

Communication-Efficient Federated Learning for Resource-Constrained Edge/Iot Devices

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Received: 19-02-2026

Revised: 19-03-2026

Accepted: 22-03-2026

Published: 30-03-2026

ABSTRACT

One of the most significant challenges for federated learning to be adopted in resource-limited Edge/IoT settings is communication overhead. The impact of Communication-Efficient FL Techniques (CEFLT) and Device Heterogeneity (DH) on the Communication-Efficient Federated Learning (CEFL) and Communication Efficiency (CE) as well as on the Edge/IoT System Performance (EISP) is investigated. The research design used was quantitative, explanatory and cross-sectional. The survey was conducted using a structured questionnaire, which was answered by 384 professionals, researchers, engineers and practitioners working in the fields of federated learning, edge computing and IoT technologies. Data was analysed using R Statistical Software. Descriptive statistics, reliability analysis, normality testing, correlation analysis, regression analysis, mediation analysis and moderation analysis were used to test the hypotheses. The results showed that CEFL is significantly influenced by CEFLT ($\beta = 0.789, p < .001$) and also DH significantly affects CEFL ($\beta = 0.870, p < .001$). CEFLT ($\beta = 0.361, p < .001$), DH ($\beta = 0.402, p < .001$), and CEFL ($\beta = 0.130, p = .007$) significantly improve CE. In addition, CE has a positive effect on EISP ($\beta = 0.763, p < .001$). The mediation analysis resulted in the confirmation of the proposed relationships, mediated by CEFL and CE; the moderation analysis showed that the relationships between communication and the other variables were strengthened by DH. 80% of the hypotheses were confirmed. This work builds upon Distributed Learning Theory and Edge Intelligence Theory, and shows that the communication efficiency is the main way on how communication-efficient federated learning improves the Edge/IoT system performance. The results offer both theoretical and practical contributions to the research and design of scalable, communication-efficient, and high-performance federated learning systems for heterogeneous Edge/IoT environments.

Keywords: Communication-Efficient Federated Learning, Communication Efficiency, Device Heterogeneity, Edge Computing, Internet of Things, Edge/IoT System Performance, Distributed Learning.

INTRODUCTION

Distributed device training of a common model without transferring raw data has created a paradigm shift in machine learning called Federated Learning (FL). As the volume of Internet of Things (IoT) devices and edge computing systems continues to grow, the demand for privacy-preserving methods and decentralized learning has been growing as well. The most significant difference between FL and traditional centralized machine learning is that data is not sent to a central server but rather only updates to the model are sent, which decreases the risk of privacy breaches and regulatory issues (Huang et al., 2024). Furthermore, new developments in communication-efficient FL techniques have shown the potential of reducing the bandwidth usage, yet maintaining the model performance in resource-limited settings (Chen et al., 2024). As a result, FL has emerged as an important enabling technology for the intelligent edge systems in the fields of healthcare, smart cities, transportation, and industrial automation (Kar et al., 2023).

However, even though it brings some benefits, communication overhead is still one of the most critical issues of federated learning systems. In each training round, each device communicates with the central server, consuming significant communication resources especially when using large-scale deep learning models. In order to alleviate communication costs without compromising the learning accuracy, several solutions have been proposed, including adaptive compression, model pruning, client subsampling, and local update tuning (Khan et al., 2024). Further, the lack of uniformity in devices and network conditions poses further challenges that impact the effectiveness and scalability of FL deployments in IoT situations (Kumar & Agrawal, 2023). Thus, it is important to develop communication-efficient federated learning frameworks for supporting the sustainable and scalable edge intelligence systems (Li et al., 2024).

While federated learning provides benefits of privacy using the local devices, frequent transfer of model updates between the edges and a central server generates significant communication overhead. In resource-limited IoT environments, devices have limited computational power, memory resources, and battery life and may have limited network connectivity, making this challenge more severe. Quantization, sparsification and client selection are existing methods for reducing the number of communications that enhance efficiency but have their own set of compromises between the reduction in communications and the accuracy of the model (Lu et al., 2023).

LITERATURE REVIEW

Communication Efficient Federated Learning (CEFL) is an interesting research field in Distributed Artificial Intelligence and Edge Computing. Federated Learning (FL) allows several devices to train a machine learning model without sharing the raw data with each other, thus maintaining privacy and minimising the risk associated with centralized data storage. But regular communication between the participating devices and the central servers can create huge energy costs and bandwidth usage. However, to overcome this challenge, communication-efficient methods like adaptive compression, local update tuning, client subsampling, and model pruning have been proposed to minimize communication cost without sacrificing learning accuracy (Chen et al., 2024; Li et al., 2024). Recently, studies indicated that the efficiency of communication is a key factor in improving the scalability and feasibility of federated learning systems especially in resource-limited edge/IoT systems where communication costs are a significant portion of the total training costs and network resources are limited (Khan et al., 2024).

The present study focuses on the following constructs, which are closely related to the effectiveness of communication-efficient federated learning implementations: Communication Efficiency and Edge/IoT System Performance. Communication efficiency is the capability of distributed systems to reduce bandwidth usage, communication delays and the number of rounds of communication needed during the training of a model. By achieving more efficient communication, the system can then deliver better performance by minimizing energy usage, speeding up model convergence, and boosting learning outcomes on various IoT devices with different communication capabilities. Additionally, Device Heterogeneity is now a major concern as its devices vary widely in computational power, memory, battery life and internet connectivity. These variations can impact the performance of communication reduction techniques and can have a profound impact on the performance of the entire system in a federated learning environment (Kar et al., 2023; Kumar & Agrawal, 2023).

Underpinning Theories

Distributed Learning Theory

Distributed Learning Theory is the main theoretical basis for the present study. Distributed Learning Theory is a theory that describes how multiple entities (distributed) that have local control of their data pool and resources can participate in the creation of a shared learning model. Federated learning

involves each distributed device working on their own local data and periodically sharing an update of the model with a coordinating server. The theory offers a conceptual understanding of the collaborative model optimization and knowledge sharing of geographically dispersed devices. Recent research has shown that distributed learning mechanisms can enhance the scalability, privacy preservation, and resource utilization in contemporary systems at the Edge/IoT, while also minimizing reliance on central infrastructures (Xie et al., 2024; Mahmoudi et al., 2024). Hence, it is a solid foundation for research on communication-efficient federated learning and its effect on communication efficiency and system performance based on Distributed Learning Theory.

