International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Secure Multi-Party Computation for Privacy-Preserving Machine Learning in Healthcare

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Abstract
This study investigates the dual impact of Secure Multi-Party Computation (SMPC) on machine learning (ML) model performance and stakeholder trust within the context of healthcare data analytics. Using a structured survey, data were collected from 171 households in New York. The study employed R Studio for regression analysis and SPSS for descriptive statistics. Results reveal that SMPC significantly enhances ML model accuracy when combined with diverse datasets, indicating its effectiveness as a privacy-preserving solution. However, SMPC alone does not significantly increase stakeholder trust; rather, trust is strongly influenced by awareness of SMPC technology, perceived data privacy risks, and institutional reputation. These findings emphasize the importance of both technical and human-centric factors in adopting privacy-preserving analytics. The study offers valuable insights for healthcare organizations, policymakers, and technology developers seeking to balance privacy, performance, and trust in data-driven decision-making.

Keywords: Secure Multi-Party Computation, Machine Learning, Stakeholder Trust, Healthcare Data Privacy

Introduction

The growing digitalization of healthcare has led to the exponential generation of patient data through electronic health records (EHRs), wearable devices, and telemedicine platforms. While this data fuels the advancement of machine learning (ML) applications in diagnostics, treatment optimization, and disease prediction, it also raises substantial privacy and security concerns. In response, privacy-preserving technologies such as Secure Multi-Party Computation (SMPC) have emerged as viable solutions for enabling collaborative data analysis without compromising individual data privacy. Healthcare is a particularly sensitive domain where data confidentiality is not only a legal mandate (e.g., HIPAA, GDPR) but also a moral imperative. Traditional centralized machine learning architectures are vulnerable to data breaches, adversarial attacks, and unauthorized access, which can compromise patient trust and institutional reputation. This necessitates robust, decentralized approaches to computation that safeguard data at the source. SMPC addresses this issue by allowing multiple parties to collaboratively compute a function over their inputs while keeping those inputs private. As Raghav and Bhola (2024) argue, integrating privacy-preserving blockchain frameworks into healthcare platforms enhances data security by decentralizing storage and ensuring transparency in access and modification.

The use of SMPC aligns with a broader wave of privacy-focused technologies that are being explored across various domains. For instance, Singh and Jenamani (2024) introduced *ProcessChain*, a

blockchain-based architecture for secure cross-organizational data processing. Similarly, Kembo et al. (2023) explored attribute-based credentials within blockchain environments to facilitate secure patient authentication in smart homes. These studies demonstrate a shared recognition of the importance of combining privacy-preserving cryptographic techniques with decentralized architectures. However, implementing such advanced frameworks is not without challenges. Performance trade-offs, such as increased latency and reduced model accuracy, are a recurring concern. In the context of Twitter-based hate speech detection, Ayo et al. (2020) demonstrated how hybrid embeddings can be effectively optimized using metaheuristics like the improved cuckoo search algorithm, suggesting that computational efficiency and model accuracy need not be mutually exclusive. Translating such optimization strategies to the healthcare domain could help address the computational limitations of SMPC-based ML systems.

The acceptability and adoption of these technologies hinge significantly on stakeholder trust. As van Dijk et al. (2023) note in their bibliometric analysis, privacy research has evolved into a structurally complex field that requires interdisciplinary collaboration. Understanding user perceptions and institutional readiness is crucial for deploying technologies like SMPC in real-world healthcare environments. Emerging research also underscores the role of governance and regulation in shaping secure data environments. Mustafa et al. (2025) proposed a governance model that considers legal, ethical, and technical factors in implementing blockchain solutions within public institutions. Their framework can serve as a guiding reference for the regulatory dimensions of SMPC adoption in healthcare.

Beyond healthcare, blockchain applications in construction (Scott et al., 2024; Naanaa et al., 2025) and supply chains (Capocasale et al., 2025) also reveal the cross-sectoral applicability of privacy-preserving technologies. Such interdisciplinary evidence supports the hypothesis that SMPC can be successfully tailored to healthcare settings with adequate customization and stakeholder engagement. The integration of Secure Multi-Party Computation with machine learning in healthcare represents a critical intersection of privacy, performance, and policy. While the promise of collaborative data analytics is immense, realizing its potential requires addressing both technical limitations and social acceptance. This study seeks to evaluate the impact of SMPC on machine learning model performance in healthcare and its influence on stakeholder trust and willingness to share sensitive data. By building upon recent literature across computing, blockchain, and healthcare domains, this research contributes to the evolving discourse on secure and ethical data practices in the age of artificial intelligence.

