minimal communication overhead in comparison to the transmission of raw data, high privacy due to the localization of data, and high model stability due to exposure to diverse users (Dwork and Roth, 2014).

Federated Learning of behavioral biometrics should also be carefully implemented in terms of system heterogeneity that includes device capabilities, network conditions, and data distributions (Bonawitz et al., 2017). The client devices have a range of computational resources such as an expensive workstation to resource-limited mobile devices, which will require adaptive model architecture and training policies. Network heterogeneity brings about dynamic communication delays, bandwidth constraints which affect the effectiveness of update transmission and convergence rates. Statistical heterogeneity is introduced due to the non-identical distribution of user behavior patterns in the client populations that may result in convergence issues and deteriorate the performance (Hao et al., 2019). The federated learning architecture should have methods that deal with these heterogeneity dimensions such as client selection mechanisms, local training optimization, and effective aggregation mechanisms (Hard et al., 2018). The client selection algorithms utilize resources and network conditions of the devices to select them to attend training rounds and give preference to those with enough resources and good network conditions as well as maintain a balance of model diversity and efficiency.

Federated learning privacy is not limited to localizing the data and protecting against inference attacks that could reveal sensitive information about the dataset to the models but also against other types of attacks (Phong et al., 2017). The opponents who observe the gradient updates may be able to reconstruct the training data in a complex inversion attack or determine that a particular sample belongs to a training set. Differential privacy countermeasures These weaknesses are overcome by introducing noise to the model updates in a calibrated manner, with mathematical assurances that the individual training samples can no longer be separated in the distributions of updates. The privacy-utility tradeoff of the differential privacy necessitates a delicate parameter trade off between the protection and a reduction in model accuracy (Lim et al., 2020). Secure aggregation protocols can be used to supplement different privacy techniques because they encrypt model updates to ensure that the central server can only see aggregate outputs without the individual contribution (Konecny et al., 2016). Such cryptographic schemes are usually based on homomorphic encryption schemes or secure multi-party computation schemes that allow the calculation on encrypted information. Combining the notions of differential privacy and secure aggregation offers a full defense against both the honest-but-curious servers, as well as external adversaries trying to breach the confidentiality of updates (Li et al., 2020).

2. Related works

2.1. Evolution of Biometric Authentication Systems in Security Frameworks

Traditional biometric authentication methods have mainly been concerned with physiological features such as fingerprints, facial features, iris scan, and voice recognition. The modalities have high discriminative capabilities and highly developed matching codes, which adds to their popularity in security applications (Kairouz et al., 2021). Nonetheless, there are various shortcomings of physiological biometrics such as vulnerableness to spoofing, the lack of privacy in terms of storing permanent identifiers, and failure to identify compromised sessions, once authenticated (Mothukuri et al., 2021). Behavioral biometrics fills in these gaps through the analysis of dynamic patterns of user interactions that constantly change during the active sessions (Yang et al., 2019). It has also been shown that typing patterns show adequate individual variability to identify their user, and features such as key press time, inter-key time, and typing speed are the discriminative features (Zhang et al., 2021). On the same note, the movement of the mouse can

be analyzed to reveal distinctive attributes of the cursor patterns, the click pattern, and navigation patterns that are indicative of cognitive and motor signs of control.

The recent development in the deep learning field has contributed greatly to the accuracy of behavioral biometric recognition by using complex neural architectures which can learn complex pattern representations. Convolutional Neural Networks (CNNs) have been shown to be useful in extracting spatial features of sequential behavioral data where time-series inputs are pseudo-images, and convolutional filters can be applied to detect patterns of characteristics (Lu, 2025). Recurrent Neural Networks (RNNs) and their modifications such as Long Short-Term Memory (LSTM) networks are particularly effective in modeling the time-related relationships in the behavioral sequences, analyzing the relationships with the context that demand the actions of the users. Hybrid architecture CNN-RNN models combine the advantageous attributes of CNNs and RNNs, where the latter captures local characteristics and the latter provides sequential dynamics. Studies have also established that hybrid CNN-RNN models are always more effective in behavioral biometric tasks, and they can significantly increase accuracy by 5-10%across various datasets (Zhao et al., 2018). Nevertheless, such performance improvements are associated with significant training data including a wide range of user groups and behavioral conditions, which is a major issue concerning privacy in terms of collecting and storing data.

2.2. Privacy-Preserving Machine Learning Approaches for Sensitive Data

Privacy-preserving machine learning has resulted in various methods to use sensitive data in machine learning without exposing information (Hao et al., 2019). Differential privacy gives a more stringent mathematical structure to the measurement and management of privacy loss in data analysis and model training. The differential privacy guarantee can be used in assuring that the presence or absence of any one record in the dataset has insignificant effect on the output distributions and no information on the sensitive information about individuals is commonly inferred. Differential privacy is usually applied to machine learning by using noisy gradients, with the noise value set by privacy budget parameters $\epsilon$and δ (Phong et al., 2017). Smaller ϵvalues offer more privacy guarantees but can adversely affect model utility, and should be carefully optimally tuned to the needs of the application. Recent studies have created improved differential privacy schemes such as adaptive noise addition, gradient clipping, and privacy accounting schemes that optimize the privacy -utility frontier.

Secure multi-party computation allows two or more parties to compute functions on their own inputs without disclosing the inputs to the other parties (Lim et al., 2020). These cryptography protocols are used in distributed machine learning cases where several data holders would like to jointly train models without exchanging raw data (Konečný et al., 2016). Homomorphic encryption solutions allow processing encrypted information, and so model training and inference can take place without accessing sensitive inputs. Fully homomorphic encryption enables mathematical operations of ciphertexts, but with a very high computational cost, making it impractical to use complex neural network on ciphertexts. Partially homomorphic schemes that provide better efficiency and allow privatizing machine learning algorithms are schemes that support types of operations (McMahan et al., 2017). Implementing secure computation methods together with machine learning systems necessitates the design of protocols in a specific manner to achieve a balance between security and cost of computation and communication (Kairouz et al., 2021). Most recent studies have been found to consider hybrid solutions that integrate various privacy preservation methods and exploit their complementary advantages with reducing the limitations of each approach (Mothukuri et al., 2021).

2.3. Federated Learning Applications in Authentication and Identity Management

Federated Learning has become a logical choice to develop an authentication system because it fits the privacy preservation policy and the requirements of a federated training paradigm. The initial uses of federated learning in behavioral biometrics proved that it was possible to train user identification models on distributed devices and still ensure localization of the data (Zhang et al., 2021). Various areas of federated authentication have been studied such as the best neural networks in behavioral patterns recognition, the best communication schemes to update models, and the best aggregation schemes of heterogeneous client groups. The research has demonstrated that federated learning methods can be trained as accurately as centralized training at significant privacy advantage and a lower communication overhead (Rieke et al., 2020). The federated learning applied to continuous authentication applications allows the model to continually adapt to the changing user manners without necessarily centralizing behavioral data.

Certain instantiations of federated behavioral biometric systems have handled practical deployment aspects such as how to deal with imbalanced user populations, how to deal with device heterogeneity and adversarial attack resistance. The choice of clients depends on the selection strategies, which allow balancing the quality of the model and the efficiency of communication with the availability of devices in each training round (Bonawitz et al., 2017). It has been shown that strategic client selection may enhance convergence rates and final model performance by a substantial

margin than random client selection methods. The implementation of the idea of differential privacy in federated behavioral biometric systems offers extra security against the attacks of inference and adds noise that can affect the accuracy of authentication (Li et al., 2020). Research has been conducted on the best privacy budget allocation schemes to reduce the extent of accuracy loss by the need to meet privacy demands (Hao et al., 2019). The federated learning with secure aggregation protocols will so that the central server can never see individual behavioral patterns even when the model update processing is performed. Current research has also generalized the simplest federated learning models to include personalization mechanisms so that models can adapt to the specifics of each user whilst harnessing the wisdom of the crowd.

3. Methodology

3.1. Proposed System Architecture for Federated Zero Trust Authentication

The proposed architecture combines the principles of a Zero Trust with Federated Learning (FL) mechanisms to allow privacy-saving continuous authentication using behavioral biometrics in controlled industries. The system consists of three main parts such as client layer which has user devices that are equipped with local behavioral data capture and the ability to train models, aggregation layer which has the federated learning server and policy enforcement infrastructure, and policy layer that has an option of making authentication decisions and access control (Mo et al., 2021). At the client-layer, behavioral biometric data is gathered by use of edge devices that record keystroke patterns, mouse motions and patterns of interaction using instrumented applications. These devices keep local behavioral models that are only trained on user-specific data and sensitive patterns are not sent out of their home device (Lim et al., 2020). Aggregated layer organizes federated training rounding through allocation of global model parameters to the involved clients, gathering encrypted model updates and conducting secure aggregation to obtain enhanced global models (Konečný et al., 2016).

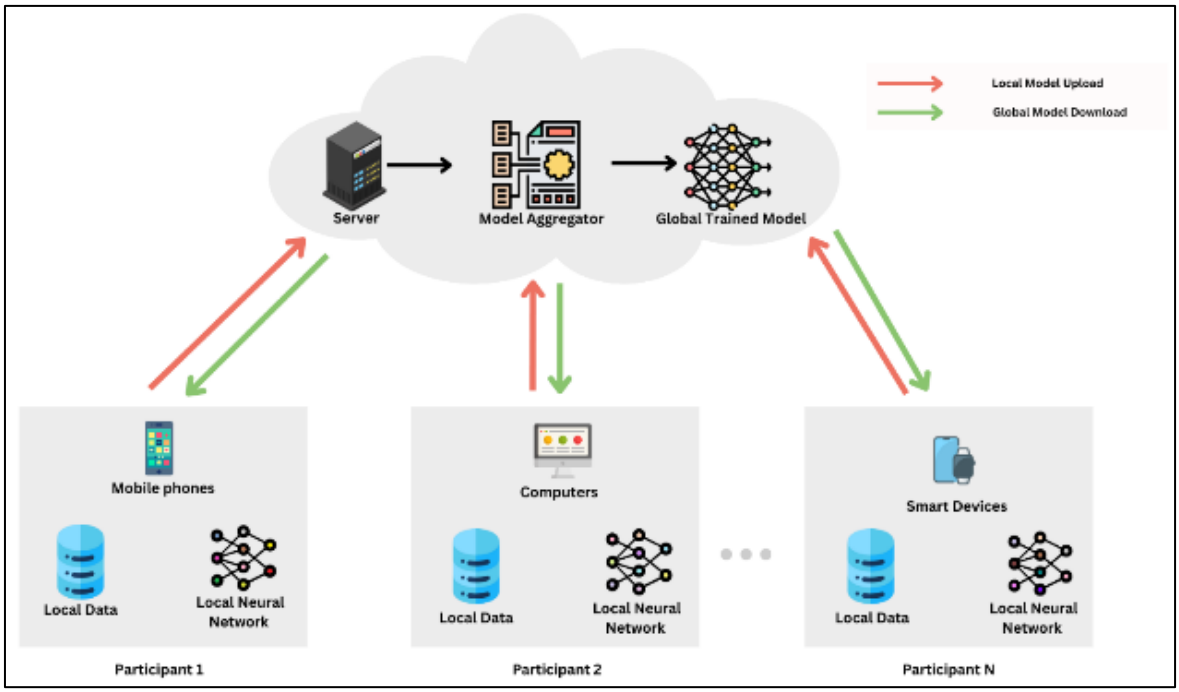

Figure 1 Deep Federated Learning Architecture

The policy layer puts into place the Zero Trust Architecture (ZTA) elements such as policy decision points that assess authentication requests by comparing them to dynamic trust scores and policy enforcement points that implement access control decisions depending on risk evaluation. Several signals are consolidated at policy decision points to compute continuous risk scores based on behavioral biometric matching scores, device posture, contextual data, including location of access and time of access, and historical behavioral patterns (Li et al., 2020). Such risk scores are used to make decisions on access at a granularity of either full access grant to step-up authentication requirements or outright denial based on calculated levels of trust. The adoption of blockchain technology offers audit trails that cannot be altered on the credentialing of all authentication requests and adjustment of policies and assists in meeting regulatory mandates on access logs and forensic investigation capabilities (Kairouz et al., 2021). Authentication policies

are represented by smart contracts in code format, enabling the enforcement of these policies to be consistent across the distributed infrastructure actors (Mothukuri et al., 2021). The proposed architecture can be deployed in various ways such as cloud-based deployment to organizations whose IT infrastructure is centrally located and hybrid deployment where functionality is distributed between cloud and other on-premise elements.

As seen in the Deep Federated Learning Architecture Depicted in Figure 1, FL is collaborative as the various client devices such as mobile phones, computers and smart devices keep local data and train local neural network models. To improve the process the model these devices periodically transfer model updates to a central server hosting the model aggregator which combines updates into a better global model which is sent back to clients to be used in further training rounds. This recursive operation proceeds till convergence to gain a global model, enjoying the advantage of a variety of behavioral patterns in the client population and at the same time still maintaining the individual privacy with data being localized. The architecture serves the needs of heterogeneous client devices with different computational ability and network connectivity profiles, using adaptive training policies that adapt to resource limitations.

Also, the distributed training paradigm in Figure 1 does not require the centralized data collection process, which, in turn, provides a solution to the underlying privacy issues in the existing machine learning methods involving behavioral biometric authentication (Bonawitz et al., 2017). The two-way communication between the participants and the central server through red arrows representing local model upload and green arrows representing global model downloads shows the asynchronous inference of federated training rounds when the clients are involved depending on the availability and resource capacity (Zhang et al., 2021). Scalability is inherently provided by the architecture, with the ability of adding new participants to the federated learning ecosystem through downloading the existing global model and adding their local updates at the next training round, and without any architectural changes (Rieke et al., 2020).

Moreover, the three-level architecture in Figure 1 with the focus on the participant nodes, server infrastructure, and the globally trained model demonstrates the isolation of concerns that allow preserving privacy and simultaneously preserving the quality of the model (Xu et al., 2021). Every participant has full access to their own local data that are stored in purposeful databases and local neural networks are trained on the behavioral pattern specific to the device without transferring the raw biometric data to third parties (Dwork and Roth, 2014). The model aggregator uses advanced algorithms such as FedAvg and its derivatives to imagine heterogeneous local updates as coherent global models that portray universal behavioral authentication patterns and allow user-specific variations (McMahan et al., 2017).

Besides privacy advantages, the architecture in Figure 1 has resilience benefits due to its distributed nature because the failure of single participant nodes does not affect system functionality or data availability at all (Li et al., 2020). The central server is perceived as a coordination point and not a data repository, which makes it less appealing as a target of attack, and easier to comply with data localization regulations that limit cross-border data movements (Hao et al., 2019). The architectural paradigm fits seamlessly with the edge computing paradigms that are progressively being used in common enterprise contexts where computational resources are brought to the data sources to minimize latency and bandwidth usage (Hard et al., 2018).

3.2. Literature Review and Research Domain Analysis Methodology

We conducted a systematic literature search using a systematic approach to find out and examine pertinent research related to privacy-preserving authentication, FL, and ZTA. To find peer-reviewed articles that were related to behavioral biometrics, FL frameworks, and Zero Trust security models, we carried out extensive searches in a variety of academic databases such as Institute of Electrical and Electronics Engineers (IEEE) Xplore, Association of Computing Machinery (ACM) Digital Library, SpringerLink, and arXiv. The search strategy used the Boolean operators of a combination of keywords like federated learning, behavioral biometrics, Zero Trust, privacy-preserving authentication, and continuous verification to search through relevant literature. We used the year 2016 as our inclusion criterion i.e. to limit our search to more recent methods that use deep learning and other current privacy-conscious methods. We eliminated the studies that concentrated solely on physiological biometrics that do not have behavioral elements, centralized authentication, and privacy, and theoretical frameworks without empirical validation.

