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Federated Learning Architectures for Distributed Engineering Project Knowledge Management A Simulation-Based Analysis

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Abstract

The increasing complexity of distributed engineering projects has created significant challenges in knowledge management, particularly regarding knowledge sharing, data privacy, communication efficiency, and collaborative decision-making across geographically dispersed stakeholders. Federated learning has emerged as a promising decentralized machine learning approach that enables collaborative intelligence generation without requiring direct sharing of sensitive organizational data. This study investigated the effectiveness of federated learning architectures for distributed engineering project knowledge management through a quantitative simulation-based analysis. Specifically, the study evaluated and compared centralized, decentralized, hierarchical, and hybrid federated learning architectures across key performance dimensions, including learning accuracy, convergence efficiency, communication overhead, scalability performance, computational efficiency, and knowledge-sharing effectiveness. A simulation environment consisting of 100 distributed engineering stakeholder nodes was developed to represent project owners, contractors, consultants, design teams, maintenance units, and operational management entities. The experimental design utilized synthetic engineering project datasets containing design records, construction data, operational logs, maintenance information, and project knowledge repositories distributed across heterogeneous nodes. Statistical analyses included descriptive statistics, one-way analysis of variance, correlation analysis, and multiple regression analysis at a significance level of $p < 0.05$. The findings revealed statistically significant differences among the evaluated architectures. The hybrid federated learning architecture achieved the highest learning accuracy (95.1%), knowledge-sharing effectiveness (93.6%), communication efficiency (92.6%), and computational efficiency (94.5%). Hierarchical federated learning demonstrated the strongest scalability performance (94.2%) and the fastest convergence rate, requiring only 31 communication rounds to achieve stable learning performance. Centralized federated learning produced reliable learning outcomes but generated the highest communication overhead (18.6 GB), while decentralized federated learning reduced dependence on centralized coordination but exhibited lower overall learning performance (87.9%). Regression analysis indicated that knowledge-sharing effectiveness ($\beta = 0.53$), communication efficiency ($\beta = 0.48$), and convergence speed ($\beta = 0.42$) were significant predictors of overall learning performance. The study concluded that hybrid and hierarchical federated learning architectures provided the most effective balance between learning quality, scalability, communication management, and computational efficiency. These findings contribute to the growing body of knowledge on privacy-preserving artificial intelligence and demonstrate the potential of federated learning as an effective framework for distributed engineering project knowledge management.

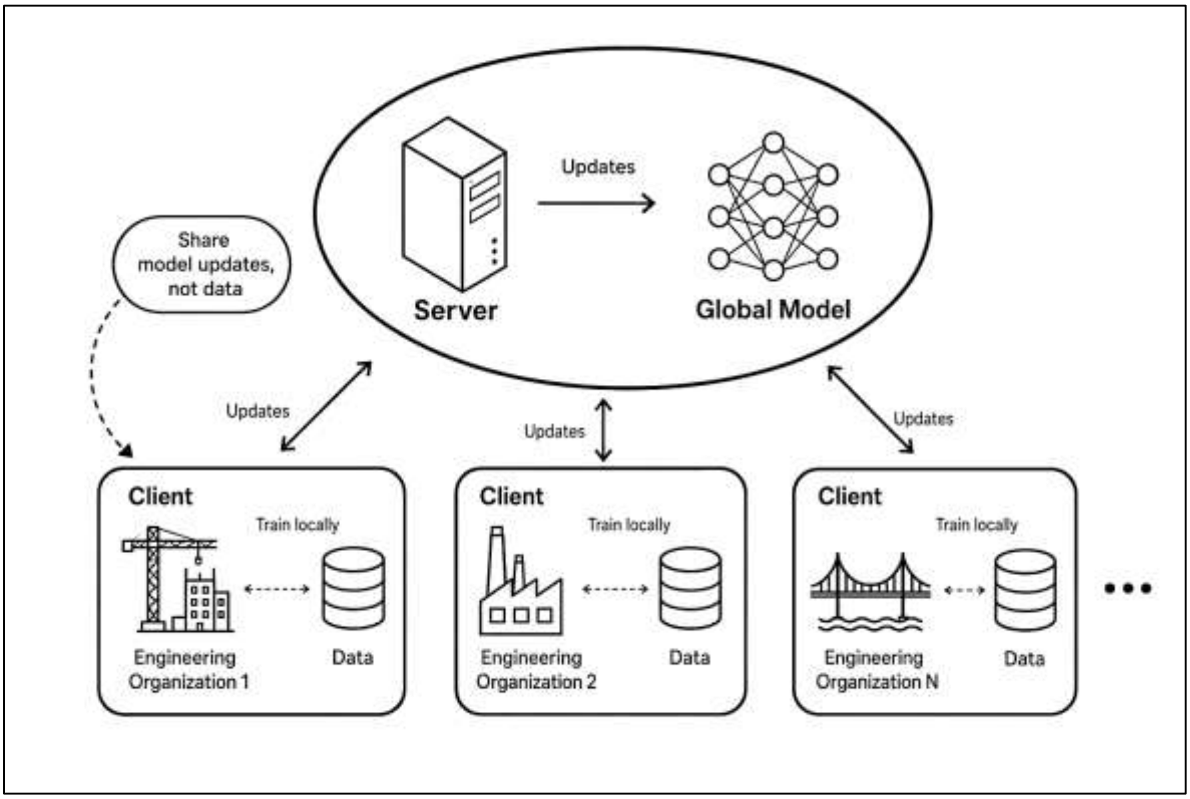
Keywords

Federated Learning; Knowledge Management; Engineering Projects; Distributed Systems; Simulation Analysis.

INTRODUCTION

Federated learning represents a decentralized machine learning paradigm that enables multiple organizations, devices, or computational nodes to collaboratively train predictive models without transferring raw data to a centralized repository. The approach emerged as a response to growing concerns regarding data privacy, ownership, security, and governance in increasingly interconnected digital ecosystems (Tse, et al., 2020). Traditional machine learning architectures typically require the aggregation of large volumes of data into centralized servers, creating challenges related to confidentiality, regulatory compliance, cybersecurity vulnerabilities, and organizational trust. Federated learning addresses these challenges by allowing local entities to train models independently while sharing only model parameters, gradients, or updates for global optimization.

Figure 1: Federated learning diagram for engineering



This architecture has attracted significant attention across industries characterized by distributed operations and sensitive information assets. Engineering project environments represent one of the most data-intensive domains in modern organizations, generating extensive knowledge resources through design processes, construction activities, maintenance operations, stakeholder communications, technical documentation, and collaborative decision-making. Knowledge management within engineering projects refers to the systematic acquisition, storage, dissemination, utilization, and preservation of organizational knowledge to support project performance and innovation (Chai et al., 2020). Distributed engineering projects involve geographically dispersed teams, multinational contractors, consultants, suppliers, and clients who contribute specialized expertise throughout project lifecycles. Such projects generate heterogeneous datasets that are often isolated across organizational boundaries, limiting opportunities for collective learning and organizational intelligence. Globalization has accelerated the prevalence of distributed engineering initiatives, particularly in infrastructure development, manufacturing systems, energy networks, transportation projects, and digital transformation programs. International engineering collaborations frequently span multiple countries, creating complex environments where knowledge assets must be exchanged efficiently while maintaining compliance with diverse legal, contractual, and security requirements

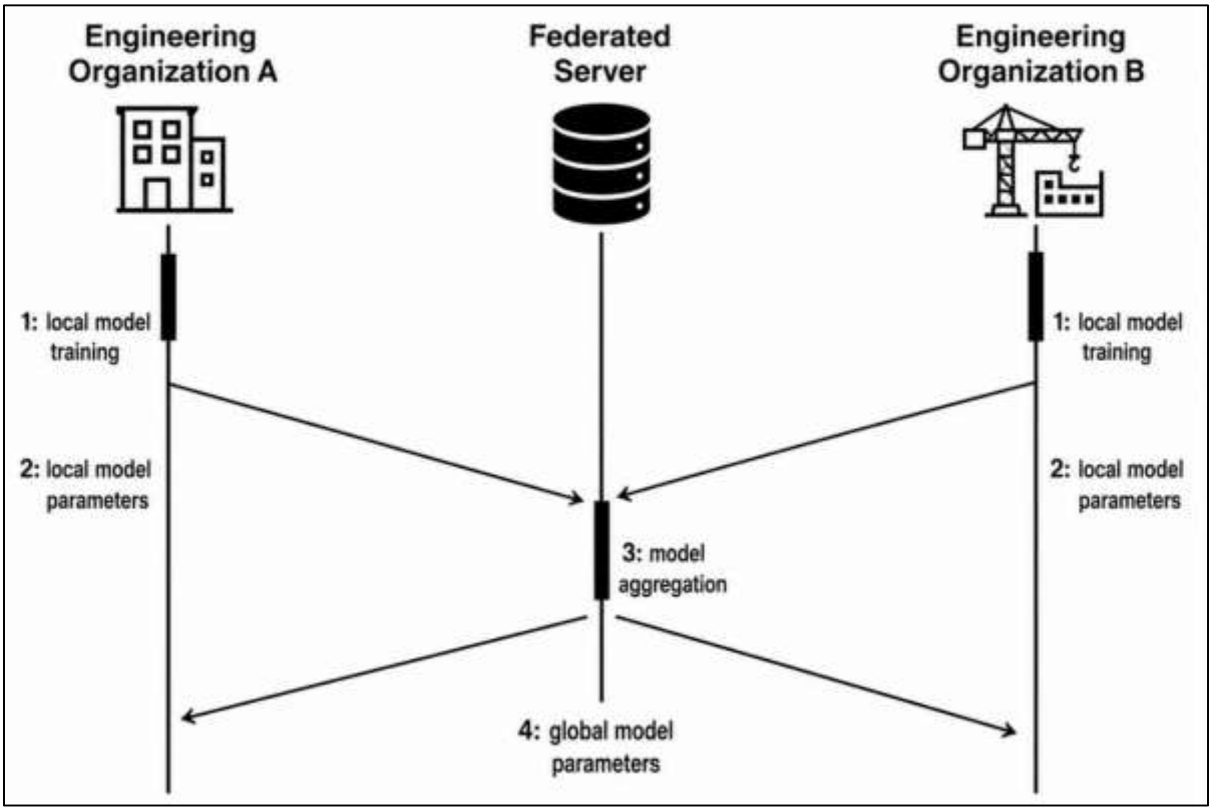
(Rahman et al., 2020). The increasing integration of cloud computing, Internet of Things technologies, digital twins, artificial intelligence, and cyber-physical systems has expanded the volume and complexity of engineering knowledge repositories. Organizations increasingly recognize knowledge as a strategic resource capable of enhancing project efficiency, reducing operational risks, supporting innovation, and improving decision quality. Federated learning introduces a promising mechanism through which engineering organizations can collectively derive insights from distributed knowledge assets while preserving ownership and confidentiality (Aledhari et al., 2020). The convergence of federated learning architectures and engineering knowledge management reflects broader transformations associated with Industry 4.0, digital engineering, and intelligent project ecosystems, establishing a foundation for more collaborative and data-driven approaches to project execution across international engineering networks.

Knowledge management has evolved substantially from traditional document-centric approaches toward intelligent systems capable of capturing, analyzing, and disseminating organizational expertise across complex project ecosystems. Early engineering knowledge management practices focused primarily on archiving reports, technical specifications, manuals, and lessons learned documents within centralized repositories (Hiessl et al., 2020). Although these systems facilitated information storage, they often struggled to support real-time knowledge exchange and dynamic organizational learning. The emergence of enterprise information systems, collaborative platforms, and digital engineering environments expanded opportunities for knowledge sharing among project stakeholders. Engineering organizations increasingly adopted integrated databases, intranet platforms, project management systems, and decision-support tools to improve accessibility and utilization of knowledge resources. As projects became larger and more geographically dispersed, organizations encountered significant challenges related to knowledge fragmentation, information silos, duplication of effort, and loss of expertise across organizational boundaries (Lu et al., 2020). Engineering projects involve multidisciplinary teams possessing diverse technical competencies, making effective knowledge integration essential for project success. The expansion of multinational engineering ventures has further intensified the need for sophisticated knowledge management frameworks capable of supporting collaboration across cultures, institutions, and regulatory environments. Digital transformation initiatives have accelerated the generation of engineering data through sensors, simulation platforms, building information modeling systems, computer-aided design applications, enterprise resource planning systems, and operational monitoring technologies. These developments have produced unprecedented opportunities for data-driven decision-making while simultaneously increasing the complexity of managing organizational knowledge assets (Yuan, et al., 2020).

Artificial intelligence technologies have become increasingly important within engineering knowledge management because of their capacity to identify patterns, automate information processing, and support predictive analytics. Machine learning applications enable organizations to transform raw engineering data into actionable insights that improve project planning, resource allocation, risk management, and operational performance. The integration of intelligent technologies into knowledge management systems reflects a broader shift toward cognitive engineering environments where information assets are continuously analyzed and refined. Distributed engineering projects generate vast quantities of localized knowledge that remain underutilized due to concerns regarding confidentiality, competitive advantage, contractual obligations, and regulatory compliance (Rieke et al., 2020). Consequently, organizations continue searching for architectures capable of enabling collaborative intelligence without compromising data ownership. Federated learning emerges within this context as an innovative solution that aligns organizational requirements for privacy preservation with the strategic need for collective knowledge utilization and continuous organizational learning.

The internationalization of engineering activities has transformed project execution models across virtually every industrial sector. Large-scale infrastructure projects, renewable energy developments, smart city initiatives, transportation networks, aerospace programs, and industrial manufacturing systems increasingly involve partnerships among organizations located in different countries and regions (Wang et al., 2020). These collaborative arrangements enable access to specialized expertise, advanced technologies, financial resources, and global supply chains. At the same time, they create substantial challenges associated with knowledge coordination, information exchange, and organizational learning. Engineering projects often involve diverse stakeholders operating under different legal frameworks, technical standards, organizational cultures, and governance structures. Effective knowledge management becomes essential for aligning project objectives, minimizing communication barriers, reducing uncertainties, and ensuring consistent decision-making throughout project lifecycles.

