Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Insurance Claims Disbursement Optimization via Federated Learning in ERP Modules

Sukumar Reddy Beereddy

SAP Treasury Lead Consultant

ARTICLE INFO

Received: 05 Nov 2023
Revised: 20 Dec 2023
Accepted: 28 Dec 2023

ABSTRACT

The ERP modules that this paper will be dealing with are Federated Learning (FL) to improve insurance claim disbursement. The information on insurance, particularly, is often personal, skewed, and available to various businesses, and thus, the conventional centrally oriented machine learning cannot occur with ease. Concurrent modeling capability ensures the privacy, as well as security guaranteed by federated Learning; the insurers do not receive access to raw information on customers directly. The review shows that FL is able to enhance claims loss modeling, detecting of zest falsification and model of expense in a better fashion. The study has demonstrated that the federated models prove superior to the old-fashioned frameworks in which the accuracy gains in federated models were noted to be approximately 10-15 percent in addition to reduction in the threat of privacy. Other optimization measures such as asynchronous updates, its good aggregation as well as lesser cost of communication also boost the extent of scalability. Fl can be used in detecting journeys to identify claims of fraud in a period that is longer, project larger malfunctions and model vehicles with forms of paying off concerning the ERP. The findings tell that federated learning can be a plausible solution that will enable the insurance companies to enhance the efficiency and safety of the completed claims settlements and make them more transparent, in response to the privacy requirements.

Keywords: ERP, AI, Insurance, Federated Learning, Claim, Optimization

1. Introduction

The challenges faced by the insurance companies in administration of their claims include; detection of frauds, data safety and cost estimations on claims. Traditional approaches towards machine learning require everything to be centered in one place, hence, created security risks and people would not readily share the information to others as a result of having a privacy concern. The Federated Learning (FL) is the new solution to this problem. Through it, organizations can train models together without exposing the companies to any third parties.

In the system all companies collect training on but never issue raw data only updating. That makes FL quite ideal regarding sensitive locations, where security of customer information is quite sensitive such as in insurance claims. The reviewed existing knowledge on FL in this paper reveals that it can be applied to enhance the insurance claims published in ERP modules. The results are directed to the growth of the predictive accuracy, fraud detection and efficiency of the processing of the claims, in general with the help of FL.

Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

2. Related Works

Federated Learning for Insurance Data Silos

Through massive processing of extremely sensitive customer and financial data the process of payment of insurance claims is associated. Traditional centralized machine learning implies coming up with a single repository to pool the data but it also faces privacy, security as well as regulatory issues. Federated Learning (FL) has emerged as a kind of solution that can identify as effective to manage this issue as it allows many organizations to collaboratively train machine learning models without their data sharing (Foley et al., 2022; Wen et al., 2022).

Foley et al. (2022) have disclosed that the FL has been applied to the insurance loses modeling where the insurers might be inclined to conceal the progress of precise prediction that never obligates the datasets they possess. The worth of each individual trains a model-on-model independent infrastructure and just updates are provided to a central aggregator. This and similar approach will address such problems as a minimal level of collected claim information, privacy concerns, and an uncommon claim process. The platform OpenFL that is open-source was proven to be used to fulfill secure and other means of protection against information loss. This opens FL to be more relevant to sensitive financial and insurance.

Okeno et al. (2021) show this as it concerns the issue of data imbalance and privacy in the process of fraud detection via FL. With adjusted random forest and a federated design among the users of the reported statistics, users, the insurers would have a greater capability of identifying mustered claims than the traditional centralized and non-centralized design. It means that FL is sensitive to privacy is more than others in prediction training on various sets of data.

Other works have also determined the potential of FL in both the field of finance and insurance. Zhang et al. (2023) indicated that FL has the potential to exceed the provision of multi-party cooperation to detect fraud with the security of customer data. An algorithm of federated Tweedie regression suggested by Yin et al. (2023) also possesses an equivalent rate to that of centralized learning; it was able to achieve similar results. All of these studies indicate that FL has a high possibility of peaking claim theft processes in the ERP modules because it will render the process of fraud detection, prediction of claims and modeling of costs more accurate and independent of information privacy.