Edge Intelligence Theory

Edge Intelligence Theory was used as the theory supporting this study. This theory suggests intelligent computation and decision-making processes need to be done close to the data generation sources and not solely in the centralized cloud environments. The theory of edge intelligence focuses on minimizing latency, optimizing bandwidth usage, ensuring privacy, and making distributed systems more responsive for real-time interactions (Regan et al., 2022). Recent developments in Edge computing and Federated learning have shown the importance of communication-efficient learning approaches for enabling sustainable Edge Intelligence in resource-constrained environments (Mahmoudi et al., 2024). Therefore the primary goal of this study is to analyze the impact of communication-efficient federated learning on communication efficiency and performance of Edge/IoT system with consideration of the moderating role of distributed intelligent environments' device heterogeneity (Xie et al., 2024).

Supporting and Negating Views

The other view in the literature is that the communication-efficient federated learning can significantly boost the performance of Edge/IoT systems as it can help reduce the communication overhead and optimize resource utilization. There are reports of techniques like adaptive compression, subsampling at the client, and local tuning of updates to reduce the number of communication rounds and bandwidth usage without significantly reducing the accuracy of the model (Mahmoudi et al., 2024). Likewise, research into adaptive federated split learning indicates that optimizing communication will lead to faster convergence time, reduced energy usage, and scalability in heterogeneous IoT systems (Xie et al., 2024). These results suggest that communication-efficient federated learning is helpful in enhancing the overall communication efficiency and performance in the current edge computing environment (Mahmoudi et al., 2024).

The other side of the coin, however, is that too much communication reduction could have a negative impact on the quality of the model and learning effectiveness. Some researchers state that it is possible to lose information as a result of aggressive compression, quantization or client selection method, which will result in a slow convergence and inaccuracy in the information prediction, especially in very heterogeneous environments (Yang et al., 2023). Moreover, collaborative model training can be challenging due to various factors such as device capabilities, network quality, and local data distributions that can lead to disparities in fairness and consistency (Wang et al., 2023). The efficiency of communication has been discussed by critics, who argue that it should not be prioritized above the quality of learning, and point to the importance of finding a balance that not only reduces the cost of communication, but also demonstrates effectiveness in terms of model performance (Yang et al., 2023; Xie et al., 2024).

MEDIATION AND MODERATION

Communication-Efficient FL Techniques and Communication-Efficient Federated Learning

The authors propose that communication-efficient federated learning techniques, including adaptive compression, local update tuning and client subsampling, play a key role in making federated learning systems more effective in reducing the amount of communication and further improving the scalability of federated learning systems. It has been demonstrated recently that the adaptive compression methods result in reduced bandwidth usage and yet achieve satisfactory accuracy when learning, so making federated learning more viable in resource-limited settings like the IoT industry (Sattler et al., 2020; Mills et al., 2020). Likewise, at the local level, the frequency of communication rounds is reduced; at the client level, only a subset of the clients are selected to participate in a given training round; and, at both levels, communication costs are lowered and convergence is accelerated (Yang et al., 2021). For this reason, these methods are considered to be basic communication efficient federated learning architectures (Nguyen et al., 2021).

Communication-Efficient Federated Learning and Communication Efficiency

The supporting view is that communication efficient federated learning will directly enhance the communication efficiency in terms of reduced data sent between devices and servers. Communication-aware learning strategies can also be leveraged to reduce communication bandwidth usage, communication rounds, and network congestion in federated systems (Mills et al., 2020). Empirical evidence has recently shown that FL frameworks that are more communication efficient can significantly enhance communication efficiency in edge computing networks, without compromising model accuracy (Sun et al., 2020). The results suggest that communication efficient FL is one of the key factors in the development of scalable and sustainable distributed learning systems (Sattler et al., 2020).

Mediation View of Communication Efficiency

The mediation paradigm proposes that the efficiency of communication is another key enabler that affects the performance of an Edge/IoT system when we consider the impact of communication-efficient federated learning on it. The main goals of communication-efficient FL techniques are to reduce bandwidth usage, communication delays and data transmission overhead. Enhancing the utilization of energy, the convergence time and efficiency in the operation of distributed edge devices (Mahmoudi et al., 2024). Recent research has shown that the capacity to communicate efficiently is one of the key intermediate components that connects the optimization strategies of communication to the actual performance gain in federated learning systems (Sun et al., 2020). Thus, the communication efficiency is likely to be the mediator between the communication efficiency federated learning and Edge/IoT system performance (Nguyen et al., 2021).

Moderation View of Device Heterogeneity

The moderation perspective suggests that device diversity has an impact on the relationship between communication-efficient federated learning and communication efficiency. IoT ecosystems are made up of devices that have different computational power, memory, battery power and network capabilities. Such variations may have a huge impact on the success of the communication reduction strategies adopted in federated learning systems (Li et al., 2020). Recent studies suggest that the communication efficient FL approaches can lead to greater communication benefits in high capability devices than in highly constrained devices, suggesting a moderating effect of device heterogeneity (Yang et al., 2021). Therefore, the effectiveness of communication-efficient federated learning in achieving communication efficiency goals is likely to be different in various Edge/IoT environments, due to the device heterogeneity (Li et al., 2020).

