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How does federated learning impact decision-making in firms: A systematic literature review using TCCM

Shweta Kumari Choudhary
Department of Management Studies
Indian Institute of Technology, New Delhi
shweta124chaudhary@gmail.com
0000-0002-5475-6247

Arpan Kumar Kar
Department of Management Studies
Indian Institute of Technology, New Delhi
0000-0003-4186-4887

Yogesh K. Dwivedi
Digital Futures for Sustainable Business & Society Research Group, School of Management, Bay Campus
Swansea University Wales, UK
Symbiosis International (Deemed University), Pune, Maharashtra, India
0000-0002-5547-9990

Abstract:

Federated Learning (FL) is a transformative, distributive computational approach that revolutionizes decision-making capabilities through decentralized data computation. Despite notable operational advantages stemming from FL implementation, the optimal selection of methods from the existing literature and the design of resource-efficient and model trained solutions continue to evolve. This research presents a comprehensive systematic literature review, offering insights into the current state of FL advancements. Our study amalgamates various pivotal components influencing FL performance and elucidates their associations, fostering sustainable competitiveness. To evaluate the progress in this domain, we adopt the Theory-Context-Characteristics-Methodology (TCCM) framework, which systematically assesses the theories, contextual factors, characteristics, and methodologies employed in FL research. We identify distinct methods which have been combined with the FL algorithm by the organisation and its host, or in collaboration to reach goals and support efficient decision making. We complement the findings of our literature review by providing an illustrative diagram to aid academicians and diverse stakeholders in strategically leveraging FL for informed decision-making.

Keywords: Federated learning, Game theory, TCCM, Systematic literature review, Decision-making, Sustainability

1 Introduction

Federated Learning (FL), proposed by Google in 2016, demonstrated how to train global data with many participants in a distributed way (Zhang et al., 2021). It has now been introduced as a distributed machine learning (ML) model to offload centralized tasks. Computer science researchers have extensively investigated the feasibility of FL and have unveiled its vast potential for enhancing decision-making processes (Ibitoye et al., 2022; Zhang et al., 2023) due to its feature of providing eases in data collection from the end device by creating a global model and sending it to end devices as an initial point to perform a local ML training model (Zhang et al., 2021). However, it is yet to be examined in a very detailed manner in Information Systems (IS) literature, which is a major gap, given its potential for information management. In business and management research, researchers seek to deploy FL frameworks and other AI-based algorithms driven for decision-making (Yamany et al., 2021). An in-depth analysis of the empirical and theoretical foundations of research linked to the standardization and adaptation of emerging AI-based FL methods for management and business can be achieved through comprehending the theoretical perspective of FL. Its potential lies in offering data-driven multiagent decision-making, where multiple parties have distinct business practices and requirements (Eseryel et al., 2020).

FL research is more prominent in information technology (IT) industries and its provision for privacy and security (Lin et al., 2022) and model training (like for face recognition, health monitoring (Zhang et al., 2022), improving convergence rate, learning quality, model training, training time reduction), cyber-attack evasion, edge computation, IoT (Internet of things) and advance computing (client computing, drones, mobile communication, accuracy, and customization). Many FL-led models are transforming smart industrial applications due to various technological advancements, particularly the increasing role of blockchain, big data, and ML. Implementing FL has impressive results over the existing ML technologies concerning privacy, reducing computational overhead, risk management, information management, storage overheads, environmental concerns due to high energy requirement (Mehmood et al., 2018). The demand for energy needed to do computational work will keep rising because of big data. As per statistics, energy consumption to do computational work has increased by 300,000X from 2012 to 2018 (Qiu et al., 2020), which shows the severe impact of carbon footprints on the environment. FL-based decisions impact long-term environmental goals as it has proven itself as a sustainable paradigm in various aspects, such as energy harvesting and UAV communication, compared to the existing model (Liu et al., 2022).

However, how FL can bring a sustainable perspective and help make decisions more informed is still unexplored. They can also be based on the understanding obtained through the systematic review. In literature, few theories that are only loosely used as backgrounds or frameworks, indicating lack in strong theoretical foundations (Chen et al., 2023; Hui et al., 2022). Hence, researchers must incorporate a variety of complementary theories that can define both external and internal factors as these theories can captivate the process-based characteristics of marketing standards and adaptation in ever-changing market environments must be adopted.

Hence, we explore the following research questions:

- *RQ1) How has the literature on FL progressed in terms of theories, research context, characteristics, and methods?*
- *RQ2) How does FL-led decentralized data sharing improve decision-making in different sectors and what theoretical perspectives have been adopted in these studies?*
- *RQ3) How FL-dependent decision making promotes drivers of sustainability?*

This study will be a crucial addition to IS research, as with changing data dynamics, FL has become peremptory for firms seeking high computational requirements daily. We collected data using a systematic literature review and applied TCCM framework (Jebarajakirthy et al., 2021) to explore the research questions. The TCCM framework is adept at examining the theoretical perspectives underpinning FL-led decentralized data sharing and its impact on decision-making in various sectors. It provides a structured approach to assess the interconnectedness between theoretical foundations and practical applications, ensuring a holistic exploration (Chopra et al., 2023). TCCM can effectively capture and analyze how FL-dependent decision-making contributes to sustainability drivers. By integrating theoretical perspectives within the matrix, it offers a robust method to identify, organize, and evaluate the key elements influencing sustainability outcomes in the context of FL. The remainder of this paper is structured as follows: In section 2, we present literature review of the study. Secondly, we describe the research method in section 3 followed by a general overview of the identified articles. Further, section 4 presents the result of this study in a systematic manner by assessing the theories, contexts, constructs, and methods that have been used to investigate the relationship between business method adoption and decision making. Finally, we discuss key insights from our review and outline an agenda for future research in section 5. Lastly, section 6 presents the conclusion of this study.