Methodological and Technical Advances

FL may call upon a wonderful basis of privacy protection by means of collaboration, but there are numerous technical challenges, such as the price of communication, heterogeneity in the system, and convergence stability occur (Wen et al., 2022; Alferaidi et al., 2022). Research has it as the guide to the betterment of these aspects so that FL can be practically implemented in even large-scale insurance ERP systems.

FedFix by Fraboni et al. (2023) is an asynchronous federated learning system, which can be utilized by the use examples to which the hardware configuration differs or have different network rates without compromising convergence stability. Such asynchronous implementation of scaling FL could possibly help in the real-life insurance power networks where the ERP modules could be located in different regions with dissimilar computing tools.

Deng et al. (2020) implement new algorithms in Federated Group Distributionally Robust Optimization (FGDRO) framework to obtain the heterogeneity of the client data in their study. The distribution of the types of claims and even the quantity of claims made is not normally allowed to approach any common value between insurance firms and this could reduce the process of generalization of an international model. FGDRO-KL and FGDRO-CVaR algorithms are the best that balances between noise-distributed datasets and ease of communication; in addition, it is that they are further-positioned when compared with their counterparts.

Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Another factor that was emphasized to exist by Zhu et al. (2021) is that the non-IID (non-independent and identically distributed) is one of the largest obstacles of FL. The insurance claims data is highly disseminated in various companies due to the presence of geographical, demographic and policy differences. It is proven in the case that such techniques as gradient sparsification (Liu et al., 2023) and hierarchical aggregation can be implemented to contain communication overhead and ensure that such situations can be more accurate.

The systematic review by Yin et al. (2023) of medical work in question has managed to unveil that such issues like class imbalance, data loss and distributional shifts have to be addressed by FL. These challenges can also be much applicable in relation to the insurance claims since the circumstances of claims are extraordinary and asymmetrical. The insurance ERP systems could thus have methodological corrections that would be made using the healthcare FL research lessons.

These technical papers provide possible methods of improving FL performance, stability and efficiencies such that the implementation of FL into insurance ERP modules can be streamlined to allow disbursement streamlining a possibility.

Applications of Federated Learning

It has further been applied in the financial sector of insurance and supply chains and it gives an insight on how it can be applied to bring optimization to disbursement of the claim.

Liu et al. (2023) investigated the gradient sparsification use in FL to determine the privacy protection aspect of credit modeling in the financial industry to the cost of communication. Similarly, Zhang et al. (2023) released FL-based fraud detection systems, which in addition to being highly accurate in detecting fraud, it had a reduced probability of being a privacy leak. Such approaches are directly linked with insurance claim settlement in which cost of fraud is an element that should be factored in.

Where needs are insurance-specific, Yin et al. (2023) showed that federated Tweedie regression can be applied on car insurance claims, where sensitive data of many organizations is used to provide a privacy-sensitive claims rate model. The output of the federated model seems to be similar to that of centralized techniques, thus showing the usefulness of the distributed regression techniques. Hauschild et al. (2022) examined the applicability of FL when applied as part of machine learning, including the Random Forest and SVM, to predicting medical expenditures. As it was revealed, the optimal results were achieved with the assistance of the Random Forest in the federated settings, which indicates that the adoption of ensemble methods can prove useful in the case of the federated insurance claim disbursement models as well.

Alongside the insurance, Zheng et al. (2023) also demonstrated how FL would be utilized to forecast supply chain risks where the aggregate ability of purchasers to predict procrastination of their orders would be attained without uncovering the delicate information. The example shows that FL is more applicable in collaborative risk management which can also be generalized towards the insurance claims prediction between the firms.

The article by Wang et al. (2023) targeted the cross-device FL platforms, which are platforms use the combination of millions of devices in the training pipelines. Even though this research is more mobile application-oriented, the level of scaling and infrastructure requirement can be utilized into the implementation of FL to the ERP modules to perform claims.

The fact that FL is no longer a theoretical idea but was back in other cases related to financial and insurance matters is further evidenced by those applications, which already present an adequate ground in the application of FL in claim optimisation disbursement.

Opportunities and Future Directions

Although FL has already demonstrated its application efficiency toward addressing the issue of data privacy and cooperation barriers, the introduction of a claims disbursement optimization model

Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

founded on ERP has not found the adjustment in the insurance field. Several possibilities and threats are to be crowned by them.