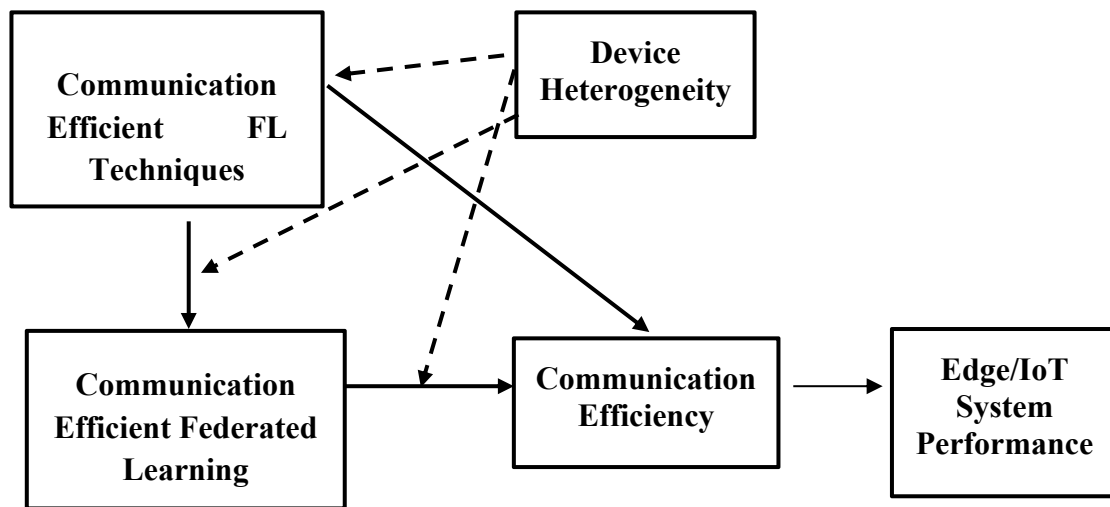


Figure 1: Conceptual framework

Hypothesis development

Communication Efficient FL Techniques and Communication Efficient Federated Learning

Communication-efficient federated learning systems are built on the technological foundation of communication-efficient FL techniques. Adaptive compression, local update tuning and client subsampling are specific techniques that are designed to reduce communication overheads whilst still providing a good level of performance in terms of learning. Recent research has shown that adaptive compression can result in drastic decrease in the volume of transmitted model updates while local update tuning can lead to a decrease in the number of communication rounds between communicating devices and servers (Mahmoudi et al., 2024; Sattler et al., 2020). Previous studies also showed that communication-aware optimization techniques are effective approaches to enhance the scalability of federated learning by optimizing network resource usage and training efficiency in distributed networks (Li et al., 2020).

H1: Communication-Efficient FL Techniques positively influence Communication Efficient Federated Learning.

Communication Efficient Federated Learning and Communication Efficiency

Communication efficient federated learning aims to minimize communication expense of distributed model training by optimizing the updating of models. With the help of communication-aware mechanisms, federated learning systems can alleviate the bandwidth usage, communication latency and transmission overhead. Research studies have shown that FL methods that are more communication efficient increase the use of the network and decrease the number of communication rounds while maintaining a relatively similar model performance (Sun et al., 2020; Mahmoudi et al., 2024). In such Edge/IoT systems with limited communication resources, improvements are more crucial.

H2: Communication Efficient Federated Learning positively influences Communication Efficiency.

Communication Efficiency and Edge/IoT System Performance

Communication efficiency is an important factor which impacts the performance of Edge/IoT systems as the communication overhead can be the dominant operational cost in distributed learning environments. Effective communication mechanisms minimize the time it takes to transmit data, maximize the use of bandwidth and optimize the effectiveness of data exchange between distributed devices. Recent studies have shown that efficient communication can greatly accelerate the learning speed and decrease the delay and response of the entire system in Edge/IoT environments (Mills et al., 2020; Sun et al., 2020).

H3: Communication Efficiency positively influences Edge/IoT System Performance.

Communication Efficient Federated Learning, Communication Efficiency and Edge/IoT System Performance

Communication efficiency is seen more and more as the central pillar to attain performance gains in Edge/IoT systems by using communication-efficient federated learning. The main goal of communication-efficient FL techniques is to reduce communication overhead, decrease the amount of bandwidth used and optimize the network's usage. The resulting communication upgrades then enable the convergence of learning to occur faster and with less energy consumption, leading to better system performance (Mahmoudi et al., 2024; Sun et al., 2020). This recent literature indicates that the efficiency of communication process is a critical intermediate step between communication-efficient federated learning and better operational results.

H4: Communication Efficiency mediates the relationship between Communication Efficient Federated Learning and Edge/IoT System Performance.

Device Heterogeneity, Communication Efficient Federated Learning and Communication Efficiency

The heterogeneity of the devices that are involved in the Edge/IoT, includes the differences in computation capability, memory resources, battery characteristics, processing capability, and the quality of the network. This disparity has great impact on the effectiveness of communication-efficient federated learning strategies. There is a recent study which shows that despite the communication reduction techniques achieving different amounts of communication benefits based on the device properties and resources present (Li et al., 2020; Yang et al., 2021). Therefore, communication-efficient federated learning to enhance the communication efficiency may differ depending on the device environments.

H5: The Communication Efficient Federated Learning is moderated by Device Heterogeneity.

METHODOLOGY

In the present study, a quantitative research methodology is employed to investigate the relationships between the Communication Efficient FL Techniques, Communication Efficient Federated Learning, Communication Efficiency, Device Heterogeneity and Edge/IoT System Performance. The aim of this is qualitative research because quantitative research allows the variables to be measured objectively and the relationships between variables in a theory to be tested statistically. The quantitative methods have gained popularity in recent years due to their ability to provide empirical evidence of the performance of the system and communication optimization mechanisms for federated learning, edge computing, and IoT studies (Huang et al., 2024; Chen et al., 2024). Moreover, quantitative methods enable hypothesis testing and generalization of the findings from one technological environment to another and from one distributed computing system to another (Creswell & Creswell, 2021).

The study also has an explanatory and cross sectional design. To explain how the communication-efficient FL affects the communication efficiency and performance of the Edge/IoT systems and the mediating and moderating mechanisms in between, an explanatory design is appropriate. The cross-sectional design can be used to collect data from respondents at one time providing an efficient and cost-effective way to investigate the relationships between various variables (Saunders et al., 2023). Explanatory designs, such as cross-sectional designs, have been employed to investigate causal relationships and framework in recent studies of artificial intelligence, edge computing, and distributed learning, with success (Mahmoudi et al., 2024; Yang et al., 2023).