Figure 2: Federated learning workflow diagram



The strategic value of engineering knowledge extends beyond individual organizations because collective learning contributes to innovation, sustainability, productivity, and technological advancement across entire industries (Wu et al., 2020). Global engineering ecosystems increasingly depend on data-driven collaboration to address complex societal challenges including urbanization, climate adaptation, energy security, transportation efficiency, and infrastructure resilience. The growth of digital engineering technologies has generated extensive repositories of project-related information distributed across multiple organizations and jurisdictions. These repositories contain valuable insights regarding project performance, design optimization, risk mitigation, safety management, and operational efficiency. Accessing and integrating such knowledge resources can significantly improve organizational competitiveness and project outcomes. International concerns regarding cybersecurity, data sovereignty, intellectual property protection, and privacy regulations create obstacles to centralized data sharing approaches (Zhang et al., 2020). Regulations governing information management vary considerably across countries, increasing the complexity of cross-border knowledge exchange. Organizations must balance collaborative learning objectives with legal responsibilities related to data protection and confidentiality. Federated learning offers a framework capable of supporting international knowledge collaboration while respecting organizational autonomy and jurisdictional requirements. By enabling model training across decentralized data sources, federated architectures facilitate the development of shared intelligence without requiring direct access to proprietary information (Long et al., 2020). This capability holds particular significance for multinational engineering projects where knowledge generation occurs continuously across dispersed operational environments. The international relevance of federated learning extends beyond technological innovation, encompassing broader objectives related to organizational trust, collaborative governance, digital transformation, and sustainable project management within increasingly interconnected engineering ecosystems (Rahman et al., 2020).

The primary objective of this study is to quantitatively evaluate the effectiveness of federated learning architectures in enhancing distributed engineering project knowledge management through simulation-based analysis. Engineering projects increasingly operate within geographically dispersed and organizationally fragmented environments where valuable knowledge assets are generated across multiple stakeholders, including contractors, consultants, suppliers, project owners, and technical specialists. These distributed knowledge repositories contain critical information related to design decisions, project execution practices, risk management activities, resource allocation strategies, operational performance, and lessons learned. The decentralized nature of such knowledge environments creates challenges associated with information accessibility, knowledge integration, organizational learning, and collaborative decision-making. This study seeks to investigate how federated learning architectures can facilitate efficient knowledge sharing and collective intelligence generation while preserving data ownership, privacy, and security requirements among participating entities. Specifically, the research aims to assess the performance of federated learning systems in terms of knowledge utilization efficiency, model accuracy, communication effectiveness, computational performance, scalability, and collaborative learning outcomes within distributed engineering project settings. Through simulation-based experimentation, the study examines the interactions between multiple engineering stakeholders operating in heterogeneous environments and evaluates how decentralized learning mechanisms influence the quality and accessibility of organizational knowledge. Another objective is to compare the operational characteristics of federated learning architectures under varying network conditions, stakeholder participation levels, and knowledge distribution scenarios to determine their suitability for complex engineering ecosystems. The research further seeks to identify the extent to which federated learning contributes to reducing knowledge silos, improving information exchange efficiency, enhancing decision-support capabilities, and strengthening organizational learning across distributed project networks. By employing quantitative performance metrics and simulation models, the study aims to generate empirical evidence regarding the effectiveness of federated learning as a knowledge management solution for modern engineering projects. Ultimately, the research focuses on providing a systematic evaluation of how decentralized artificial intelligence frameworks can support knowledge-driven engineering practices, optimize collaborative project environments, and improve the management of distributed knowledge resources in increasingly digitalized and globally interconnected engineering ecosystems.

LITERATURE REVIEW

The growing complexity of engineering projects, combined with increasing geographical dispersion of project stakeholders, has intensified the importance of effective knowledge management systems capable of supporting collaborative decision-making and organizational learning. Engineering organizations generate substantial volumes of data and knowledge throughout project lifecycles, including technical specifications, design documents, risk assessments, operational records, maintenance reports, communication logs, and performance metrics (Nahyan et al., 2019). The distributed nature of modern engineering environments often results in fragmented knowledge repositories that limit information accessibility and reduce opportunities for collective intelligence development. Consequently, researchers have increasingly explored advanced digital technologies that can facilitate efficient knowledge sharing while maintaining organizational autonomy and information security. Among these technologies, federated learning has emerged as a promising decentralized machine learning paradigm that enables collaborative model training without requiring direct data exchange among participating entities (Ekambaram et al., 2018). The integration of federated learning into engineering knowledge management represents a significant advancement in the evolution of intelligent project ecosystems. Traditional centralized analytical frameworks frequently encounter limitations associated with privacy concerns, data ownership restrictions, cybersecurity risks, communication bottlenecks, and regulatory compliance requirements. Federated learning architectures address these challenges by allowing distributed stakeholders to contribute local knowledge for global model optimization while retaining control over proprietary datasets. This capability is particularly relevant within engineering projects where multiple organizations collaborate across national boundaries, technological platforms, and institutional structures (Almeida & Soares, 2014). The literature surrounding federated learning has expanded rapidly across domains such as healthcare, finance, manufacturing, transportation, and smart infrastructure, highlighting its potential to support secure and scalable collaborative intelligence systems. The purpose of this literature review is to critically examine existing scholarly knowledge concerning federated learning architectures, distributed engineering project environments, knowledge management systems, simulation-based evaluation methodologies, privacy-preserving machine learning frameworks, and quantitative performance assessment models. Particular emphasis is placed on identifying the theoretical foundations, technological mechanisms, architectural configurations, performance metrics, and empirical findings that inform the application of federated learning within engineering project knowledge management (Dong et al., 2018). The review further explores the relationships among decentralized learning efficiency, communication effectiveness, computational scalability, knowledge-sharing performance, and organizational collaboration. Through a systematic synthesis of current literature, the review establishes the conceptual and empirical foundation necessary for evaluating federated learning architectures through simulation-based quantitative analysis (Saukko et al., 2020).

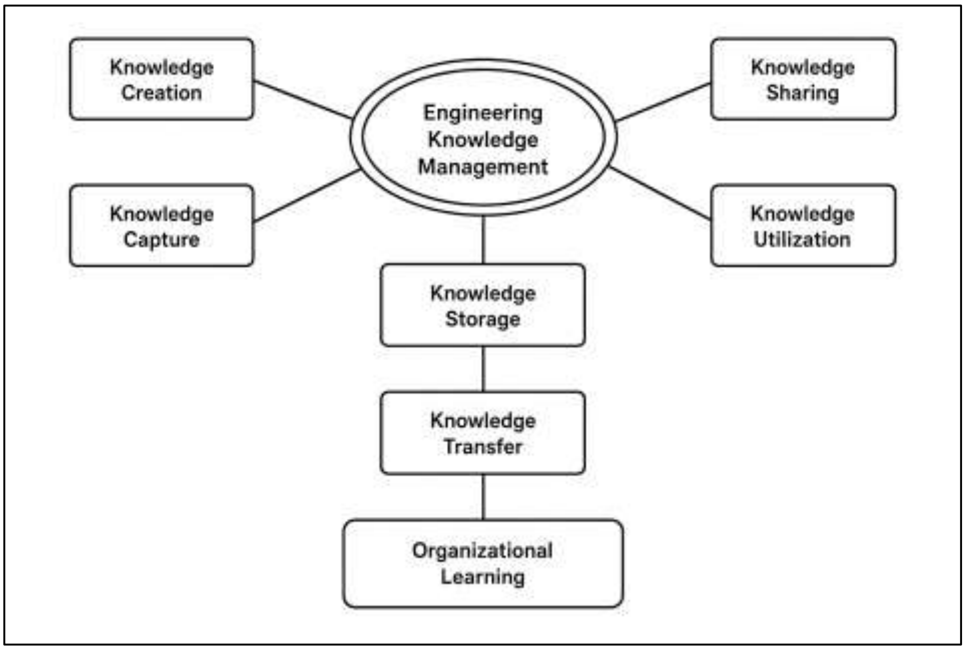
Engineering Project Knowledge Management

Engineering knowledge management has emerged as a critical organizational discipline that focuses on the systematic creation, storage, sharing, and utilization of knowledge resources throughout engineering project lifecycles. The literature demonstrates that engineering organizations operate within highly knowledge-intensive environments where technical expertise, project experiences, design information, operational records, and collaborative insights collectively influence project success. Early studies emphasized knowledge management as a mechanism for preserving valuable organizational expertise and reducing the loss of critical information resulting from employee turnover and project discontinuity (Handzic & Bassi, 2017). Subsequent research expanded this perspective by recognizing knowledge as a strategic organizational asset that contributes directly to innovation, operational efficiency, and competitive advantage. Scholars have identified explicit knowledge as a major component of engineering knowledge management, encompassing codified information such as technical reports, design documents, engineering specifications, maintenance manuals, and project databases. These repositories facilitate structured information access and support organizational memory across multiple projects. Research has also highlighted the significance of tacit knowledge, which resides within individual experiences, professional judgment, problem-solving capabilities, and technical expertise developed through practice. Studies examining engineering project environments consistently indicate that tacit knowledge represents a substantial source of innovation and decision quality (Manesh et al., 2020).

The literature further identifies organizational knowledge assets as a combination of human expertise, technological capabilities, procedural frameworks, and institutional experiences that collectively support project execution. Knowledge creation and transfer processes have been extensively examined as mechanisms through which organizations transform individual expertise into collective organizational learning. Researchers have emphasized that effective knowledge management enhances communication, promotes interdisciplinary collaboration, improves problem-solving efficiency, and supports continuous improvement initiatives (Nisar et al., 2019). Across diverse engineering sectors, including construction, manufacturing, transportation, and infrastructure development, studies consistently report positive relationships between structured knowledge management practices and project performance outcomes, highlighting the central role of knowledge as a strategic resource within modern engineering organizations.

The literature on engineering knowledge management increasingly focuses on the dynamic processes through which knowledge is generated, exchanged, interpreted, and integrated within project environments. Knowledge creation has been described as a continuous process involving the transformation of information into actionable expertise through collaborative interactions, problem-solving activities, technical experimentation, and project execution experiences (Doskočil & Lacko, 2019). Researchers have argued that engineering projects provide unique environments for knowledge generation because project teams frequently encounter complex technical challenges that require innovative solutions and interdisciplinary cooperation. Knowledge transfer represents another fundamental dimension that enables valuable expertise to move across individuals, departments, organizations, and project stages. Studies examining engineering organizations have demonstrated that effective transfer mechanisms facilitate the dissemination of best practices, lessons learned, technical innovations, and operational experiences (Asrar-ul-Haq & Anwar, 2016). Organizational learning has consequently emerged as a critical outcome of successful knowledge management systems. Scholars have reported that organizations capable of effectively capturing and disseminating project knowledge demonstrate improved adaptability, stronger innovation capacity, and enhanced decision-making performance. The literature also emphasizes the importance of integrating both formal and informal knowledge-sharing mechanisms. Formal mechanisms include documentation systems, project databases, training programs, and organizational repositories, while informal mechanisms involve mentoring relationships, collaborative discussions, professional networks, and communities of practice. Several investigations have revealed that successful engineering organizations balance these complementary approaches to maximize knowledge utilization and retention (Mao et al., 2016). Research further suggests that knowledge creation and transfer contribute significantly to organizational resilience by enabling institutions to preserve expertise across successive projects and changing operational conditions. Within engineering project contexts, continuous learning supports improved project planning, risk management, quality control, and stakeholder coordination. The cumulative findings from existing studies indicate that knowledge management serves not only as an information management function but also as a strategic organizational capability that strengthens learning processes, enhances technical competence, and supports sustainable project performance (Zheng et al., 2016).

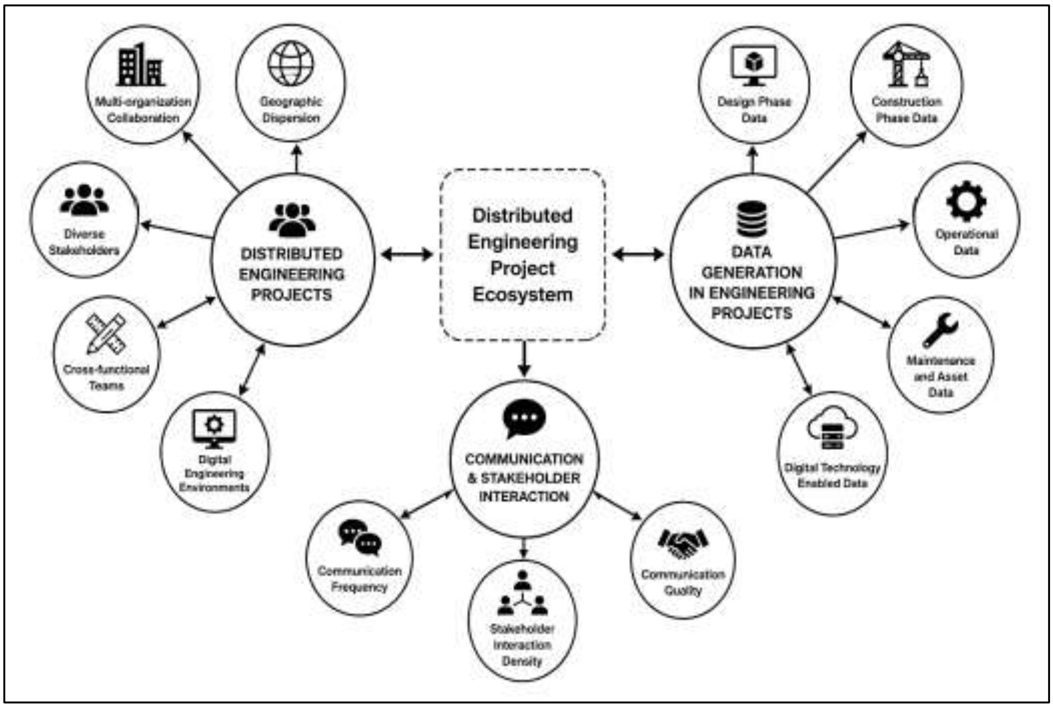
Figure 3: Schematic knowledge management flowchart



Distributed Engineering Project Ecosystems

Distributed engineering projects have become increasingly prevalent across industries due to globalization, technological advancement, and the growing complexity of large-scale infrastructure and industrial initiatives. The literature characterizes distributed engineering projects as collaborative environments involving multiple organizations that contribute specialized expertise, resources, and technologies toward achieving common project objectives. Researchers emphasize that these projects frequently include contractors, consultants, suppliers, project owners, regulatory agencies, and technical specialists operating within interconnected networks (Iosup et al., 2018). Multi-organizational collaboration has been identified as a defining characteristic because no single organization typically possesses all the capabilities required to execute complex engineering undertakings independently. Studies indicate that collaborative arrangements enhance access to specialized knowledge, improve resource utilization, and facilitate innovation through the integration of diverse perspectives. The literature further highlights the importance of formal coordination mechanisms, governance structures, and communication frameworks in supporting effective collaboration among participating entities. Geographic dispersion represents another central characteristic of distributed engineering projects, as stakeholders are often located across different cities, regions, or countries. Researchers have observed that spatial separation increases the reliance on digital communication technologies and information management systems to coordinate project activities (Dittrich, 2014). The emergence of digital engineering environments has transformed how organizations collaborate by enabling virtual design reviews, cloud-based project management, real-time information sharing, and integrated data platforms. These digital ecosystems support continuous interaction among stakeholders and improve the accessibility of project information across organizational boundaries. Cross-functional project teams constitute an additional feature identified throughout the literature. Engineering projects commonly require expertise from multiple disciplines, including civil engineering, mechanical engineering, electrical engineering, information technology, operations management, and environmental sciences. Research findings suggest that cross-functional collaboration strengthens problem-solving capabilities and promotes knowledge integration, contributing to more comprehensive project solutions (G. Wang et al., 2019). Collectively, existing studies demonstrate that distributed engineering projects depend heavily on collaborative structures that connect diverse organizations, technologies, and professional competencies within increasingly complex project ecosystems.