2 Literature review

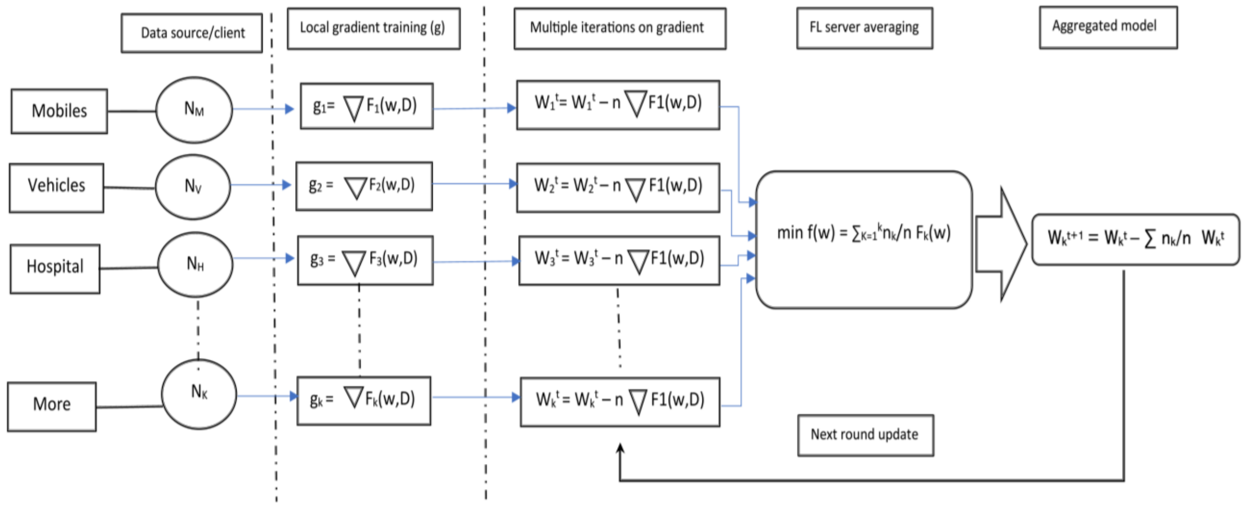
Massive growth in IT devices results in an enormous amount of data everyday (Li et al., 2020). Due to which ML approaches such as supervised, unsupervised, deep learning have reached significant heed in recent years in different areas of business-like operations, services, and marketing management (Kumar et al., 2021; Kar et al., 2022). Presently, most other ML models are centralized, i.e., they process all data at a centralized server which causes computational overload, high electricity consumption, emissions, and information assurance challenges (Wang et al., 2019; Singh et al., 2022). To subsist this issue, FL was adopted where a learning model is trained over remote devices under the control of the centralized location, called server (Li et al., 2020).

Further, moving a significant volume of data for training purposes also comes with bandwidth and IT expenditures (Fang et al., 2021). Hence many researchers have used the game theory perspective to understand how to make decisions in such cases using FL to maintain the competitiveness of the firms (Chen et al., 2023; Hui et al., 2022). Like, the firm performs game theory to make decisions in the optimal allocation of resources (Lim et al., 2021), analyzes actions of other players when incentives are distributed, multi-hop relay selection scheme (Zeng et al., 2022), risk management, negotiation, and bargaining among the participating players, and optimal data size allocation. Hence, game theory emerged as a vital decision-maker in the adoption and performance of FL. So, in this section first we explain the working procedure of FL, followed by game theory concepts. Afterwards we explain the practical application of FL for sustainability practices.

2.1 Background of Federated Learning

The study of FL is no longer synonymous with a sole focus surrounding computational data work (Zhang & Hanzo, 2020). Instead, the growth of FL is a new answer to decentralized computation, decision-making, and sustainability issues (Chen et al., 2023). In some of the literature, FL is viewed as emerging, fast-paced technology, with the researchers willing to explore how FL advancements could influence the knowledge capabilities of the organization when it comes to managing customer requirements and maintaining privacy, and managing threats related to data.

In Figure 1, we provide a brief process showing the FL working procedure, which starts by collecting data from N different types of sources (e.g., mobile devices (N_M), vehicles (N_v), patient data (N_H), and more) (Manimuthu et al., 2022). In the following step, the user and server collaborate to train a unified model using stochastic gradient descent (SGD). Each user computes the gradient based on the local dataset (g). The third step consists of a process to increase convergence and accuracy rate, and each user shares their local gradient through the server. The server will aggregate all gradients and give results to the user. Lastly, each user will update the model (W_K^t) to minimize f(w), which is the main aim of implementing this learning (Montazeri et al., 2022; Pham et al., 2021).



[f(w) = global statistical model, n = learning rate, F=loss function, K= no. of participants, t = no. of rounds/iterations, w= weight vector for model, W= aggregate parameters (weight update in SGD), g = model gradient, t+1 = global model round]

Figure 1: Steps in FL, synthesized from literature.

2.2 Game theory perspective in decision-making

In today's digital era, where the market is very competitive, multiple drivers like market competition, emerging technologies, and climate tech decisions in the industry impact firms' decision-making (Li et al., 2022b; Li, 2022a). Under these circumstances, game theory is a widely accepted strategy for gaining a competitive advantage in decision-making. Game theory (GT) is a mathematical model for decision-making where different alternative options are available (Liang et al., 2022; Wakolbinger et al., 2013). It employs players who are competitors of each other in the same industries and play using different kinds of preferences in conflicting situations (Hui et al., 2022). It involves three major components: players, rules, and a payoff system. For example, in these studies to explain 'FL's informed decision,' they have considered two players: the data owners and the model trainer. Firms choose from the set of alternative models according to the rules and requirements of each player to participate in FL model building, given their heterogeneous sizes of local datasets. The server solves the participation dilemma to realize individual and global optimization by collecting accurate information from local devices, and the payoff is the output or results they get depending on the selected strategies of the players.