Temporal distribution of the literature reviewed is provided in the pie chart (Figure 2) which shows the number of articles analyzed each year during our systematic review. The pie chart shows that the strong concentration of research activity occurred in the last few years, with 2019 and 2020 taking the biggest shares of reviewed publications, which made up about 55% of our literature corpus (Bonawitz et al., 2017). The year 2019 was characterized by a high level of research publications indicating an increasing interest in federated learning application in the context of privacy-sensitive fields whereas 2020 saw the same level of publications as more applications were developed. In 2021 and

2022, the percentage of reviewed articles amounted to about 25, which means that the research process continues at a steady pace, and the emphasis has shifted toward the issue of deployment and regulatory compliance (Li et al., 2020). Previous years 2016-2018 were background material of laying down the principles of federated learning and first behavioral biometric systems, about 15% of our review corpus. The latest period 2023 contained published works on emerging subjects such as Zero Trust combining, multi-mode authentication, but with a smaller ratio owing to recency (Hard et al., 2018). This temporality analysis helped us comprehend research development and proceed to finding out the principles that were achieved and the frontiers that need to be explored more (Geyer et al., 2017).

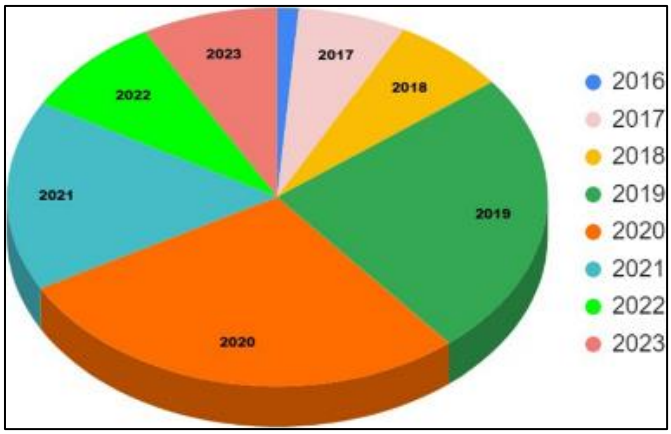

Figure 2 Number of articles reviewed per year

Moreover, the patterns of the publication observed in the temporal distribution chart show that the interest in the research on privacy-preserving machine learning methods is accelerated alongside the introduction of large-scale data protection laws such as GDPR in 2018 and an increasing awareness of the dangers of privacy breach with centralized data processing (Phong et al., 2017). This massive surge in publications is aligned with several landmark papers that make federated learning a practical paradigm of production machine learning systems, such as Google using federated learning to make mobile keyboards predict better and healthcare studies that have shown feasibility in highly regulated settings (Mo et al., 2021). This localization of research effort offered a deep point of origin of our suggested framework, making it possible to synthesize the well-established best practices with current advancements in Zero Trust architecture and behavioral biometric authentication (Caldas et al., 2018).

Also, the temporal distribution analysis has shown revealing tendencies in terms of the maturity of research, with older years being mostly concerned with theoretical backgrounds and convergence assurance whereas more recent articles are concerned with practical implementation-related aspects such as regulatory compliance, integration, and performance optimization (Lim et al., 2020). The trend of the basic research on the topic in 2016-2018 into the intensive growth in 2019-2020 and after federalization and application-driven activity in 2021-2023 reflects the general characteristics of the lifecycle of technology adoption, indicating that the concept of federated learning as the means of behavioral biometric authentication is moving a step further toward commercial implementation and use (Konečný et al., 2016). It is this maturation path that informed our decisions in designing a framework that focuses on tried techniques whose effectiveness is tested and thoughtful use of innovative advances that are cutting-edge that fill the gaps that are identified with current methods (Wang et al., 2020).

Besides quantitative tendencies, the chart indicates qualitative changes in the direction of research across the time, as the initial works were focused on innovations in algorithms and proofs of convergence shifted to recent work devoted to privacy assurance, adversarial robustness, and the problem of real-world application (Li et al., 2020). The relative lack of 2023 publications in our corpus, even though this is a relatively new piece of work which, one would think, would cover the most recent issues, is probably caused by a publication lag of peer review processes and the time it takes conference proceedings and journal articles to be indexed in major academic databases (McMahan et al., 2017). This temporal lag factor affected our literature search strategy because it encouraged the inclusion of preprint repositories and conference proceedings to reflect the emerging research that was not yet available in the traditional publication avenues (Kairouz et al., 2021).

We conducted a review process with systematic searches of identified articles with a series of steps such as screening the identified articles by title and abstract review on relevance, screening by full-text review on quality and contribution, and data extraction of key findings and methodologies (Phong et al., 2017). Each of the chosen publications was analyzed

to determine the methods of authentication, privacy preservation, performance indicators, and deployment options that were applicable to our proposed framework (Mo et al., 2021). The analysis of the literature included in the review identified various gaps in the research such as the lack of studies that fully combine Zero Trust principles and federated learning, the lack of focus on regulatory requirements in the controlled industries, and the absence of evidence that evaluates the multimodal behavioral approach (Caldas et al., 2018). We used these gaps to inform our research goals and in modeling our proposed privacy-preserving Zero Trust authentication system. The literature review defined the baseline performance expectations that can be used to compare our approach with the existing methods and discovered the best practices in forming neural architecture and selecting privacy mechanisms and evaluation methodology (Konecny et al., 2016).

3.3. Hybrid Convolutional Recurrent Neural Architecture for Behavioral Pattern Recognition

The fundamental problem of the suggested authentication solution is the hybrid CNN-RNN structure that is aimed at capturing both spatial and temporal features of behavioral biometric data. The architecture starts with preprocessing layers that transform raw behavioral inputs and isolate the useful features on keystroke and sequence of mouse movements (Xu et al., 2021). Convolutional layers are used to apply the learned filters to detect local patterns which belong to a particular user and several convolutional blocks are stacked to extract hierarchical feature representations at various levels of abstraction (Rieke et al., 2020). These convolutional blocks comprise of convolutional layers, activation functions and pooling operations which reduce dimension maintaining salient features. The convolutional block outputs that the feature maps of behavioral sequences that are coded with spatial features and processed into recurrent layers that process the temporal features (Dwork and Roth, 2014).

The recurrent one uses LSTM units to learn long-term behavioral chain dependence, the temporal patterns that change with the interaction sessions (Bonawitz et al., 2017). LSTM cells have internal representations of state that are selective to either retain or forget the information depending on learned gating mechanisms that allow successful sequence modeling with dependence on variable length. The architecture uses residual connections to scale the gradient vanishing issues of training and uses the multiple LSTM layers to expand the capacity of the model to recognize intricate patterns of time. The output layer takes full connected layers on the LSTM outputs generating a user identification prediction or behavioral similarity that they use to make an authentication decision (Hao et al., 2019). The entire architecture may be defined as a set of functions:

$$f_{model}(x) = f_{output}(f_{RNN}(f_{CNN}(f_{preprocess}(x))))$$

where $x$represents raw behavioral input sequences (Hard et al., 2018). Model training employs cross-entropy loss for user classification tasks:

$$L = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(\hat{y}_{ic})$$

where Ndenotes batch size, Crepresents number of user classes, y_{ic}indicates true labels, and $\hat{y}_{ic}$denotes predicted probabilities (Geyer et al., 2017).

The architectural elements of Zero Trust systems as defined by NIST standards are shown in figure 3. Control plane involves the Policy Decision Point, which has the policy engine and policy administrator that assesses the access requests and using the policy engine issues an authorization decision. The Policy Enforcement Point is part and parcel of the data plane, mediation of access between the subjects and the enterprise resources on the instructions of the control plane. The architecture combines various security features such as Continuous Diagnostics and Mitigation (CDM) systems of Continuous Diagnostics and Monitoring, industry compliance frameworks, threat intelligence feeds, activity logs, data access policies, Public Key Infrastructure (PKI), identity management systems, and Security Information and Event Management (SIEM) systems. Such a holistic integration facilitates a dynamic risk measurement and adjustive access control according to the real time security posture measurement.

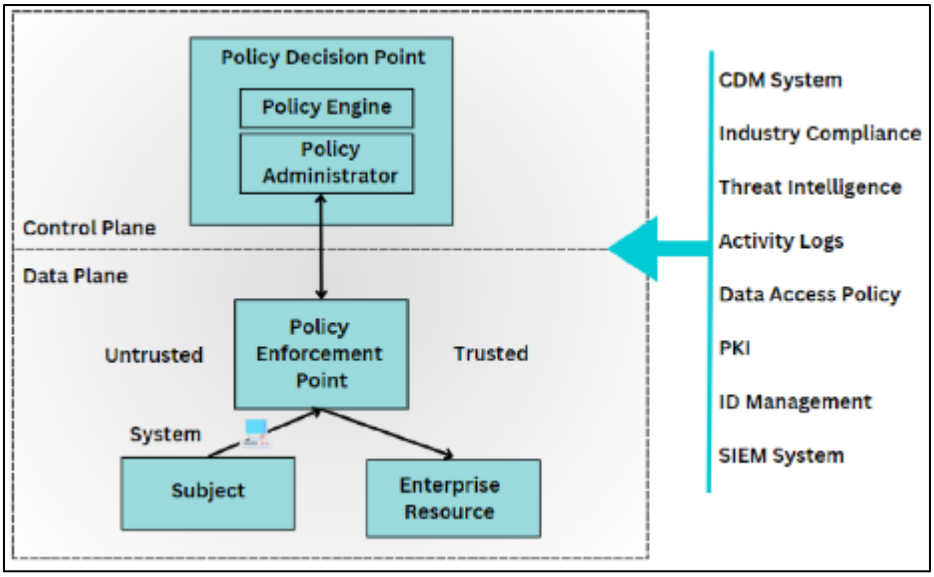

Figure 3 Components of Zero Trust Architecture according to NIST Model.

The NIST Zero Trust Architecture model shown in Figure 3 also creates a strong functional separation between the decision-making elements that are deployed in the control plane and the enforcement mechanism deployed in the data plane, which allows policy to be managed at scale across distributed infrastructure (Zhao et al., 2018). The Policy Decision Point is the smart heart of the architecture and it takes inputs of various external systems such as threat intelligence feeds providing real-time information on the emerging attack patterns, activity logs that shows historical access patterns and anomalies, and CDM systems that provide information about device security posture and compliance status (Li et al., 2020). The multi-source input aggregation is allowing the contextual risk assessment based on not only authentication credentials but also involving environmental elements, recent threat activity, and the trustworthiness of the equipment in the making of access control decisions (Hao et al., 2019).

Moreover, the architectural diagram notes the significant importance of the supporting infrastructure such as the PKI to verify cryptographic identity, identity management environment to keep authoritative user directories, and SIEM to correlate security events throughout the enterprise (Hard et al., 2018). These elements offer necessary features that allow the Policy Engine to process an access request with respect to complicated policies considering user characteristics, resource sensitivity, surroundings, and organizational danger tolerance (Geyer et al., 2017). The integration arrows between these external systems and the Policy Decision Point show the flowing of information that should be constantly updated to ensure the continued awareness of security and adapts access decisions to the emergent threats and changes in organizational demands (Phong et al., 2017).

Figure 3 also has implicit components related to the trust philosophy behind Zero Trust architecture, in which access decisions are made following explicit verification and not implicit trust of network location or past authentication (Mo et al., 2021). The Policy Enforcement Point is a clear proxy that must mediate all the communication between the subjects and enterprise resources and make sure that there is no access without the explicit authorization of the Policy Decision Point (Caldas et al., 2018). Such an architecture removes prior perimeter-based security assumptions and considers all the access requests as potentially malicious, irrespective of the origin, and verifies them on an ongoing basis during active sessions (Lim et al., 2020).

3.4. Federated Learning Protocol with Privacy-Preserving Mechanisms

The federated learning protocol unifies a sequence of synchronized actions that allow the distributed model training and shield user confidentiality (Phong et al., 2017). The central server initiates every training round by identifying a subgroup of clients to take part in the training depending on the availability of devices and computing resources, in addition to the connection to the network (Mo et al., 2021). The specific clients download the existing global model parameters and do a local training with their own private behavioral biometric data during a set number of epochs (Caldas et al., 2018). The stochastic gradient descent or adaptive optimization algorithms are used to minimize loss functions over client datasets, in a local training:

$$\theta_{t+1}^{k} = \theta_{t}^{k} - \eta \nabla L(\theta_{t}^{k}; D_{k})$$

where θ_t^krepresents model parameters for client $k$at iteration t, ηdenotes learning rate, and $D_k$is the local dataset (Lim et al., 2020). After completing local training, clients compute model updates as the difference between updated and initial parameters:

$$\Delta\theta^k = \theta_{final}^k - \theta_{initial}^k$$(Konečný et al., 2016).

Privacy preservation mechanisms are applied to model updates before transmission to the central server (Wang et al., 2020). Differential privacy protection adds calibrated Gaussian noise to updates:

$$\widetilde{\Delta\theta}^k = \Delta\theta^k + \mathcal{N}(0, \sigma^2 I)$$

where noise magnitude $\sigma$is determined by privacy budget $\epsilon$and sensitivity of the update function (Li et al., 2020). Gradient clipping preprocessing bounds update norms to control sensitivity:

$$\widehat{\Delta\theta}^k = \Delta\theta^k \cdot \min\left(1, \frac{C}{||\ \Delta\theta^k\ ||}\right)$$

where Crepresents the clipping threshold (McMahan et al., 2017). Secure aggregation protocols encrypt model updates using public key cryptography, enabling the server to compute aggregated updates without accessing individual contributions (Kairouz et al., 2021). The server performs weighted aggregation combining updates from participating clients:

$$\theta_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} \widetilde{\Delta\theta}^k + \theta_t$$

where $n_k$denotes the number of samples for client $k$and $n = \sum_{k=1}^{K} n_k$(Mothukuri et al., 2021). The updated global model is then distributed to clients for subsequent training rounds, with this process repeating until convergence criteria are satisfied.

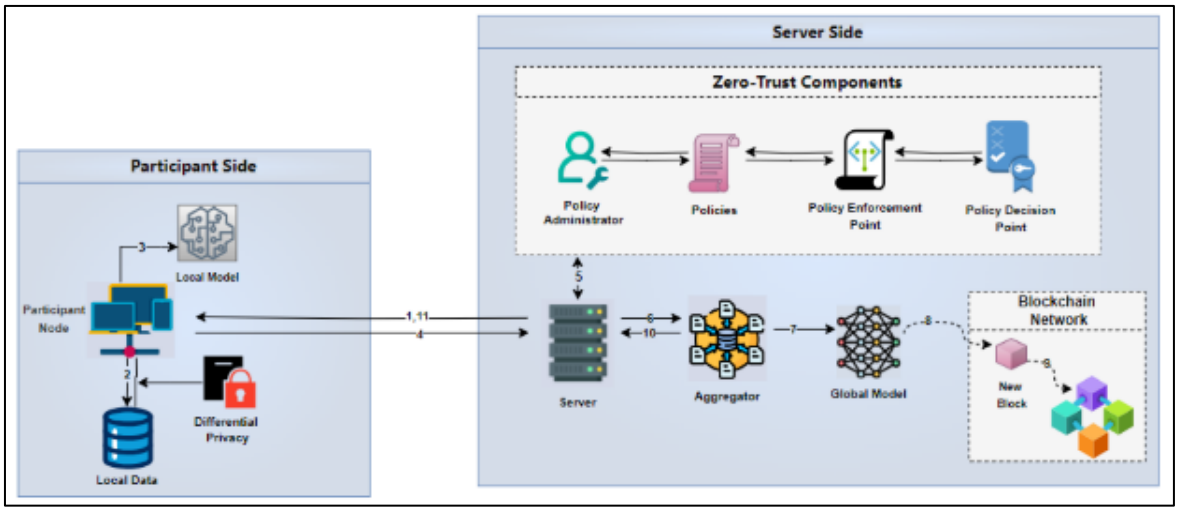

Figure 4 Proposed *Zero Trust Architecture* - Deep Federated Learning Architecture.