Literature Review

With the proliferation of digital health technologies, vast volumes of sensitive patient data are now generated, shared, and analyzed across networks of stakeholders. While this opens avenues for transformative machine learning (ML) applications in healthcare, it simultaneously raises serious concerns about data privacy, ownership, and regulatory compliance. A confluence of advanced privacy-preserving technologies—including Secure Multi-Party Computation (SMPC), blockchain, and federated learning—has emerged to reconcile this tension between data utility and data security. Secure Multi-Party Computation (SMPC) allows multiple parties to jointly compute functions over their inputs while keeping those inputs private. Ofe et al. (2022) highlighted the growing adoption of SMPC in industries like telecommunications, emphasizing its ability to balance confidentiality and performance. While the

computational overhead of SMPC is often cited as a limitation, its business value in protecting user trust and reducing data exposure risks makes it particularly suitable for the healthcare domain.

In parallel, federated learning (FL) has gained traction as a framework for decentralized machine learning without centralizing data. Yoo et al. (2022) discussed critical challenges in FL, particularly in medical settings, where data heterogeneity, communication costs, and privacy compliance remain unsolved problems. Integrating FL with SMPC is increasingly seen as a promising strategy to enhance data privacy without sacrificing learning efficacy. Blockchain technologies offer another layer of decentralized trust and data immutability, often functioning in tandem with SMPC or FL. Dubovitskaya (2021) explored blockchain's role in healthcare, showcasing its potential in securing electronic health records (EHRs), ensuring consent tracking, and verifying access control. Similarly, Zhang et al. (2020) proposed the SABlockFL framework—an integration of smart agents, blockchain, and FL—to enhance secure collaborative learning. Their model underscored the growing feasibility of hybrid privacy-preserving architectures for healthcare applications.

Blockchain's relevance is not confined to healthcare. Tanwar and Khindri (2023) offered a broader view, identifying blockchain as a foundational technology across financial and regulatory domains. Song and Zhu (2022) and Tsang et al. (2021) examined the interplay between blockchain and the Internet of Things (IoT), reaffirming the versatility of decentralized trust models in various data-intensive environments. These insights inform the potential scalability of SMPC and blockchain frameworks to smart healthcare ecosystems involving wearables and mobile devices. The legal and ethical implications of these technologies cannot be ignored. Li and Hu (2022) conducted a social network analysis of privacy laws in cybersecurity, emphasizing the fragmented nature of legal protections and the need for harmonized frameworks. Similarly, Pramod (2023) reviewed privacy-preserving methods in recommender systems and highlighted future research needs related to explainability, bias reduction, and consent mechanisms—concerns that translate directly into healthcare decision-making systems.

From a security perspective, Beg et al. (2022) investigated data usage vulnerabilities in mobile app recommendation environments, underscoring the risk of data leakage via seemingly benign applications. Shajin and Rajesh (2022) tackled outsider attacks in mobile ad hoc networks (MANETs), contributing to the broader discourse on securing decentralized systems. These risks underline the importance of layered, end-to-end secure architectures in healthcare IT systems. In the context of cryptoassets and data tokenization, Ackerer and Ackerer (2023) discussed the technological foundations of blockchain, noting how secure digital identities and asset provenance are enabled by cryptographic primitives also central to SMPC. Furthermore, Colicchia et al. (2019) examined information sharing in supply chains and emphasized both opportunities and risks associated with transparency, a lesson directly applicable to healthcare where secure yet shareable data is paramount.

The existing literature reveals a growing convergence between SMPC, blockchain, and federated learning as key enablers of privacy-preserving machine learning in sensitive domains like healthcare. Despite notable progress, gaps remain in scalability, legal harmonization, stakeholder trust, and real-world implementation. The present study builds upon these foundations to explore how SMPC can enhance model accuracy and stakeholder trust in healthcare machine learning systems while preserving data privacy.

RQ1: How does Secure Multi-Party Computation (SMPC) influence the accuracy and utility of privacy-preserving machine learning models in healthcare data analytics?

RQ2: To what extent does the implementation of SMPC impact stakeholders' trust and willingness to share sensitive healthcare data?