Studies used Nash equilibrium GT in which players want to reach a stable state and achieve the best outcome (Kreps,1989) so that data owners and model trainers communicate with each other, discuss their strategies, build agreements, and work together to reach their objectives. Let's assume there are two players $N = \{O, T\}$ where O represents the "owner," and T represents the "trainer," and the strategy of the owner will be S_O and the strategy of the trainer will be S_T from which players can choose. Now let's assume P_i implies players i payoff using a combination of strategy (1, 2…4) (Lopez et al., 2022). The game is played per each player's requirement from the strategy space, like sharing a sub-set of data in the FL training model for privacy preservation or high-speed data computation. Existing literature has assumed that the players know all the strategy space and payoff under each decision. Therefore, firms and players select a strategy by interacting to enhance their objectives. This is explained using Figure 2.

Data owners'		All features	Subset of features
	All data	P_O_1, P_T_1	P_O_3, P_T_3
	Sub-set of data	P_O_4, P_T_4	P_O_2, P_T_2
		Model trainers' strategy	

Figure 2. Explaining decision-making among players

The data owner will decide the kind of data they want to share as per the model trainers' expectations and requirements (features) and adjust their decision. The optimal strategy for both players can be represented using equation 1 & 2 (Mazalov, 2014):

$$\text{Owner,}\quad S\_O^{*} = arg\ max\ s\_o\{min\ s\_t\{p\_o\ (s\_o, s\_t),\ p\_t\ (s\_o, s\_t)\}\} \tag{1}$$

$$\text{Trainer,}\quad S\_T^{*} = arg\ max\ s\_t\{min\ s\_o\{p\_o\ (s\_o, s\_t),\ p\_t\ (s\_o, s\_t)\}\} \tag{2}$$

Payoffs, P_O, and P_T, depend on the context and the characteristics of the data and model being used. This payoff matrix can help the firm decide the data they want to share. For example, the data owner can report all the information resources for making an informed decision or is willing not to inform the model trainer about the tampered data. Similarly, model trainers can decide the features they need to model for the predictive decision-making model or the network allocation as per the customer's request.

However, earlier work focused more on designing the distributed model without putting effort into the users' privacy, resource management, data modulation, and energy optimization (Wang et al., 2023; Li et al., 2022). But the impending requirements from the government have considerably raised awareness of data management while maintaining the sustainability aspects of the modeling (Turedi & Zhu, 2019).

2.3 Practicing FL for sustainable practices

For the last couple of years, research has highlighted the potential of FL for strategic advantage (Fang et al., 2020; Lee et al., 2021) through various modes such as efficiency improvement (Li et al., 2023; Wang et al., 2023), reducing energy consumption (Zhu et al., 2022), data differentiation (Friha et al., 2023), efficient bandwidth allocation (Qiao et al., 2022), power control, and optimized transmission model. The existing technologies and methods depict the gap in the current sustainability models (Pham et al., 2021). FL can help highlight various areas where significant changes need to be performed to build sustainable technology by leveraging collective information-making while maintaining data privacy and security. It can help firms build accurate predictive models for making better resource-sharing decisions and risk assessments (Lau et al., 2021). Also, it minimizes the environmental impact (energy efficiency) of ML by removing the requirement for data at centralized server. In this context FL has benefits but it is important to understand that the real environmental effect depends on several factors, such as the model's size, number of devices, and nature of the data (Xiao et al., 2021). It is feasible to modify FL algorithms to be energy efficient. The total consumption of energy can be decreased, for instance, by implementing the communication strategy, local training updates, and aggregation mechanisms (Pham et al., 2021). For example, Pham et al. (2022) emphasized how wireless power transmission enabled by unmanned aerial vehicles (UAVs) allows long-lasting FL-based wireless networks. Using the FL model, UAVs can transmit power efficiently via a joint optimization of transmission time and bandwidth allocation. He also predicted that FL-based wireless networks could reduce UAV transmission by 32.95% compared with the benchmark. In essence, firms seek innovative strategies to reinforce themselves with emerging sustainability challenges.

Further, by upending established data processing paradigms, FL, a decentralized ML technique, has a profound impact on management and IS. FL allows sensitive data to remain on the edge devices, thereby lowering the possibility of data breaches and improving privacy and security (Lau et al., 2021). Within the field of IS management, FL streamlines the process for gathering and implementing knowledge from multiple sources without asking data aggregation (Shaik et al., 2022; Unal et al., 2021). This helps mitigate concerns about data ownership and privacy adherence. However, sustaining the integrity of the collaborative framework, handling communication overhead, and dealing with model aggregation complexity are all challenges that must be tackled when managing a FL system (Chen et al., 2022; Yang et al., 2021). For organizations to fully utilize FL potential benefits and deal with its inherent complexities, IS requires proficient management strategies. Overall, FL has the potential to reinforce sustainable development by promoting collaboration, knowledge sharing, and efficient utilization of resources.

During the literature review we established the connection between FL, game theory in decision making, and sustainability. During this process we presented the background of this study. Now we are moving towards organizing the research methodology to examine research questions.

3 Research methodology

To fully harness FL's potential benefits and navigate its complexities, proficient management strategies within IS are imperative, hence transitioning to the study focusing on, a comprehensive analysis of publication, journals, and network analysis of FL-related keywords provides valuable insights.

3.1 Literature selection process

In this study, first, we present descriptive statistics containing publication trends, productive and influential journals, and network analysis of the keyword. The descriptive analysis uncovers year-wise publications and journals that have published FL-related research, followed by network analysis uncovers the topics in which research is ongoing. This will help the researcher understand emerging methods in FL and year-wise publications and which journals are prominent in FL methods.