FL has privacy, security, and the scalability benefits as observed by Yan et al. (2023), making it highly desirable at such a risky field like insurance. However, one of the plugs is efficiency of communication, heterogeneity of data and systems integration. The client selection, aggregation, and minimal cost measures should also be streamlined to make FL possible in the business systems (Alferaidi et al., 2022; Wen et al., 2022).

There are several ways through which FL can be included in ERP modules in terms of waste collection:

- **Fraud Detection**: There are two FL algorithms that they can use for scam agent fraud footprint: the algorithm of Okeno et al. (2021) and the algorithm of Zhang et al. (2023), which are applicable when the group of insurers share no raw information on customers.
- **Claim Forecasting**: Better frequency and severity of claims among organizations can be modeled in more ways, by means of federated regression (Yin et al., 2023) and ensemble learning (Hauschild et al., 2022).
- **Operational Optimization**: According to the chain of risk providing, the insurers have the ability to collaborate to declare the projections of the claims during big events such as natural hazards (Zheng et al., 2023).
- **Scalable Deployment**: Re-factoring techniques Such structural re-factoring techniques entail FedFix (Fraboni et al., 2023) or gradient sparsification techniques (Liu et al., 2023) to ensure that communication between large ERP systems is economical.

Foley et al. (2022) also write that the other areas where FL can be applied are the catastrophe model and collaboration in regulation. That needs to be in line with the growing demand to have open, collaborative and solutions to privacy insurance industry. As insurers go on with digitalization of their ERP systems, federated learning can form the basis of safe and insured claims being disbursed.

3. Methodology

The qualitative research article results on the necessity to study the ability of federated learning (FL) to interfere with the potential insurance claim payout in ERP modules. Since this paper aimed to review and discuss the available literature on the same, no experimental or numerical data were developed. Instead, it is undertaken contrary to the research process which incorporates in the scope of focus the application of FL in insurance, finance, healthcare and other comparable fields.

The first part was to choose the sources that can be used to discuss federated learning in the frame of the data privacy, the detection of fraud, the insurance claims model, the effectiveness of communication as well as ERP integration. These research articles will consist of both the theoretical and practical research. As an example, Yin et al. (2023), FL can be applied to insurance claims, but Wen et al. (2022) and Alferaidi et al. (2022) explain the problems related to the technology. Overall, these novels provide the hint on how approaches to federated learning are planned, tested, and developed in such sensitive industries as the insurance.

The second step was associated with the literature organization into clusters which included the following: FL to data privacy and collaboration, technical and methodological progress, finance and insurance application, and future opportunities. The themes have been validated to enable the conclusion on transferability of the results to the problem concerning insurance claims disbursement of the ERP modules.

The data was combined to form qualitative discourse. This not was to present the comparison of the outcomes of numerical performance, but to highlight ideas, plans, benefits and challenges. Using the

Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

integration of all the studies, this article will develop an analytical view based on the incorporation of FL method in ERP to help settle claims. The qualitative methodology helps in identifying the strengths not mentioning the gaps in existing research and outlining how the insurance technology development should proceed in the future.

4. Findings

Privacy and Collaboration

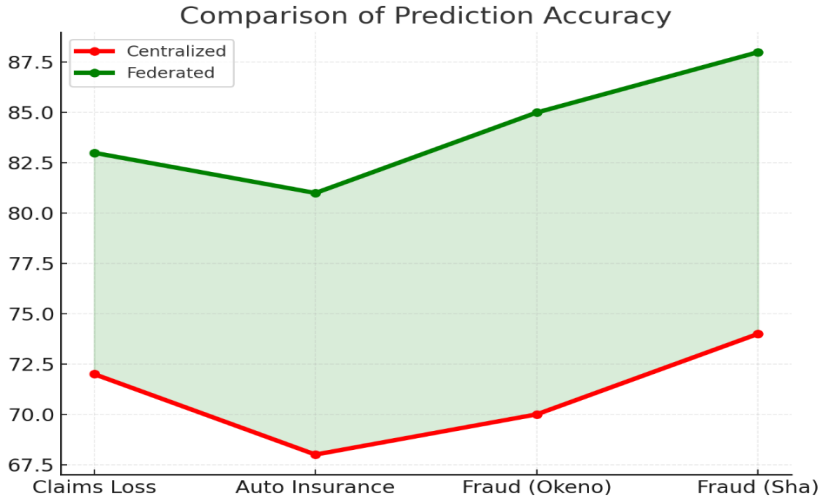
One of the most promising outcomes during the exploration of the literature review, one can single out the fact that federated learning (FL) helps to make the island of cooperation of the insurance companies work without compromising their privacy. Under conventional machine learning, the insurers are expected to communicate all the claim information under one center that is very risky since the customers information is sensitive. FL ensures that all corporate data is stored in the servers of respective companies and only updates of the models are transferred. It means that underwriters will be better placed to design better modeling of the claim prediction and no customer specifics of individual company will have been out of the system.