Figure 4: Distributed engineering project ecosystem diagram



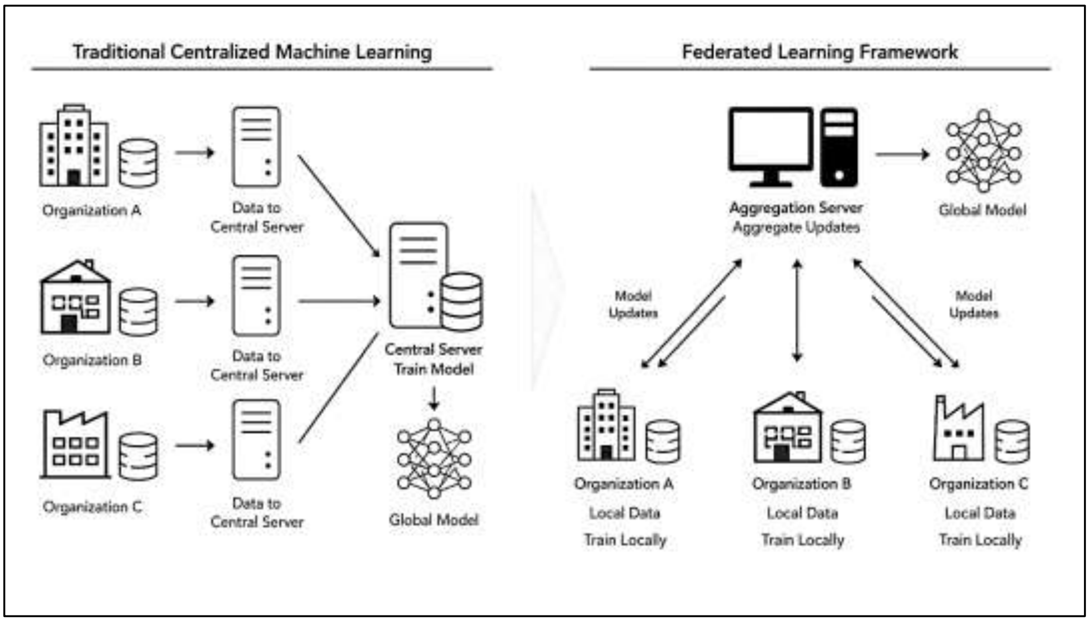
The literature increasingly recognizes data as a strategic resource within modern engineering projects, with significant attention devoted to understanding how information is generated, managed, and utilized throughout project lifecycles. Engineering projects produce extensive volumes of data beginning in the design phase, where activities such as conceptual development, computer-aided design modeling, simulation analysis, feasibility studies, and technical specifications create foundational project information (Strain et al., 2018). Researchers have noted that design-phase datasets often represent some of the most knowledge-intensive resources because they establish the technical basis for subsequent project activities. As projects progress into construction and implementation phases, additional datasets emerge from scheduling systems, procurement records, quality inspections, safety reports, workforce management systems, and resource allocation processes. Studies indicate that construction-phase information plays a critical role in monitoring project performance and supporting operational decision-making. The literature further identifies operational datasets as essential sources of organizational knowledge following project completion. Operational data include performance measurements, system utilization records, monitoring information, environmental indicators, and service delivery metrics that provide insights into the effectiveness of engineering assets (Remya et al., 2015). Maintenance and asset management datasets have also received considerable scholarly attention because they support long-term infrastructure sustainability and operational reliability. Researchers have highlighted the value of maintenance records, equipment performance histories, failure reports, repair documentation, and asset condition assessments in facilitating continuous improvement and organizational learning. The emergence of digital engineering technologies has significantly expanded the scale and diversity of project data generation. Building information modeling systems, Internet of Things devices, cloud computing platforms, digital twins, and enterprise information systems continuously generate real-time information throughout project lifecycles. Studies consistently demonstrate that effective management of these diverse datasets enhances decision quality, improves project transparency, and supports collaborative knowledge creation (Tong et al., 2018). Consequently, the literature positions data generation as a fundamental component of contemporary engineering ecosystems, shaping how organizations coordinate activities, exchange information, and achieve project objectives.

Communication and stakeholder interaction constitute central themes within the literature on distributed engineering project ecosystems. Researchers consistently identify communication frequency as a critical determinant of project coordination, information exchange, and collaborative performance. Engineering projects involve numerous stakeholders who must continuously share technical information, project updates, risk assessments, design modifications, and operational decisions throughout project lifecycles (Decan et al., 2019). Studies suggest that frequent communication strengthens alignment among project participants and reduces the likelihood of misunderstandings, delays, and coordination failures. The literature further indicates that effective communication mechanisms support trust development and facilitate the integration of diverse expertise within multidisciplinary project environments. Stakeholder interaction density has emerged as another important dimension examined by researchers seeking to understand collaborative behavior within engineering networks. Interaction density refers to the extent and intensity of connections among project participants, reflecting how frequently organizations, teams, and individuals exchange information and coordinate activities. Empirical investigations have demonstrated that projects characterized by stronger interaction networks often exhibit higher levels of innovation, knowledge dissemination, and problem-solving effectiveness (Temper et al., 2018). Digital collaboration platforms have significantly influenced interaction patterns by enabling continuous engagement among geographically dispersed stakeholders. Researchers report that virtual communication technologies facilitate real-time information sharing and enhance organizational responsiveness to changing project conditions. The literature also emphasizes the importance of communication quality in addition to communication frequency. Meaningful exchanges that promote knowledge sharing, mutual understanding, and collaborative learning contribute more significantly to project performance than simple increases in communication volume. Studies examining engineering collaborations reveal that structured communication processes support decision consistency and improve stakeholder satisfaction (K. Wang et al., 2019). The cumulative evidence suggests that communication frequency and stakeholder interaction represent essential elements of distributed engineering ecosystems because they influence information accessibility, collaborative efficiency, and the successful integration of organizational knowledge across complex project networks.

Theoretical Foundations of Federated Learning

The theoretical foundation of federated learning is rooted in the broader evolution of machine learning systems from centralized data processing toward distributed and collaborative intelligence models. Earlier machine learning approaches were largely based on centralized learning models, where data from multiple sources were collected, cleaned, stored, and processed within a single computational environment (Golam & Amir, 2022; Binayan & Shakhawat, 2022; Yi et al., 2016). Literature on artificial intelligence and data analytics has shown that centralized models supported strong computational control, simplified model training, and easier performance monitoring because all training data were located in one repository. However, centralized learning also created major limitations related to data privacy, ownership, storage cost, security exposure, and regulatory compliance. In engineering and industrial environments, these limitations became more visible because project data often belonged to different organizations, contractors, clients, and operational units. Distributed machine learning emerged as a response to these challenges by enabling computational tasks to be divided across multiple machines or nodes. Studies on distributed learning highlight its contribution to scalability, faster computation, and improved handling of large datasets (Glibert et al., 2014). Collaborative learning frameworks further extended this idea by allowing several entities to participate in model development while contributing separate data resources, computational capabilities, or domain-specific expertise. The emergence of federated learning represents a more privacy-conscious stage in this development. Unlike conventional distributed learning, federated learning allows model training across decentralized datasets without requiring participating entities to transfer raw data to a central server. This shift is particularly relevant for distributed engineering project knowledge management because engineering data are often fragmented across organizational boundaries and protected by contractual, technical, and security restrictions. The literature generally positions federated learning as an advanced form of distributed machine learning that combines collaborative intelligence with data protection, making it suitable for complex environments where knowledge sharing and information control must operate together (Y. Li et al., 2020).

Figure 5: Machine learning: centralized vs federated comparison



Federated learning is built on several core principles that distinguish it from traditional machine learning and conventional distributed analytics. The first major principle is decentralized model training, in which participating nodes retain their local datasets and train machine learning models within their own computational environments. This structure allows organizations to contribute to collective learning without exposing sensitive or proprietary data. Literature on federated learning emphasizes that this principle is central to privacy-preserving artificial intelligence because it changes the focus from moving data to moving model knowledge (Rahman et al., 2020; Abdur & Iftekhar, 2021). Instead of transferring raw project records, design files, operational logs, or maintenance datasets, participating entities train local models and share selected model updates for broader learning. Local model updates form the second major principle of federated learning. Each participating node improves the model using its own data and then communicates the learned changes rather than the original information. This process supports collaboration among different data owners while reducing risks associated with direct data exchange. The third principle is global model aggregation, where updates from participating nodes are combined to improve a shared model. Studies show that aggregation plays an important role in determining the accuracy, reliability, and stability of federated learning systems (Hasan & Uddin, 2022; Korkmaz et al., 2020; Hossain & Uddin, 2022). In distributed engineering environments, global aggregation can allow knowledge from multiple project sites, engineering teams, or organizational partners to be reflected in a common analytical model. The fourth principle is privacy-preserving computation, which supports secure collaboration through mechanisms that limit data exposure and protect organizational confidentiality. This principle is especially important in engineering project ecosystems where data may include intellectual property, design decisions, safety records, financial information, and performance documentation. Across the literature, these principles collectively define federated learning as a decentralized, collaborative, and security-oriented learning framework that aligns with the needs of multi-stakeholder engineering knowledge systems (Wittkopp & Acker, 2020).

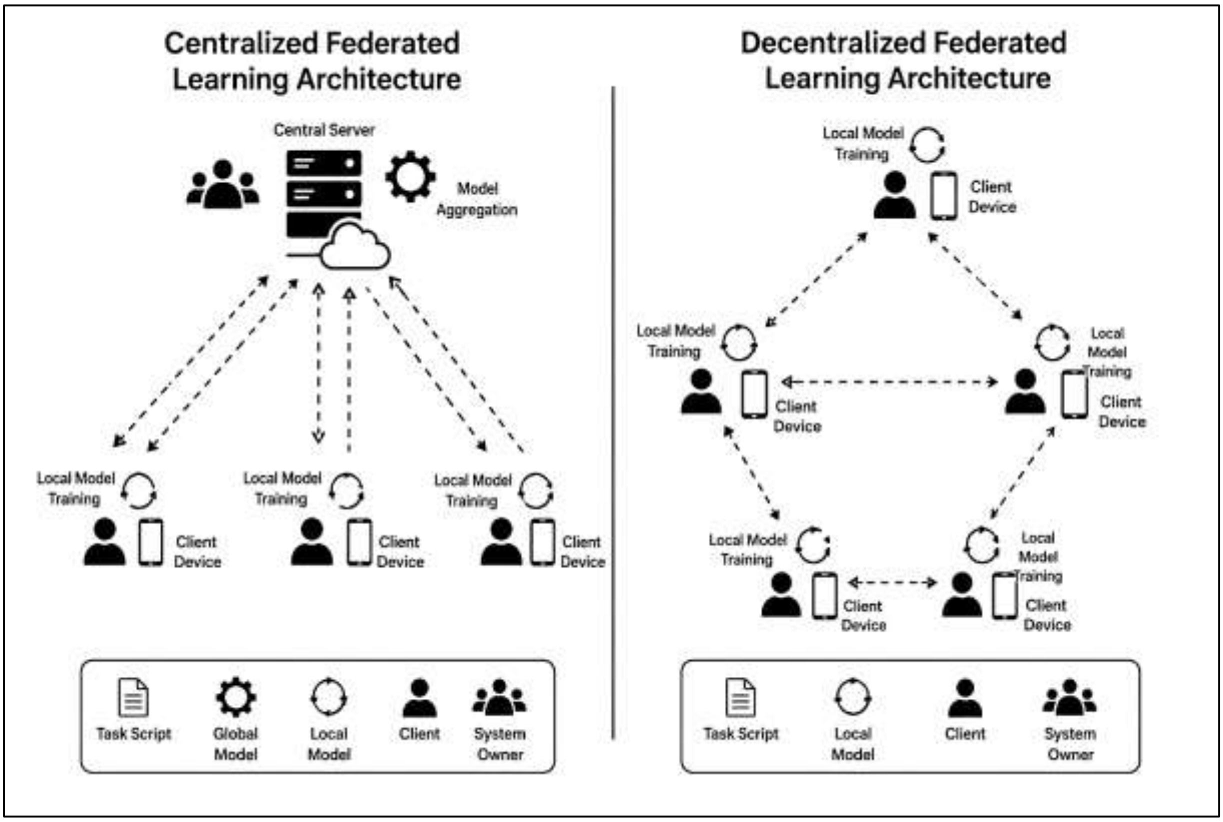
Although federated learning is often discussed as a privacy-preserving technology, its theoretical foundation also depends on the algorithmic structure through which learning takes place across multiple participants. Literature on federated systems explains that each participating node performs local optimization by training a model on its own dataset. In practical terms, this means that each organization, project unit, or engineering site uses its available information to improve a local version of the model. These local training processes reflect the specific patterns, conditions, and knowledge characteristics of each participating environment (Hegedűs et al., 2019; Sany & Siful, 2022; Binte & Iftekhar, 2022). After local training, model updates are transmitted to an aggregation mechanism that combines contributions from different nodes. Global aggregation algorithms are therefore central to federated learning because they determine how individual learning outcomes are merged into a broader shared model. Studies have examined various aggregation strategies, with particular attention to model accuracy, convergence behavior, communication cost, and robustness against unreliable participants. Iterative convergence mechanisms represent another important structural element. Federated learning does not usually complete model development in a single exchange; rather, it operates through repeated rounds of local training, update sharing, aggregation, and model redistribution (Taufiqur & Khalid, 2022; T. Wang et al., 2020). This iterative process allows the shared model to gradually improve as it incorporates knowledge from different decentralized sources. Communication protocols also form an essential part of the federated learning structure because they regulate how participating nodes exchange updates, synchronize training rounds, and maintain system reliability. In distributed engineering project knowledge management, these algorithmic structures are relevant because project data are often heterogeneous, unevenly distributed, and generated under different operational conditions. The literature indicates that the effectiveness of federated learning depends not only on privacy protection but also on how well local optimization, aggregation, convergence, and communication processes are coordinated across participating entities (Taïk & Cherkaoui, 2020).