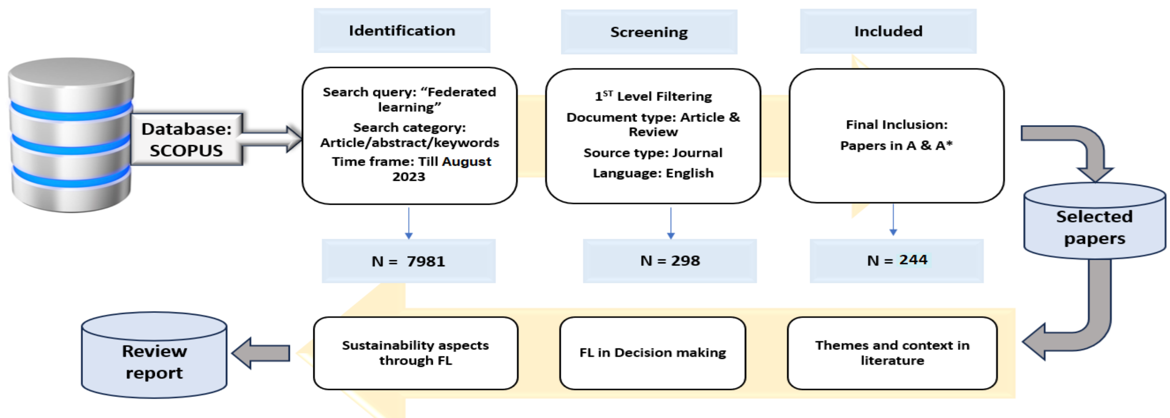


Figure 3. The framework adopted for research

3.1.1 Publication trends in FL

Developments in the number of publications over a time may indicate changes around research. This may indicate that researchers are becoming less engaged in certain areas or that new interests are emerging (Kumar et al., 2023). Figure 4 explains how FL-related research has been increasing in recent years. Though it is a current topic, its research area is broadening with respect to time. Also, we can see every year the average count is increasing. However, in 2019, we 'don't see any good publications. This might be because this is a new topic and needs more understanding. After that, it again gained pace.

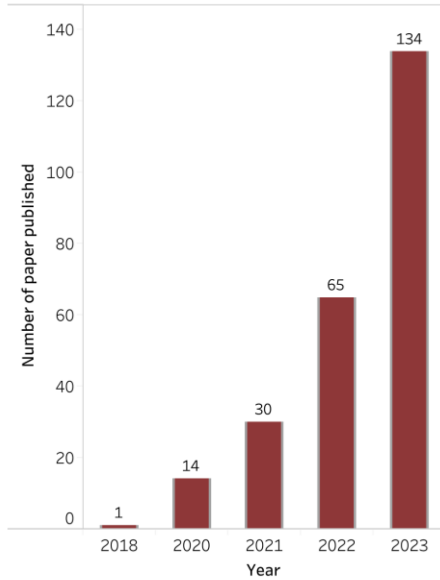


Figure. 4. Year-wise publications count till August 2023

3.1.2 Journals for FL research

Publications in quality journals indicate research undergoing a rigorous peer-review process and substantially contributes to the database of knowledge that exists in the field. The study probably offers answers to significant queries or issues, strengthening our understanding of the field (Wang et al., 2013). The selected 244 papers are published in 31 quality journals (A and A* categories) as indicated by ABDC journal ranking. Figure 5 presents the most influential journals indicating "IEEE Transaction on Vehicular Technology" has published most paper related to FL, followed by "IEEE Transaction on Intelligent Transportation systems".

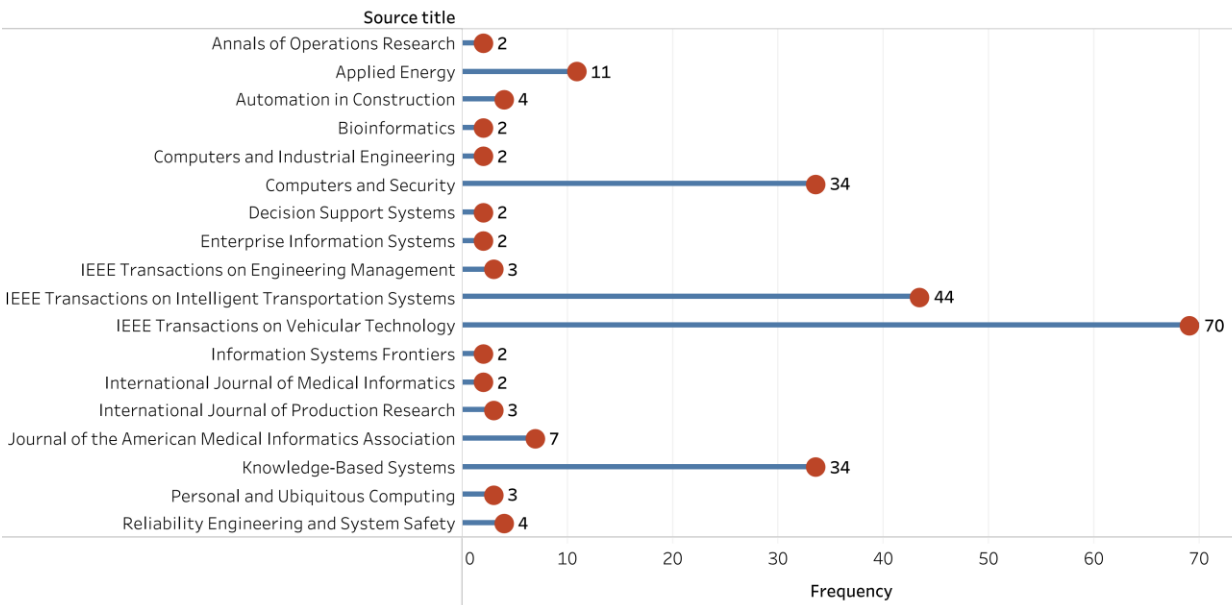


Figure. 5. Journals focusing on FL research dissemination

3.1.3 Network analysis of Keywords surrounding FL

We used the VOSviewer tool to establish an implied connection between keywords and the central theme surrounding FL (Martínez-López et al., 2020). Figure 6 presents three clusters; the first cluster (red color) represents FL strong connection with data privacy, privacy protection, internet of things (IoT), blockchain. It implies privacy is the most common topic discussed in conjunction with the FL. It shows people, IS managers and management are moving towards an AI-based FL model to prevent their data from getting breached and violated. Moving to the second cluster (green color) is towards algorithms discussion. It contains keywords such as computational modeling, task analysis, convergence, optimization, etc. which have a significant impact on management procedures, particularly when it comes to resource distribution, decision-making, and process modification. These models may imitate various circumstances in management, assisting managers in comprehending complex connections and reaching wise decisions. Lastly, industry 4.0 is depicted by the third cluster (blue color), featuring multiple FL applications in areas like deep learning, industrial IoT, mobile computation, resource allocations, energy efficiency, and more. Real-time monitoring and operation optimization are made feasible by industrial IoT, while predictive analytics and deep learning make it easier for effective resource allocation decision-making which encourages energy efficiency. Agile management instruments are made possible by mobile computation and digital twin technologies, which ensure adaptive strategies in dynamic industrial environments.