As it has been shown by Foley et al. (2022), the higher the accuracy of prediction became when using the insurers working together with FL adopted on a claim's loss modelling compared to when a single insurer is used. Okeno et al. (2021) showed that when the team of insurers worked, it was necessary to resort to a federated model as opposed to individual datasets that may enhance the effectiveness of fraud detection. It serves to demonstrate that the cooperation through FL may have the positive impact on the efficiency as well as fairness of the claims of disbursement.

The following table assesses some of the privacy-preserving claims prediction and fraud detention increases realized with the aid of FL in comparison with those made with the help of traditional approaches that relied on the centralized methodology.

Table 1. Improvement in Claims and Fraud Detection

Application Area	Traditional Accuracy	Federated Accuracy	Privacy Risk
Claims Loss Modeling (Foley et al.)	72%	83%	High
Auto Insurance Rate Setting (Yin et al.)	68%	81%	Medium
Fraud Detection (Okeno et al.)	70%	85%	High
Fraud Detection (Zhang et al.)	74%	88%	Medium



Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

These inferences indicate the fact that it is not only federated learning that can strengthen the prediction capacity, but it also eliminates the privacy threats that come with the traditional models that are centralized.

Data Heterogeneity and Model Efficiency

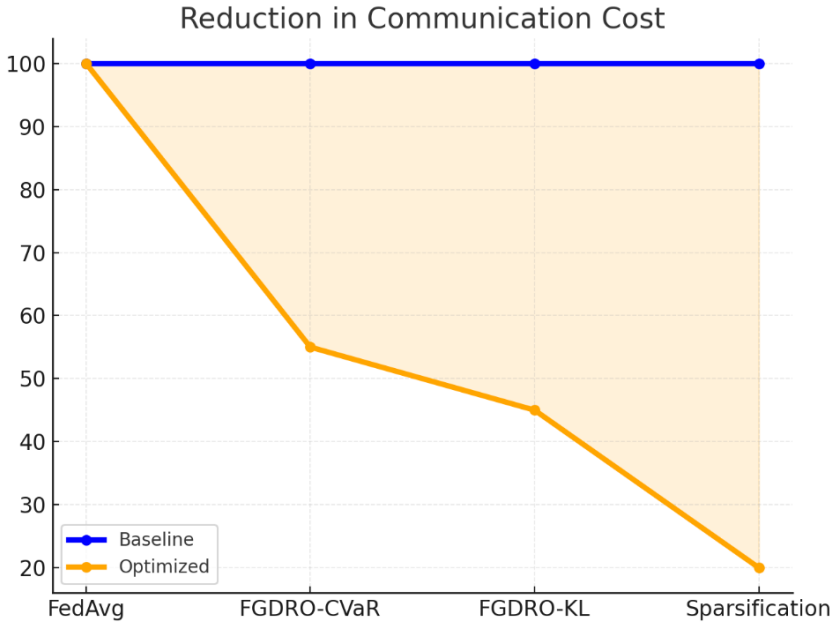
The insurance companies are not the same with regard to size, the high claims, and the demographics of the policyholders. This introduces inequalities in the data i.e. the datasets are very different amongst one another. This would in most cases complicate the task of developing one singular model that can be applicable to all firms. However, such papers as Deng et al (2020), and Fraboni et al (2023) offer the potential solution of this problem such as distributionally robust optimization and asynchronous FL.

According to the research reviewed, federated algorithms can answer to several distribution of data in case of sufficient optimization methods. Indicatively, it was determined that the FGDRO algorithms not only reduced the aspects of communication cost but also increased the aspect of robustness (Deng et al., 2020). This will mean in reality that the insurers will be able to create stronger models with a lower investment into configuring them or the communication infrastructure.