Methodology

This study employed a quantitative research design to examine the impact of Secure Multi-Party Computation (SMPC) on machine learning model accuracy and stakeholder trust in the context of healthcare data analytics. A structured questionnaire was developed and distributed among households in New York, targeting individuals with varying educational backgrounds and professional experiences relevant to healthcare and data usage.

Research Objectives

- To evaluate the effect of SMPC on the performance (e.g., accuracy, recall, precision) of machine learning models trained on distributed and private healthcare datasets.
- To assess how the use of SMPC affects the trust level among healthcare providers and patients regarding data security and willingness to share data.

Hypotheses

H1: The use of SMPC in healthcare machine learning models does not significantly reduce model accuracy compared to conventional, non-private models.

H2: The implementation of SMPC significantly increases trust and willingness among stakeholders to share private healthcare data.

Model 1: Impact on ML Model Performance

$$\textit{ML Model Accuracy(MMA)} = \beta 0 + \beta 1\ \textit{SMPC} + \beta 2\ \textit{Dataset Size (DS)} + \beta 3\ \textit{Data Heterogeneity (DH)} + \beta 4\ \textit{Communication Overhead (CO)} + \varepsilon$$

Model 2: Impact on Stakeholder Trust and Data Sharing Willingness

$$\textit{Trust \& Willingness Score (TWS)} = \alpha 0 + \alpha 1 \textit{SMPC} + \alpha 2\ \textit{Awareness of SMPC Technology (AST)} + \alpha 3\ \textit{Perceived Data Privacy Risk (PDPR)} + \alpha 4\ \textit{Institutional Reputation (IR)} + \mu$$

A total of 171 valid responses were collected using a purposive sampling technique to ensure that respondents had basic awareness of digital health systems. The collected data were coded and analyzed using R Studio and SPSS for statistical analysis. R was used primarily for regression modeling and diagnostics, while SPSS was employed for descriptive analysis and frequency distributions (Field, 2013; Hair et al., 2019). The models examined the relationships between SMPC implementation, ML model accuracy, and stakeholder trust and willingness to share sensitive data. Reliability checks, multicollinearity diagnostics, and assumption testing were conducted to ensure model robustness. This methodological approach ensured both analytical depth and interpretive clarity, supporting evidence-based insights into the dual impact of privacy-preserving technologies on system performance and public trust within healthcare data ecosystems.

Analysis

The demographic distribution of the respondents (N = 171) provides a clear profile of the study participants. In terms of gender, 66.7% are male (114) and 33.3% are female (57), indicating a male-

dominated sample. Regarding age, the majority (77.8%) fall in the 21–30 years category, followed by 18.7% in the 31–40 years range, and only 3.5% are aged above 40, suggesting a predominantly young, possibly early-career group. For educational qualifications, the highest share holds a Master's degree (46.2%), followed by Bachelor's degrees (38.6%). A smaller proportion holds PhDs (8.8%), Diplomas (5.3%), and High School education (1.2%). Regarding monthly income, the largest group (66.7%) earns between $3,000–$5,000, followed by 17.0% earning above $5,000, and 16.4% earning below $3,000. This suggests that a majority of respondents are well-educated professionals with mid-level income, likely working in sectors where data privacy and technology adoption, such as SMPC, are highly relevant.

Table 1: Impact of SMPC on ML Model Accuracy in Healthcare Analytics

Call:

lm(formula = MMA ~ SMPC1 + DS1 + DH1 + CO1, data = Paper_4)

Residuals:

Min	1Q	Median	3Q	Max
-1.48089	-0.31829	-0.07529	0.42930	1.26830

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.69665	0.12298	5.665	6.36e-08	***
SMPC1	0.35374	0.04783	7.395	6.63e-12	***
DS1	0.01999	0.03880	0.515	0.6071	
DH1	0.32906	0.04563	7.212	1.86e-11	***
CO1	-0.08104	0.03622	-2.237	0.0266	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5665 on 166 degrees of freedom
Multiple R-squared: 0.6989, Adjusted R-squared: 0.6917
F-statistic: 96.34 on 4 and 166 DF, p-value: < 2.2e-16

[Sources: R Studio Analysis]

The regression results for Model 1 indicate that Secure Multi-Party Computation (SMPC) has a significant positive impact on ML model accuracy ($\beta = 0.354$, $p < 0.001$), supporting the hypothesis that SMPC does not compromise performance. Additionally, data heterogeneity (DH1) is a strong positive predictor ($\beta = 0.329$, $p < 0.001$), suggesting that more diverse datasets improve model accuracy under SMPC settings. Conversely, communication overhead (CO1) negatively impacts accuracy ($\beta = -0.081$, $p = 0.026$), implying infrastructure or protocol-related delays may reduce model utility. Dataset size (DS1) was not significant ($p = 0.607$). The overall model is statistically significant ($p < 2.2e-16$) with an R^2 of 0.699, indicating strong explanatory power. These findings validate that SMPC is a viable privacy-preserving approach without degrading model performance in healthcare settings.