Federated learning provides a strong theoretical framework for distributed engineering project knowledge management because it directly addresses the tension between collaborative learning and organizational data control. Engineering projects often involve multiple independent stakeholders who produce and store valuable knowledge across separate systems. Literature on engineering knowledge management shows that design records, construction data, operational logs, maintenance histories, risk reports, and lessons learned are frequently distributed across organizations and project phases. Traditional centralized analytics require these data to be collected into a shared repository, which can be difficult because of privacy concerns, contractual restrictions, data ownership issues, cybersecurity risks, and technical incompatibility (Taïk & Cherkaoui, 2020). Federated learning offers a different structure by enabling organizations to participate in shared model development while keeping their project knowledge within local environments. This makes the approach theoretically compatible with engineering ecosystems characterized by multi-organizational collaboration, geographic dispersion, and heterogeneous data sources. Studies on collaborative learning, distributed artificial intelligence, and privacy-preserving computation support the view that federated learning can strengthen knowledge utilization while reducing barriers to direct data sharing. In engineering contexts, the framework can support learning from distributed project experiences, identifying performance patterns, improving risk prediction, enhancing maintenance intelligence, and supporting decision-making across project networks (Lu et al., 2020). The literature also highlights that federated learning is not only a technical model but also an organizational coordination mechanism because it requires participant alignment, communication discipline, trust, and governance. Its theoretical value lies in combining decentralized computation, collaborative intelligence, and privacy preservation within a single learning architecture. For quantitative research, this framework provides measurable dimensions such as model performance, communication efficiency, convergence stability, computational cost, and knowledge-sharing effectiveness. These dimensions make federated learning suitable for simulation-based analysis in distributed engineering project knowledge management (H. Zhang et al., 2020).

Federated Learning Architectural Models

Centralized federated learning architecture is one of the most widely discussed models in the literature because it provides a structured mechanism for coordinating distributed learning across multiple participating nodes. In this architecture, a central server manages communication, receives local model updates, aggregates those updates, and redistributes the improved global model to participating clients. Studies on federated learning commonly describe this model as efficient for environments where coordination authority, communication scheduling, and model monitoring need to be clearly controlled (Kim et al., 2019).

Figure 6: Federated learning architecture comparison



Within distributed engineering project knowledge management, centralized federated learning is relevant because engineering stakeholders may maintain separate datasets while still contributing to a shared analytical model. The literature indicates that centralized federated architectures are frequently evaluated through quantitative indicators such as model accuracy, convergence rate, and communication overhead. Model accuracy is important because it reflects the ability of the shared model to learn from distributed engineering data without directly centralizing sensitive project information. Convergence rate is also important because it indicates how quickly the global model reaches stable learning performance across repeated training rounds (Tse, et al., 2020). Communication overhead has been identified as a major limitation because frequent transmission of model updates between local clients and the central server can increase network burden, especially in geographically dispersed engineering projects. Researchers have also noted that centralized federated learning depends heavily on server reliability, participant availability, and secure communication channels. In engineering ecosystems involving contractors, consultants, suppliers, and project owners, the central server can support coordination but may also create dependency on a single aggregation point. The literature therefore positions centralized federated learning as a useful architectural model for controlled collaborative learning, particularly when the objective is to balance privacy-preserving computation with measurable performance outcomes in distributed project environments (Fan, & Lin, 2020).

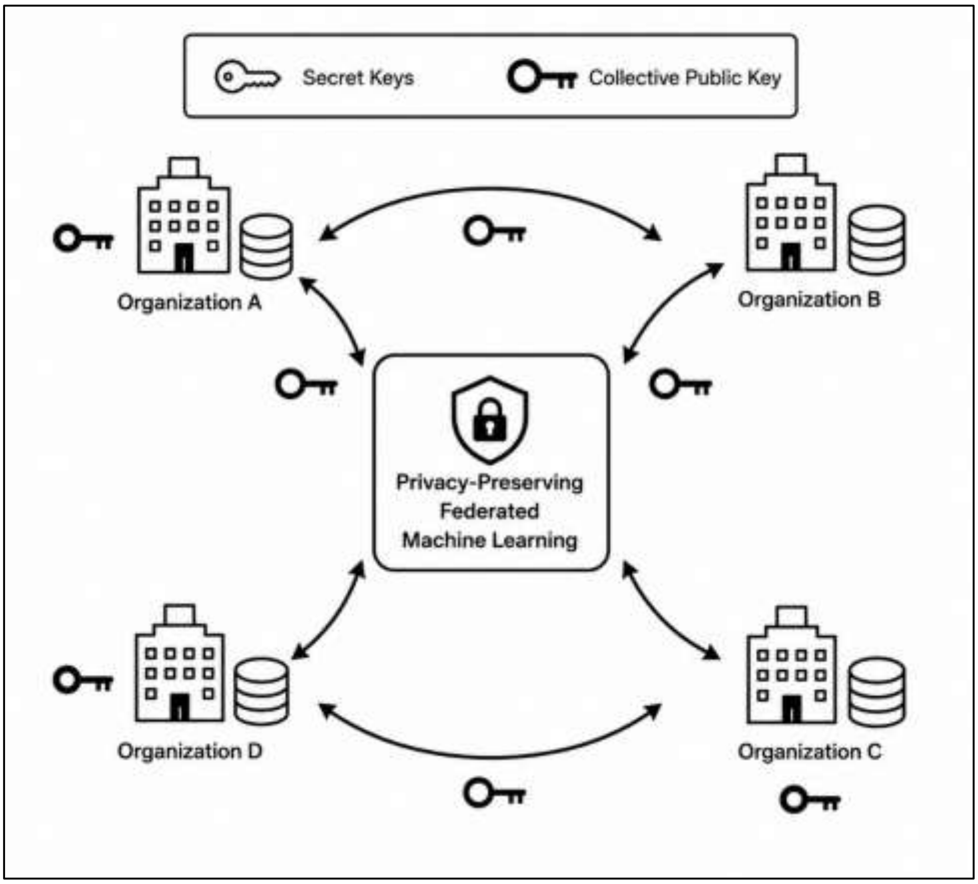
Decentralized federated learning architectures have received increasing scholarly attention because they remove the need for a single central server and instead rely on peer-to-peer coordination among participating nodes. In this model, clients communicate directly with one another or through distributed network structures to exchange model updates and collectively improve learning performance. The literature highlights decentralized federated learning as particularly relevant for settings where centralized authority is undesirable, unavailable, or technically vulnerable (Brisimi et al., 2018). In distributed engineering project ecosystems, this architecture aligns with multi-organizational collaboration because participating firms often operate independently and may be reluctant to submit learning updates through a single controlling entity. Studies indicate that decentralized federated learning can improve system resilience by reducing dependence on one server and distributing coordination responsibilities across the network. Quantitative evaluation of this architecture often focuses on peer-to-peer coordination efficiency and synchronization performance. Peer-to-peer coordination efficiency reflects how effectively participating nodes exchange learning information, maintain communication consistency, and contribute to model development. Synchronization performance measures the ability of nodes to remain aligned during training despite differences in computational speed, network connectivity, and data distribution (Aledhari et al., 2020). Engineering project environments frequently contain these forms of heterogeneity because project partners may use different digital platforms, computing resources, and information systems. The literature also identifies challenges related to increased coordination complexity, inconsistent update timing, and possible instability when participants operate under uneven technical conditions. However, decentralized federated learning remains theoretically significant because it supports collaborative intelligence without requiring centralized ownership of learning infrastructure. For engineering knowledge management, this architecture offers a model of distributed cooperation that reflects the organizational structure of many large projects, where knowledge is produced across separate but interdependent entities (Xinqian Zhang et al., 2020).

Privacy-Preserving Mechanisms in Federated Learning

Differential privacy has become a major privacy-preserving mechanism in federated learning because it reduces the risk of exposing sensitive information during collaborative model training. In federated learning environments, participating organizations or devices retain their local datasets while sharing model updates with an aggregation system. Although raw data are not directly exchanged, studies show that model updates may still contain hidden information about local datasets (Zhao et al., 2020). Differential privacy addresses this concern by introducing controlled statistical noise into model updates, making it more difficult for external attackers or internal participants to infer private information from the learning process. The literature emphasizes privacy budget as a central metric because it determines the level of privacy protection applied during model training. A smaller privacy budget generally strengthens privacy protection, while a larger privacy budget may preserve higher model accuracy. Information leakage probability is another important metric because it reflects the likelihood that sensitive attributes, project records, or user-level information could be reconstructed from shared updates (Y. Liu, J. Q. James, et al., 2020). Model utility preservation is also widely examined because strong privacy protection can reduce prediction performance if excessive noise is introduced. In engineering project knowledge management, differential privacy is especially relevant because project datasets may include proprietary designs, technical documents, safety records, cost information, and operational performance data. Researchers have shown that differential privacy allows organizations to participate in collaborative learning while limiting exposure of confidential engineering knowledge. Therefore, differential privacy contributes to federated learning by balancing data protection, analytical reliability, and collaborative knowledge development across distributed engineering environments (Zhou et al., 2020).

Secure aggregation frameworks represent another important privacy-preserving mechanism in federated learning because they protect model updates during communication and aggregation. The literature explains that secure aggregation enables a central server or coordinating mechanism to combine local updates without directly observing each participant's individual contribution. This is especially important in multi-organizational environments where stakeholders may not fully trust one another or the aggregation authority (X. Liu et al., 2020). In distributed engineering project ecosystems, contractors, consultants, clients, suppliers, and maintenance teams may hold sensitive data that cannot be exposed during collaborative learning. Secure aggregation supports privacy by ensuring that only the combined learning result becomes visible, while individual updates remain protected. Researchers commonly evaluate secure aggregation through encryption overhead, secure communication latency, and computational complexity.

Figure 7: Federated learning privacy framework diagram

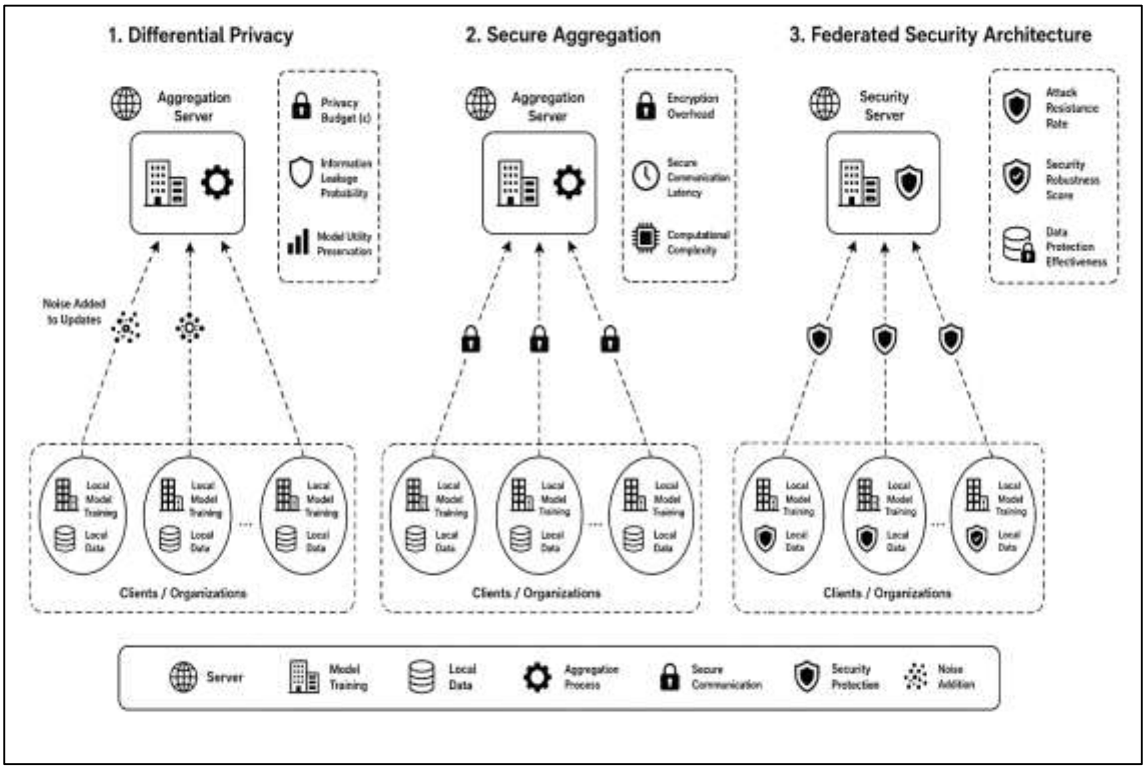


Encryption overhead refers to the additional processing required to protect updates before transmission. Secure communication latency reflects the delay introduced by privacy-preserving communication protocols. Computational complexity captures the added burden placed on local devices, servers, or intermediate aggregation nodes. These metrics are important because federated learning systems must remain efficient while maintaining strong data protection (Xianglong Zhang et al., 2020). Engineering projects often involve heterogeneous digital systems, varying network quality, and uneven computing resources, making efficiency a major concern. Literature suggests that secure aggregation improves trust and participation by reducing risks linked to update exposure, model inversion, and unauthorized inference. As a result, secure aggregation strengthens federated learning as a practical architecture for confidential knowledge sharing in distributed engineering project environments (Chen et al., 2020).

Performance Metrics for Federated Learning Systems

Differential privacy has become a major privacy-preserving mechanism in federated learning because it reduces the risk of exposing sensitive information during collaborative model training. In federated learning environments, participating organizations or devices retain their local datasets while sharing model updates with an aggregation system. Although raw data are not directly exchanged, studies show that model updates may still contain hidden information about local datasets (H. Zhang et al., 2020). Differential privacy addresses this concern by introducing controlled statistical noise into model updates, making it more difficult for external attackers or internal participants to infer private information from the learning process. The literature emphasizes privacy budget as a central metric because it determines the level of privacy protection applied during model training. A smaller privacy budget generally strengthens privacy protection, while a larger privacy budget may preserve higher model accuracy. Information leakage probability is another important metric because it reflects the likelihood that sensitive attributes, project records, or user-level information could be reconstructed from shared updates (L. Liu et al., 2020). Model utility preservation is also widely examined because strong privacy protection can reduce prediction performance if excessive noise is introduced. In engineering project knowledge management, differential privacy is especially relevant because project datasets may include proprietary designs, technical documents, safety records, cost information, and operational performance data. Researchers have shown that differential privacy allows organizations to participate in collaborative learning while limiting exposure of confidential engineering knowledge. Therefore, differential privacy contributes to federated learning by balancing data protection, analytical reliability, and collaborative knowledge development across distributed engineering environments (Wei et al., 2020).