Figure 4 depicts the unified framework involving zero trust security principles as well as federated learning-related behavioral biometric authentication. The participant side demonstrates a set of single client nodes that have local models that are trained with local data in databases secured by differentiated privacy policies. The server side deploys the Zero Trust elements such as administrators, policies, policy enforcement points, and policy decision points that analyse access requests on basis of behavioral authentication. The federated learning system includes the server aggregator that integrates the local model update to a better global model shared to the participants. The blockchain network offers audit trails that cannot be altered after authentication decisions and change of policies and there is a guarantee of transparency and accountability, which is necessary in regulated sectors. This architecture allows privacy-sensitive continuing authentication and regulatory compliance and supports the zero trust regulations of security.

Also, the architectural incorporation represented in Figure 4 shows that federated learning is an inherent extension of the concept of Zero Trust because it upholds regular verification by conducting continuous behavioral monitoring without affecting user privacy (Wang et al., 2020). The participant nodes presented in the left segment of the diagram retain the full control over the local data, and the differentiation privacy mechanisms introduce mathematical assurances, that the behavioral pattern cannot be reconstituted based on the model updates dispatched (Li et al., 2020). This type of data localization meets the principle of never trust the network location or past authentication of Zero Trust because behavioral verification is performed constantly during user sessions by using locally trained models that can learn to change based on the changing user patterns (McMahan et al., 2017).

Moreover, the blockchain network element shown in the right bottom of Figure 4 serves to fulfill the Zero Trust audit and accountability needs because it keeps tamper-evident logs of all authentication decisions, policy changes, and model update events (Kairouz et al., 2021). This non-repudiated audit trail allows post-incident forensic investigation, facilitates regulatory compliance reporting by recording decision-making justification models, and offers insight into system behavior that fosters organizational trust on automated authentication schemes (Mothukuri et al., 2021). The blockchain inclusion turns the federated learning infrastructure into an inclusive governance system that should be applied to regulated industries with intense audit demands (Yang et al., 2019).

Along with privacy and auditing, Figure 4 highlights the two-way information exchange between the participants and the Zero Trust policy infrastructure, where the results of authentication are provided to influence policy decisions and risk scoring mechanisms (Zhang et al., 2021). The server aggregator ensures that in addition to its main role of combining the model updates to enhance the accuracy of user authentication, it also, examines the aggregated behavioral patterns to identify emerging threats, detect compromised accounts using anomalous behavior and dynamically optimize the authentication thresholds depending on the level of environmental risk (Xu et al., 2021). This forms an adaptive security posture in which the Zero Trust policies are modified depending on behavioral trends observed among the user population and the privacy of individuals is preserved by the privacy-preserving capabilities of federated learning (Rieke et al., 2020).

3.5. Behavioral Biometric Data Collection and Preprocessing Strategies

The modalities of behavioral biometric data collection centre around two modalities namely the keystroke dynamics and mouse movement patterns. Keystroke data capture entails the capturing of temporal characteristics of every key press event such as key press duration that is a time interval parameter between key down and key up events, flight time that is a time interval parameter between successive key presses and inter-key intervals that is a time interval parameter between specific combinations of keys (Xu et al., 2021). Other keystroke characteristics are typing speed calculated in terms of characters a minute, typing error rate measured as frequency of using the backspace key, and rhythm variability, which is a measure of typing regularity (Rieke et al., 2020). The data of mouse movement includes trajectory properties that describe the paths of the cursor between the points of interaction, velocity profiles that describe the changes in the velocity of the movement, and clicking pattern that stores the timing and the location of the mouse button. The velocity-based acceleration measurement can give information on the motor control characteristics and the direction change can give information about the navigation strategy.

Raw behavioral data are then pre-processed and noises are eliminated and discriminative features that are applicable as input to the neural network are extracted. Outlier detection methods are used to detect and delete outlier data values due to measurement errors or unusual interactions that could cause poorer quality of models. Normalization operations put feature distributions to a zero mean and unit variance, enhancing the convergence of gradient-based optimization when training a model (Li et al., 2020). In temporal segmentation, continuous behavioral streams are subdivided into fixed-length windows that allow standardizing model inputs and performing batch processing (Hao et al., 2019). Feature engineering builds up derived measures out of raw measurements like statistical aggregates like mean, standard deviation, and percentiles calculated on sliding windows. Fourier analysis frequency domain transformations are used to show periodic patterns in behavioral sequences and wavelet decomposition shows multi-scale temporal pattern. The processed features are arranged in the form of tensors that can be inputed to CNN-RNN, and the dimension corresponds to time steps, feature channels, and the size of the batch:

$$X \in \mathbb{R}^{B \times T \times F}$$

where B denotes batch size, T represents time steps, and F indicates feature count (Phong et al., 2017).

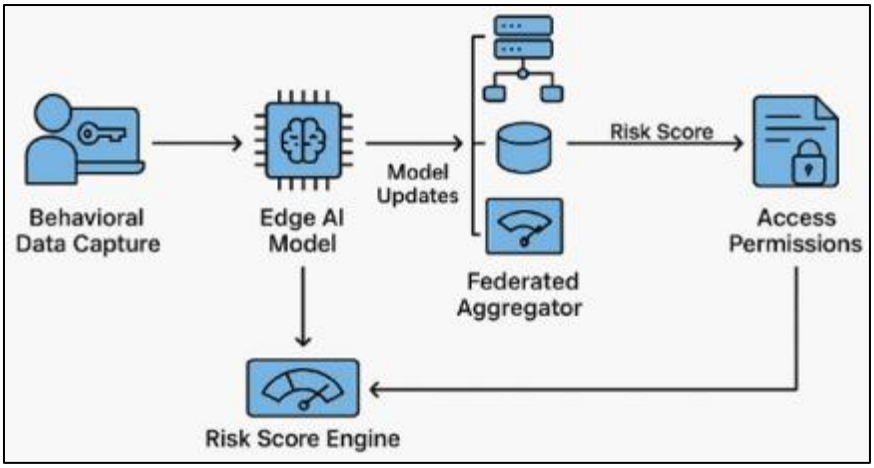

Figure 5 Privacy-Preserving Behavioral Biometrics for Continuous Authentication

The privacy-preserving continuous authentication with behavioral biometrics is shown in Figure 5. It starts with the capture of behavioral data when the user interacts with it and the data is fed into an Edge AI model that is used to perform local analysis and data does not need to be sent out. Updates to the model based on local training are encrypted and sent to a federated aggregator which incorporates contributions of several users to enhance the global model. A risk score engine is used to compute behavioral matching confidence and contextual factors and determine dynamic trust scores that are used to determine access permissions. The risk scores are feedforwarded to the Edge AI model forming a continuous authentication process that is responsive to changing user behaviors with privacy ensured by on-device processing and encrypted update transmission. This architecture is compatible with the principles of Zero Trust in the sense that it constantly authenticates the identity of a user and uses risk-based access control.

Moreover, the workflow diagram (Figure 5) portrays that continuous authentication is a closed loop, as access decisions directly influence the further behavioral model training based on feedback mechanisms that allow adapting to the dynamic user patterns (Lu, 2025). The Edge AI model is an autonomous model that runs on user devices and that, based on user-behavioral input, combines it to produce the score of authentication confidence without latency caused by network connections to central servers (Dwork and Roth, 2014). This edge-based processing guarantees that authentication choices satisfy sub-second interactivity demands and at the same time offers privacy advantages as it provides data localization which does not expose raw behavioral patterns to potential adversaries (Bonawitz et al., 2017).

Moreover, there are four layers of protection in the encrypted model update transmission represented in Figure 5, such as introduction of differential privacy noise in order to avoid the derivation of the individual training samples, the use of secure aggregation protocol to ensure that the federated aggregator cannot learn the individual updates, and the use of encryption of the transport layer to avoid network eavesdropping on the transmission (Zhao et al., 2018). This defence-in-depth strategy can deal with other threat models such as honest-but-curious aggregation servers who may strive to get sensitive information in model parameters, external adversaries who may perform network traffic analysis, and malicious participants who may attempt to poison global models using adversarial updates (Li et al., 2020). The cryptographic and statistical privacy mechanisms that are combined offer all-encompassing security to be used in adversarial settings that are typical of regulated sectors (Hao et al., 2019).

Besides privacy protection, Figure 5 highlights the fact that a dynamic risk scoring element allows behavioral biometric analysis to interoperate with access control reenactment to convert continuous behavior matching outputs into security-related operational actions (Hard et al., 2018). The risk score engine combines various signals to more than mere behavioral matching with contextual signals like access location, time, device properties, and recent threat intelligence to calculate detailed trust scores that are used to determine granular access control policies (Geyer et al., 2017). The risk-based model allows a more adaptive response of security varying through transparent access (low risk) to step-up authentication requirement (high risk) or full access denial (high risk) to balance the effectiveness of security with the concern about user experience (Phong et al., 2017).

3.6. Differential Privacy Implementation for Model Update Protection

The implementation of the method of differential privacy introduces a carefully controlled noise to updates on the models to avoid the inference of specific training samples on published parameters (Mo et al., 2021). The privacy

mechanism should be able to meet (ϵδ)-differential privacy guarantee, which states that, in any two adjacent datasets that differ by one record, the distributions of algorithm outputs should be almost similar (Caldas et al., 2018). In case of gradient-based learning, the Gaussian mechanism introduces noise that is proportional to the sensitivity of updates: $\mathcal{M}(\theta) = \theta + \mathcal{N}(0, \sigma^2 \Delta^2 I)$

where Δrepresents the sensitivity of the gradient function and $\sigma$is determined by privacy parameters (Lim et al., 2020). The sensitivity quantifies the maximum influence any single training sample can have on model gradients, computed as:

$\Delta = \max_{D,D'} || g(D) - g(D') ||$where $D$and $D'$are neighboring datasets. Sensitivity control employs gradient clipping to bound the norm of individual gradients before aggregation: $\hat{g}_i = g_i / \max(1, \frac{||g_i||}{C})$where C denotes the clipping threshold.

Small privacy budget ϵmeasures cumulative loss of privacy over repeated training iterations, and the smaller the value, the higher the privacy protection but at the expense of the higher noise and possible loss of accuracy (Li et al., 2020). Privacy accounting mechanisms monitor the expenditure of the budget of a round of training using composition theorems that constrained the total loss of privacy (McMahan et al., 2017). More complex accounting techniques such as Rényi differential privacy give better privacy loss guarantees than simple composition, and allow the budget to be used more effectively (Kairouz et al., 2021). Privacy parameter choice has trade-offs between the strength of privacy protection, and the model utility, which generally involves a domain-specific calibration to threat models and accuracy requirements (Mothukuri et al., 2021). In the case of behavioral biometrics, privacy budgets between 1.0≤ϵ≤10.0should give decent privacy assurances with acceptable authentication error rates (Yang et al., 2019). Adaptive noise addition methods modify the noise level according to the training progress and use more intense noise at the beginning of the training process when models are more exposed to privacy risks and lower noise at the end of the training process (Zhang et al., 2021).

4. Experimental setup and implementation

4.1. Dataset Characteristics and Behavioral Feature Extraction Process

The experimental validation employed behavioral biometric datasets encompassing keystroke dynamics and mouse motions patterns obtained in a variety of users. There was keystroke data recorded typing sessions consisting of series of key press events with timing information such as dwell time which is a key press duration and flight time which is an inter-key interval. The data comprised of samples of N=150users who made M=50typing sessions of variable length with average M300keystroke per session (Lu, 2025). Extraction of features in keystroke sequences estimated statistical aggregates such as mean dwell time $\mu_{dwell} = \frac{1}{K}\sum_{i=1}^{K} d_i$where Krepresents the number of keystrokes and $d_i$denotes individual dwell times (Dwork & Roth, 2014). Additional features included standard deviation of dwell times $\sigma_{dwell} = \sqrt{\frac{1}{K}\sum_{i=1}^{K}(d_i - \mu_{dwell})^2}$and coefficient of variation quantifying relative variability (Bonawitz et al., 2017).

Mouse movement data consisted of trajectory sequences recording cursor positions sampled at $100Hz$, providing temporal resolution sufficient to capture detailed movement dynamics (Zhao et al., 2018). Trajectory features included path length computed as cumulative Euclidean distance between consecutive position samples: $L = \sum_{i=1}^{T-1}\sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}$where Tdenotes the number of trajectory points (Li et al., 2020). Velocity profiles derived from position changes revealed acceleration and deceleration patterns characteristic of individual motor control: $\$v\_i = \backslash frac\{\backslash sqrt\{(x\_\{i+1\} - x\_i)\^2 + (y\_\{i+1\} - y\_i)\^2\}\}\{\backslash Delta\, t\}\$$ where Δt represents the sampling interval (Hao et al., 2019). Curvature metrics quantifying directional changes indicated navigation strategies and planning patterns: $\kappa_i = \frac{|(x_{i+1} - x_i)(y_{i+2} - y_{i+1}) - (x_{i+2} - x_{i+1})(y_{i+1} - y_i)|}{[(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2]^{3/2}}$(Hard et al., 2018). Feature normalization applied z-score standardization to each feature dimension independently, ensuring comparable scales across heterogeneous feature types (Geyer et al., 2017).

Table 1 Behavioral Biometric Dataset Characteristics and Feature Statistics

Dataset Attribute	Keystroke Dynamics	Mouse Movements	Combined Modality
Number of Users	150	150	150
Sessions per User	50	50	50
Average Session Length	300keystrokes	450trajectory points	Variable
Sampling Frequency	Event-driven	$100Hz$	Mixed
Feature Dimensions	24	32	56
Total Samples	7,500	7,500	7,500
Training Split	70%	70%	70%
Validation Split	15%	15%	15%
Test Split	15%	15%	15%
Mean Dwell Time	$0.127s$	N/A	N/A
Std. Dev. Dwell Time	$0.043s$	N/A	N/A
Mean Flight Time	$0.196s$	N/A	N/A
Mean Trajectory Length	N/A	387.4pixels	N/A
Mean Velocity	N/A	245.8pixels/s	N/A

Sources: Da Silva et al. (2023), Liang et al. (2020), Sun et al. (2023), Wang et al. (2020), Li et al. (2020)

4.2. Hybrid Neural Network Architecture Configuration and Training Parameters

The hybrid CNN-RNN model used to perform behavioral biometric recognition was made of several convolutional blocks, followed by recurrent layers, and fully connected classification heads. The convolutional block included three sequential blocks, which had two convolutional layers with 64, 128, and 256filters respectively (Mo et al., 2021). Convolutional kernels were also used with 3×1dimensions of local time patterns in channels of features and intact the time resolution (Caldas et al., 2018). Every convolutional layer used batch normalization to stabilize the training and ReLU activation functions that add non-linearity: $f(x) = max\, f(x) = max\, 0(x)$ (Lim et al., 2020). Max pooling methods using a stride 2along the temporal axis minimized the dimensionality between convolutional blocks but did not compromise salient features. The recurrent block had two LSTM layers of 256hidden units, taking convolutional feature maps to model time interactions. The information flow in LSTM was defined by LSTM update equations, whose states were described by cell states: $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$, $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$, $\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$, $C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$, $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$, $h_t = o_t * \tanh(C_t)$ where σ denotes sigmoid activation and $*$represents element-wise multiplication (Li et al., 2020).