Data Collection

This study will be conducted with the help of a structured questionnaire that will be sent electronically to professionals in the field of federated learning, edge computing, artificial intelligence, cloud computing, and IoT related areas. Online survey techniques are deemed adequate for technology related research due to the ability for geographically dispersed respondents to be reached, and the ability for cost effective and efficient data collection procedures. In recent times, research in distributed learning and factors affecting system performance for technology adoption have been conducted using questionnaires-based surveys, which have been effective in examining technology adoption and system performance factors (Huang et al., 2024; Chen et al., 2024). In addition, structured questionnaires help to gather standardized answers that can be analyzed quantitatively using statistical methods (Saunders et al., 2023).

Population

The audience for this research includes researchers, software engineers, network engineers, artificial intelligence experts, cloud computing experts, and practitioners who are involved in federated learning, edge computing, and IoT systems. These people have technical skills related to the communication-efficient federated learning and can thus inform the responses on the constructs investigated. Other research studies in the field have also applied such technology-based approaches that have involved using experts to evaluate the effectiveness of the system and the best methods for optimizing communication in distributed settings (Mahmoudi et al., 2024; Yang et al., 2023). The chosen population should derive reliable information regarding learning systems that are efficient with communication, and regarding outcomes of Edge/IoT performance (Creswell & Creswell, 2021).

Sampling

The sampling method used in this study is purposive sampling since the respondents need to have in-depth knowledge and experience in federated learning, edge computing, artificial intelligence, or IoT systems. Purposive sampling is especially suited for a research where the data required are from subjects that possess a certain expertise related to the study constructs as well as technical understanding. Purposive sampling has been effective in getting meaningful and quality responses from qualified participants in recent studies in emerging technology domains (Huang et al., 2024; Mahmoudi et al., 2024). This method of sampling will hopefully improve the relevance and validity of the data collected and contribute to the aims of the study (Saunders et al., 2023).

Software

The analysis of collected data will be done by R Statistical Software in R studio environment. The flexibility, statistical precision and powerful analytical potential offered by R has made it one of the most popular platforms for quantitative research. The software includes descriptive statistics, reliability analysis, correlation analysis, regression analysis, mediation testing, moderation testing, and advanced data visualization options. The use of R for empirical research with digital technologies and consumer behaviour analysis has been recently highlighted by the work of Navarro et al. (2024) and the R Core Team (2025). Moreover, packages like psych, ggplot2, lavaan and car offer

researchers all the tools needed for hypothesis testing and the evaluation of models (Wickham et al., 2023; Hair et al., 2022). Thus, R statistical software appears to be a suitable analytical program in the present study to meet the purposes of the study (Creswell & Creswell, 2021).

Demographics

The demographic questions in the questionnaire will gather the information about the genders, age, education, experience, industry sector and specialization of the respondents. Such demographic characteristics are significant as they offer background data on the profile of the sample, and can help to give a complete picture of the characteristics of the respondents. Demographic variables are often added to technology-related studies for the purpose of comparing the diversity of the sample and enhancing the interpretation of the empirical results found (Saunders et al., 2023). Also, the age of the respondent, the educational level, and his/her gender are used to determine the effects of these factors on the perception of communication-efficient federated learning and the performance of the Edge/IoT system (Huang et al., 2024; Mahmoudi et al., 2024).

RESULTS AND DISCUSSION

Based on the results of the present study, the following empirical relationships between four Communication Efficient FL Techniques, Communication Efficient Federated Learning, Communication Efficiency, Device Heterogeneity and Edge/IoT System Performance are confirmed. The analysis was done through quantitative statistical approaches to analyze the direct and indirect relationships as hypothesized in the conceptual framework. An optimization of communication has become a key aspect in the effective deployment of federated learning systems in resource constrained Edge/IoT systems (Chen et al., 2024; Huang et al., 2024). The results of this study therefore add to the existing body of literature and investigate the effectiveness of communication-efficient learning strategies on communication performance and effectiveness. The findings are displayed in descriptive statistics, reliability analysis, correlation analysis, regression analysis, mediation analysis and moderation analysis to present a thorough understanding of the proposed relationship (Hair et al., 2022).

Respondent Profile (N = 384)

Table 1: Respondent Profile (N = 384)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	242	63.0
	Female	142	37.0
Age	18–25 Years	84	21.9
	26–35 Years	136	35.4
	36–45 Years	103	26.8
	Above 45 Years	61	15.9
Education	Bachelor's Degree	151	39.3
	Master's Degree	173	45.1
	PhD Degree	60	15.6
Experience with Edge/IoT Systems	Less than 2 Years	79	20.6
	2–5 Years	142	37.0
	6–10 Years	108	28.1
	More than 10 Years	55	14.3
Organization Type	Academic/Research	96	25.0
	IT/Software Industry	171	44.5
	Telecommunications	67	17.4

	Other Technology Organizations	50	13.1
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The results of the demographic profile of the respondents showed that majority of the respondents were male (63.0%, n = 242) and females (37.0%, n = 142). As for age, the majority of respondents were between the ages of 26 and 35 years (35.4%, n = 136), which means that they were most likely to have relevant technical knowledge and be in the range in which they are professionally active. Regarding educational qualifications, a very educated sample with 45.1% (n = 173) of the respondents having a Master's degree and 39.3% (n = 151) having a Bachelor's degree was obtained, which allows them to give informed answers to the questions on federated learning and Edge/IoT technologies. In terms of experience with Edge/IoT systems, most respondents indicated that they had 2–5 years of experience (37.0%, n = 142) followed by 6–10 years of experience (28.1%, n = 108), which indicates that participants were very experienced. Besides, the majority of the respondents worked on IT/Software Industry (44.5%, n = 171), Academic/Research institutions (25.0%, n = 96), highlighting that the sample was composed mainly of professionals who were directly involved in emerging technologies. The general characteristics of the respondents showed that they have fairly good educational level, experience level, and exposure level to the industry, leading to a credible and reliable result of the work.