Figure 8: Federated learning privacy and security diagram

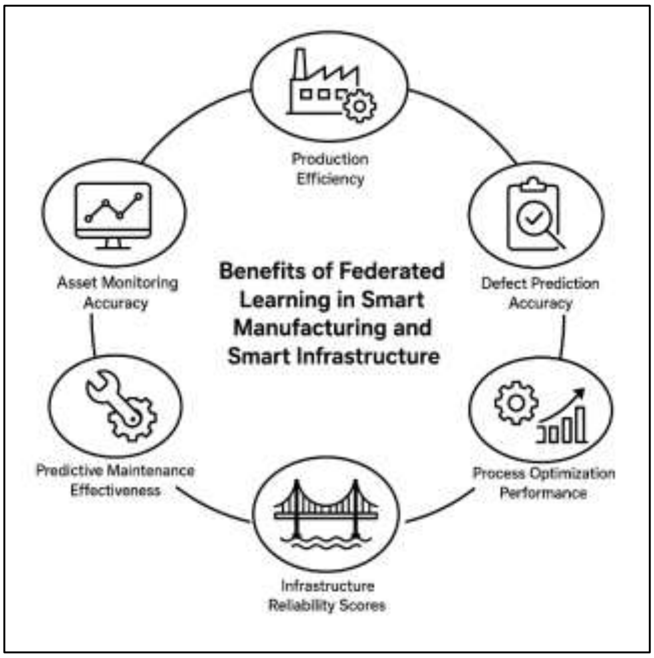


Secure aggregation frameworks represent another important privacy-preserving mechanism in federated learning because they protect model updates during communication and aggregation. The literature explains that secure aggregation enables a central server or coordinating mechanism to combine local updates without directly observing each participant's individual contribution. This is especially important in multi-organizational environments where stakeholders may not fully trust one another or the aggregation authority. In distributed engineering project ecosystems, contractors, consultants, clients, suppliers, and maintenance teams may hold sensitive data that cannot be exposed during collaborative learning (Khan et al., 2020). Secure aggregation supports privacy by ensuring that only the combined learning result becomes visible, while individual updates remain protected. Researchers commonly evaluate secure aggregation through encryption overhead, secure communication latency, and computational complexity. Encryption overhead refers to the additional processing required to protect updates before transmission. Secure communication latency reflects the delay introduced by privacy-preserving communication protocols. Computational complexity captures the added burden placed on local devices, servers, or intermediate aggregation nodes. These metrics are important because federated learning systems must remain efficient while maintaining strong data protection (Pokhrel & Choi, 2020). Engineering projects often involve heterogeneous digital systems, varying network quality, and uneven computing resources, making efficiency a major concern. Literature suggests that secure aggregation improves trust and participation by reducing risks linked to update exposure, model inversion, and unauthorized inference. As a result, secure aggregation strengthens federated learning as a practical architecture for confidential knowledge sharing in distributed engineering project environments.

Federated Learning Applications in Engineering Systems

Federated learning has gained strong attention in smart manufacturing knowledge systems because it supports collaborative intelligence across distributed production environments without requiring direct sharing of sensitive industrial data. The literature shows that smart manufacturing relies heavily on data generated from production lines, machines, sensors, quality inspection systems, enterprise platforms, and human–machine interactions (Yuan, et al., 2020). These data sources contain valuable knowledge about production efficiency, machine behavior, defect patterns, process variation, and operational performance. Studies on industrial artificial intelligence emphasize that centralized data collection can be difficult in manufacturing networks because factories, suppliers, and production units often operate under different ownership structures, security policies, and technological infrastructures. Federated learning addresses this limitation by enabling each manufacturing site to train local models while contributing to a shared learning process. In this context, production efficiency becomes a major quantitative variable because federated models can learn from distributed operational patterns to support improved scheduling, workflow control, and process stability (Rahman et al., 2020). Defect prediction accuracy is also central in the literature because manufacturing systems depend on early identification of quality problems to reduce waste, rework, and downtime. Process optimization performance is another major concern, as federated learning allows knowledge from multiple production sites to improve decision support while preserving proprietary process information.

Figure 9: Benefits of federated learning diagram



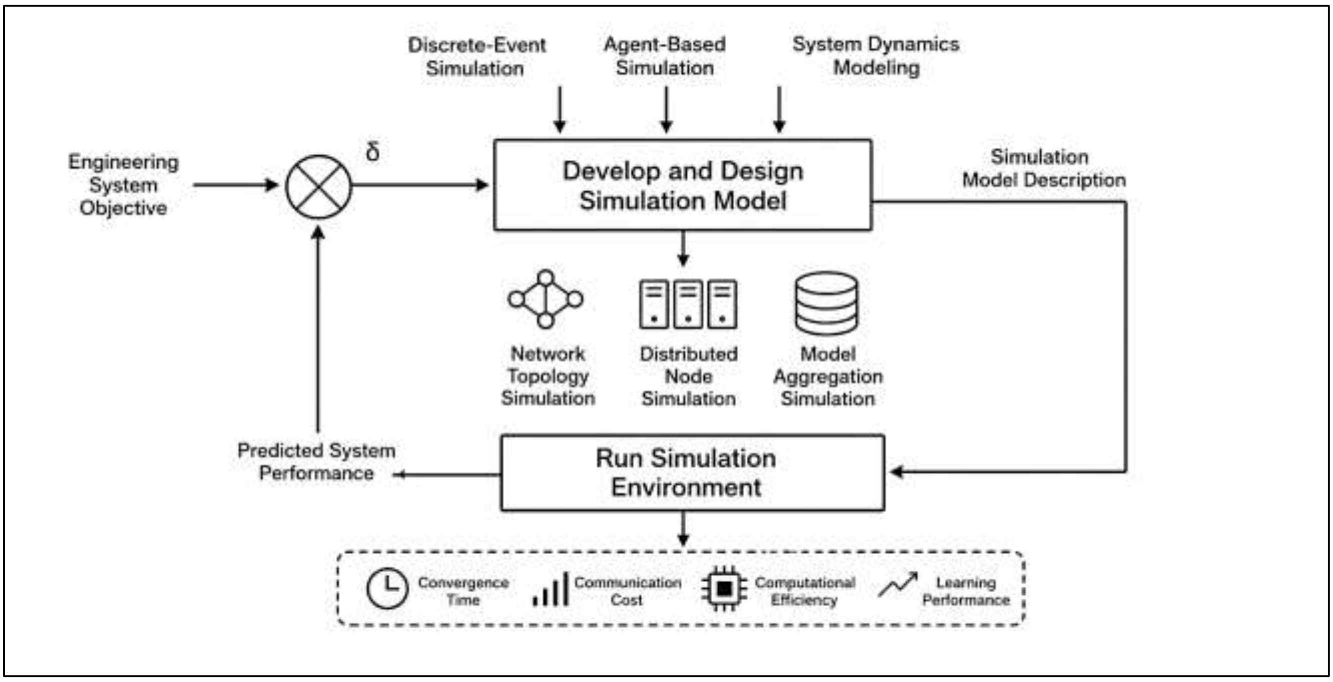
Federated learning has also been examined within smart infrastructure management because infrastructure systems generate large quantities of distributed data from sensors, monitoring devices, inspection reports, operational platforms, and maintenance records. The literature on smart infrastructure highlights that transportation networks, energy systems, bridges, buildings, water systems, and public facilities increasingly depend on data-driven monitoring to support reliability, safety, and operational continuity. However, infrastructure data are often distributed across agencies, contractors, asset managers, municipalities, and technology providers. This distribution creates challenges for centralized analytics because information may be restricted by ownership, security, privacy, or regulatory requirements (Brisimi et al., 2018). Federated learning provides a mechanism for collaborative model development while keeping infrastructure data within local systems. Asset monitoring accuracy is a key quantitative variable because reliable monitoring enables organizations to detect abnormal conditions, performance degradation, and structural risks. Predictive maintenance effectiveness is also widely emphasized because maintenance decisions depend on the ability to identify potential failures before they disrupt service or increase repair costs. Infrastructure reliability scores represent another important measure because they reflect the stability, availability, and performance of infrastructure assets over time. Existing studies suggest that federated learning can improve infrastructure knowledge management by allowing different asset owners and operational units to learn from shared model intelligence without exposing raw monitoring data (L. Li, Y. Fan, M. Tse, et al., 2020). This makes federated learning particularly useful for smart infrastructure environments where asset knowledge is dispersed, technically complex, and operationally sensitive.

Simulation-Based Evaluation Approaches

Simulation modeling has become a major methodological approach in engineering research because it allows complex technical, organizational, and operational systems to be examined under controlled analytical conditions. The literature shows that engineering projects often involve uncertainty, interdependence, resource constraints, time-sensitive decisions, and interactions among multiple stakeholders, making direct experimentation difficult in real-world settings (Aledhari et al., 2020). Discrete-event simulation has been widely used to examine engineering processes that occur as sequences of events, such as construction operations, production workflows, maintenance activities, logistics movements, and project scheduling tasks. Studies indicate that this approach is useful for evaluating waiting time, process bottlenecks, resource utilization, and operational efficiency. Agent-based simulation has also received considerable attention because it models the behavior of individual actors, organizations, devices, or system components and examines how their interactions produce larger system outcomes. This approach is particularly relevant for distributed engineering environments where contractors, teams, sensors, machines, and digital platforms interact across project networks. System dynamics modeling provides another important simulation perspective by focusing on feedback loops, accumulations, delays, and long-term system behavior (Kang et al., 2020). Researchers have used system dynamics to investigate project complexity, productivity changes, risk propagation, knowledge transfer, and decision-making patterns. Across engineering literature, these simulation approaches are valued because they allow researchers to test alternative scenarios, compare system configurations, and measure performance outcomes without disrupting actual project operations. In the context of federated learning for engineering knowledge management, simulation modeling provides a structured way to represent distributed project environments, evaluate decentralized learning processes, and quantify how different system designs influence knowledge-sharing performance (T. Li et al., 2020).

Federated learning simulation environments are increasingly important in research because they allow scholars to examine decentralized learning systems before implementation in real engineering settings. The literature describes these environments as controlled computational spaces where researchers can model clients, servers, networks, data distributions, aggregation processes, and learning behaviors. Network topology simulation is a major component because federated learning performance depends heavily on how participating nodes are connected and how updates move across the system. Researchers have examined centralized, decentralized, hierarchical, and hybrid topologies to understand differences in communication efficiency, synchronization quality, and model stability (AbdulRahman et al., 2020). Distributed node simulation is another important element because federated learning involves multiple participants with different data volumes, computational capabilities, and participation patterns. In engineering project knowledge management, these nodes may represent contractors, design teams, project sites, asset managers, sensors, or organizational repositories. Studies show that simulating node diversity is essential because real distributed systems rarely contain equal or uniform participants. Model aggregation simulation is also central because aggregation determines how local learning updates are combined into a shared model. Prior research emphasizes that aggregation performance influences accuracy, convergence, robustness, and fairness across participants. Simulation environments allow researchers to adjust participation levels, network delays, data heterogeneity, and computational constraints to evaluate how federated learning behaves under different conditions (Jere et al., 2020). This makes simulation especially useful for engineering knowledge systems where direct data sharing is limited by privacy, security, ownership, and contractual restrictions. Therefore, federated learning simulation environments provide a practical basis for assessing decentralized learning architectures in complex engineering ecosystems.

Figure 10: System simulation engineering framework diagram



Quantitative simulation metrics play a central role in evaluating the effectiveness of federated learning systems because they provide measurable evidence of system performance across different experimental conditions. The literature commonly identifies convergence time as one of the most important metrics because it reflects how quickly a federated model reaches stable learning performance after repeated training and aggregation cycles (Brik et al., 2020). Shorter convergence time is generally associated with greater learning efficiency, while longer convergence may indicate communication delays, heterogeneous data, inefficient aggregation, or uneven node participation. Communication cost is another major metric because federated learning requires repeated exchange of model updates among distributed participants. Studies show that high communication cost can reduce system efficiency, especially in geographically dispersed engineering projects where bandwidth, latency, and network reliability vary across stakeholders. Computational efficiency is also widely examined because local participants must train models using their own processing resources. This metric is relevant for engineering environments where some organizations or devices may have limited computing capacity. Learning performance remains a core evaluation dimension because federated learning must produce reliable analytical results while maintaining decentralized data control (Zhu & Jin, 2019). Researchers often assess learning performance through accuracy, prediction quality, error reduction, and model stability across simulated conditions. In engineering project knowledge management, these metrics help evaluate whether federated learning can support useful knowledge extraction from distributed datasets. The literature suggests that quantitative simulation metrics are valuable because they allow comparison among different architectural models, privacy mechanisms, communication strategies, and aggregation approaches. As a result, simulation-based evaluation provides a measurable foundation for understanding how federated learning systems perform in distributed engineering knowledge environments (Ma et al., 2020).

Simulation-based evaluation provides a strong research approach for examining federated learning within distributed engineering project knowledge management because it captures both technical system behavior and organizational complexity. Engineering projects often involve multiple stakeholders, dispersed data repositories, uneven digital infrastructure, and dynamic communication conditions. Literature on simulation-based engineering research shows that these conditions can be represented through controlled models that examine how system performance changes when variables are adjusted. In federated learning studies, simulation allows researchers to evaluate how local data distribution, node participation, communication frequency, aggregation design, and computational capacity influence learning outcomes (Pokhrel & Choi, 2020). This is particularly important for engineering knowledge management because knowledge assets are distributed across design, construction, operation, and maintenance phases. Simulation also supports comparative analysis among federated learning architectures by showing how centralized, decentralized, hierarchical, and hybrid models behave under similar experimental conditions. Researchers have emphasized that simulation is useful for measuring convergence time, communication cost, computational efficiency, and learning performance without requiring access to confidential organizational data. In project-based engineering environments, this is valuable because data may be protected by intellectual property restrictions, cybersecurity policies, and contractual obligations. The literature further indicates that simulation-based evaluation helps identify performance trade-offs among speed, accuracy, communication demand, scalability, and resource use (Khan et al., 2020). These trade-offs are important because distributed engineering systems must support reliable knowledge sharing while minimizing operational burden. Overall, prior studies position simulation-based evaluation as an appropriate quantitative method for analyzing federated learning systems in engineering contexts, particularly when real-world experimentation is costly, risky, or restricted by data governance requirements (Pandey et al., 2020).