3.2 Analysis and lens

Further, to analyze RQ1, we adopted the TCCM framework proposed by Paul & Rosado-Serrano (2019) to extract more accurate and insightful findings from a systematic literature review. The outcomes are covered in four heads for this. First, we provided valuable insights into the well-known and highly used theories in FL. Second, the context presents most well-known sectors investigations are conducted has been debated. Thirdly, we introduced the essential characteristics of FL that have made it a promising ML model in the coming years. Fourthly, the methodologies used with FL in existing research have also been analyzed. For our RQ2, we performed a comparative analysis of the existing ML models and FL advantage over the existing model in decision-making. Finally, for the RQ3, we analyzed domains where FL proved to be a sustainable model.

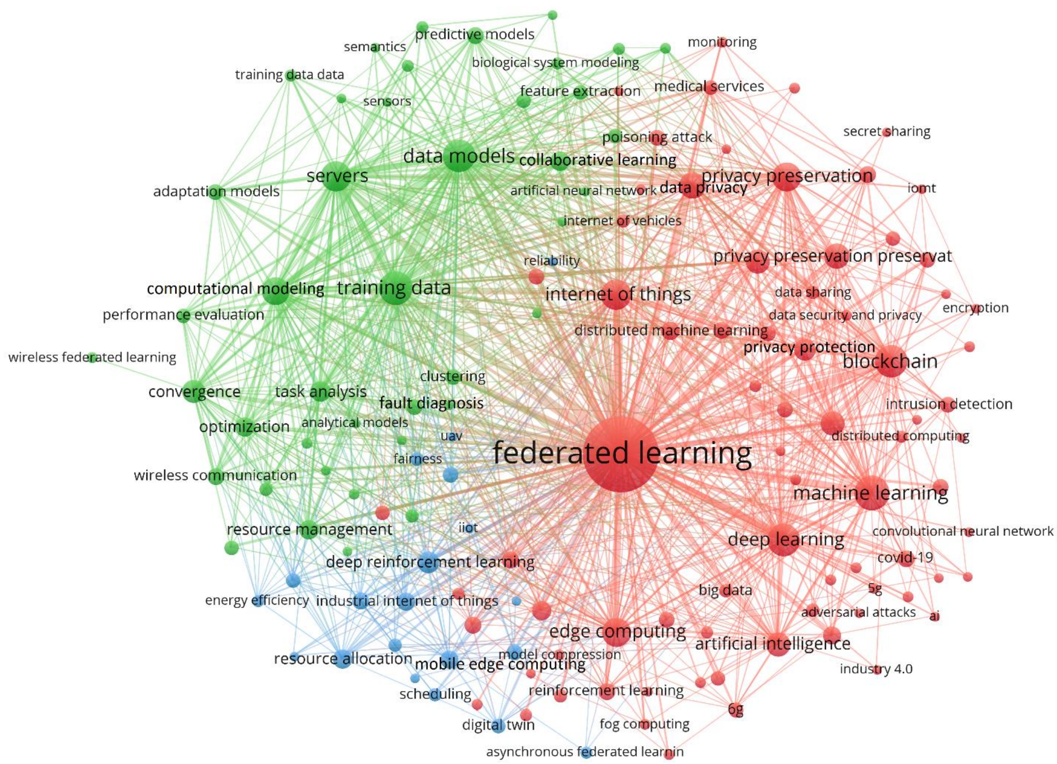


Figure 6. Network diagram of keywords surrounding FL

4 Results

4.1 Results from the TCCM framework

4.1.1 Theories applied in FL research

FL research has used various theoretical frameworks from different disciplines to explain the working mechanism. Out of 244 papers we found, 21 papers have used at least one theory. We found that the GT in the FL-based research is the most common to explain the phenomenon. Further, we discussed the most used theories in FL research (Li et al., 2022; Chen et al., 2023).

(A) Game theory:

Stackelberg game: Researchers use it in many areas like operations and supply chain management to analyze demand from both the buyer and the receiver side. Firms use this model to drive an optimal demand to increase the profit ratio (Yu et al., 2009). Also, researchers have suggested that an order for data divided by replenishment cycle is recommended for coordinating a decentralized operation. Also, the Stackelberg game approach provides an interaction between utility companies and 'n' users, where optimization problems will help to select the best strategy from the existing systems (Yu & Hong, 2016). It has also gained much attraction from researchers in hierarchical decision-making processes by many decision-makers in energy management schemes. Also, it has one of the most significant applications in management science in designing pricing strategies, where leaders are dominant firms and followers are small retailers. Here, if leaders can predict the requirements of small firms, they can use this information to set prices that will maximize their profits.

Evolutionary GT: It is a type of GT used in management science to study how strategic behavior has evolved. It is useful when players adapt and change their strategies as per the requirement, which leads to a change in their behavior (Tian et al., 2014). It has one of the significant implications in studying innovation and technological change. For example, if a firm is adopting new technology, it may want to understand how the adoption of new technology affects the behavior of the other players in the market. In information security, bound rationality, repeated games, service attacks, and network security are the context of evolutionary GT (Tian et al., 2019). One of the significant applications of evolutionary GT in FL is to model the behavior of different participating players after adopting the FL. Here, each client is viewed as a player in a repeated game, where the goal will be to optimize the ML model while also contributing to the collective model trained by the federation (Lim et al., 2021). By analyzing the results of the repeated games, researchers can understand different FL algorithms and drive cooperation and competition among the participating devices.