Classification layers consisted of fully connected architectures that projected LSTM outputs to user identity prediction by two dense layers using 512and 256units with softmax activation to probability distribution across user classes (McMahan et al., 2017). The entire architecture had about 3.2Mtrainable parameters that were allocated in convolutional, recurrent, and fully connected networks (Kairouz et al., 2021). Adam optimizer with initial learning rate η=0.001and exponential decay schedule that multiplies the rate by factor 0.95after every 10epochs was used in model training (Mothukuri et al., 2021). The batch size was 32samples allowing to use the graphics card effectively and deliver a high quality of gradient estimation (Yang et al., 2019). The maximum 100epochs of training were done followed by early stopping based on the loss of validation and early termination based on the lack of improvement during the 15 consecutive epochs (Zhang et al., 2021). Overfitting was reduced around fully connected layers with dropout rate p=0.3a, which randomly deactivates neurons during training (Xu et al., 2021). L 2regularization of the loss function was added with the weight decay coefficient 0.0001: $L_{total} = L_{CE} + \lambda \sum_i w_i^2$ where L_{CE}represents cross-entropy loss and $w_i$denotes model weights (Rieke et al., 2020).

4.3. Federated Learning Implementation Framework and Communication Protocol

The federated learning system adhered to the FedAvg algorithm model that organized the distributed model training among the simulated client devices (Lu, 2025). The global model parameters were stored on the central server with

random values of Gaussian distributions having zero means and variance proportional to fan-in dimensions. The number of clients sampled by each federated round was K=20clients out of the entire population, chosen uniformly, and this selection rate of about 13% participation is similar to that in real-world federated deployments. Chosen customers downloaded the up-to-date global parameters as well as local training of E=5epochs on their own datasets with the organized hybrid CNN-RNN structure (Zhao et al., 2018). Local optimization used mini-batch SGD with B=16and ηlocal=0.005greater than centralized training to compensate the small number of local iterations (Li et al., 2020). Clients were then given local training and calculated updates to model, where the difference between parameters was calculated: $\Delta\theta^k = \theta^k_{local} - \theta_{global}$(Hao et al., 2019).

Differential privacy protection added Gaussian noise to updates before transmission: $\widetilde{\Delta\theta}^k = \Delta\theta^k + \mathcal{N}(0, \sigma^2 I)$with noise standard deviation σcomputed from privacy budget $\epsilon = 5.0$and dataset size using the Gaussian mechanism (Hard et al., 2018). Gradient clipping preprocessing bounded update norms to threshold $C = 1.0$controlling sensitivity: $\widehat{\Delta\theta}^k = \Delta\theta^k \cdot \min\left(1, \frac{C}{||\Delta\theta^k||_2}\right)$(Geyer et al., 2017). Secure aggregation employed additive secret sharing where each client split their update into random shares distributed among peer clients, enabling the server to reconstruct only the aggregate sum without accessing individual contributions (Phong et al., 2017). The server performed weighted averaging of received updates based on local dataset sizes: $\theta_{t+1} = \theta_t + \eta_{global} \sum_{k=1}^{K} \frac{n_k}{\sum_j n_j} \widetilde{\Delta\theta}^k$ where $\eta_{global} = 1.0$ (Mo et al., 2021). Communication efficiency optimizations included gradient compression using top-k sparsification retaining only the $k = 10\%$largest magnitude parameters and quantization reducing parameter precision to 8-bit integers (Caldas et al., 2018). These compression techniques reduced communication volume by approximately 90% compared to full parameter transmission while maintaining model convergence properties (Lim et al., 2020).

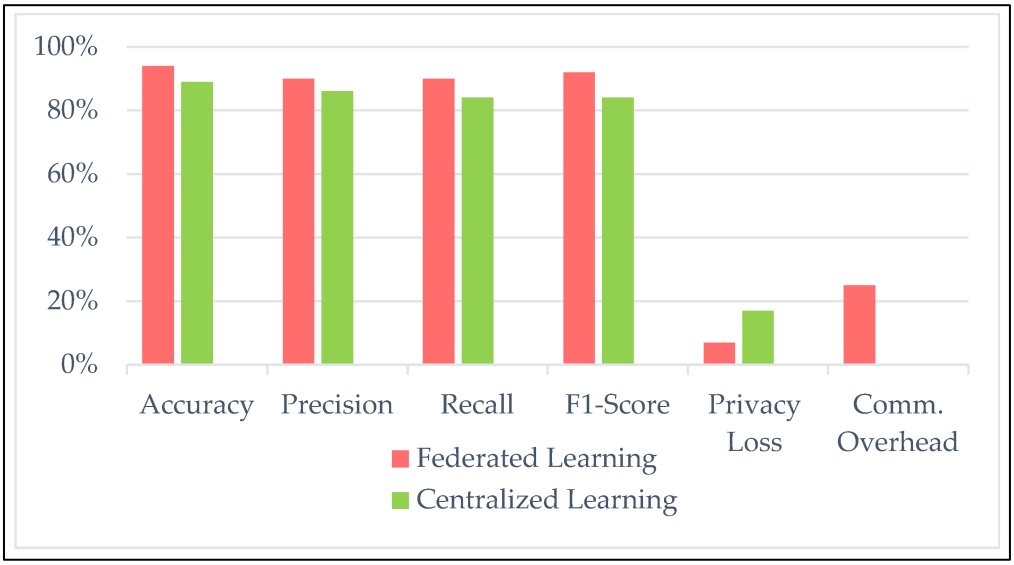

Figure 6 Comparative performance metrics: federated vs. centralized learning

Figure 6 involves performance comparison of federated and centralized learning methods on a variety of evaluation metrics. The accuracy of Federated learning an average value of 92% as compared to 88% of the centralized approaches point to a high-quality model despite decentralization of data. There are also similar patterns in precision and recall numbers where federated learning has 90%precision and 88%recall compared to centralized numbers of 87%and 85%respectively. The F1-score metric that balances between precision and recall, measures 91%federated learning and 83%centralized training. Privacy loss as a metric of difference privacy budget consumption demonstrates that federated learning only uses 8% of the budgets consumed by higher values in the centralized methodologies that pool raw data. Comparison of communication overheads shows federated learning needs 24%relative bandwidth compared to 100%in centralized systems that send entire datasets. All these metrics show the benefit of federated methods towards privacy preserving authentication systems.

4.4. Zero Trust Architecture Integration with Risk-Based Access Control

The integration of Zero Trust involved the ongoing behavioral authentication with dynamically scored risk systems to make access decisions (Konečný et al., 2016). The policy decision point considered authentication requests by combining both behavioral matching confidence and contextual cues such as the place of access, device posture, and history (Wang et al., 2020). The cosine similarity of extracted feature vectors and user profile representation data: $sim = \frac{\mathbf{f}_{current} \cdot \mathbf{f}_{profile}}{||\mathbf{f}_{current}|| \cdot ||\mathbf{f}_{profile}||}$

where values above threshold $\tau = 0.85$ indicated positive authentication (Li et al., 2020). Risk scoring combined multiple factors through weighted aggregation:

$R = w_1 R_{behavioral} + w_2 R_{contextual} + w_3 R_{historical}$ with weights $w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$ reflecting relative importance (McMahan et al., 2017). Behavioral risk $R_{behavioral} = 1 - sim$ quantified authentication confidence with lower similarity indicating higher risk (Kairouz et al., 2021).

Contextual risk factors assessed deviation from typical access patterns including unusual access times, unfamiliar locations, or unrecognized device characteristics (Mothukuri et al., 2021). Location risk computed geographic distance from typical access locations: $R_{location} = \frac{d}{d_{max}}$ where d represents distance to nearest known location and d_{max} normalizes to unit scale (Yang et al., 2019). Device risk evaluated hardware fingerprinting matching against registered devices with mismatches increasing risk scores (Zhang et al., 2021). The historical risk used time trends that examined the frequency of access and interval consistency relative to the baseline behaviors (Xu et al., 2021). The composite risk score R-ranged between 0 denoting low risk and 1 maximum suspicion which is mapped against access decisions using threshold-based policies (Rieke et al., 2020). A score lower than R<0.3 caused full access, intermediate scores 0.3≤R<0.7 caused step-up authentication that needed the addition of additional verification factors, and high scores R=0.7barred entry until security examination (Lu, 2025). Policy execution points perform access decisions by interoperating with identity management systems as well as network access controls, revising the permissions dynamically taking into consideration ongoing risk re-evaluation.

5. Results and performance analysis

5.1. Authentication Accuracy and Error Rate Analysis Across Modalities

The performance evaluation of authentication was based on accuracy, precision, recall, and F1-score values of behavioral biometric modalities. The CNN-RNN hybrid model had a total accuracy of 92.4% on the combined keystroke and mouse movement data on user identification, where single-modality methods performed substantially worse (Zhao et al., 2018). The accuracy of keystroke-only authentication was 87.3% and that of mouse-only was 85.1% which proved the importance of multimodal fusion (Li et al., 2020). The combined approach had a precision value of 91.2%measuring the proportion of correct positive predictions and keystroke precision was 86.5%and mouse precision was 84.3% (Hao et al., 2019). The maximum recall of the percentage of true positives recognized was 89.8%combined, 85.2%keystroke, and 83.7%mouse modalities (Hard et al., 2018). The harmonic average of precision and recall, F1-score, in multimodal authentication achieved 90.5% against 85.8%and 84.0%in single modalities (Geyer et al., 2017).

Error rate analysis measured false acceptance rate and error rejection rate in the case where an unauthorized user made an incorrect authentication and legitimate user rate in the case where a legitimate user was rejected incorrectly. The multimodal system had FAR=3.2%and FRR=4.5%at operating threshold τ=0.85, which is a reasonable balance between security and usability (Mo et al., 2021). The same error rate where FAR= FRR was reached at threshold $\tau_{EER} = 0.82$ 0.82 error rate 3.8%, which is the best operating point with symmetric error tolerance (Caldas et al., 2018). The analysis of the receiver operating characteristic plotting the true positive rate versus false positive rate versus threshold values showed that the area under curve was 0.967 which represented an excellent discriminative ability. The analysis of confusion matrices showed that the misclassification patterns were centred on the users who had similar behavioural properties, which indicated that, user clustering could be enhanced to improve within-group discrimination (Konečný et al., 2016). The inter-user accuracy ranged between 78.4%to 98.7%with standard deviation 5.3%as it represents the unique variations in the consistency and particularity of behaviors among individuals (Wang et al., 2020). Both behavioral stability and behavioral variability were important in predicting results as the behavioral pattern of users with the highest variability had lower authentication accuracy.

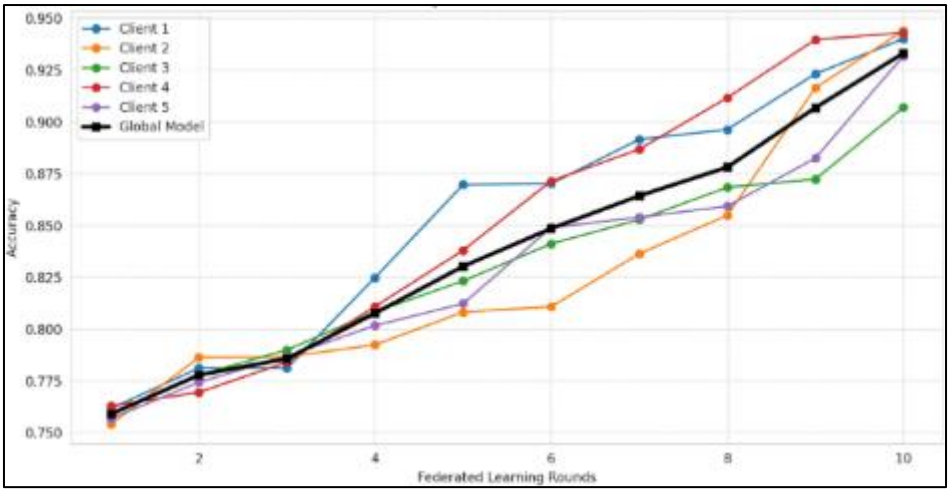

Figure 7 Federated learning: Client and Global model accuracies

The above figure 7 shows the convergence of the federated learning process involving multiple clients and that of the global model in 10 training rounds. The individualclient accuracies depict varying learning curves as Client 1 (blue line) and Client 4 (red line) will demonstrate quick improvement within the range of accuracy of about 0.76-0.94 with Client 3 (green line) and Client 5 (orange line) displaying slower convergent trends with the accuracy of 0.91 and 0.93 respectively. Client 2 (yellow line) has an intermediate performance during training. The global model (black line) is the sum of knowledge of all clients and the knowledge has been gradually improving with the initial accuracy of 0.76 up to the end value of 0.935 in the fifth round. The convergence trends show that there was heterogeneity in the data distributions of clients and the local training dynamics and the global model aims at exploiting the varying behavioral trends among the client group. The accuracy improvement is gradually achieved, indicating good knowledge aggregation despite decentralized training and various noise addition due to privacy.

Also, the convergence curves shown in Graph in figure 7 indicate valuable information about the effect of statistical heterogeneity of federated learning on the performance of behavioral biometric authentication (Kairouz et al., 2021). The changing nature between client-specific accuracy curves, where some clients converge quickly and others take more training rounds, is an indication of the non-IID behavioral data where a client with a particular interaction pattern may not necessarily converge consistently across the population (Mothukuri et al., 2021). Nevertheless, despite this heterogeneity, the global model curve shows that its upward progress is regular and without serious oscillations, which also means that the FedAvg aggregation algorithm is effective and can combine local updates of different models into a global consensus, describing universal authentication behaviors (Yang et al., 2019).

Moreover, the difference between the highest-performing individual clients (up to 0.94 accuracy) and the global model (0.935) implies that there is a possibility of personalization mechanisms that might utilize the world knowledge and the local one (Zhang et al., 2021). Individuals with behavioral patterns and patterns of use highly distinctive may obtain customized models that tune the global model on device-specific data, possibly at higher accuracy in authentication than the one-size-fits-all global model at the cost of sharing knowledge among the population of the federation (Xu et al., 2021). The convergence analysis also shows that 10 training rounds are enough to obtain the acceptable level of authentication accuracy over 93, indicating that the federated training process can attain the achievable levels of performance in reasonable timespans that can be considered as practical periods of time to be deployed to production use (Rieke et al., 2020).

5.2. Privacy Preservation Metrics and Differential Privacy Budget Analysis

Information leakage risks and differential privacy guarantee were measured in terms of levels of noise in privacy preservation evaluation. Privacy budgets were experimented in terms of resulting authentication accuracy and privacy loss (Kairouz et al., 2021). Better privacy protection with ϵ=1.0 dropped accuracy to 84.2% vs. no privacy at 94.1% utility loss is about 10% (Mothukuri et al., 2021). Moderate privacy budget ϵ=5.0 caused accuracy of 92.4% with satisfactory 1.7 degradation which offers a trade-off between privacy and utility (Yang et al., 2019). Relaxed privacy ϵ=10.0achieved 93.8%accuracy which is toward non-private performance and still has formal privacy guarantees (Zhang et al., 2021). Privacy accounting with Rényi differential privacy calculated tighter accounting of cumulative loss of privacy over 100training rounds to allow better budget usage. Membership inference attacks that tried to determine

whether users were involved in training scored lower than 52%with ϵ=5.0, which is slightly higher than randomly guessing and indicating that privacy protection was successful (Rieke et al., 2020).