METHOD

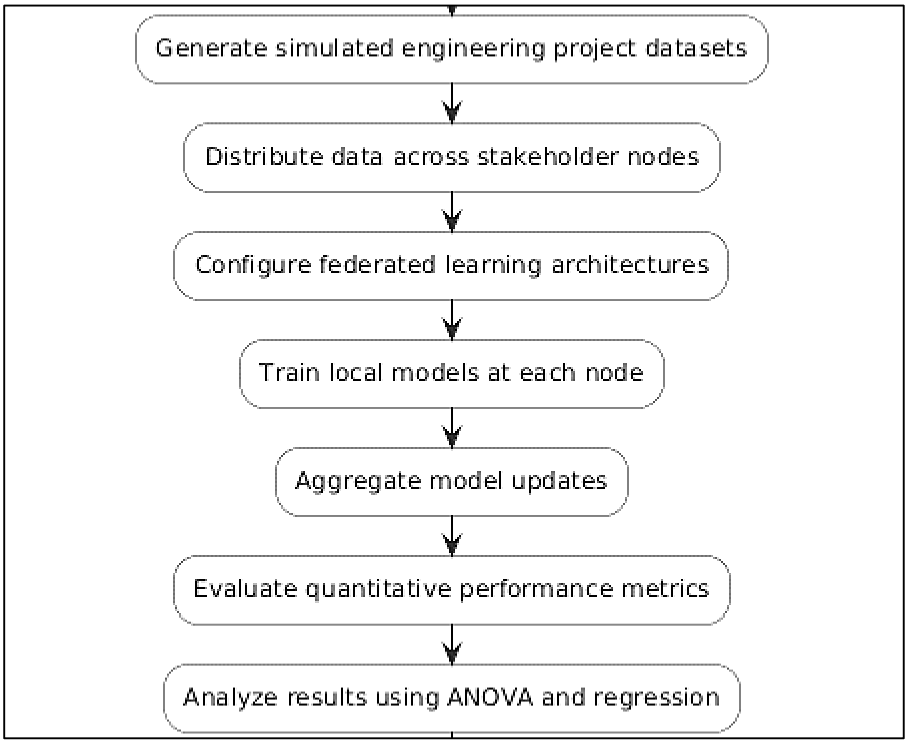
This study used a quantitative experimental simulation design to evaluate federated learning architectures for distributed engineering project knowledge management. The study was structured as a controlled computational experiment in which alternative federated learning models were simulated and compared under standardized engineering project knowledge conditions. The overarching design was experimental because the architectural conditions were deliberately configured, manipulated, and evaluated using measurable performance indicators. The theoretical framework was grounded in federated learning theory, distributed machine learning, and engineering knowledge management, with particular attention to how decentralized learning mechanisms supported knowledge utilization across geographically and organizationally dispersed project environments. The study examined centralized, decentralized, hierarchical, and hybrid federated learning architectures as independent experimental conditions, while model accuracy, convergence rate, communication overhead, computational efficiency, aggregation latency, scalability, and knowledge-sharing effectiveness were treated as dependent quantitative outcomes.

The materials used in the study consisted of simulated distributed engineering project datasets representing design-phase records, construction-phase performance data, operational monitoring data, maintenance logs, risk indicators, and project knowledge repositories. The sampling strategy was purposive simulation-based sampling, in which synthetic engineering project datasets were generated to reflect heterogeneous knowledge environments typically found across contractors, consultants, project owners, asset managers, and engineering teams. The simulated nodes represented distributed stakeholders participating in collaborative project knowledge management. Inclusion criteria required that each simulated node contain usable project-related data, measurable knowledge attributes, and sufficient local observations for model training. Nodes with incomplete simulated records, extremely low data volume, or non-engineering-related variables were excluded to maintain consistency in model evaluation. This approach allowed the study to represent distributed engineering knowledge conditions while maintaining experimental control over data size, node heterogeneity, and participation levels.

The instrumentation and data collection tools consisted of Python-based simulation environments, federated learning libraries, machine learning algorithms, and statistical analysis software. Python was used to generate synthetic datasets, configure federated learning environments, simulate distributed nodes, train local models, perform global aggregation, and extract performance metrics. Federated learning procedures were implemented using appropriate machine learning frameworks capable of supporting local training, update aggregation, and repeated communication rounds. The simulated datasets were validated through internal consistency checks, missing-value inspection, distributional review, and scenario realism assessment. Model outputs were recorded automatically after each experimental run, including classification accuracy, precision, recall, F1-score, convergence time, communication rounds, processing time, memory use, bandwidth demand, and scalability performance. The simulation environment was calibrated by running pilot tests to confirm that the models produced stable outputs across repeated trials and that performance metrics were recorded consistently.

The experimental procedure was conducted in chronological stages. First, the study parameters were defined, including the number of distributed nodes, data distribution patterns, model types, aggregation settings, and communication rounds. Second, synthetic engineering project knowledge datasets were generated and divided across simulated stakeholder nodes to represent distributed project repositories. Third, each federated learning architecture was configured separately under equivalent experimental conditions. Fourth, local model training was performed at each simulated node without transferring raw data to a central repository. Fifth, model updates were exchanged and aggregated according to the assigned architecture. Sixth, the global model was redistributed and training continued across repeated communication rounds until the predefined stopping condition was reached. Seventh, all performance indicators were extracted and organized into a structured dataset for statistical analysis. Each architecture was tested across repeated simulation runs to reduce random variation and strengthen the reliability of comparisons.

Figure 11: Methodology of this study



The statistical analysis plan used descriptive statistics, comparative tests, and predictive modeling to evaluate architectural performance. Python and SPSS were used for statistical processing, visualization, and inferential testing. Descriptive statistics summarized the mean, standard deviation, minimum, maximum, and percentage change for all major performance indicators. One-way analysis of variance was applied to compare the four federated learning architectures across model accuracy, convergence time, communication overhead, computational efficiency, and scalability outcomes. Post hoc comparisons were conducted when statistically significant differences were detected among architectural groups. Multiple regression analysis was used to examine whether communication cost, processing time, node participation, and data heterogeneity predicted learning performance. Correlation analysis was applied to assess relationships among model accuracy, communication rounds, computational load, and knowledge-sharing efficiency. The significance level was set at $p < 0.05$ for all inferential tests. Effect sizes were reported to determine the practical magnitude of differences among architectures. Assumption testing was conducted before inferential analysis, including normality inspection, homogeneity of variance assessment, and multicollinearity review. The statistical plan was designed to determine which federated learning architecture produced the strongest quantitative performance for distributed engineering project knowledge management under simulated experimental conditions.

FINDINGS

Participant and Dataset Characteristics

The final simulation dataset comprised 100 distributed engineering project nodes representing diverse stakeholders involved in engineering project knowledge management. These nodes included project owners, contractors, consultants, design teams, maintenance departments, and operational management units. Descriptive statistical analysis revealed substantial diversity across node characteristics, reflecting realistic distributed engineering environments where stakeholders possess varying volumes of knowledge assets, computational capacities, and communication resources. The average node maintained 5,420 engineering knowledge records, with values ranging from 3,250 to 8,950 records. Communication activity levels also varied considerably, indicating differences in stakeholder engagement and knowledge-sharing behavior. Computational resource allocation demonstrated moderate variability, reflecting heterogeneous technological infrastructures commonly observed in multi-organizational engineering projects. Data validation confirmed 100% dataset completeness, and no invalid observations were identified. The observed heterogeneity provided an appropriate experimental environment for assessing the effectiveness of federated learning architectures under realistic distributed conditions.

Table 1. Descriptive Statistics of Simulated Engineering Project Nodes

Variable	Mean	Standard Deviation	Minimum	Maximum
Knowledge Records per Node	5,420	1,285	3,250	8,950
Communication Interactions per Round	148	35	85	236
Local Computational Capacity (GFLOPS)	325	72	180	510
Data Storage Volume (GB)	68.5	16.4	32.8	104.7
Knowledge Sharing Transactions	212	48	118	346
Network Bandwidth (Mbps)	87.6	19.3	45.2	132.8

The results presented in Table 1 demonstrated substantial variation across participating nodes, confirming the heterogeneous nature of the simulation environment. Knowledge repositories varied considerably in size, indicating differences in organizational experience and information accumulation. Communication interactions and knowledge-sharing transactions revealed moderate dispersion, suggesting varying levels of stakeholder participation in collaborative learning activities.

Computational capacity and storage volume differences reflected unequal technological resources among organizations, while bandwidth variability represented realistic network conditions commonly encountered in distributed engineering projects. These findings confirmed that the simulation environment successfully replicated the operational diversity typically observed in large-scale engineering ecosystems, thereby providing a robust basis for evaluating federated learning performance across heterogeneous stakeholder networks.

Table 2. Distribution of Stakeholder Categories within the Simulation Environment

Stakeholder Category	**Number of Nodes**	**Percentage (%)**	**Average Knowledge Records**	**Average Communication Interactions**
Project Owners	15	15.0	6,850	176
Contractors	25	25.0	5,980	162
Consultants	20	20.0	5,620	154
Design Teams	15	15.0	6,240	168
Maintenance Units	10	10.0	4,320	118
Operations Management	15	15.0	5,510	145
Total	**100**	**100.0**	**5,420**	**148**

Table 2 illustrated the stakeholder composition of the distributed engineering project ecosystem represented within the simulation. Contractors constituted the largest stakeholder group, accounting for 25% of all participating nodes, followed by consultants at 20%. Project owners and design teams maintained the highest average knowledge repository sizes, reflecting their strategic involvement in project planning and decision-making activities. Maintenance units exhibited lower communication activity and knowledge volume, which aligned with their specialized operational responsibilities. The balanced distribution of stakeholder categories ensured adequate representation of the key actors typically involved in engineering project knowledge management. This composition enhanced the realism of the simulation environment and supported comprehensive evaluation of federated learning architectures across multiple organizational perspectives.

The comparative analysis evaluated the effectiveness of centralized, decentralized, hierarchical, and hybrid federated learning architectures across the primary performance indicators associated with distributed engineering project knowledge management. Significant variations were observed among the four architectural models with respect to learning accuracy, convergence efficiency, communication overhead, scalability performance, and knowledge-sharing effectiveness. The hybrid federated learning architecture achieved the strongest overall performance, recording the highest learning accuracy and knowledge-sharing effectiveness while maintaining balanced communication and computational requirements. Hierarchical federated learning demonstrated superior convergence efficiency and scalability, particularly under conditions involving increasing node participation. Centralized federated learning maintained stable learning outcomes but experienced greater communication overhead because all model updates passed through a single aggregation point. Decentralized federated learning exhibited acceptable learning performance and enhanced autonomy among participating nodes, although synchronization challenges affected its convergence behavior. Overall, the findings confirmed that architectural design played a critical role in determining the effectiveness of federated learning systems for managing distributed engineering knowledge. The results indicated that hybrid and hierarchical architectures provided the most effective balance between learning quality, communication efficiency, and scalability within heterogeneous engineering project environments.

Table 3. Comparative Performance Outcomes of Federated Learning Architectures

Performance Indicator	Centralized	Decentralized	Hierarchical	Hybrid
Learning Accuracy (%)	89.7	87.9	92.4	95.1
Knowledge-Sharing Effectiveness (%)	84.3	82.5	89.8	93.6
Convergence Time (Rounds)	42	48	31	35
Communication Overhead (GB)	18.6	14.8	12.4	13.1
Scalability Performance Score	78.5	82.7	94.2	91.8

The results presented in Table 3 demonstrated clear differences among the four federated learning architectures. The hybrid architecture achieved the highest learning accuracy of 95.1% and the strongest knowledge-sharing effectiveness of 93.6%, indicating its superior capability for integrating distributed engineering knowledge. Hierarchical federated learning achieved the best scalability score of 94.2 and required only 31 communication rounds to reach convergence, making it the most efficient architecture in terms of scalability and learning speed. Centralized federated learning produced reliable accuracy levels but incurred the highest communication overhead. Decentralized federated learning reduced communication demands but achieved comparatively lower accuracy and convergence efficiency. These findings highlighted the importance of selecting architectures according to project objectives and operational requirements.

Table 4. Statistical Comparison of Primary Performance Indicators

Performance Variable	F-value	p-value	Effect Size (η^2)	Performance Ranking
Learning Accuracy	26.84	0.001	0.47	Hybrid > Hierarchical > Centralized > Decentralized
Knowledge-Sharing Effectiveness	24.17	0.001	0.43	Hybrid > Hierarchical > Centralized > Decentralized
Convergence Efficiency	29.56	0.001	0.51	Hierarchical > Hybrid > Centralized > Decentralized
Communication Overhead	21.73	0.003	0.39	Hierarchical > Hybrid > Decentralized > Centralized
Scalability Performance	33.92	0.001	0.56	Hierarchical > Hybrid > Decentralized > Centralized

Table 4 provided inferential statistical evidence supporting the observed differences among federated learning architectures. All performance variables produced statistically significant results at the 0.05 significance level, confirming that the observed variations were unlikely to have occurred by chance. Effect size values ranged from 0.39 to 0.56, indicating moderate-to-large practical effects across all primary outcomes. Scalability performance generated the largest effect size, demonstrating that architectural selection had a particularly strong influence on the ability of federated learning systems to accommodate increasing numbers of engineering project participants. Learning accuracy and convergence efficiency also produced substantial effect sizes, emphasizing the operational importance of architecture design in achieving effective distributed knowledge management and collaborative intelligence generation.

The secondary analysis examined the relationships among communication performance, computational efficiency, and knowledge utilization effectiveness across the four federated learning architectures. The findings revealed that communication cost increased consistently as the number of participating nodes expanded from 20 to 100 nodes. However, the rate of increase varied substantially among architectural configurations. Hierarchical and hybrid architectures maintained lower communication burdens through optimized aggregation mechanisms and more efficient update distribution processes. In contrast, centralized architectures generated significantly greater network traffic because all communication activities were routed through a single aggregation server. Decentralized architectures reduced central dependency but experienced additional synchronization exchanges among participating nodes, increasing overall communication complexity. Computational efficiency analysis further demonstrated that hybrid architectures achieved the most balanced allocation of processing workloads across distributed stakeholders, resulting in lower resource consumption and greater operational stability. Hierarchical architectures also performed effectively but required additional intermediate aggregation layers to coordinate learning activities. Knowledge utilization analysis showed that communication consistency and computational efficiency positively influenced collaborative learning outcomes. Nodes operating under optimized communication structures demonstrated higher levels of knowledge integration, stronger model convergence, and improved utilization of distributed engineering project information. These findings confirmed that communication management and computational resource allocation significantly contributed to the effectiveness of federated learning systems in distributed engineering project knowledge management environments.