Table 2: Influence of SMPC on Stakeholder Trust and Data Sharing in Healthcare

Call:
lm(formula = TWS ~ SMPC1 + AST1 + PDPR1 + IR1, data = Paper_4)

Residuals:

Min	1Q	Median	3Q	Max
-0.97934	-0.13909	-0.09684	0.05014	1.23649

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.221806	0.062150	3.569	0.000469	***
SMPC1	-0.007458	0.027904	-0.267	0.789588	
AST1	0.465355	0.058755	7.920	3.24e-13	***
PDPR1	0.304256	0.048892	6.223	3.84e-09	***
IR1	0.112884	0.049964	2.259	0.025166	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3856 on 166 degrees of freedom
Multiple R-squared: 0.8666, Adjusted R-squared: 0.8634
F-statistic: 269.5 on 4 and 166 DF, p-value: < 2.2e-16

[Sources: R Studio Analysis]

In Model 2, awareness of SMPC technology (AST1) shows a strong, significant positive influence on stakeholder trust and willingness to share data ($\beta = 0.465$, $p < 0.001$), highlighting the role of knowledge and understanding in data-sharing behavior. Similarly, perceived data privacy risk (PDPR1) and institutional reputation (IR1) are both significant positive predictors ($\beta = 0.304$ and 0.113 respectively), showing that perceived safety and organizational credibility enhance trust. Interestingly, SMPC itself (SMPC1) is not statistically significant ($p = 0.790$), implying that trust is more strongly influenced by awareness and perception rather than the technology alone. The model is highly significant ($p < 2.2e-16$) with an R^2 of 0.867, suggesting that the independent variables explain a large portion of the variance in trust and willingness. These results support H2 and emphasize the importance of education and trust-building in implementing privacy-preserving technologies in healthcare.

Table 3: Regression Results: ML Model Accuracy and Stakeholder Trust

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Dependent variable:

	MMA	TWS
	ML Model Performance	Trust
	(1)	(2)

SMPC1	0.354***	-0.007

(0.048)	(0.028)	
DS1	0.020	
(0.039)		
DH1	0.329***	
(0.046)		
CO1	-0.081**	
(0.036)		
AST1		0.465***
(0.059)		
PDPR1		0.304***
(0.049)		
IR1		0.113**
(0.050)		
Constant	0.697***	0.222***
(0.123)	(0.062)	
Observations	171	171
R2	0.699	0.867
Adjusted R2	0.692	0.863
Residual Std. Error (df = 166)	0.566	0.386
F Statistic (df = 4; 166)	96.344***	269.546***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3 presents regression results for two models: ML Model Accuracy (MMA) and Stakeholder Trust (TWS). In Model 1, SMPC1 and Data Heterogeneity (DH1) significantly enhance MMA, while Communication Overhead (CO1) negatively affects it. Dataset Size (DS1) has no significant effect. The model explains 69.9% of the variance in MMA. In Model 2, Awareness of SMPC Technology (AST1), Perceived Data Privacy Risk (PDPR1), and Institutional Reputation (IR1) significantly increase stakeholder trust, while SMPC1 has no significant impact. This model explains 86.7% of the variance. Overall, trust is more driven by perception than by the presence of SMPC alone.