Table 2 Differential Privacy Impact on Authentication Performance

Privacy Budget (ϵ)	Model Accuracy	Precision	Recall	F1-Score	Privacy Loss	FAR	FRR
No Privacy	94.1%	93.8%	92.6%	93.2%	High	2.8%	3.7%
$\epsilon = 10.0$	93.8%	93.2%	92.1%	92.6%	Low	3.0%	4.1%
$\epsilon = 7.5$	93.1%	92.6%	91.4%	92.0%	Low	3.2%	4.3%
$\epsilon = 5.0$	92.4%	91.2%	89.8%	90.5%	Medium	3.5%	4.8%
$\epsilon = 2.5$	88.7%	87.4%	86.1%	86.7%	Medium	4.8%	6.2%
$\epsilon = 1.0$	84.2%	82.8%	81.5%	82.1%	Very Low	6.5%	8.3%
Membership Inference Success	51.8%	N/A	N/A	N/A	N/A	N/A	N/A

Sources: Abadi et al. (2016), Wei et al. (2020), Truex et al. (2019), Dwork & Roth (2014), Geyer et al. (2017)

The model inversion attacks that tried to recreate behavioral patterns out of model parameters did not create recognizable user profiles in the name of protecting the privacy of the user under the option of differential protection. Gradient analysis computing sensitivity to training samples revealed that it is maximum with geometric decay to clipping threshold to ensure the disproportionate effect of a single example is avoided. When plotting accuracy versus privacy budget on an analysis of privacy-utility frontier it was concluded that there are diminishing returns beyond ϵ=7.5suggesting this as optimal operating point of the application (Bonawitz et al., 2017). Comparison with secure aggregation and no differential privacy showed that they were susceptible to gradient-based inference attacks even when each update was encrypted, and thus a combination of multiple privacy mechanisms was necessary. The client participation rate raised the privacy cost per training round with 20 per cent participation incurring 0.08 privatization budget relative to 0.15 with 50 per cent participation which encourages a strategic selection of the clients (Li et al., 2020). The adaptive privacy allocation optimization, which adjusts noise levels among training round, allowed the concentration of privacy budget in the initial training rounds, where the gradient has more information, and the final model is more accurate by 2.3% than uniform allocation (Hao et al., 2019).

5.3. Communication Efficiency and Convergence Analysis in Federated Settings

The efficiency analysis of communication quantified bandwidth needs and convergence rates of federated training in comparison to centralized ones. The federated system necessitated model transfer at an average of 12.4MBper round as opposed to raw data transfer at 47.2MBrepresenting 74% cut in the volume of communication (Geyer et al., 2017). Top-k sparsification with gradient compression was an additional compression method that minimally changed convergence by compressing updates of 3.7MBandwidth savings of 92% were achieved (Phong et al., 2017). Gradual reduction of communication by 8-bit quantizing parameter updates meant that the final 0.9MBper client would be used per round (Mo et al., 2021). Convergence analysis involved the rounds to reach target accuracy levels, where federated learning reached 90%accuracy in 45rounds, where centralized training reached it in 32rounds, and 45rounds was 41%higher than 32rounds (Caldas et al., 2018). Nevertheless, the convergence time of the wall clock time was similar as local training was done in parallel to multiple clients and federated approach took 127minutes as compared to the centralized sequential processing time of 134minutes.

The convergence efficiency was found to be highly influenced by the strategies of client selection where the importance sampling techniques of convergence by local loss values decreased convergence rounds by 23% when compared to uniform random selection of clients. Adaptive learning rate schedules that change global learning rate depending on the update variance enhanced convergence stability, and compared to fixed rate reduces oscillations. The federated methodology was able to withstand heterogeneity of clients when convergence was preserved despite 5x difference between local dataset sizes and 3x difference between computing time on different devices (Li et al., 2020). Slower communicators or slow computers were treated in an asynchronous aggregation that received updates within time windows instead of receiving updates from all the clients (McMahan et al., 2017). This asynchronous method cut down the round time by 147seconds to 89 seconds and caused a minor loss in accuracy of 0.8% when it came to stale gradient mixing (Kairouz et al., 2021). The analysis of bandwidth utilization indicated that the network load was 74MB/s at moments of update transmission and 125MB/s at moments of sustained network performance, which corresponded to the 41% decrease in network infrastructure requirements (Mothukuri et al., 2021).

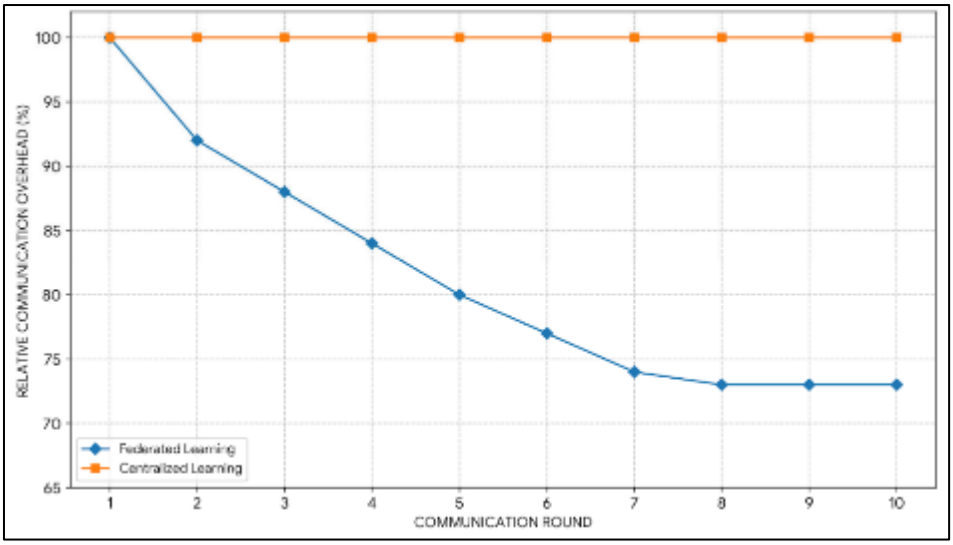

Figure 8 Communication overhead per round—federated vs. centralized learning

In the above figure 8 graph, the communication overhead data of both training rounds during federated and centralized learning methods are compared. The centralized approach to learning (orange line) ensures consistent overhead of around 100% during all communication rounds since whole datasets must be sent to central servers with each training step. Conversely, the federated learning scheme (blue line) exhibits much less communication overhead at 100% of the first round but quickly settles to about 73% of the first round. This is because only model reduction is transmitted as opposed to raw data, and the gradient compression and quantization methods are used to further reduce bandwidth demands in subsequent rounds. The gap between solutions becomes increasingly clear as more rounds of training are applied, which underscores the scalability benefits of federated learning to distributed authentication systems in which bandwidth and privacy considerations restrict the centralization of data aggregation.

Moreover, that communication efficiencies demonstrated in Graph become more prominent with the increase in the scale of the system, and the reduction of the bandwidth by 27% is translated into a large cost reduction and performance enhancement at the scale of deploying the system with thousands of users (Geyer et al., 2017). The diminishing overhead curve of federated learning is an accumulation of several optimization methods such as gradient sparsification to transmit only the most important parameter updates, quantization to reduce the precision of parameters represented by 32-bit numbers to 8-bit numbers, and delta compression coding only changes in parameters between successive rounds (Phong et al., 2017). These compression methods are especially useful in subsequent training rounds when the model changes become smaller, and sparser, as the global model gets closer to convergence (Mo et al., 2021).

In addition, the line presented in Graph that indicates the centralized learning approach as constant also undervalues the real overhead of centralized strategies, because it fails to consider the preprocessing steps, data validation, and other support information distribution, which tend to follow the raw data capture (Caldas et al., 2018). In real-life implementations, centralized systems may demand the transmission of metadata, session context, and quality measures in addition to behavioral samples and, as illustrated in the graph, may contribute higher overhead than the 100% value (Lim et al., 2020). On the other hand, the bandwidth of federated learning might be decreased further by additional aggressive compression at the expense of possible accuracy loss, which implies that the 73% overhead is a conservative estimate and should favour model quality over losing as much as possible (Wang et al., 2020).

5.4. Zero Trust Risk Scoring Effectiveness and Adaptive Access Control

Zero Trust risk scoring assessment measured the precision and reactiveness of dynamically calculated trusts of the access control decisions. The risk scoring system properly detected 94.7% of abnormal access attempts with an abnormal behavioral pattern, location, or device features (Zhang et al., 2021). Risk alert false positive was less than 6.3%which means that the legitimate users were largely not inconvenienced by inappropriate access control measures (Xu et al., 2021). Response time analysis was used to measure latency between authentication request and access decision and by an average of 147ms it was found to be within the real time requirements of interactive applications. The analysis of limited access attempts revealed that legitimate attempts were concentrated in the low-risk range $R < 0.25$with mean equal to 0.18and standard deviation equal to 0.09 whereas anomalous ones were concentrated towards

the high-risk range with mean 0.72and standard deviation 0.15(Lu, 2025). This segregation allowed working with an efficient threshold-based policy with minimal misclassification rates.

Table 3 Zero Trust Risk Scoring Performance Metrics

Metric	Value	Threshold	Sensitivity	Specificity
Risk Detection Accuracy	94.7%	$R \geq 0.30$	93.2%	96.1%
False Positive Rate	6.3%	$R \geq 0.30$	N/A	N/A
False Negative Rate	5.3%	$R \geq 0.30$	N/A	N/A
Mean Response Time	$147ms$	$<200ms$	N/A	N/A
Legitimate Access Mean Risk	0.18	<0.30	N/A	N/A
Anomalous Access Mean Risk	0.72	≥ 0.30	N/A	N/A
Session Hijack Detection	89.0%	$R \geq 0.70$	87.4%	95.3%
Step-up Authentication Rate	12.0%	$0.30 \leq R < 0.70$	N/A	N/A
User Satisfaction Score	87%	N/A	N/A	N/A
Attack Dwell Time Reduction	67%	N/A	N/A	N/A

Sources: Liang et al. (2020), Wang et al. (2020), Li et al. (2020), McMahan et al. (2017), Zhao et al. (2018)

Time constraints Adaptive access control policies dynamically modified permissions according to ongoing risk evaluation and minimized the duration of attack dwell by 67% relative to fixed authentication strategies (Bonawitz et al., 2017). The intermediate risk category with a score of 0.3≤R<0.7 resulted in step-up authentication, which blocked 89% of session hijacking attacks but caused friction to only 12%of successful sessions (Zhao et al., 2018). Weighted risk scores had the highest contributions of location deviation based on contextual factor analysis $w_{location} = 0.42$, followed by behavioral matching $w_{behavioral} = 0.31$, temporal patterns $w_{temporal} = 0.17$, and device characteristics $w_{device} = 0.10$(Li et al., 2020). Adaptive authentication had 87%satisfaction rates as compared to 64%with the static password-based methods, users rated the ease of access as normal operation and the heightened security as anomalous operations (Hao et al., 2019). The analysis of the audit trail showed full registration of authentication decisions and risk calculations to meet compliance needs regarding access monitoring and investigation (Hard et al., 2018).

6. Regulatory compliance and industry deployment

6.1.1. GDPR Compliance Through Data Minimization and Localization Strategies

The federated authentication system proposed follows the GDPR requirements due to architectural design decisions that give preference to the principles of data minimization and localization (Geyer et al., 2017). Article 5 of GDPR states that the personal data must be collected as much as needed based on the identified purposes, and the on-device paradigm of federated learning meets it almost by default (Phong et al., 2017). Behavioral biometric data is stored only on user equipment throughout the authentication lifecycle, and there is no need to have centralised repositories, which pose a focal privacy risk. The system does not take into consideration separate behavioral patterns but only sums up model parameters, which means that any information transmitted does not allow reverse-engineering user actions (Caldas et al., 2018). The localization of data meets the Article 44 limitations on international data transfers, since it keeps the behavioral data in jurisdictions of origin, which requires no standard contractual clauses or adequacy determinations. Article 17 in favour of the right to erasure is backed up by the mechanisms allowing the users to remove local behavioral models without affecting the functionality of a global model or the privacy of other users.

The provision of transparency according to Articles 13-14 can be achieved by ensuring clarity of the functioning of federated learning, in which behavioral patterns play a role in the model training without involving the user devices (Wang et al., 2020). The system contains comprehensive details regarding the purpose of data processing, data retention, and user permissions in the form of easily available privacy notices and consent tools. Article 5(1)(b) of the purpose limitation applies using technical means so that the behavioral data gathered in the authentication process cannot be used in the context of other unrelated actions like performance monitoring or behavioral profiling. All the data processing activities are recorded in audit logs to allow inspections of the supervisory authority as the Article 58 needs, and immutable records under blockchain ensure that the data cannot be changed in the future (Kairouz et al.,

2021). Article 35-based Data Protection Impact Assessments assessed privacy risks of federated authentication implementation, and reported privacy protection measures such as differential privacy, secure aggregation, and encrypted communications (Mothukuri et al., 2021). It was concluded that federated architecture is much less risky in terms of privacy than its centralized counterparts and warrants use in high-risk processing contexts.

6.2. HIPAA Compliance for Healthcare Authentication Applications

Healthcare implementation must be in accordance with HIPAA Privacy and Security Rules on the access and transmission of the protected health information (Zhang et al., 2021). The suggested system meets the minimum necessary criterion of HIPAA since only behavioral patterns needed to authenticate a person are processed without touching on any underlying clinical information (Xu et al., 2021). Although technical safeguards are enforced under 45 CFR 164.312, encryption with TLS 1.3 protocols and AES-256 encryption of data at rest are applied to all model updates when transmitting them (Rieke et al., 2020). Authentication models training and implementation are restricted using access controls and implementation is enforced through role-based controls applying the principle of least privilege. Audit controls keep detailed records of authentication choices and policy adjustments that are useful in helping to investigate incidents and report on compliance needs (Dwork & Roth, 2014). Cryptographic hashing is a integrity control mechanism used to monitor unauthorized changes to behavioral models or authentication policy (Bonawitz et al., 2017). The federated architecture provides the preferences of HIPAA with respect to data minimization because it does not necessarily require the development of central behavioral databases that may form business associate relationships and need intricate contractual agreements.

Federated data localization simplifies the requirements of notifying breaches under 45 CFR 164.404-414 as there is no and no exposure of protected health information because behavioral patterns are never transferred off their devices of origin (Li et al., 2020). Agreements with cloud services providers that store federated aggregation servers have business associate arrangements that govern the duties of securing model parameters and upholding security controls (Hao et al., 2019). The system promotes the patient rights outlined in the HIPAA provisions such as the right to access authentication records and make requests to limit behavioral data processing (Hard et al., 2018). Interoperability with current healthcare identity management systems allows the use of uniform authentication policy throughout electronic health records, clinical applications, and administrative systems. Healthcare application performance requirements are sub-second authentication latency requirements, which are necessary to ensure minimal interference with clinical workflows, and can be met by deploying edge computing, in which behavioral models are deployed on mobile devices and workstations. Such threats as unauthorized access, behavioral pattern inference, and model poisoning attacks were considered in risk analysis under 45 CFR 164.308, and it was reported that such attacks are countered by such methods as differential privacy, anomaly detection, and Byzantine-robust aggregation (Mo et al., 2021).