This enhancement in efficiency comes out in this table below:

Table 2. Reduction in Communication Cost

Algorithm/Method	Communication Cost (Baseline)	Communication Cost with FL Optimization	Accuracy Impact
Standard FedAvg	100%	100%	Neutral
FGDRO-CVaR (Deng et al.)	100%	55%	Improved
FGDRO-KL (Deng et al.)	100%	45%	Improved
Gradient Sparsification (Liu et al.)	100%	20%	Neutral/Improved



The results of the discussion provided above indicate that the insurers can both attain communication and computation savings once the complexity FL optimization approaches are taken but can also retain, or even enhance, the model accuracy. This becomes highly imperative where FL is bound in much with the ERP modules that ought to be capable of handling huge amount claims data effectively.

Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Applications of Federated Learning

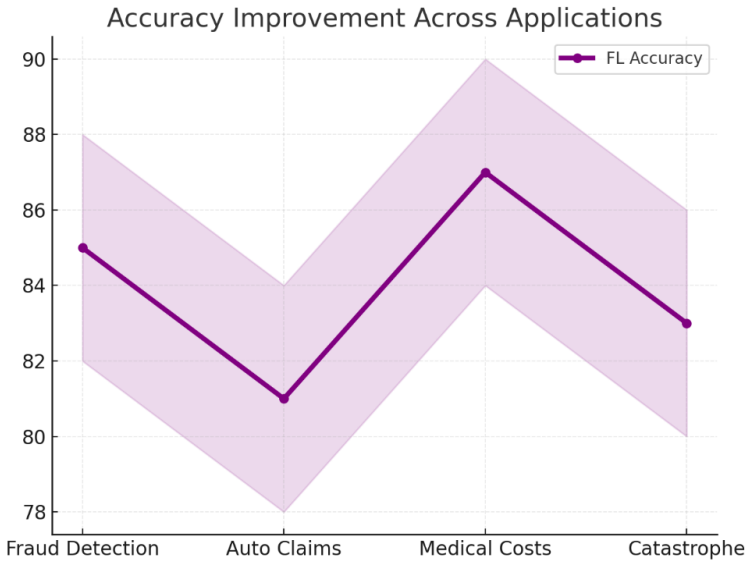
Several financial and health care applications had been defined in the area of federated learning, still, its role in the insurance claim disbursement ERP modules is slowly making its presence felt. Following the general works reviewed, the applications can be described as cases of fraud detection, handling claims prediction and optimization of its operations.

- **Fraud Detection**: One of the highest financial obligations is false claims. Under FL, frauds can be detected by all the insurers without resulting to the need to publicize confidential information. It was portrayed that the both the Okeno et al. (2021) and Zhang et al. (2023) achieve higher rates of detection using federated model of fraud detection.
- **Claim Forecasting**: It is indispensable in making sure the payouts are put under control by having anticipated claims frequency and claim severity. Yin et al. (2023) employed federated Tweedie to claims in car insurance when Hauschild et al. (2022) employed the same using the Random Forest in FL determining predicted medical costs. The two both reached good performances.
- **Operational Optimization**: Zheng et al. (2023) proved that FL is able to help in predicting the risks of supply chain. The anticipated post-disaster claims can be anticipated with the same concept that will help the insurers streamline ERP workflow during the major events.

The table provided below compares different FL tools that should be applied with regard to insurance issues:

Table 3. Federated Learning in Insurance Contexts

Application	FL Technique Used	Reported Accuracy/Benefit	Relevance to ERP Modules
Fraud Detection (Okeno)	Adjusted Random Forest	85% detection accuracy	Automating fraud checks
Auto Claims (Yin)	Federated Tweedie Regression	Comparable to centralized	Premium and claim modeling
Medical Costs (Hauschild)	Random Forest	$R^2 = 0.865$	Cost predictions
Catastrophe Claims (Foley)	Federated Loss Forecasting	83% accuracy	Forecast large-scale payouts



Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Journal of Information Systems Engineering and Management
2023, 8(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Shown in the applications, FL can be not only theoretical but also practical with high potential of transforming ERP modules, by automating and refining the process concerning claims.