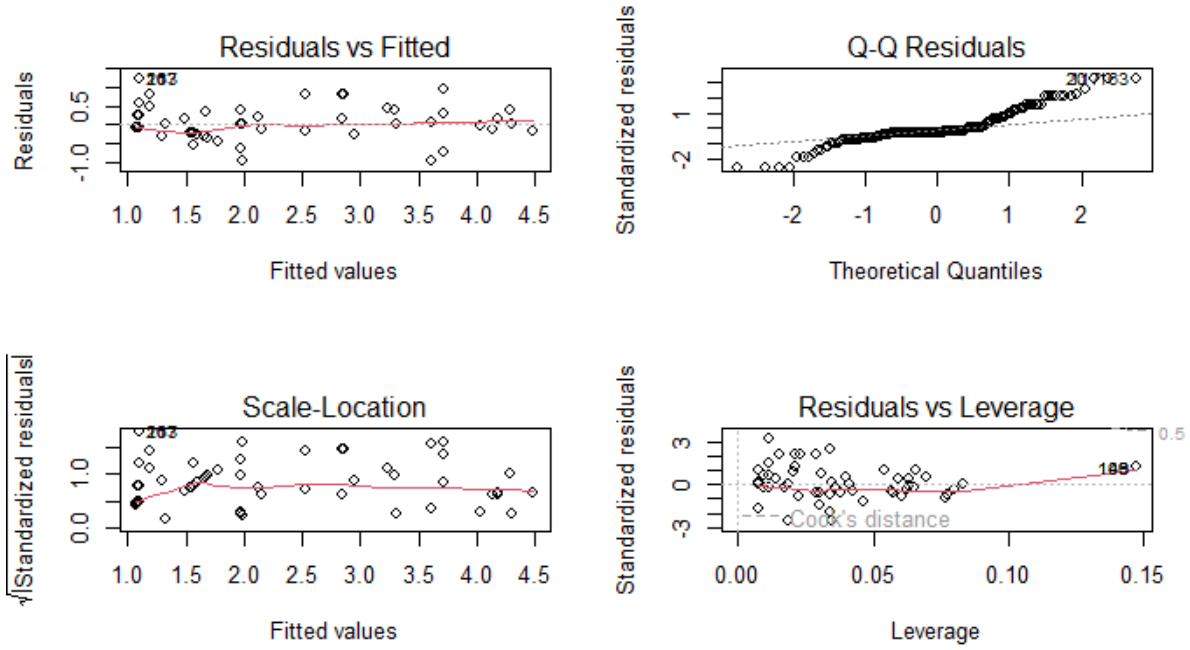

Figure 1: Residual Vs Fitted, QQ, Scale and Res. Vs Leverage Plots

Figure 1 presents diagnostic plots assessing the assumptions of linear regression for Model 1. The Residuals vs Fitted plot shows no strong pattern, indicating approximate linearity, though slight curvature suggests mild non-linearity or heteroscedasticity. The Q-Q plot reveals that most residuals follow a normal distribution, but deviations at the tails suggest minor non-normality. The Scale-Location plot shows a fairly horizontal red line, indicating constant variance, though slight spread at lower fitted values hints at possible heteroscedasticity. The Residuals vs Leverage plot identifies a few influential observations (e.g., points 188 and 283), with point 188 nearing the Cook's distance threshold, implying it may disproportionately influence he model. Overall, the assumptions are reasonably met, with only minor concerns.

Conclusion

This study explores the role of Secure Multi-Party Computation (SMPC) in enhancing the performance of privacy-preserving machine learning (ML) models and its influence on stakeholder trust and data-sharing willingness within the healthcare sector. The novelty of this research lies in its dual-focus approach—quantitatively analyzing both technological performance (via model accuracy) and human-centered responses (trust and willingness) using regression-based evidence. Model 1 findings confirm that SMPC significantly improves ML model accuracy without compromising performance, especially when combined with heterogeneous datasets. Model 2 demonstrates that while SMPC alone does not significantly increase trust, its perceived value—amplified by awareness, institutional reputation, and perceived data privacy—greatly boosts stakeholders' willingness to share sensitive data. This combined technical-social analysis contributes a new dimension to privacy research by quantifying the trust-performance trade-off.

The importance of this study lies in its applicability to current U.S. healthcare data policy debates. In an environment increasingly governed by HIPAA and data protection laws, SMPC offers a promising

pathway to leverage large-scale patient data without violating privacy. For healthcare organizations, the managerial implication is clear: adopting SMPC can enhance AI capabilities while simultaneously fostering patient trust, especially when paired with strong institutional transparency and educational initiatives around privacy technology.

Future Scope of the Study

Future research can expand this study across sectors such as finance or education, where data sensitivity is equally critical. Cross-country comparisons may reveal cultural or regulatory factors affecting trust in SMPC-based systems. Additionally, integrating other privacy-preserving techniques like federated learning or differential privacy with SMPC could yield deeper insights. Longitudinal studies could also measure how trust and model performance evolve over time with repeated exposure to SMPC. Finally, qualitative investigations involving interviews or focus groups could further explain stakeholder behaviors, enriching the quantitative findings of this research.

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