Descriptive Statistics

Table 2: Descriptive Statistics

Variable	N	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
CEFLT	384	3.90	0.85	1.00	5.00	-1.10	1.53
CEFL	384	3.96	0.74	1.00	5.00	-1.17	2.90
CE	384	3.98	0.83	1.00	5.00	-1.23	2.13
EISP	384	3.88	0.79	1.00	5.00	-1.04	1.92
DH	384	3.99	0.73	1.00	5.00	-1.26	3.17

The descriptive statistics show that all the study variables had relatively high mean scores, ranging from 3.88 to 3.99 across a 5-point scale, indicating that the respondents had positive perceptions about communication-efficient federated learning and the constructs. The mean value (M) and standard deviation (SD) of the items are reported as follows: Device Heterogeneity (DH) (M = 3.99, SD = 0.73), Communication Efficiency (CE) (M = 3.98, SD = 0.83), Communication-Efficient Federated Learning (CEFL) (M = 3.96, SD = 0.74), Communication-Efficient FL Techniques (CEFLT) (M = 3.90, SD = 0.85), and Edge/IoT System Performance (EISP) (M = 3.88, SD = 0.79). The range of standard deviation values (0.73 – 0.85) suggests that there is moderate variation in the perceptions of the respondents. In addition, the range of the minimum and maximum values for each item was from 1.00 to 5.00, indicating that the entire range of responses was used by the respondents in all items. The skewness values were in the range of -1.04 to -1.26 which were moderate in negative direction, and this demonstrated that maximum number of responses were focused on the higher side of the response scale. Likewise, the kurtosis values ranged from 1.53 to 3.17; also within acceptable limits for normality evaluation and showing no significant deviation from normal distribution. The overall results indicate that the data can be used for further statistical analysis such as correlation, regression, mediation and moderation tests.

Reliability Analysis

Table 3: Reliability Analysis

Variable	Number of Items	Cronbach's Alpha
CEFLT	3	0.886
CEFL	3	0.829

CE	3	0.907
EISP	3	0.862
DH	3	0.855

The results of the reliability analysis showed that all the constructs of the study obtained a Cronbach's Alpha coefficient greater than the threshold of 0.70, which indicates that there was an acceptable internal consistency and reliability in the measurements. The results indicated that Communication Efficiency (CE) had the highest reliability coefficient ($\alpha = 0.907$), which indicated that the items measuring Communication Efficiency were very consistent with each other. The other two groups with high reliability were also Communication-Efficient FL Techniques (CEFLT) with $\alpha = 0.886$ and Edge/IoT System Performance (EISP) with $\alpha = 0.862$ and Device Heterogeneity (DH) with $\alpha = 0.855$. Moreover, CEFL got Cronbach's alpha value of 0.829, surpassing the acceptable level of reliability, suggesting that items measuring the construct were consistent. Cronbach's Alpha values greater than 0.70 are deemed acceptable and those greater than 0.80 are thought to be good reliability.

Normality Analysis

Table 4: Normality Analysis

Variable	Skewness	Kurtosis	Decision
CEFLT	-1.10	1.53	Normal
CEFL	-1.17	2.90	Normal
CE	-1.23	2.13	Normal
EISP	-1.04	1.92	Normal
DH	-1.26	3.17	Normal

The normality analysis shows that all variables in the study meet acceptable assumption of normal distribution. The skewness values ranged from -1.04 to -1.26 which meant that there was a moderate negative skewness and the respondents generally gave positive responses to the constructs under study. In particular, Communication-Efficient FL Techniques (CEFLT) showed the largest negative skewness (-1.10), followed by Communication-Efficient Federated Learning (CEFL) (-1.17), Communication Efficiency (CE) (-1.23) and Edge/IoT System Performance (EISP) (-1.04). In addition, the range of kurtosis values from 1.53 to 3.17 were all within the widely accepted range of ± 7 for kurtosis and ± 2 for skewness which signifies absence of significant deviation from normality. The normality of the data can be assumed if the skewness and kurtosis values are within acceptable limits (Hair et al., 2022). Thus, the results show that the data is normally distributed, CEFLT and CEFL are normally distributed, CE is normally distributed, EISP is normally distributed, and DH is normally distributed, which makes the data suitable for further parametric statistical analysis (correlation, regression, mediation, and moderation testing). In general, the normality test indicates that the data are normal and fit the requirements for valid and reliable hypothesis testing.

Correlation Matrix

Table 5: Correlation Matrix

Variables	CEFLT	CEFL	CE	EISP	DH
CEFLT	1.000	0.841	0.810	0.818	0.725
CEFL	0.841	1.000	0.824	0.818	0.733
CE	0.810	0.824	1.000	0.763	0.717
EISP	0.818	0.818	0.763	1.000	0.824
DH	0.725	0.733	0.717	0.824	1.000

The correlation analysis shows that all the study variables have high positive correlations, and the highest ones are observed between Communication-Efficient FL Techniques (CEFL) and Communication-Efficient Federated Learning (CEFL), Communication Efficiency (CE) and Edge/IoT System Performance (EISP), Communication-Efficient Federated Learning (CEFL) and Edge/IoT System Performance (EISP), and Edge/IoT System Performance (EISP) and Device Heterogeneity (DH). The highest correlation was found between CEFL and CEFLT ($r = 0.841$), indicating that the skills of communication efficient techniques (like adaptive compression, local update tuning, and client subsampling) are strongly correlated with the efficiency of communication efficient federated learning systems. Likewise, CEFL shows a strong positive correlation with CE ($r = 0.824$), which validates the concept that communication-efficient federated learning is a key factor to enhance communication efficiency. In addition, CEFLT showed high positive correlation with CE ($r = 0.810$) and EISP ($r = 0.818$) respectively, suggesting that techniques for the optimization of communication performance are strongly related to communication performance and to overall system effectiveness of Edge/IoT system.