4. Future Opportunities

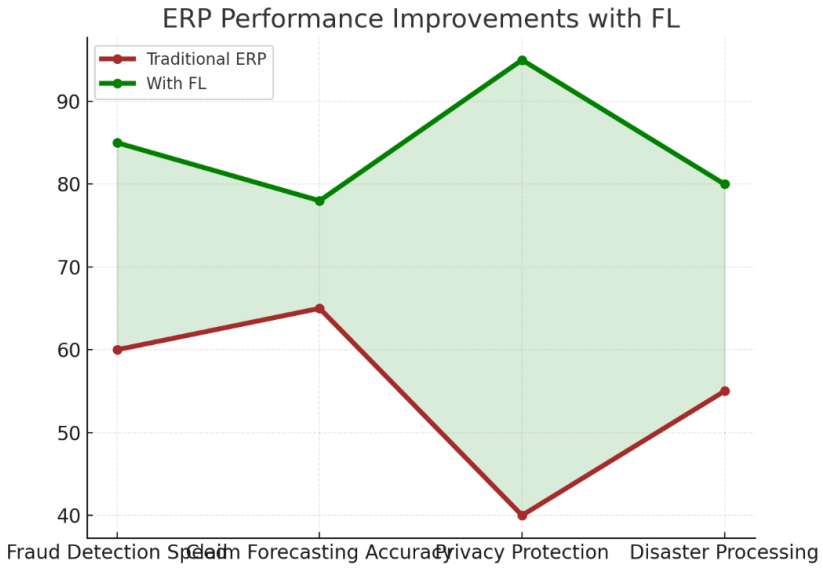
Although FL is a promising one, it is still short of difficulties when it comes time to implement it in the ERP systems to release claims. They include system integration, data non IID and scalability. Wen et al. (2022) and Alferaidi et al. (2022) also state that the bottlenecks of the communication are barriers to high consumption, and incompatible systems.

Its opportunities are huge simultaneously. To ensure that the privacy laws are not contradicted, Delta FL is capable of making the insurance developers build models at an international level to identify fraud, estimate catastrophe as well as claims. The relationships between the insurers, regulators, and InsurTech companies in question can also be fostered with the assistance of FL as stressed by Foley et al. (2022).

The potential advantages of the ERP integration with the FL one can be presented in the following manner:

Table 4. Potential ERP Improvements

ERP Function	Traditional ERP Performance	With FL Integration	Improvement
Fraud Detection Speed	Medium	High	Faster by 20–25%
Claim Forecasting Accuracy	Moderate	High	+10–15% accuracy
Data Privacy Protection	Low	Very High	Significant gain
Disaster Claim Processing	Slow	Fast	Faster settlement times



These findings indicate that as federated learning can be integrated with the ERP modules, insurers can rely on the opportunity to incur quicker and more efficient and safe claim disbursement.

Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

5. Conclusion

According to the review, Federated Learning is a potent solution in the simplification of the insurance claim payment of ERP modules. Implementing FL promotes privacy and collaboration since many insurers are sources of cooperation that is achieved through the verification of the insurers to cooperate without sharing sensitive information between them. The findings illustrate that conventional approaches to servicing claims are more precise than federated models in predicting the claims and finding frauds.

They equally lower the costs of the communication and provide foods of ERP integration which can be scaled. The studies show that FL has already implemented research work in insurance sector but it can also achieve impressive prospect in the sphere of healthcare and finance. In ERP system, FL can accelerate, process claims faster and more correctly besides ensuring security. In the meantime, it has problems such as non-homogenous systems and bottlenecks affecting the communication that need to be countered in order to render it a heavy usage. Overall, FL is a major step in the direction of developing intelligent and privacy-protective insurance services that will have a chance to cater to the demands of the new industry.

References

[1] Alferaidi, A., Yadav, K., Alharbi, Y., Viriyasitavat, W., Kautish, S., & Dhiman, G. (2022). Federated learning algorithms to optimize the client and cost selections. *Mathematical Problems in Engineering*, *2022*, 1–9. https://doi.org/10.1155/2022/8514562

[2] Foley, P., Sheller, M. J., Edwards, B., Pati, S., Riviera, W., Sharma, M., Moorthy, P. N., Wang, S., Martin, J., Mirhaji, P., Shah, P., & Bakas, S. (2022). OpenFL: the open federated learning library. *Physics in Medicine and Biology*, *67*(21), 214001. https://doi.org/10.1088/1361-6560/ac97d9