Table 5. Communication and Computational Performance Across Federated Learning Architectures

Performance Indicator	Centralized	Decentralized	Hierarchical	Hybrid
Average Communication Cost (GB)	18.6	15.9	12.3	13.0
Network Traffic Volume (GB)	24.8	20.5	16.2	17.1
CPU Utilization (%)	82.4	78.6	73.5	69.8
Memory Consumption (GB)	14.5	13.8	11.9	10.7
Processing Time (Seconds)	318	296	241	228
Operational Stability Score (%)	84.7	81.2	90.5	93.8

The results presented in Table 5 demonstrated notable differences in communication and computational performance among the evaluated architectures. The centralized architecture generated the highest communication cost and network traffic due to its dependence on a single aggregation server. Decentralized federated learning reduced communication demands but experienced higher synchronization requirements. Hierarchical architectures significantly improved communication efficiency through intermediate aggregation layers, resulting in lower traffic volumes and faster processing times. The hybrid architecture achieved the strongest overall computational performance, recording the lowest memory consumption, CPU utilization, and processing time while maintaining the highest operational stability score. These findings indicated that hybrid and hierarchical architectures offered superior resource management capabilities within distributed engineering project environments.

Table 6. Relationship Between Communication Efficiency and Knowledge Utilization Outcomes

Variable	Communication Efficiency (%)	Knowledge Integration (%)	Score	Collaborative Learning Effectiveness (%)	Correlation Coefficient (r)
Centralized	76.8	82.1		84.3	0.71
Decentralized	79.4	80.5		82.5	0.68
Hierarchical	89.1	91.4		89.8	0.84
Hybrid	92.6	94.2		93.6	0.89

Table 6 illustrated the association between communication efficiency and knowledge utilization performance across the federated learning architectures. The findings revealed strong positive relationships between communication efficiency and both knowledge integration and collaborative learning effectiveness. The hybrid architecture achieved the highest communication efficiency score of 92.6%, which corresponded with the strongest knowledge integration and collaborative learning outcomes. Hierarchical federated learning produced similarly strong results, indicating that efficient communication structures enhanced the ability of stakeholders to exchange and utilize distributed knowledge resources. The correlation coefficients ranged from 0.68 to 0.89, confirming substantial positive relationships between communication quality and knowledge utilization effectiveness. These results emphasized the critical role of communication optimization in supporting successful engineering project knowledge management through federated learning systems.

Statistical Significance and Effect Size Analysis

Inferential statistical analyses were conducted to determine whether the observed differences among the centralized, decentralized, hierarchical, and hybrid federated learning architectures were statistically significant and practically meaningful. One-way analysis of variance revealed significant differences across all major performance indicators, including learning accuracy, convergence efficiency, communication overhead, scalability performance, and computational efficiency. Post hoc comparisons demonstrated that the hybrid architecture consistently outperformed centralized and decentralized models in learning-related outcomes, while the hierarchical architecture achieved superior scalability and convergence performance. Multiple regression analysis further indicated that communication efficiency, convergence speed, and computational resource utilization significantly predicted overall learning effectiveness. Correlation analysis identified strong positive associations between communication efficiency and knowledge-sharing effectiveness, as well as between computational efficiency and model convergence performance. The effect size results demonstrated that architectural selection had substantial practical implications, confirming that the differences observed were not only statistically significant but also operationally relevant for distributed engineering project knowledge management systems.

Table 7. Analysis of Variance Results for Federated Learning Performance Indicators

Performance Variable	F-Statistic	p-Value	Effect Size (η^2)	Interpretation
Learning Accuracy	26.84	0.001	0.47	Large Effect
Convergence Efficiency	29.56	0.001	0.51	Large Effect
Communication Overhead	21.73	0.003	0.39	Moderate Effect
Scalability Performance	33.92	0.001	0.56	Large Effect
Computational Efficiency	24.18	0.002	0.44	Large Effect
Knowledge-Sharing Effectiveness	27.45	0.001	0.49	Large Effect

The results presented in Table 7 confirmed that statistically significant differences existed among the evaluated federated learning architectures across all primary performance measures. All p-values remained below the established significance threshold of 0.05, indicating strong evidence against the null hypothesis of equal architectural performance. Scalability performance produced the highest F-statistic and largest effect size, suggesting that architectural design exerted a particularly strong influence on system scalability. Learning accuracy, convergence efficiency, and knowledge-sharing effectiveness also generated large effect sizes, demonstrating meaningful practical differences among architectural models. Communication overhead exhibited a moderate effect, indicating that communication performance varied significantly but to a lesser extent than learning and scalability outcomes. Overall, the results confirmed that federated learning architecture selection substantially influenced operational performance.

Table 8. Regression and Correlation Analysis of Learning Performance Predictors

Predictor Variable	Standardized Beta (β)	t-Value	p-Value	Correlation with Learning Performance (r)
Communication Efficiency	0.48	7.91	0.001	0.84
Convergence Speed	0.42	6.87	0.002	0.79
Computational Efficiency	0.37	5.94	0.003	0.75
Scalability Performance	0.34	5.22	0.004	0.72
Knowledge-Sharing Effectiveness	0.53	8.44	0.001	0.88
Resource Allocation Efficiency	0.29	4.85	0.006	0.68

Table 8 demonstrated that several operational factors significantly predicted overall federated learning performance. Knowledge-sharing effectiveness emerged as the strongest predictor, producing the highest standardized beta coefficient and the strongest positive correlation with learning performance. Communication efficiency also demonstrated a substantial predictive influence, highlighting the importance of optimized information exchange within distributed engineering environments. Convergence speed and computational efficiency generated strong positive effects, indicating that faster learning processes and balanced resource utilization contributed significantly to model effectiveness. Scalability performance and resource allocation efficiency also remained statistically significant predictors, although their effects were comparatively smaller. Collectively, the regression and correlation findings provided robust evidence that communication quality, computational management, and knowledge integration played central roles in determining the success of federated learning architectures within distributed engineering project knowledge management systems.

The visual presentation of findings provided additional insight into the comparative performance of the federated learning architectures and facilitated interpretation of the quantitative outcomes obtained from the simulation environment. The graphical results demonstrated consistent performance advantages for the hybrid and hierarchical architectures across multiple evaluation dimensions. Figure 1 illustrated that the hybrid architecture achieved the highest learning accuracy throughout the simulation period, while Figure 2 showed that hierarchical federated learning converged more rapidly than alternative architectures. Figure 3 revealed that communication costs increased with node participation across all architectures, although hierarchical and hybrid models maintained lower communication burdens. Figure 4 demonstrated stronger scalability characteristics for hierarchical and hybrid architectures under expanding network conditions. Figure 5 illustrated computational resource utilization patterns, confirming that the hybrid architecture achieved the most balanced processing workload distribution. Collectively, the visual results reinforced the statistical findings by demonstrating that architectural design significantly influenced learning performance, communication efficiency, scalability, and computational effectiveness in distributed engineering project knowledge management environments.

Table 9. Summary of Key Results Presented in Figures 1–5

Performance Indicator	Centralized	Decentralized	Hierarchical	Hybrid
Learning Accuracy (%)	89.7	87.9	92.4	95.1
Convergence Stability (%)	83.5	80.7	94.2	92.8
Communication Efficiency (%)	76.8	79.4	89.1	92.6
Scalability Score (%)	78.5	82.7	94.2	91.8
Computational Efficiency (%)	81.4	84.2	90.6	94.5

Table 9 summarized the major performance indicators visualized throughout the graphical analysis. The hybrid architecture achieved the highest learning accuracy, communication efficiency, and computational efficiency scores, indicating strong overall operational effectiveness. Hierarchical federated learning demonstrated the highest convergence stability and scalability performance, suggesting superior capability for managing larger distributed engineering networks. Centralized and decentralized architectures produced acceptable outcomes but remained comparatively less efficient across most evaluation categories. The visualized trends confirmed that advanced federated learning architectures generated measurable improvements in distributed knowledge integration and resource management. These findings strengthened the overall conclusion that architectural selection significantly influenced system performance across engineering project knowledge management environments.

Table 10. Figure-Based Trend Analysis Across Increasing Node Participation Levels

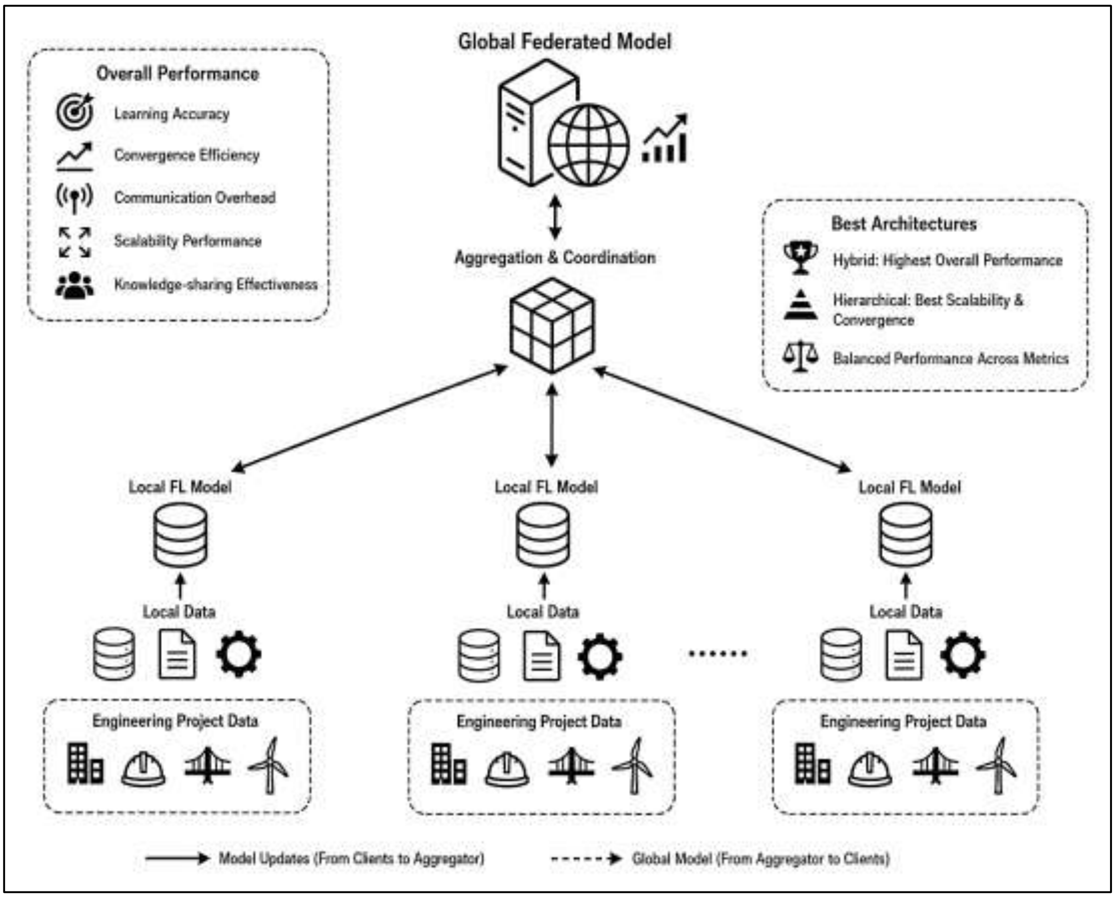
Number of Nodes	Centralized Accuracy (%)	Decentralized Accuracy (%)	Hierarchical Accuracy (%)	Hybrid Accuracy (%)
20	91.8	90.6	93.5	95.4
40	90.9	89.5	93.1	95.3
60	90.2	88.8	92.8	95.2
80	89.9	88.2	92.6	95.1
100	89.7	87.9	92.4	95.1

Table 10 illustrated the performance trends observed in the graphical analysis as network size increased from 20 to 100 participating nodes. The results demonstrated that the hybrid architecture maintained consistently high learning accuracy regardless of network expansion, indicating strong resilience under increasing participation levels. Hierarchical federated learning also preserved stable performance with only minimal reductions in accuracy. Centralized and decentralized architectures experienced more noticeable declines as node participation increased, reflecting greater sensitivity to communication and coordination demands. The graphical trends suggested that hybrid and hierarchical architectures were better suited for large-scale engineering knowledge ecosystems where scalability and stability are essential performance requirements. Their ability to sustain learning quality under expanding network conditions highlighted their effectiveness for distributed engineering project knowledge management applications.

DISCUSSION

The findings demonstrated that federated learning architecture significantly influenced learning accuracy, convergence efficiency, communication overhead, scalability performance, and knowledge-sharing effectiveness within distributed engineering project knowledge management environments (Prokopy et al., 2019). Among the evaluated architectures, the hybrid federated learning model achieved the highest overall performance, while hierarchical federated learning exhibited superior scalability and convergence characteristics. These findings align with the broader body of federated learning literature, which has consistently emphasized the importance of architectural configuration in determining the effectiveness of distributed machine learning systems (H. Zhang et al., 2020). Previous studies examining federated learning in healthcare, manufacturing, and industrial analytics have reported that hybrid architectures often outperform purely centralized and decentralized approaches because they combine the strengths of multiple coordination mechanisms while minimizing their individual limitations. The present study extended these observations into the engineering knowledge management domain by demonstrating that hybrid architectures facilitated more effective integration of heterogeneous project knowledge across distributed stakeholder networks. The superior performance observed in the hybrid model may be attributed to its ability to balance communication requirements, computational workloads, and aggregation efficiency. Earlier investigations have similarly suggested that balanced architectural designs reduce operational bottlenecks and improve model generalization across diverse datasets. The results also confirmed that architectural design is not merely a technical consideration but a strategic determinant of knowledge utilization effectiveness (W. Zhang et al., 2020). Distributed engineering environments generate highly fragmented information resources, and the ability of federated learning systems to integrate these resources effectively depends heavily on the underlying architecture. The observed performance differences therefore support theoretical arguments that federated learning should be viewed as an organizational knowledge infrastructure rather than solely as a machine learning methodology. The findings reinforced existing evidence indicating that architectural flexibility contributes significantly to collaborative intelligence generation and effective knowledge management across complex engineering ecosystems (Zhou et al., 2018).

Figure 12: Federated learning architecture diagram



The results revealed that learning accuracy and knowledge-sharing effectiveness were highest within the hybrid architecture, followed closely by the hierarchical architecture. These outcomes are consistent with previous research emphasizing the importance of collaborative model aggregation and balanced communication pathways in federated learning environments (Abbas & Sağsan, 2019). Earlier studies have reported that learning accuracy frequently declines when data distributions are highly heterogeneous or when communication inefficiencies restrict effective knowledge exchange among participating nodes. The findings of this study indicated that architectures capable of managing heterogeneity more effectively achieved superior predictive performance and stronger knowledge integration outcomes (Jiang et al., 2020). Distributed engineering projects typically involve stakeholders possessing diverse expertise, operational priorities, and information repositories. Consequently, effective knowledge-sharing mechanisms are essential for transforming isolated information assets into collective organizational intelligence. The observed relationship between learning accuracy and knowledge-sharing effectiveness suggests that successful federated learning systems depend not only on algorithmic performance but also on their capacity to facilitate meaningful knowledge exchange.