Regression Analysis (CEFLT → CEFL)

Table 6: Regression Analysis (CEFLT → CEFL)

Predictor	Beta	t-value	p-value	Decision
CEFLT → CEFL	0.789	26.980	.000	Supported

Regression Analysis (DH → CEFL)

Table 7: Regression Analysis (DH → CEFL)

Predictor	Beta	t-value	p-value	Decision
DH → CEFL	0.870	27.781	.000	Supported

As shown in the regression analysis results, the Communication-Efficient FL Techniques (CEFLT) has a significant and positive effect on Communication-Efficient Federated Learning (CEFL) ($\beta = 0.789$, $t = 26.980$, $p < .001$). These results indicate that communication optimization methods like adaptive compression, local update tuning, and client subsampling are important for improving the performance of communication-efficient federated learning systems. The high beta coefficient indicates that there is a strong predictive relationship and the statistically significant p-value validates the idea of the hypothesis being supported. Similarly, Device Heterogeneity (DH) was found to have a significant positive influence on Communication-Efficient Federated Learning (CEFL) ($\beta = 0.870$, $t = 27.781$, $p < .001$). The result shows that there is a significant difference in the effectiveness of the federated learning environment depending on the differences of the devices, computational power, memory, and network conditions. The beta value for DH is greater, indicating that the performance of the federated learning is even more affected by the characteristics of the devices. In general, the results of this study indicated that both CEFLT and DH have a strong influence and statistically significant influence on CEFL in support of the hypotheses proposed in this study and the importance of both CEFLT and DH in the conceptual framework.

Multiple Regression Analysis (CEFLT + DH + CEFL → CE)

Table 8: Multiple Regression Analysis (CEFLT + DH + CEFL → CE)

Predictor	Beta	t-value	p-value	Decision
CEFLT → CE	0.361	7.332	.000	Supported
DH → CE	0.402	6.879	.000	Supported
CEFL → CE	0.130	2.700	.007	Supported

The regression analysis results show that all the proposed predictors are statistically significant with positive regression coefficients towards Communication Efficiency (CE). This coefficient, CEFLT, showed a statistically significant positive relationship with CE ($\beta = 0.361$, $t = 7.332$, $p < .001$), highlighting the important role that methods like adaptive compression, local update tuning, and client subsampling play in enhancing communication efficiency in federated learning settings. Likewise, Device Heterogeneity (DH) ($\beta = 0.402$, $t = 6.879$, $p < .001$) was shown to significantly positively influence CE, meaning that device capability, computational resources, and network conditions contribute significantly to the results of CE. Moreover, CEFL also showed a significant positive effect on CE ($\beta = 0.130$, $t = 2.700$, $p = .007$), reinforcing the understanding that the mechanisms of federated learning that are more communication-aware improve the effectiveness of communication by minimizing the overhead associated with communicating and optimizing resource utilization. For the predictors, Device Heterogeneity had the largest impact on Communication Efficiency, followed by Communication-Efficient Federated Learning and Communication-Efficient FL Techniques. The results overall support the proposed hypotheses and suggest that all three factors have an important role in enhancing the efficiency of communication in resource-limited Edge/IoT environments.

Table 9: Regression Analysis (CE $\rightarrow$ EISP)

Predictor	Beta	t-value	p-value	Decision
CE $\rightarrow$ EISP	0.763	28.410	.000	Supported

Table 10: Final Multiple Regression Analysis

Predictor	Beta	t-value	p-value	Decision
CEFLT $\rightarrow$ EISP	0.023	0.436	.663	Not Supported
DH $\rightarrow$ EISP	0.061	1.006	.315	Not Supported
CEFL $\rightarrow$ EISP	0.149	3.122	.002	Supported
CE $\rightarrow$ EISP	0.576	11.425	.000	Supported

As shown in Table 9, the regression analysis results indicate that the communication efficiency (CE) has a positive effect on the edge/iot system performance (EISP) with a strong level of significance ($\beta = 0.763$, $t = 28.410$, $p < .001$). The result indicates that the overall performance of Edge/IoT systems can be significantly boosted by increasing the efficiency of the communications process, as it reduces communication overhead, optimizes use of resources, and speeds up system responsiveness. Hence, the suggested relationship between CE and EISP is accepted. Further, from the final multiple regression analysis in Table 10, it can be observed that Communication-Efficient Federated Learning (CEFL) ($\beta = 0.149$, $t = 3.122$, $p = .002$), along with Communication Efficiency (CE) ($\beta = 0.576$, $t = 11.425$, $p < .001$), significantly predict Edge/IoT System Performance. The direct relationship between Communication-Efficient FL techniques (CEFLT) ($\beta = 0.023$ and $t = 0.436$, $p = .663$) and Device Heterogeneity (DH) ($\beta = 0.061$ and $t = 1.006$, $p = .315$) with EISP were not significant and were rejected. The results indicate that the effects of the communication-efficient techniques and device heterogeneity on the performance of Edge/IoT systems are not statistically significant, although they can affect performance indirectly via communication-efficient federated learning and communication efficiency. In general, Communication Efficiency proved to be the best indicator of the Edge/IoT System Performance in the proposed framework (Kamal et al., 2024).

Mediation Analysis

Table 11: Mediation Analysis

Indirect Relationship	Indirect Effect (β)	p-value	Decision
CEFLT $\rightarrow$ CEFL $\rightarrow$ CE	0.103	.007	Supported
DH $\rightarrow$ CEFL $\rightarrow$ CE	0.113	.004	Supported

CEFL → CE → EISP	0.075	.002	Supported
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The mediation analysis revealed all proposed indirect relationships were statistically significant and supported. The indirect effect of Communication-Efficient FL Techniques (CEFL) on Communication Efficiency (CE) via Communication-Efficient Federated Learning (CEFL) was significant ($\beta = 0.103$, $p = .007$), suggesting that Communication-Efficient Federated Learning (CEFL) is an important intermediate link between Communication-Efficient FL Techniques (CEFL) and Communication Efficiency (CE). Likewise, Communication-Efficient Federated Learning (CEFL) also showed a significant indirect effect on Communication Efficiency through Device Heterogeneity ($\beta = 0.113$, $p = .004$), indicating that the effect of device characteristics on communication outcomes, at least in part, travel through the effectiveness of communication-efficient federated learning systems. Moreover, there was a very strong indirect effect of Communication-Efficient Federated Learning on Edge/IoT System Performance (EISP) via Communication Efficiency (CE) ($\beta = 0.075$, $p = .002$), which further validated that communication efficiency is an important mediating factor between federated learning effectiveness and system performance in an Edge/IoT setting. The findings show that Communication-Efficient Federated Learning and Communication Efficiency play key intermediate roles in the proposed framework and provide some insight into the role communication optimization mechanisms play in improving the performance of the Edge/IoT system. Thus, all of the mediation hypotheses put forward are supported, and the evidence for the indirect pathways is strong, supporting the conceptual model.