(B) Forecasting theory:

It is a theory that IS researchers use to predict future trends and make informed decisions. It used statistical techniques to analyze data, identify patterns, and extrapolate future trends. Time series analysis can determine sales, inventory, and website traffic (Fernández et al., 2022). Regression analysis also uses it to predict the number of visitors based on market requirements. It is also being used in connection with federated learning. For example, FL can improve the forecasting models' accuracy by allowing firms to extract a data pool while preserving privacy and security. It also has applications in areas like supply chain forecasting, where many firms can employ multiple data to improve the accuracy of the forecast. Forecasting theory and FL have complementary effects in the field of AI.

(C) Contract theory:

It provides an agreement between parties with different goals and interests. It has many applications in market regulation, data procurement, etc. Contract theory can incentivize organizations to participate in the FL model by offering rewards for participating in data leveraging or enhancing the model. For example, Montazeri et al. (2022) have mentioned optimal contracts in the FL task when the road units as task publishers have incomplete information about the private information of the vehicles (i.e., data quality). This contract is modeled such that the road unit will provide vehicle incentive rewards and computational resources to achieve optimal FL task allocation. Contract theory provides a skeleton to design mechanisms under asymmetric information. In this framework, the task publisher as a designer includes incentive rewards to data owners to persuade them to join the FL task and report their information truthfully (Nisan et al., 2007).

(D) Expected utility theory:

A structure used in decision theory to estimate individual preferences when faced with uncertain outcomes. Here, individuals make decisions as per expected utility by weighing their associated probabilities. It imitates participants' behavior in the FL setting (Fantacci & Picano, 2020). This theory can be used to explain how participants decide whether they want to participate in the training model and how they want to allocate their resources (e.g., network bandwidth) for the training process. Also, this theory explains how participants want to give their resources for the training process if they believe that by doing that, they will get higher utility or payoff. Hence, it helps guide participants' behaviors in an FL setting and helps build efficient and effective FL systems.

(E) Prospect theory:

Economic theory determines how participants make decisions under uncertainty. It determines payoff in terms of gains and losses as per reference point; this theory highlights participants are risk averse when there is gain and risk-taking when considering losses. Concerning federated learning, this theory can frame how participants make decisions rather than participate in the training process as per the potential payoff (like improving the model's accuracy) concerning reference points (Fantacci & Picano, 2020). However, they are less willing to participate if they find potential costs (computational resources) concerning reference points.

Overall, prospect theory anticipates applicable models for building the decision-making behavior of participants in the FL setting and provides an effective incentive mechanism to encourage participation and resource allocation. Table 1 presents the research context using the FL and their comparative analysis is indicated in Appendix 1.

Table 1: Research context studied using FL

Research Context	Theories in FL							
	Game theor y	Forecast ing theory	Actor-critic framework	Stackelberg game	Evolutionary game-based theory	Contract theory	Lyapunov theory	Martingale theory
IT (privacy & security)	+					+		
Cooperation and integration		+						
Integration energy sector			+					
Communication				+		+		
Unmanned aerial vehicles network	+++			++		+		+
Wireless computation network					+			
Client/Edge computation				+			+	+
Mobile computation	+			+				

+ = Presents the number of times the theory is used

Our results indicate there is immense scope to theorise about the IT artefact of FL in existing IS literature given the newer types of affordances and distributed computational capabilities it provides, which is yet to be explored. In particular, we foresee a lack of behavioral theorization surrounding the adoption, use and impacts of FL in business.

4.1.2 Context

Here we analyze and discuss industries/sectors that have focused on FL research. Figure 7 indicates the context (i.e., industries and the use cases) examined in the FL research. There is an emerging prevalence of decentralized data in various industries like hospitality, transportation, automobiles, automated vehicles, and more. We have used the global industry classification standard (GICS) to classify our sub-sector into various industries (Fan et al., 2016). The significant finding demonstrates that FL research is more prevalent in services that are facilitated by technologies. Cyber-attack evasion, edge computation, IoT (Internet of things), and advance computation (client computing, drones, wireless communication, precision, and customization) are a few of the domains in which it has been used as a new field illustrating performance. Other fields include security and confidentiality (maximum uses of FL) (Lin et al., 2022; Wang et al., 2023), ML, and learning models (for face recognition).

After the technology sector, healthcare is another industry that has extensively used FL for various computation work such as facial fatigue, health management, patient monitoring, and image reconstruction (Shaik et al., 2022; Unal et al., 2021). In the industrial sector, FL has proven its uses in collision avoidance, coordination in demand and supply (Zhu et al., 2022), travel time estimation, travel trajectory modeling, and process optimization. Also, in the oil and gas sector, FL is used in emission trading, integration of energy sectors (Zhu et al., 2022), managing charging stations, pollution attack forecasting, and more, making FL a prominent method for sustainable model building. Also, FL uses can also be seen in transportation (edge computation, gradient accuracy, resource optimization, and time optimization) and consumer goods management.