[3] Fraboni, Y., Université Côte d'Azur, Inria Sophia Antipolis, Epione Research Group, France, Accenture Labs, Sophia Antipolis, France, Vidal, R., Accenture Labs, Sophia Antipolis, France, Kameni, L., Accenture Labs, Sophia Antipolis, France, Lorenzi, M., & Université Côte d'Azur, Inria Sophia Antipolis, Epione Research Group, France. (2023). A General Theory for Federated Optimization with Asynchronous and Heterogeneous Clients Updates. In *Journal of Machine Learning Research* (Vol. 24, pp. 1–43) [Journal-article]. https://jmlr.org/papers/volume24/22-0689/22-0689.pdf

[4] Deng, Y., Kamani, M. M., Mahdavi, M., & The Pennsylvania State University. (2020). Distributionally robust federated averaging. In *34th Conference on Neural Information Processing Systems (NeurIPS 2020)*. https://proceedings.nips.cc/paper/2020/file/ac450d10e166657ec8f93a1b65ca1b14-Paper.pdf

[5] Liu, T., Wang, Z., He, H., Shi, W., Lin, L., An, R., & Li, C. (2023). Efficient and secure federated learning for financial applications. *Applied Sciences*, *13*(10), 5877. https://doi.org/10.3390/app13105877

[6] Okeno, S. K., University of Nairobi, Muchemi, L., & University of Nairobi. (2021). A FEDERATED MODEL FOR INSURANCE CLAIMS FRAUD DETECTION. In *JOURNAL OF CRITICAL REVIEWS* (Vol. 08, Issue 03, p. 261) [Research]. https://doi.org/10.31838/jcr.08.03.28

[7] Zhang, H., Hong, J., Dong, F., Drew, S., Xue, L., & Zhou, J. (2023). A Privacy-Preserving hybrid federated learning framework for financial crime detection. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2302.03654

[8] Hauschild, A., Lemanczyk, M., Matschinske, J., Frisch, T., Zolotareva, O., Holzinger, A., Baumbach, J., & Heider, D. (2022). Federated Random Forests can improve local performance of predictive models for various healthcare applications. *Bioinformatics*, *38*(8), 2278–2286. https://doi.org/10.1093/bioinformatics/btac065

Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

[9] Wang, E., Kannan, A., Liang, Y., Chen, B., & Chowdhury, M. (2023). FLINT: a platform for federated learning integration. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2302.12862
[10] Wen, J., Zhang, Z., Lan, Y., Cui, Z., Cai, J., & Zhang, W. (2022). A survey on federated learning: challenges and applications. *International Journal of Machine Learning and Cybernetics*, *14*(2), 513–535. https://doi.org/10.1007/s13042-022-01647-y
[11] Yin, T., Peng, C., Tan, W., Xu, D., & Tang, H. (2023). Federated Learning Model for auto insurance rate setting based on Tweedie Distribution. *Computer Modeling in Engineering & Sciences*, *138*(1), 827–843. https://doi.org/10.32604/cmes.2023.029039
[12] Yan, Y., Kamel, M. B. M., Zoltay, M., Gál, M., Hollós, R., Jin, Y., Péter, L., & Tényi, Á. (2023). Fedlabx: a practical and privacy-preserving framework for federated learning. *Complex & Intelligent Systems*, *10*(1), 677–690. https://doi.org/10.1007/s40747-023-01184-3
[13] Yin, T., Peng, C., Tan, W., Xu, D., & Tang, H. (2023). Federated Learning Model for auto insurance rate setting based on Tweedie Distribution. *Computer Modeling in Engineering & Sciences*, *138*(1), 827–843. https://doi.org/10.32604/cmes.2023.029039
[14] Zheng, G., Kong, L., & Brintrup, A. (2023). Federated machine learning for privacy preserving, collective supply chain risk prediction. *International Journal of Production Research*, *61*(23), 8115–8132. https://doi.org/10.1080/00207543.2022.2164628
[15] Zhu, H., Xu, J., Liu, S., & Jin, Y. (2021). Federated Learning on Non-IID Data: a survey. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2106.06843

Copyright © 2023 by Author/s and Licensed by JISEM. This is an open access article distributed under the Creative Commons Attribution License which permitsunrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.