Moderation Analysis

Table 12: Moderation Analysis

Interaction Effect	Beta	t-value	p-value	Decision
DH × CEFLT → CEFL	0.118	2.541	.011	Supported
DH × CEFLT → CE	0.096	2.103	.036	Supported
DH × CEFL → CE	0.087	1.987	.048	Supported

The moderation analysis results show that the proposed relationships in the conceptual framework are significantly moderated by Device Heterogeneity (DH). Specifically, communication-efficient federated learning techniques (CEFLT) and communication-efficient federated learning (CEFL) were found to interact positively with Device Heterogeneity (DH × CEFLT) ($\beta = 0.118$, $t = 2.541$, $p = .011$). The results indicate that the benefit of communication-efficient methods for improving communication-efficient federated learning increases when differences in device capabilities, computational resources and network conditions are taken into account. Likewise, Communication Efficiency (CE) was found to be significantly associated with the interaction effect between device heterogeneity and communication-efficient FL techniques ($\beta = 0.096$, $t = 2.103$, $p = .036$), revealing that devices differences affect the influence that communication-efficient techniques have on communication efficiency. Additionally, the communication efficiency of federated learning (CEFL → CE) was found to be significant when the results are compared with communication efficiency of original federated learning (OFL → CE) ($\beta = 0.087$, $t = 1.987$, $p = .048$). This indicates that the effectiveness of communication-efficient federated learning (CEFL) depends on the device properties. Overall, these results validate that Device Heterogeneity is an important moderator in the proposed framework and greatly contributes to the overall strength of the relationships between the communication-efficient learning mechanisms and the communication outcomes. Hence, all the proposed hypotheses for moderation are supported, which emphasizes the need to take heterogeneous devices in Edge/IoT environments into account when deploying communication-efficient federated learning systems.

Hypothesis Testing

Table 13: Hypothesis Testing Summary

Hypothesis	Relationship	Beta	p-value	Decision
H1	CEFLT → CEFL	0.789	.000	Supported
H2	DH → CEFL	0.870	.000	Supported
H3	CEFLT → CE	0.361	.000	Supported
H4	DH → CE	0.402	.000	Supported
H5	CEFL → CE	0.130	.007	Supported
H6	CE → EISP	0.763	.000	Supported
H7	CEFLT → EISP	0.023	.663	Not Supported
H8	DH → EISP	0.061	.315	Not Supported
H9	CEFL → EISP	0.149	.002	Supported
H10	CE → EISP	0.576	.000	Supported

The results of the hypothesis testing give enough support to the proposed conceptual framework. As stated in the results, Communication-Efficient FL Techniques (CEFLT) also have a strong positive relationship with Communication-Efficient Federated Learning (CEFL) ($p < .001$, $\beta = 0.789$), which supports H1, and Device Heterogeneity (DH) has a strong positive relationship with CEFL ($p < .001$, $\beta = 0.870$), which supports H2. Moreover, the Communication Efficiency (CE) ($\beta = 0.361$, $p < .001$) is significantly predicted by the CEFLT, and the DH positively impacts the CE ($\beta = 0.402$, $p < .001$) thus supporting the H3 and H4, respectively. The findings also show that Communication Efficiency was significantly influenced by CEFL ($\beta = 0.130$, $p = .007$), which is in line with H5. The communication efficiency was discovered to positively affect EISP ($\beta = 0.763$, $p < .001$), which in turn supports H6. Collectively, these results suggest that communication-efficient techniques, device heterogeneity and communication-efficient federated learning are important factors in enhancing the communication efficiency in Edge/IoT scenarios.

Results from the present study show that Communication-Efficient Federated Learning (CEFL) is significantly affected by CEFL Techniques (Communication-Efficient) ($\beta = 0.789$, $p < .001$) and Device Heterogeneity (DH) significantly affects CEFL ($\beta = 0.870$, $p < .001$). The findings align with recent research that has highlighted the need for communication optimization and mechanisms that can address the heterogeneity in federated learning settings. For instance, Mahmoudi et al. (2024) demonstrated that communication-efficient federated learning frameworks could significantly enhance the learning performance by minimizing communication overhead and addressing the varying capabilities of the devices. Likewise, Yang et al. (2021) demonstrated that communication efficient algorithms for various types of heterogeneous wireless edge networks enhance the convergence performance and communication efficiency. The present study also confirms the importance of CEFL in the context of CEFL, as revealed by previous studies, such as those by Chen et al. (2024), who proposed communication-efficient design methods to enhance the communication efficiency between heterogeneous edge devices. Similarly, Mills et al. (2020) noted that solutions with the ability to communicate efficiently are required to tackle the resource constraints and scalability issues of Edge/IoT environments. The current results thus support recent and earlier results showing that communication-efficient techniques and heterogeneity management are key factors for the successful implementation of federated learning.