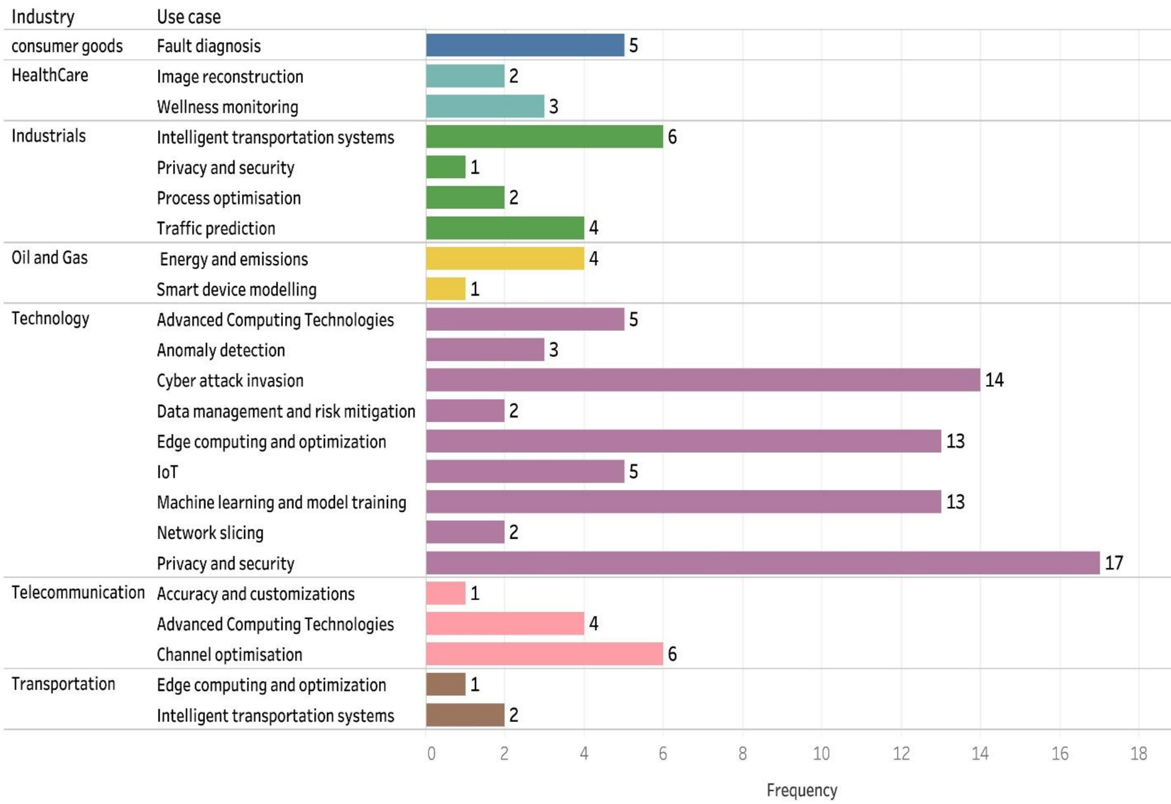


Figure 7. Industries-wise use cases

4.1.3 Characteristics

This section discusses the various features associated with the FL research, and the frequency was tested to check emerging phenomenon surrounding these factors. Figure 8 shows that the FL is employed vastly for security, privacy, and reliability (Lin et al., 2022; Wang et al., 2023) because of the decentralized nature of the FL. Other than that, lower latency and power consumption, decentralized data management, reduced computation time, prevention of malicious attacks, and high bandwidth allocation are the different characteristics that FL possesses over the other ML-based methods. The important illustration drawn from this evaluation is that current ML models usually are unable to address conventional problems like anonymity, massive operations learning, and expensive networks of communication. For many decades, privacy represented a significant challenge. However, FL methods that sustain privacy can be more effective over alternative methods given that they integrate statistical modelling of data on each device and across potentially massive networks. FL helps organizations in articulating the fundamental issues and codifying the problem with the present setup.

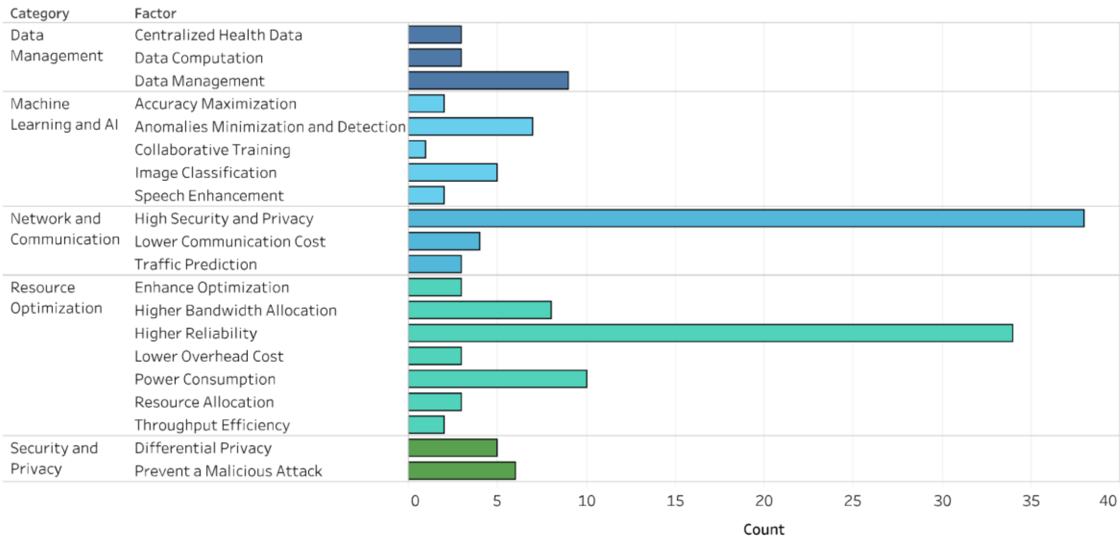


Figure 8. Major benefits of FL implementation

4.1.4 Methods

Researchers have combined various ML methods with base FL to improve service delivery performance (Table 2). In Figure 9, we have presented the researchers' highly used methods in the existing literature. The Figure shows that federated deep reinforcement learning is a highly used method for efficiently delivering the model (Zhang et al., 2022; Yuan et al., 2022). Blockchain-based FL technology is another method that researchers are highly using for smart environment management, distributed malicious attack detection, IoT learning, big data analytics, knowledge sharing, supporting vehicular networks, message dissemination, intelligent transport system, and other performance management system.

Other than the method displayed in the Figure, we found other methods as well which are less frequent. However, these methods are still present in enough research papers. These methods are byzantine-robust FL, Chronos-induced FL, CoFED, Fed MARL, FedBatch, FedRelay, FEMNIST, NN-based FL, OQFL, Stacked FL, TernGrad FL, and more. In Table 2, we have classified all the methods in the existing paper in various domains. Also, we have provided the reference for the same.