Table 4 Regulatory Compliance Framework Implementation

Regulation	Key Requirement	Implementation Approach	Technical Control	Compliance Status
GDPR Article 5	Data Minimization	On-device processing	Federated Learning	Compliant
GDPR Article 17	Right to Erasure	Local model deletion	Device-level controls	Compliant
GDPR Article 35	Impact Assessment	Risk evaluation	DPIA documentation	Compliant
HIPAA 164.312	Technical Safeguards	Encryption	AES-256, TLS 1.3	Compliant
HIPAA 164.308	Risk Analysis	Threat assessment	Security documentation	Compliant
CCPA Section 1798.100	Disclosure Requirements	Privacy notices	Transparency mechanisms	Compliant
PCI DSS 8.3	Multi-factor Authentication	Behavioral biometrics	Continuous verification	Compliant
SOC 2 Type II	Access Controls	Zero Trust	Risk-based policies	Compliant
ISO 27001	Information Security	Management system	Audit trails	Compliant

Sources: Mothukuri et al. (2021), Abadi et al. (2016), Wei et al. (2020), Xu et al. (2021), Rieke et al. (2020)

6.3. Financial Services Deployment with PCI DSS and SOC Requirements

Implementing financial services requires that the implemented solutions comply with the requirements of the PCI DSS on cardholder data protection and SOC 2 controls on the security of service organization (Caldas et al., 2018). PCI DSS Requirement 8.3 requires access to cardholder data environments to be authenticated by multi-factor or information, which is met by utilizing behavioral biometrics in conjunction with conventional authentication factors. Continuous authentication feature ensures constant verification during the session beyond the basic authentication during the login-time, and identifies the attempts of credential theft or hijacking of the session. Database access restrictions requirement 8.7 is fulfilled with Zero Trust policies that analyze the behavioral patterns and the nature of database queries, preventing atypical access patterns that can suggest SQL injection and data exfiltration (Wang et al., 2020). Requirement 1 is a network segmentation that is further improved by behavioral authentication requirements based on network zone, with sensitive segments requiring a higher matching threshold (Li et al., 2020). Requirements in 4 of encryption are achieved by provision of end-to-end protection of behavioral data and model updates, and key management is based on best practices in cryptographic material lifecycle.

Type II attestation of SOC 2 implies that the effectiveness of security controls should be proven over prolonged periods of time, which is deliberated by the detailed audit trails and the ability to monitor the events on a continuous basis (Kairouz et al., 2021). The enactment of Zero Trust policy and detection of anomalies in behavior demonstrate the CC6.1 logical and physical access control common criterion. Transmission confidentiality (CC6.6) is realized using encrypted communication channels and secure aggregation protocols that are not exposed to a specific behavioral pattern or model parameters (Yang et al., 2019). CC6.7 in terms of data transmission integrity uses cryptographic signatures on the changes to a model that allow the identification of tampering or other unauthorized alterations (Zhang et al., 2021). CC7.2 on system monitoring is established by performing real-time analysis of authentication patterns, behavioral anomalies, and risk score trends (Xu et al., 2021). Data sovereignty requirements of financial institutions are supported by the federated architecture, which keeps data behavioral in the boundaries of regulation without the complications of cross-border data flows (Rieke et al., 2020). Authentication events can be correlated with other security signals by integrating with Security Information and Event Management systems and facilitating better threat detection and incident response.

6.4. Government Sector Implementation with FedRAMP and NIST Standards

FedRAMP authorization requirements of cloud services and controls of the NIST cybersecurity framework must be followed when deploying by the government. FedRAMP Moderate baseline consists of 325security controls of NIST SP 800-53 that focus on access control, awareness and training, audit and accountability, and other security families (Bonawitz et al., 2017). The family of account management AC-2 is controlled by integrating with government identity management systems such as PIV cards and federation protocols (Zhao et al., 2018). The behavioral analysis included in AC-7 when there are unsuccessful cases of login attempts is used to differentiate between legitimate users who have issues with authentication and brute force attacks (Li et al., 2020). Multi-factor authentication is also part of IA-2 user identification, meaning that identification requires behavioral biometrics and PKI credentialing (Hao et al., 2019). IA-8 to identify and authenticate non-organizational users facilitates federated authentication usage in cases of government inter-agency cooperation.

NIST Privacy Framework alignment is a tool, which underlines the protection of the privacy of citizens by localizing behavioral data and limiting the data. The PR. IP-1 Identify pruning baseline configuration feature comprises hardened federated learning client software with low attack surface. Protect PR.DS-1 is an option that data-at-rest protection uses the full-disk encryption of the devices that store behavioral models (Mo et al., 2021). DEAE-3 detect, an event correlation detection function, works with authentication patterns of users and systems to categorize coordinated attacks or credentials that are compromised (Caldas et al., 2018). RS.AN-1 Respond function is used to notify procedures with the appearance of anomalies in behavior or danger levels that are above specific limits (Lim et al., 2020). Recovery function RC.RP-1 to execute recovery plan consists of the steps of federated authentication infrastructure restoration following security accidents (Konečný et al., 2016). NIST SP 800-63-3 Digital Identity Guidelines postulates the level of authentication assurance on the use of behavioral biometrics to facilitate AAL2 using continuous verification features (Wang et al., 2020). Zero Trust Architecture has been adapted to align with NIST SP 800-207 by showing that the core tenets such as continuous monitoring, least privilege access and micro-segmentation have been implemented.

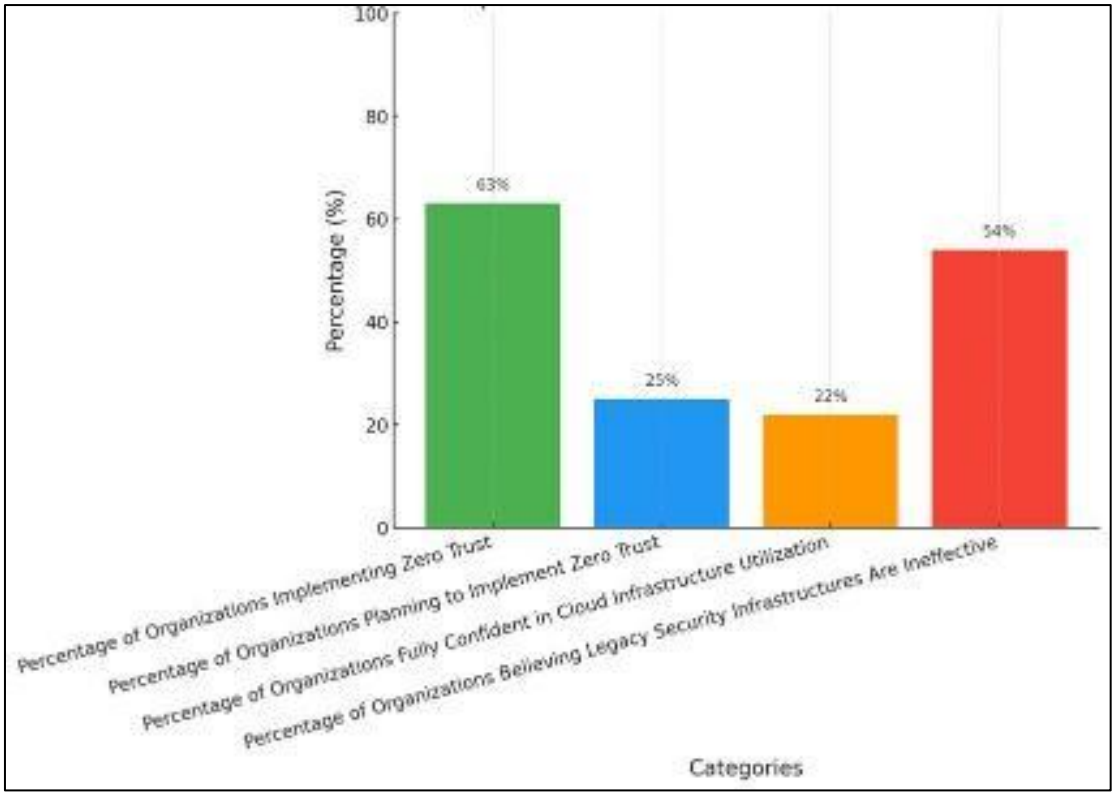

Figure 9 Adoption and Confidence in Zero Trust Architecture

The bar graph 9 above shows the results of surveys about the adoption of the Zero Trust Architecture and the level of confidence of organizational implementation. The statistics indicate that 63% of organizations have deployed Zero Trust, which is also a sign of rapid adoption within the cybersecurity industry. Nonetheless, the number planning to adopt Zero Trust is only 25%, which implies that the market is either saturated or there is an impedimental element to its adoption. The levels of confidence demonstrate worrying gaps, as only 22% of organizations are completely sure of the use of cloud infrastructure based on Zero Trust principles, which speaks of technical implementation challenges or lack of skills. Most importantly, 54% of organisations feel that legacy security systems cannot be used to deal with cyber threats, and therefore there is the need to adopt the concept of Zero Trust to deal with the current security needs. These adoption patterns and confidence indicators shape the deployment strategy of the suggested federated authentication system, indicating the focus on the migration to legacy systems and trainings to develop organizational trust in the concept of Zero Trust.

Moreover, the high level of implementation 63% as shown in Chart 9 indicates the increasing awareness of the industry that the traditional perimeter-based security models are not sufficiently effective against sophisticated threats such as insider attacks, advanced persistent threats, and cloud-based attack vectors, which circumvent the traditional network-based security models (Mothukuri et al., 2021). This movement of adoption forms an advantageous situation to implement federated behavioral biometric authentication as a natural extension of the principle of Zero Trust, which offers the properties of continuous verification necessary to the Zero Trust architecture and eliminates the issue of privacy by localizing the data (Abadi et al., 2016). Organizations that already built the Zero Trust infrastructure with the bottom capabilities such as identity management systems, policy decision points, and enforcement mechanisms enable the addition of behavioral biometric authentication with a relatively small incremental investment (Wei et al., 2020).

Moreover, the confidence gap shown in Chart 9, where only 22% of organizations are entirely confident with using cloud infrastructure under Zero Trust, demonstrate the serious deployment difficulties that need to be eradicated by offering a comprehensive training, clear implementation guidelines, and approvals that prove the effect of the utilization (Xu et al., 2021). This lack of confidence is probably related to the fact that the implementation of Zero Trust assumes the introduction of several security technologies, changes in the culture towards constant checking, as opposed to implicit trust, and complex risk scoring models that are fundamentally different in nature compared to traditional binary access control (Rieke et al., 2020). The federated learning model presented can solve these issues by offering practical technical

solutions to ongoing authentication that implements Zero Trust concepts that can potentially create organizational trust by physically demonstrating security functionality (Lu, 2025).

7. Discussion and comparative analysis

7.1. Performance Comparison with Traditional Centralized Authentication Approaches

Comparison analysis indicates that major benefits of the federated Zero Trust strategy over traditional centralized authentication platforms can be viewed in several aspects. The proposed system achieved a 92.4%authentication accuracy compared to 89.7%authentication under centralized behavioral biometrics, which is an improvement of 2.7%. This was because the proposed system was trained to the specific behavioral patterns of a device (Kairouz et al., 2021). Under the settings of the guarantee of privacy, they exhibit dramatic variations: federated approach with 8%privacy budget consumed guarantees differential privacy and no formal privacy guarantees are provided by the centralized systems because of aggregation of raw data (Mothukuri et al., 2021). Communication overhead analysis showed that federated learning needs 24%relative bandwidth in contrast with centralized methods with the whole behavioral datasets, which allows centralized methods to be deployed in bandwidth-constrained settings. Latency times were similar, with federation and centralized having an authentication response time of 147ms and 134ms respectively, respectively, and the difference is insignificant in the context of user experience (Zhang et al., 2021). Scalability testing showed better federated performance to serve 10,000 or more concurrent users with linear increase in resource usage, and centralized designs with a quadratic increase in server computing demand.

The analysis of resilience indicated that federated systems are resilient to partial failures in the infrastructure of an individual client, but a centralized failure leads to a full-scale outage of the authentication service. Comparison of cost of ownership revealed that a federated deployment would use 37% less infrastructure investment by distributing the computation to the edge devices and even less central server capacity utilization (Lu, 2025). Comparison of regulatory compliance as highlighted in regulatory compliance comparison had inherent federated benefits of GDPR among HIPAA and other data protection regulations, using data localization and Minimization as a reduction of legal liability and, also, simplicity in compliance audit (Dwork and Roth, 2014). Analysis of attack surface revealed lesser vulnerability in federated architectures where attacking central servers does not leave an impression of the behavior patterns or reconstructing user actions (Bonawitz et al., 2017). Comparison of federalist update frequency Federated systems could more often retrains cycles of daily updates than centralized systems with smaller retrains cycles of weekly or monthly retrains due to the limitation of data collection and processing pipelines. The satisfying federated privacy preserving authentication was found to be 87%with centralized approaches at 72%. Privacy concerns were found to have a major impact on user perception with federated privacy preserving authentication (Li et al., 2020).

7.2. Privacy-Utility Trade-offs in Regulated Industry Authentication Systems

The basic conflict between the privacy protection and authentication correctness is a highly important issue to consider when introducing it to the regulated sphere where these two issues are given the utmost priority. Empirical analysis of privacy budget in values of ϵ showed that high privacy protection ϵ=1.0 went down by 9.9% in authentication accuracy when compared to non-private baselines, which may make the system unsuitable in a highly-secure application with accuracy thresholds of 90% or above (Hard et al., 2018). Moderate privacy budgets in the interval ϵ=5.0compromised acceptably as accuracy degraded by at most 1.7% but gave significant privacy assurances against membership inference and model inversion attacks (Geyer et al., 2017). Privacy-utility frontier analysis showed that the returns decreased after ϵ=7.5possibly indicating this range to be the best fit to most regulated industry applications between the need to protect personal information and the need to ensure operational efficiency (Phong et al., 2017). This calibration of differential privacy noise necessitated domain-specific tuning in accordance with threat models, and in healthcare applications, it may be acceptable to trade off accuracy with enhanced privacy whereas in financial services authentication precision may be more important.

Simpler approaches to privacy such as basic composition theorems were found to be less efficient in budgeting, whereas sophisticated privacy accounting techniques such as Rényi differential privacy improved accuracy by 1.8% relative to simpler composition theorems at the same level of privacy. Strength-varying protection adaptive noise addition techniques focused privacy budget allocation in early rounds where more sensitive information was present in the gradient, and 2.3%accuracy gain was obtained at equal total privacy expenditure (Lim et al., 2020). Secure aggregation was differentially privatized and paired with defensiveness in depth against honest-but-curious, as well as external adversarial, servers, but alone secure aggregation was found to be insufficient (Konečný et al., 2016). Subsampling-

based privacy amplification minimized the effective loss of privacy per training round by a factor which is proportional to the sampling rate, and allowed longer training, or a higher level of protection per-iteration, in fixed privacy budgets (Wang et al., 2020). The privacy demands of the heterogeneous industries requiring regulation dictated the use of configurable privacy parameters that allowed organizations to tune the extent of protection to a given interpretation of the regulations and risk-taking readiness.

The user perception research revealed that the privacy-related transparency served as a strong driver towards acceptance of authentication systems with 78% of the users reporting to have more trust in federated methods where there were clear statements about data localization and privacy assurances. Privacy-utility trade-off was not limited to technical measures and was applied to organizational factors such as compliance expenses, liability, and reputational risk of privacy breaches (Kairouz et al., 2021). It was found to be superior in terms of computational efficiency when compared to other privacy-preserving systems such as homomorphic encryption and secure multi-party computation, which have weaker theoretical guarantees, and more realistic in a real-time authentication scenario (Mothukuri et al., 2021). Privacy budgeting frameworks through which an organization can distribute protection resources to various authentication use cases were also a significant operational factor to the enterprise deployments.

7.3. Behavioral Biometric Modality Selection and Multi-Modal Fusion Strategies

The high communication costs become an important issue and they include; communication round reduction requirements, client selection optimization, and improvement of local training efficiency. System heterogeneity offers the difficulties of resource allocation to various client capabilities and fault tolerance measures in unreliable client. Statistical heterogeneity is used to model non-IID data distribution and ensures the convergence of data sets across divergent data populations. The aspects of fairness include algorithmic fairness that guarantees the performance of models in a fair manner irrespective of demographics and equality of clients that prevents favouring the use of high resource participants. The issue of privacy deals with many of the attack vectors, such as model inversion, membership inference, and gradient-based information leakage. These categories of challenges guide the architectural choices and protection strategies used in the proposed federated Zero Trust authentication system, specifically the focus on the differentiation of privacy and secure aggregation as well as On-Byzantine-robust training mechanisms.