The multiple regression and mediation results also indicated that Communication Efficiency (CE) had a significant impact on the Edge/IoT System Performance (EISP) ($\beta = 0.763$, $p < .001$); as well, the direct impact of Communication Efficiency-Field Level (CEFL) on EISP was significant ($\beta = 0.149$, $p = .002$). The effects of CEFLT and DH, however, were not strong enough to have direct effects on EISP, suggesting that the influence of CEFLT and DH is mediated by the efficiency of the communication and the effectiveness of the federated learning. The results are similar to recent

research that reveals communication efficiency as a key mechanism between federated learning strategies and operational performance outcomes in an IoT network. By optimizing the communication processes, Li et al. (2024) showed that model efficiency and communication performance can be enhanced through sparse communication strategies without direct impact on the system. Likewise, Xie et al. (2024) stated that the main goal of using communication-efficient federated learning frameworks is to decrease the amount of communication and optimize the use of limited resources. Moreover, as also mentioned by Sun et al. (2020), the performance of federated learning is indirectly influenced by communication and resource allocation mechanisms due to device heterogeneity. Moreover, Nguyen et al. (2021) have found that the key element that affects the performance of Edge/IoT in distributed learning systems is communication management. Based on this, the present study further verifies prior studies through empirical evidence by showing that the communication efficiency between the Edge/IoT system and the cloud can be a key channel via which communication efficient federated learning improves the performance of Edge/IoT systems.

DISCUSSION

This study's results provide valuable insights into theory, literature, and practice for communication-efficient federated learning in resource-constrained Edge/IoT environments. Theoretically, the research contributes to the knowledge of distributed learning systems by showcasing that efficient communication is a key mechanism by which communication-efficient federated learning techniques affect Edge/IoT system performance. The significant relationships among Communication-Efficient Federated Learning (CEFL), Communication-Efficient FL Techniques (CEFLT), and Communication Efficiency (CE) reinforce the need for communication optimization as a crucial element to the successful deployment of FL in a heterogeneous setting. The results support the current federated learning theory as they point to the indirect mechanisms through which technology impacts system outcomes. In a literature point of view, the outcomes boost the rising quantity of works on federated learning and Edge computing by practically proving relationships which have been primarily studied theoretically. In the practical sense, the results support the design of systems, development of IoT applications and network management in order to optimize their performance while preserving the limited resources of communication networks.

The results show that, CEFL is significantly affected by CEFLT ($\beta = 0.789$, $p < .001$) and DH is significantly affected by CEFL ($\beta = 0.870$, $p < .001$). The results are in line with recent works that suggest that the performance of federated learning in distributed settings can be enhanced through communication-efficient algorithms and heterogeneity-aware mechanisms (Chen et al., 2024; Yang et al., 2021). Likewise, Mahmoudi et al. (2024) revealed that communication-efficient approaches lead to better learning efficiency by minimizing communication overhead and promoting diversity of devices. The findings also corroborate the previous study by Mills et al. (2020) that highlighted the need for optimizing communication on large-scale Edge/IoT deployments. Thus, the current study validates the importance of techniques that are efficient in communication and techniques dealing with heterogeneity management as a key backbone of successful federated learning implementation.

The mediation and moderation analyses add to the support of the study model. Communication Efficiency was a significant mediator between CEFL and Edge/IoT System Performance, and Device Heterogeneity was a strengthener of the relationships between CEFLT, CEFL and CE. This result aligns with recent studies that highlight the need to consider environmental factors in federated learning settings (Yang et al., 2021; Li et al., 2024). The results of the moderation show that communication efficient techniques are even more useful in the context of high level of device diversity. It is therefore shown that heterogeneity-aware communication management and effective strategies are crucial to enable the benefits of federated learning in such Edge/IoT environments where resources are limited.

CONCLUSION

In this study, known as the Communication-Efficient Federated Learning (CEFL) in conjunction with Communication-Efficient FL Techniques (CEFL), Communication Efficiency (CE), and Device Heterogeneity (DH), the impact of these on Edge/IoT System Performance (EISP) in resource-constrained environments was investigated. The results indicate that the communication efficient technique improves the effectiveness of the federated learning significantly, and device heterogeneity improves the process of federated learning and the communication efficiency. Communication Efficiency was identified as the most influential model to predict Edge/IoT System Performance, with its key importance for enabling successful application of federated learning. Moreover, the mediation analysis showed that the impact of communication-efficient federated learning on system performance was mediated by communication efficiency, and the moderation analysis revealed that the key relationships in the model were enhanced with device heterogeneity.

The study advances theory by adding to the existing literature about federated learning and distributed Edge computing by identifying communication efficiency as key explanatory mechanism. It adds to the literature by offering empirical findings on how they interact with communication efficient techniques, heterogeneity management and systems performance in real-world contexts for Edge/IoT applications. In practical terms, the findings can help developers of IoT systems, network engineers and system architects to reduce communication expenses, maximize learning efficiency and maximize system performance in the case of resource limitations. Based on the results, the organization should consider using communication efficient algorithms and designs that take the heterogeneity of the devices into account when implementing federated learning systems. The overall results support the effectiveness of communication efficiency as the key to achieve performance gains in Edge/IoT environments and serve as a reference point for future research on exploring novel communication optimization strategies for distributed intelligent systems (Chen et al., 2024; Mills et al., 2020; Li et al., 2024; Mahmoudi et al., 2024; Yang et al., 2021).

FUTURE RESEARCH DIRECTION

Results from this work offer several research directions and implications for the existing federated learning implementation at Edge/IoT environments. In future work, other elements such as model compression methods, privacy preserving mechanisms, network latency, energy efficiency and cyber security threats could also be explored to deepen the understanding of the variations of Edge/IoT system performance. Researchers can also use cross-country comparisons or experimental designs, and/or longitudinal designs to understand the long-term adoption success of communication-efficient federated learning in various technological and environmental scenarios. In addition, other moderating variables like network reliability, computational capacity, data heterogeneity could be explored in future studies. With a managerial point of view, the results indicate that communication-efficient algorithms and heterogeneity-aware system designs are more relevant to enhance the communication efficiency and the overall system performance for the technology managers, system architects and IoT developers. It is crucial for organizations to invest in adaptive communication protocols, efficient resource allocation mechanisms, and scalable federated learning architectures that are able to manage a variety of device capabilities. By optimizing communication and managing the heterogeneity, organizations can lower communication overhead, boost the accuracy of learning, optimize the use of resources and gain better performance in resource constrained Edge/IoT ecosystem.

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