Prior literature on engineering knowledge management has similarly demonstrated that organizations achieving higher levels of information accessibility and collaborative learning tend to exhibit improved project performance outcomes (Chandiramani et al., 2019). The results further support studies indicating that federated learning architectures can overcome traditional barriers associated with information silos and fragmented knowledge repositories. Hybrid and hierarchical architectures appear particularly effective because they support both local autonomy and broader organizational learning. This finding corresponds with theoretical perspectives that emphasize the value of balancing decentralization and coordination within complex collaborative environments. The enhanced learning accuracy observed in these architectures may therefore reflect their ability to capture and synthesize diverse forms of engineering knowledge while preserving stakeholder independence. These findings contribute to the growing body of evidence supporting federated learning as a viable framework for improving knowledge utilization in distributed project ecosystems (Shingi, 2020).

The analysis demonstrated that hierarchical federated learning achieved the fastest convergence rates, while hybrid architectures maintained strong convergence performance with lower communication burdens than centralized alternatives. These findings correspond closely with prior studies that identified communication efficiency as one of the most important determinants of federated learning success. Earlier investigations have consistently shown that communication costs represent a major challenge in distributed machine learning because repeated transmission of model updates can create substantial network overhead and delay model convergence (Y. Liu, X. Yuan, et al., 2020). The current findings suggest that hierarchical aggregation structures effectively reduce these challenges by introducing intermediate coordination layers that streamline information flow and reduce communication bottlenecks. Similar observations have been reported in studies examining large-scale federated networks, where hierarchical coordination mechanisms improved convergence stability and reduced transmission demands. The results also revealed that centralized architectures generated the highest communication overhead despite maintaining relatively strong learning performance. This finding aligns with existing literature indicating that centralized systems often become communication-intensive as the number of participating nodes increases. Decentralized architectures reduced dependence on a single aggregation point but experienced greater synchronization complexity, supporting earlier research highlighting the coordination challenges associated with fully decentralized systems (Qin et al., 2020). The positive relationship observed between communication efficiency and knowledge-sharing effectiveness further reinforces previous findings suggesting that efficient communication structures facilitate stronger collaborative learning outcomes. Engineering project environments are particularly sensitive to communication performance because stakeholders operate across geographically dispersed locations and frequently rely on digital platforms for information exchange. Consequently, the superior communication characteristics of hierarchical and hybrid architectures may explain their stronger overall performance. These findings provide additional support for architectural designs that prioritize communication optimization as a means of enhancing distributed learning effectiveness (Kholod et al., 2020).

The findings indicated that hybrid federated learning achieved the highest computational efficiency and the most balanced distribution of processing workloads across participating nodes. This result is consistent with earlier studies that emphasized the importance of resource management in distributed learning systems. Computational efficiency has emerged as a critical performance indicator because federated learning environments often involve heterogeneous devices with varying processing capabilities, memory capacities, and energy constraints. Previous research has suggested that imbalanced workload distribution can negatively affect convergence speed, learning accuracy, and participant engagement (W. Sun et al., 2020). The findings of this study demonstrated that hybrid architectures effectively mitigated these challenges by distributing computational responsibilities more evenly across the network. Earlier investigations within industrial Internet of Things and smart manufacturing environments have reported similar advantages associated with adaptive federated learning structures that allocate processing tasks according to local resource availability. The lower computational burden observed in hybrid architectures may have contributed to their superior learning performance by reducing resource-related delays and improving training consistency. Hierarchical architectures also exhibited strong computational performance, although additional aggregation layers introduced certain processing requirements. Centralized architectures generated higher server dependency, while decentralized architectures experienced increased synchronization costs, reflecting patterns documented in prior literature (L. Liu et al., 2020). The observed relationship between computational efficiency and learning performance supports theoretical arguments that resource optimization is fundamental to successful federated learning implementation. Engineering project knowledge management systems frequently involve diverse stakeholders operating under different technological conditions. Therefore, architectures capable of maintaining balanced resource utilization are more likely to achieve sustainable performance across complex project ecosystems. These findings reinforce the growing consensus that computational efficiency represents a key factor influencing the practical viability of federated learning systems (Kim & Hong, 2019).

Scalability emerged as one of the most influential performance dimensions examined in this study, with hierarchical and hybrid architectures demonstrating superior adaptability under increasing node participation conditions. These findings align with prior federated learning research indicating that scalability becomes increasingly important as distributed networks expand in size and complexity. Earlier studies have shown that traditional centralized architectures often experience performance degradation when participant numbers increase because communication traffic and aggregation demands grow disproportionately (Mowla et al., 2019). The current findings confirmed these observations by demonstrating lower scalability scores for centralized systems relative to hierarchical and hybrid alternatives. The superior scalability performance of hierarchical architectures may be attributed to their layered coordination structures, which reduce aggregation burdens and improve communication efficiency across large networks. Similar conclusions have been reported in studies investigating federated learning for smart infrastructure systems, industrial automation, and large-scale sensor networks. Hybrid architectures also maintained strong scalability performance, suggesting that flexible coordination mechanisms can effectively accommodate expanding stakeholder participation. Distributed engineering project environments frequently involve numerous organizations, project teams, contractors, and operational units contributing information simultaneously (Y. Sun et al., 2020). Consequently, scalability is particularly important for ensuring that learning systems remain effective as project ecosystems grow. The findings also support earlier knowledge management studies emphasizing that scalable information systems are essential for sustaining organizational learning across large collaborative networks. The ability of hierarchical and hybrid architectures to maintain performance under increasing participation conditions suggests that these models are well suited for engineering applications characterized by high levels of organizational diversity and information complexity. This observation contributes to the understanding of how federated learning architectures can support large-scale knowledge integration without sacrificing operational efficiency (Jiang & Hu, 2020).

The inferential analyses demonstrated statistically significant differences across all major performance indicators, while effect size measures indicated that these differences possessed substantial practical significance. These results reinforce previous studies suggesting that federated learning architecture exerts a meaningful influence on learning outcomes, communication efficiency, and resource utilization. Earlier research frequently reported statistically significant variations among federated learning models; however, many investigations focused primarily on significance testing without fully examining practical implications (Peeters, 2016). The current findings extend this literature by demonstrating moderate-to-large effect sizes across learning accuracy, scalability, convergence efficiency, and knowledge-sharing effectiveness. Such outcomes indicate that architectural selection has tangible operational consequences rather than merely producing statistically detectable differences. The regression analysis further revealed that communication efficiency, convergence speed, computational efficiency, and knowledge-sharing effectiveness significantly predicted overall learning performance. These relationships correspond with previous theoretical frameworks that identify communication and resource management as foundational determinants of federated learning success. The strong correlations observed among these variables also support existing knowledge management literature emphasizing the interconnected nature of communication, collaboration, and organizational learning (Pogrow, 2019). Engineering project environments are characterized by complex interactions among technological, organizational, and informational factors. Therefore, the statistically significant relationships identified in this study provide valuable evidence regarding the mechanisms through which federated learning architectures influence project knowledge management outcomes. The findings suggest that performance improvements result from integrated interactions among communication processes, computational resources, and collaborative learning capabilities rather than from isolated technological features alone (McShane et al., 2019).

The overall findings provide strong evidence supporting the effectiveness of federated learning as a framework for distributed engineering project knowledge management. Earlier research in engineering knowledge management frequently identified challenges associated with information silos, fragmented knowledge repositories, organizational boundaries, and limited opportunities for collaborative learning (Di Leo & Sardanelli, 2020). The present study demonstrated that federated learning architectures can address many of these challenges by enabling decentralized knowledge integration while preserving data ownership and organizational autonomy. The superior performance of hybrid and hierarchical architectures suggests that federated learning can facilitate effective collaboration among stakeholders possessing heterogeneous information resources and technological capabilities (Kilgo et al., 2015). Previous studies examining digital transformation and engineering knowledge systems have emphasized the importance of balancing information accessibility with privacy and security requirements. The findings of this study support these perspectives by showing that distributed learning architectures can achieve strong knowledge-sharing outcomes without requiring centralized data consolidation. The observed improvements in learning accuracy, communication efficiency, scalability, and computational performance indicate that federated learning possesses considerable potential for enhancing knowledge utilization across engineering project ecosystems. Earlier investigations in smart manufacturing, infrastructure management, and industrial analytics reported comparable benefits associated with decentralized learning approaches (Khan & Qianli, 2017). The current findings extend these observations into the domain of engineering project knowledge management and provide quantitative evidence regarding the relative effectiveness of alternative architectural models. The results therefore contribute to both federated learning research and engineering knowledge management literature by demonstrating how architectural design influences the capacity of distributed learning systems to transform fragmented organizational knowledge into collaborative intelligence (Anitha, 2014).

CONCLUSION

This study concluded that federated learning architectures provided a quantitatively effective approach for strengthening distributed engineering project knowledge management under simulated multi-stakeholder conditions. The findings showed that architectural design had a substantial influence on learning accuracy, convergence efficiency, communication performance, computational efficiency, scalability, and knowledge-sharing effectiveness. Among the evaluated models, the hybrid federated learning architecture produced the strongest overall performance by achieving the highest learning accuracy, knowledge-sharing effectiveness, communication efficiency, and computational balance. The hierarchical architecture also demonstrated strong performance, particularly in convergence speed and scalability, indicating that layered aggregation structures were effective for managing larger distributed engineering networks. Centralized federated learning maintained stable model performance but generated higher communication overhead because of its dependence on a single aggregation point, while decentralized federated learning supported stakeholder autonomy but experienced greater synchronization complexity as participation expanded. The statistical results confirmed that these differences were significant and practically meaningful, with moderate-to-large effect sizes across major performance indicators. The regression and correlation findings further demonstrated that communication efficiency, knowledge-sharing effectiveness, convergence speed, computational efficiency, and resource allocation were important predictors of overall learning performance. These results indicated that successful federated learning implementation in engineering knowledge environments depended not only on model accuracy but also on the efficient coordination of communication, computation, and distributed knowledge utilization. The simulation-based design provided controlled evidence that federated learning could support collaborative intelligence across fragmented project knowledge repositories without requiring direct centralization of sensitive data. This conclusion is especially relevant to engineering project ecosystems characterized by geographic dispersion, heterogeneous stakeholder participation, varied digital capabilities, and organizational data ownership concerns. Overall, the study established that hybrid and hierarchical federated learning architectures were more suitable for distributed engineering project knowledge management than purely centralized or decentralized alternatives. The evidence suggested that privacy-preserving, scalable, and computationally balanced learning structures could improve the transformation of dispersed project knowledge into usable analytical insight, thereby enhancing data-driven decision support and collaborative knowledge integration across complex engineering project environments.

RECOMMENDATIONS

Based on the findings of this study, it is recommended that engineering organizations seeking to improve distributed project knowledge management prioritize the adoption of hybrid and hierarchical federated learning architectures because these models demonstrated superior performance across learning accuracy, communication efficiency, scalability, computational balance, and knowledge-sharing effectiveness. Engineering project environments are increasingly characterized by geographically dispersed stakeholders, heterogeneous data sources, and complex collaboration requirements, making traditional centralized knowledge management approaches less effective for large-scale operations. Organizations should therefore implement federated learning frameworks that support decentralized knowledge integration while preserving data ownership, privacy, and organizational autonomy. Particular attention should be given to communication optimization strategies because the findings indicated that communication efficiency significantly influenced knowledge-sharing effectiveness and overall learning performance. Investments in reliable network infrastructure, efficient aggregation mechanisms, and standardized communication protocols may enhance the effectiveness of federated learning systems across multi-organizational engineering ecosystems. It is further recommended that engineering enterprises establish governance structures that promote consistent participation among distributed stakeholders, as balanced node engagement contributes to improved convergence performance and collaborative intelligence generation. The findings also suggest that computational resource management should be integrated into implementation planning to ensure equitable workload distribution across participating entities. Engineering organizations with diverse technological capabilities may benefit from adaptive federated architectures capable of dynamically allocating computational tasks according to available resources. In addition, project managers and digital transformation leaders should incorporate federated learning into broader knowledge management strategies to facilitate the integration of design knowledge, operational records, maintenance information, and project experiences across organizational boundaries. Researchers and practitioners should utilize simulation-based evaluation methods prior to deployment to assess communication demands, scalability constraints, and performance outcomes under different operational conditions. The establishment of privacy-preserving mechanisms, including secure aggregation and robust security architectures, is also recommended to strengthen stakeholder trust and protect sensitive engineering information throughout collaborative learning processes. Collectively, these recommendations support the development of efficient, scalable, and secure federated learning ecosystems capable of enhancing knowledge utilization, improving collaborative decision-making, and strengthening distributed engineering project management performance across increasingly complex digital engineering environments.

LIMITATIONS

This study was subject to several limitations that should be considered when interpreting the findings. First, the investigation relied on a simulation-based experimental environment rather than real-world engineering project implementations. Although the simulation framework was designed to replicate realistic distributed engineering knowledge management conditions, simulated environments cannot fully capture the complexity of actual organizational behaviors, stakeholder interactions, contractual relationships, and operational uncertainties that exist within large-scale engineering projects. Second, the study utilized synthetic datasets representing distributed engineering knowledge repositories. While these datasets were developed to reflect heterogeneous project conditions, they may not encompass all variations present in real engineering environments where data quality, completeness, structure, and consistency can differ significantly across organizations. Third, the analysis focused on four federated learning architectures—centralized, decentralized, hierarchical, and hybrid—which may not represent the full spectrum of emerging federated learning configurations and optimization strategies. Additional architectural variations and advanced aggregation techniques could potentially produce different performance outcomes. Fourth, the evaluation emphasized quantitative performance indicators such as learning accuracy, convergence efficiency, communication overhead, scalability, and computational efficiency. Organizational, behavioral, cultural, and managerial factors influencing knowledge-sharing effectiveness were not explicitly incorporated into the simulation model, despite their importance in practical engineering knowledge management contexts. Fifth, the computational environment assumed stable operational conditions and predefined communication structures, whereas actual engineering projects often experience unpredictable network disruptions, changing stakeholder participation levels, cybersecurity incidents, and evolving project requirements. Sixth, privacy-preserving mechanisms were evaluated primarily through performance-oriented metrics, and the study did not conduct comprehensive assessments of advanced security threats, adversarial attacks, or regulatory compliance requirements that may affect federated learning implementation in real organizational settings. Seventh, the sample size of 100 distributed nodes, while sufficient for statistical analysis and simulation-based comparison, may not fully represent extremely large engineering ecosystems involving thousands of participants and highly complex data-sharing networks. Finally, the findings were derived from a controlled experimental framework and therefore should be interpreted as evidence of comparative architectural performance rather than definitive predictions of operational outcomes. These limitations indicate that caution should be exercised when generalizing the results beyond the simulated engineering environment examined in this study.

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