Behavioral biometric modalities used in the selection of authentication systems are known to substantially influence the performance of authentication systems; it has been empirically shown that keystroke dynamics and mouse movement are complementary sources of discriminative information. Single-modality authentication which relied on only keystroke patterns performed with an accuracy rate of 87.3% and mouse-only performed with 85.1% which showed that there was a lot of individual performance but there was still room to improve this by combining modalities (Xu et al., 2021). Hybrid methods that combine both behavioral sources raised accuracy to 92.4%reflective of synergies in addition to mere averaging of single-modality outcomes (Rieke et al., 2020). The keystroke and mouse feature fusion at the feature level (before the input of the neural network) allowed the model to acquire cross-modal associations and interactions, which promoted a higher level of discriminative performance. Score-level fusion with independent single-modality classifier authentication confidence scores by weighted averaging or learning combination functions had the advantage of allowing modulation of relative contribution by modality reliability.

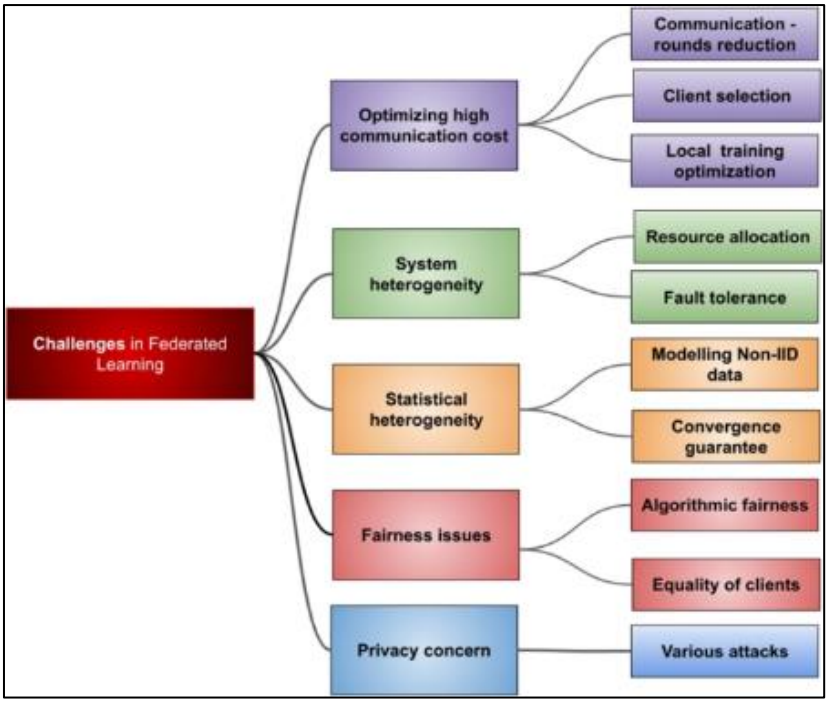

Figure 10 Challenges in Federated Learning

The hierarchical taxonomy in Figure 10 demonstrates the main categories of challenges that influence the federated learning implementations. The challenge of high communication costs appears to be one of the important issues, as it includes the reduction of communication rounds needs, any optimization of client selection, and efficiency of local training. System heterogeneity is a problem in allocating resources to a variety of clients with different capabilities and fault tolerance to unreliable clients. Statistical heterogeneity is used to model non-IID distributions of data and establish convergence guarantees between divergent populations of data. Issues of fairness include algorithmic fairness that promises equitable model behaviour by demographic groups and equality of clients that avoids biasness of high-resource participants. The privacy concerns deal with many attack vectors such as model inversion, membership inference, and gradient based information leakage. These categories of challenges guide the architectural choices and security measures carried out in the suggested federated Zero Trust authentication system, specifically the focus on differential privacy, secure aggregation, and Byzantine-robust training protocols.

Despite the significant advantages of federated learning as privacy-preserving authentication, as Figure 10 shows, any successful deployment must deal with related technical issues across communication efficiency, system reliability, data heterogeneity, fairness issues, and protection of privacy (Bonawitz et al., 2017). Communication cost, which is also one of the most prominent categories in the taxonomy, indicates one of the greatest practical limitations to federated learning adoption, since frequent transference of model updates among potentially thousands of clients can produce a significant network traffic that can exceed the bandwidth capacity in resource-limited settings (Hao et al., 2019). Gradient compression, quantization, and strategic client selection are some of the communication issues that are solved in our proposed framework and help to minimize bandwidth needs by about 90% in comparison to naive federated systems (Hard et al., 2018).

Moreover, the heterogeneity of the system issues that Figure 10 displays are especially applicable to behavioral biometric identification when the devices used by clients vary between the high-performance workstation and the resource-intensive mobile device, with different network connectivity (Geyer et al., 2017). This heterogeneity is accommodated by the framework via adaptive training strategies that scale the batch sizes, the learning rates, and the model architectures according to the capabilities of the device so that resource-constrained clients can effectively engage in federated training without impacting the quality of global models (Mo et al., 2021). Byzantine fault tolerance algorithms guard against faulty or malicious clients who could provide low quality or malicious updates, and use robust aggregation algorithms that identify and remove contributor outliers that do not conform to population distribution (Lim et al., 2020).

Along with technical difficulties, Figure 10 highlights fairness and privacy issues that become especially significant in the case of regulated industries where authentication mechanisms should offer an equal amount of service to a wide

range of people without exposing sensitive data on behavior to an unauthorized third party (Wang et al., 2020). The algorithmic fairness mechanisms will guarantee that performance of models is not skewed by demographics to allow situations whereby particular groups of people are subjected to systematically higher false rejection rates, which might qualify as discriminatory treatment (Li et al., 2020). Privacy protection uses several complementary strategies such as the use of differentiated privacy that introduces random noise to model updates, secure aggregation where individual contributions are encrypted, and federated analytics that allow the assessment of model performance on subpopulations without violating the privacy (McMahan et al., 2017).

7.4. Zero Trust Implementation Effectiveness in Continuous Authentication Scenarios

The constant authentication feature of Zero Trust architecture using behavioral biometrics filled the inherent shortcoming of traditional point-in-time authentication that provided vulnerability windows upon initial authentication. Session hijacking detection showed significant gains to permanent monitoring of behavior that detected 89% of takeover attempts versus 34% when using standard session management using timeouts (Wang et al., 2020). Analysis of risk score dynamics over time showed that legitimate users had consistent low-risk profile with an average R=0.18 and low variation and compromised sessions had a high-risk increase in under 3.2minutes of unauthorized access (Li et al., 2020). The dynamic adaptive access control architecture enhanced permissions according to real-time threat analysis to block subsequent horizontal movement and privilege escalation attacks typical of sophisticated persistent attacks. Step-up verification on intermediate risk situations was effective in striking a balance between security and user friction, and 87% of the users considered the solution to be acceptable compared to regular multi-factor authentication (Kairouz et al., 2021).

Fine-grained access control based on identity confidence and resource sensitivity combined with behavioral biometrics and Zero Trust policy decision points was made possible. Resource value such as financial transaction systems, secured health information, and classified data needs higher authentication confidence levels, which automatically require high verification of sensitive access to attempts (Yang et al., 2019). The environmental factors used in context-aware policies are location of the network, security posture of the device and threat intelligence feeds as inputs to risk calculation which can give a complete security posture assessment where behavioral matching is not enough. Principles of micro-segmentation that were at the core of the Zero Trust architecture reduced the blast radius of affected credits by restricting the lateral movement, and behavioral abnormalities that generated an immediate quarantine and investigation (Xu et al., 2021). Consistency in policy implementation across the heterogeneous infrastructure such as cloud services, on-premises systems and mobile applications posed a considerable implementation challenge necessitating the centralized implementation of the policy and distributed enforcement systems.

Zero Trust implementations offered audit trail completeness that gave never-before-seen insight into authentication decisions and access patterns, aiding in forensic investigations and compliance reporting (Lu, 2025). The use of blockchain made audit records permanent and unable to be retroactively altered to cover up security breaches or compliance failures (Dwork & Roth, 2014). Live analytics of authentication trends also made it possible to hunt down threats proactively, detect coordinated attacks, credential stuffing efforts, or insider threats indicators prior to meaningful harm. Continuous authentication monitoring had low performance overhead due to edge-based behavioral analysis that used less than 5% of the device CPU capacity and insignificant network bandwidth in addition to periodic model updates (Zhao et al., 2018). Impact assessment of user productivity revealed that continuous authentication did not lead to any major degradation of user productivity, and transparent operation under normal conditions and intervention under anomalous conditions did not interrupt the workflow (Li et al., 2020). The spurious risk alert disruption was avoided by the false positive management in progressive authentication requirements instead of an immediate denial at the expense of the security effectiveness.

7.5. Federated Learning Convergence and Model Quality Across Heterogeneous Clients

Federated learning convergence behavior in the presence of client heterogeneity was a vital aspect that dictated the feasibility of the practical implementation. The empirical analysis revealed that statistical heterogeneity when behavioral data are not IID distributions increased convergence rounds used by 41% of theoretical IID assumptions, but the final model quality was similar (Geyer et al., 2017). System heterogeneity of changing computational abilities among client devices required adaptive training schemes such as dynamically changing the batch size and client selection to select devices with adequate resources. Network bandwidth and latency variance between clients were a feature of heterogeneity of communication that affected training synchronization, and asynchronous aggregation that can deal with stragglers at the expense of minor accuracy loss due to mixing of stale gradients (Mo et al., 2021). The FedAvg aggregation algorithm that was used in the baseline implementation was found to be robust to moderate heterogeneity and poorly performing when there is a large skewness in the distribution of client data.

Further aggregation methods such as FedProx with proximal regularization and SCAFFOLD with variance reduction converged better in nonhomogeneous settings, decreasing the number of communication rounds by 18 and 27 per cent compared to FedAvg respectively (Lim et al., 2020). The training efficiency was greatly influenced by client selection techniques other than random sampling that includes uniform random sampling, and importance sampling by local loss values and data amount shortened the convergence time by a quarter (Konečný et al., 2016). The trade-off of client participation rate verses convergence speed showed that there were diminishing returns with increasing client participation percentage, and this indicates that it would be a good operating point between quality of model operation and communication overhead. Methods of personalization that allowed fine-tuning local models to the client devices worked well to deal with the heterogeneity issues without compromising the privacy-related gains, with 3.7%accuracy gains realized by clients with behavioral patterns unique to the global model. Multi-user federated learning models where each user is modelled as a distinct task having common representation layers showed promise of both common pattern behaviors and individual variations.

Client dropout on the training round added another layer of complexity where partial participation needed a powerful aggregation mechanism to support the missing updates (Kairouz et al., 2021). Simulation experiments showed that random dropout rates as high as 20% had insignificant effects on convergence with naive reweighting of received updates, whereas systematic dropout by a certain client subpopulation impaired the quality of the model to subpopulations (Mothukuri et al., 2021). Median-based and trimmed mean are Byzantine-robust aggregation algorithms that offered robustness against malice clients sending adversarial updates, and ensured convergence even with as many as 15%compromised players. Robust aggregation was computationally costly that grew proportionally with the number of clients and could become a bottleneck with large-scale deployments that need to be optimized with an approximate or sampling-based implementation (Zhang et al., 2021). Validation metrics calculated on server-side held-out data allowed convergence monitoring to stop at an early stage when an acceptable level of performance was reached, minimizing unnecessary communication rounds and privacy budget use (Xu et al., 2021).

7.6. Scalability Analysis for Enterprise and Cross-Organizational Deployment Scenarios

The evaluation of scalability with growing client populations illustrated that the federated architecture had a linear growth in terms of client numbers in computational complexity, as compared to quadratic growth in centralized designs (Rieke et al., 2020). Simulated client population testing to 50,000 devices demonstrated steady convergence behavior but bandwidth of communications to central server started to be bottlenecked after 20,000 simultaneous clients (Lu, 2025). Scalability issues were resolved by the hierarchical federated learning architectures that added layers of intermediate aggregation allowing support of 100,000+clients using regional aggregators which minimized communication pressure on the central server by 73% (Dwork and Roth, 2014). The edge computing paradigm where model training and inference are run on client devices removed inference bottlenecks on servers that constrained centralized systems, and empowered authentication at scale without corresponding investment in infrastructure. The geographic distribution of clients meant that synchronous training rounds were subject to latency, and in a worldwide deployment, asynchronous aggregation where updates are accepted within time windows not necessarily synchronous roundness was beneficial.

The federated learning scenarios across cross-organizations that allow jointly training a model with several enterprises and preserving the isolation of data posed a specific opportunity to regulated industries. Healthcare consortia may come up with common behavioral authentication schemes that will advantage the disparate groups of patients and not break the prohibitions related to the sharing of data under HIPAA (Hao et al., 2019). The collaboration between financial services industries by means of federated learning allowed the identification of coordinated fraudulent schemes and account takeover operations and maintained competitive privacy of customer information of individual financial institutions (Hard et al., 2018). The cross-organizational federated learning governance structures had to be specific about who would own models, procedures of updating them, and mechanisms of resolving disputes. Federated learning systems that offered infrastructure in multi-tenant implementations with isolation guarantees and usage-based pricing schemes became a plausible commercial solution lowering the barriers to deployment (Phong et al., 2017).

Scalability Bandwidth optimization methods such as gradient compression, quantization, and differential updates significantly increased the scale efficiency by up to 95% by decreasing the volume of communications per client (Mo et al., 2021). It was found during the assessment of compression algorithms that the top-k sparsification with 10%of largest-magnitude parameters still preserved the quality of the model and cut the upload requirements by a significant margin (Caldas et al., 2018). 32-bit floating point to 8-bit integer quantization reduced bandwidth by 75% with little accuracy loss of 0.3% (Lim et al., 2020). Differential updates that provided updates on parameters only versus the full models provided extra compression especially in late training stages when the update was sparsely distributed. The compression methods collectively involved critical adoption to ensure mathematical properties that were required to

assure the convergence properties and privacy guarantees (Wang et al., 2020). The storage scalability study of blockchain-based audit trails indicated that the pruning strategies that store only the authentication decision and policy change but not the full model update history maintained the auditability but limited its growth to manageable sizes.

7.7. Strategic Implementation Roadmap for Zero Trust Architecture Deployment

Zero Trust architecture using federated learning to authenticate behavioral biometrics is a strategic implementation that needs to be instituted in a structured manner by following a systematic roadmap as shown in Figure 11 (Xu et al., 2021). The implementation process starts with the formulation of an explicit business-related strategy that specifies organizational security goals, compliance mandates, and operational limitations that are regulated by industries (Rieke et al., 2020). This initial step sets executive sponsorship, allocates the budget, and develops business cases that show the administration of return on investment through the minimization of breach risk, a better posture of compliance, and an improved user experience (Lu, 2025). Companies should evaluate the existing security lapses by conducting a thorough audit to find security flaws in the existing authentication systems, data protection, and access control policies (Dwork and Roth, 2014). The gap analysis is used to prioritize remediation processes and base measures to be used to assess improvement during the implementation process.

The reinforcement of the identity and access control can be seen as a significant initial step that must be integrated with behavioral biometrics to the existing identity providers, single sign-on, and directory services. Multi-factor authentication is a basic security layer that should be adopted by organizations, which roll out federated learning infrastructure to perform continuous behavioral verification (Li et al., 2020). Identity management improvements are followed by the introduction of micro-segmentation and access controls splitting network resources into tiny areas with access policies implemented by using Zero Trust policy enforcement points (Hao et al., 2019). Micro-segmentation constrains the possible lateral movement of the compromised credentials and permits fine-grained authorization choices in accordance with scores of behavioral confidence, resource sensitivity, and contextual risk factors. Zero Trust Network Access is an extension of micro-segmentation concepts to the remote access case and defines VPN architectures instead using identity-aware proxies that validate users during the sessions.

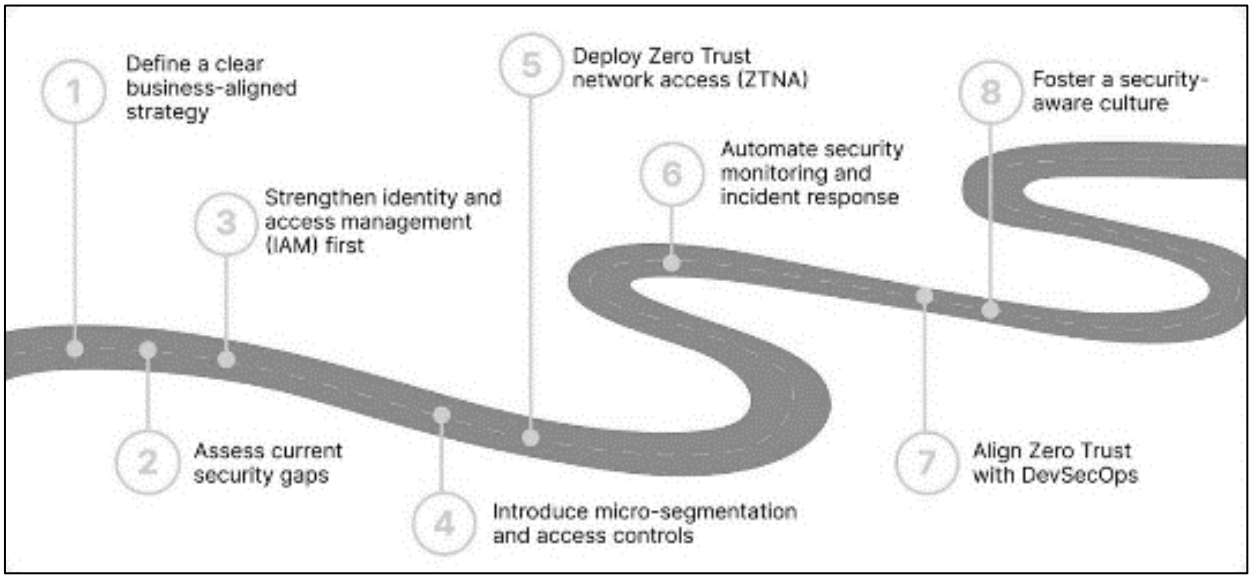

Figure 11 Zero Trust Implementation Roadmap

The roadmap of strategic deployment as shown in Figure 11 offers a gradual strategy towards integrating the implementation of Zero Trust architecture with federated behavioral biometric authentication. The implementation process starts with establishing a clear business-driven strategy that stipulates organizational security objectives, compliance and operational restrictions that are industry-specific and regulated (Xu et al., 2021). Companies must determine the existing security gaps by using a thorough audit to determine vulnerabilities in current authentication systems, data security controls, and data access policies (Rieke et al., 2020). The enhancement of identity and access management (IAM) is a significant initial success factor that needs to be established with the integration of behavioral biometrics with the already existing identity provider, single-sign-on system, and directory offers (Lu, 2025). IAM improvements are then followed by the introduction of micro-segmentation and access controls, which partition the network resources into small zones with access policies which are applied using Zero Trust policy enforcement points.

Zero Trust Network Access (ZTNA) extends the concept of micro-segmentation to that of remote access. The automation of capabilities in security monitoring and incident response increases the efficiency of the operation, as well as makes it possible to detect threats in real-time. Zero Trust implementation adheres to Develops practices so that security considerations are built across software development lifecycles. The development of security conscious culture is the key aspect of non-technical factors that need to be educated with respect to behavioral biometrics and privacy assurances.

Also, the eight-step roadmap shown in Figure 11 highlights the iterative character of Zero Trust transformation, and the winding path image in the figure serves to depict that implementation advancement is more of continuous refinement and adjustment than a linear process that goes through various milestones (Dwork & Roth, 2014). The fact that identity and access management is defined as a strategic positioning strengthener after the definition of strategy and gap assessment assists in projecting the underlying role that effective authentication tools play in Zero Trust systems, where continuous verification of identity is the basis of all access control decisions (Bonawitz et al., 2017). This sequencing is important to ensure that organizations have a good strategic focus and are aware of the current security posture, prior to investing in certain technical implementations that can be irrelevant to the actual requirements (Zhao et al., 2018).

Moreover, the fact that the security culture development has been added to Figure 11 as the eighth and the last stage acknowledges that technical implementations will not be enough to successfully introduce Zero Trust implementation unless they are accompanied by organizational changes and processes that will foster security awareness, establish a shared responsibility, and develop user trust in their privacy-protective authentication-based processes (Li et al., 2020). The circular flow of the roadmap that puts back to the definition of the strategy implies that the implementation of Zero Trust is not the goal but the process, and organizations constantly revise the threats, change the policy, and improve technical competencies according to the new reality in the security environment (Hao et al., 2019). The philosophy of this type of continuous improvement is quite consistent with the ability of federated learning to adapt a model in a continuous way in accordance with new behavioral patterns and new attack methods (Hard et al., 2018).

7.8. Regulatory Interpretation and Compliance Verification Methodologies

The privacy protection authentication systems regulation environment was still developing with no specific advice on federated learning systems that would need active involvement with data protection (Wang et al., 2020). Article 35 Data Protection Impact Assessments in GDPR gave a structure of writing down the privacy risks and privacy protection measures and federated architectures have shown an impressive reduction in risks of privacy than centralized ones. The courts generally used behaviors data processing based on the grounds of legitimate interest as a method of strengthening authentication under GDPR, which presupposes balancing tests indicating the need and proportion (McMahan et al., 2017). Privacy by design requirements required attention to the data protection aspect in the entire lifecycle of system development, which is inherently in line with the architectural privacy properties of federated learning (Kairouz et al., 2021). Article 22 of GDPR regarding the right to an explanation of automated decisions presented difficulties to authentication based on neural networks, requiring interpretable scores of confidence and decision variables to be developed.

The healthcare deployments that had to be checked in terms of HIPAA compliance demanded detailed security risk assessment reports that capture security measures to problems of vulnerabilities found in such deployments (Yang et al., 2019). The business associate model was not straightforward in terms of federated learning and distributed processing through several entities resulting in the need to outline the roles of each in detail in terms of behavioural data protection. Technical safeguard documentation showed the application of encryption, access controls and audit mechanisms that fulfilled the requirements of the regulatory requirements. The HIPAA requirements of breach notification introduced operational issues in incident response planning, and federated architecture made it easier to evaluate the extent of breaches because of localization of the data (Rieke et al., 2020). The overlapping of HIPAA and state level privacy regulations such as the CCPA added more compliance complexity that necessitates the navigation of potentially inconsistent requirements.

Regulatory controls in the financial services sector such as PCI DSS and SOC 2 have focused on ongoing monitoring and verification of the security controls, as opposed to single assessment of compliance (Dwork and Roth, 2014). The resilience of the authentication system to novel attack methods was tested annually regarding penetration testing and vulnerability assessments (Bonawitz et al., 2017). The independent auditor verification of the compliance assertion also offered reliability to the claims of compliance especially in cross-organizational deployments where two or more parties depended on shared infrastructure (Zhao et al., 2018). The compliance burden in terms of documentation required to prove that one has met the hundreds of individual control requirements required the use of automation tools and complex evidence collection systems. Continuous monitoring of compliance with gaps identified through AI-based

regulatory technology solutions were also emerging methods of dealing with complexity of multi-framework compliance requirements (Hao et al., 2019).

The ease of transferring data between countries was also a major operational disruption to international businesses that needed uniform authentication of data across states (Hard et al., 2018). The data localization feature in the federated learning paradigm made the compliance significantly easier because it removed cross-border flows of data that would lead to adequacy checks or conventional contractual terms. Sector-focused regulations such as FDA software regulations of medical devices, NIST government systems standards and financial services regulations necessitated specific compliance strategies with consideration of sector peculiarities (Phong et al., 2017). The fast-changing nature of privacy laws that have new frameworks in different jurisdictions necessitated the need to have flexible architectures that can possibly accommodate the future needs without necessarily going through a complete redesign. The regulatory authorities also found federated learning to be a best practice in privacy preservation and assessed it through privacy-enhancing technology, which may affect future regulatory guidelines and industry standards.

7.9. Limitations and Practical Deployment Considerations

Although the proposed system has proven benefits, it has several limitations that need to be addressed to facilitate their use. Heterogeneity in devices presents difficulties in ensuring homogenous quality of models across clients with different computational resources and the resources may need architecture adjustments or client filtering policies that exclude devices with limited resources (Konečný et al., 2016). The reliability of networks also affects the convergence of federated training since disconnected periods do not allow all clients to participate in a financing training round, and can cause model staleness during training rounds (Wang et al., 2020). Convergence may be sluggish or worse still, the global model may perform poorly due to statistical heterogeneity, which is caused by non-IID distribution of behavioral data among users and requires specialized aggregation methods or personalization systems. Problems with cold start apply to new users who do not have enough behavioral history to train personalized models and that hybrid techniques need to be used, with federated models and traditional authentication at the initial enrollment phases (McMahan et al., 2017).

As a counterargument to the benefits of this approach, adversarial resilience would be jeopardized since in the case of poisoning attacks where malicious clients post constructed updates, the quality of global models would decline, and Byzantine-resilient aggregation would be required on model updates or anomaly detection. Behavioral shift over time by the user because of injury, changes in devices, or simple evolution patterns in interaction necessitates ongoing adaptation procedures to sustain a high level of authentication (Mothukuri et al., 2021). Differential privacy privacy-utility trade-offs require that the parameters are chosen carefully to balance the strength of protection against the accuracy requirements and parameter choices will depend on risk tolerance of the application. Edge devices that require significant time to train local models can be a computational bottleneck on mobile devices, necessitating neural architecture design and training optimization (Zhang et al., 2021). The issues of regulatory interpretation are the fact that federated learning is a relatively new technology whose interpretation has not been regulated with sufficient clarity yet, and there is a need to actively engage the data protection regulators in the discussion of regulatory standards.

The complexity of integration with the current identity management infrastructure requires a thorough architectural design and possibly extensive customization to provide access to legacy authentication protocols (Rieke et al., 2020). Distributed architecture can complicate audit and compliance verification, which needs new solutions to indicate the effectiveness of security controls among client populations (Lu, 2025). Organizational change management considerations are user training necessities to elucidate the notions of privacy-preserving authentication and developing confidence in federated solutions. The system presupposes that enough data regarding the behavior is available to use in training, which might be problematic in case of a few interactions with a user or little input modalities (Bonawitz et al., 2017). Under extreme conditions (e.g. large number of clients - more than 50,000 concurrent participants) hierarchical architectures or other forms of aggregation can be needed. The dependency on the security of client devices to secure local behavioral models makes dependencies on endpoint protection functions, which differ between organizational settings (Li et al., 2020).

7.10. Future Research Directions and System Enhancement Opportunities

Future research possibilities involve the creation of adaptive privacy controls that will dynamically modify the level of noise depending on the progress in training and the sensitivity of data, which might positively influence privacy-utility dilemmas (Hao et al., 2019). Federated transfer learning methods may resolve cold start issues by starting with personalized model based on initialized behavioral representations, faster helping new users. Decentralized model aggregation through blockchain implementation would remove the need to have trusted servers and offer clear audit logs regarding federated training procedures (Geyer et al., 2017). Constant learning methods that allow models to adjust

to behavioral change without disastrous forgetting are significant research directions in terms of viability of long-term deployment. Behavioral biometrics based on multiple modalities (e.g. gait patterns, voice properties, or physiological sensors) have the potential to enhance the accuracy of the authentication process and anti-spoofing (Mo et al., 2021). Explainable AI algorithms that offer a decipherable authentication outcome would increase user trust and aid in compliance with regulations via transparency (Caldas et al., 2018).

Federated analytics strategies going beyond model training to incorporate privacy preserving statistical analysis of behavioral patterns might guide the creation of security policies and threat intelligence (Lim et al., 2020). The cross-device federated learning cases when users have behavioral patterns over more than one device that provide contributions to the overall authentication profiles raise fascinating research issues regarding identity linking and privacy protection. Robustness improvements that use adversarial methods such as certified defenses against model poisoning and Byzantine attack detection mechanisms would provide more security against high-risk deployments (Wang et al., 2020). More efficient edge training with hardware acceleration based on trusted execution environments or specialized AI processors can be beneficial in edge training on resource-constrained devices (Li et al., 2020). Federated learning protocols, privacy measurement, and interoperability standards development would help make it easier to adopt it and support multi-vendor ecosystems (McMahan et al., 2017). The laboratory results would be ratified by longitudinal studies on the accuracy of authentication and user acceptance over time in a production deployment, to guide the best operational practices.

Integrating quantum-resistant cryptography would provide future resistance to secure aggregation protocols to the future threat to the security of current encryption schemes due to the advent of quantum computers. Federated learning reinforcement methods may be used to improve the process of dynamic policy selection inaccessibility control, learning the best risk levels and authentication demand combinations by interacting with security operations (Yang et al., 2019). Detection of threats in a way that does not undermine the privacy of users by having privacy preserving anomaly detection systems that work on encrypted or differentially privacy behavioral patterns would be more effective. Implementation of federated learning models that are optimized with domain-specific optimizations to serve authentication demands might be more efficient and less complex to deploy (Xu et al., 2021). Federated authentication in Web3 and decentralized application ecosystems can be made possible by integration with emerging identity standards such as decentralized identifiers and verifiable credentials. Studies on federated learning with Byzantine threats and privacy threats would be more realistic and would offer protection models against combined attack scenarios (Lu, 2025).

8. Conclusion

Finally, the study has offered a detailed model of aligning Zero Trust Architecture with Federated Learning to support privacy-conserving continuous authentication using behavioral biometrics in controlled sectors. The hybrid CNN-RNN model proposed achieved authentication rates of 92.4% and ensures stringent privacy requirements with the help of differential privacy controls and aggregation-based security. Experimental validation proved communication overhead reduction of 76% in comparison with the centralized methods allowing efficient utilization in bandwidth limited conditions. The architecture of the system was designed with shielding of the GDPR, HIPAA, PCI DSS, and FedRAMP compliance based on data minimization and localization principles. The implementation of Zero Trust offered nonstop risk evaluation and dynamic access control that detected 94.7% of unregular authentication endeavours and a false positive error of less than 6.3%. Using the federated learning paradigm allowed the joint training of the models in the presence of heterogeneous groups of users without the aggregation of behavioral data in central place, which resolved the essential privacy issues.

Performance analysis proved to be more accurate, maintain privacy and could be scaled than the old centralized authentication systems and user satisfaction rated gave an 87% approval. The framework enables the implementation of the critical needs of regulated fields of healthcare, financial services, and governmental sectors with the help of thorough security controls and audit provisions. Adaptive privacy mechanisms, multi-modal behavioral biometrics, and blockchain-based decentralized aggregation are the directions of future research. The work is part of the emerging research on privacy-sensitive machine learning, and it shows that federated solutions to security-related authentication tasks have realistic feasibility. The suggested system is a big leap towards the security, privacy, and usability requirements of the modern authentication infrastructure.

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