Table 2: Classification of methods

Major classification	**Types**	**References**
Distributed and Hierarchical Approaches	Adaptive hierarchical FL	Xu et al., 2021; Guo et al., 2017
	Clustered FL	Taik et al., 2022; Al-Abiad et al., 2022
	Distributed FL	Abdel-Basset et al., 2021; Liu et al., 2021
	Fog-RAN-assisted FL	Park et al., 2022
	Hierarchical FL	Liu et al., 2021; Xu et al., 2021; Xu et al., 2021
Hybrid Approaches	Differentially private FL	Friha et al., 2023; Ibitoye et al., 2022
	Federated Adversarial Learning	Chen et al., 2023; Aljaafari et al., 2022
	IE-based FL (Information Exchange-based Federated Learning)	Yang et al., 2021
	OQFL (Optimal Quantization Federated Learning)	Li et al., 2022

	Semi-SynFed (Semi-Synthetic Federated Learning)	Liang et al., 2022
Other Methods	Blockchain-based FL	He et al., 2021; Li et al., 2022; Hei et al., 2020
	Byzantine-robust FL	Ma et al., 2022
	Chronos-induced FL	Liu et al., 2022
	EA-based FL (Evolutionary Algorithm-based Federated Learning)	Xu et al., 2021
	FCMF (Federated Collaborative Matrix Factorization)	Chen et al., 2022; Yang et al., 2021
	FedAvg (Federated Averaging)	Liu et al., 2021; Kamei & Taghipour, (2023); Liu et al., 2021
	Federated Relay learning	Li et al., 2022
	FedSVRG (Federated Stochastic Variance Reduced Gradient)	Chen et al., 2021
	NN-based FL (Neural Network-based Federated Learning)	Lee et al., 2021; Gu et al., 2022
	OQFL (Optimal Quantization Federated Learning)	Li et al 2022(a)
	Stacked FL	Shaik et al., 2022; de Carvalho Bertoli et al., 2023
Reinforcement Learning	CoFED (Cooperative Federated Learning)	Yuan et al., 2022
	Deep FL	Zhang et al., 2022; Yuan et al., 2022
	Fed DRL (Federated Deep Reinforcement Learning)	Rezazadeh et al., 2022; Sharma et al., 2022
	Newt (Natural Evolutionary Training)	Xu et al., 2021
	PPT-FL (Privacy-Preserving Transfer Federated Learning)	Chen et al., 2023
	Stacked FL	Shaik et al., 202
Supervised Learning	ANN-based FL (Artificial Neural Network-based FL)	Lee et al., 2021; Gu et al., 2022
	CNN-based FL (Convolutional Neural Network-based FL)	Zhu et al., 2021; Xie et al., 2022
	Random forest-based FL	Hauschild et al., 2022
Unsupervised Learning	Federated matrix factorization	Chen et al., 2022; Yang et al., 2021
	Fuzzy-FL (Fuzzy Federated Learning)	Unal et al., 2021; Wang et al., 2023

	HFML (Hierarchical Federated Meta-Learning)	Chai et al., 2020; Wang et al., 2022
	TernGrad FL	Dong et al., 2020

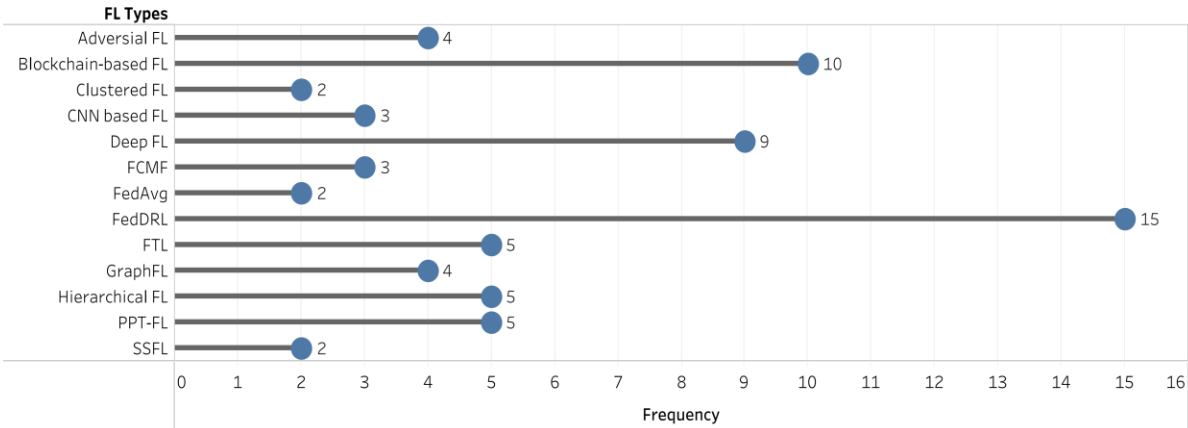


Figure 9. Prominent methods in FL

4.2 FL in decision-making (RQ2)

The factors considered for decision-making using FL are socio-technical; hence, social implications are essential in examining potential solutions in decision-making (Kordzadeh & Ghasemaghaei, 2021). The mutual dependency of social and technical aspects of a firm or society can be inferred by the socio-technical perspective. The pursuit of high standards in people's work and technical performance integrates value into the business and improves the learning of the FL model (Fernandez et al., 2022). Since FL is a new ML model, it enables adaptation and development, molding the way information is communicated both inside and outside the organisation. In addition, it emphasizes that everyone must weigh the risks associated with employing AI and ethical standards should guide the application of ML models. The combination of technology and societies led to end users performing an active role in sustaining the optimal IS design process (Fernandez et al., 2022).

In the further section, we will be discussing how FL can help make informed decision-making compared to the existing ML model by actively participating the users in the system model:

4.2.1 Comparative analysis

This section will present how FL proved to be a better decision-maker than the existing ML models. In Table 3 we have presented the comparative performance analysis of the existing ML models and FL advantage over the existing model. To put forward the comparison, an in-depth evaluation of the literature was executed. The literature review demonstrated the theory behind the preference for the FL model when conducting the subsequent evaluation.

Table 3. Comparative analysis

Sectors	**Existing ML model limitations**	**FL's advantage as a decision maker**
Mobile computation	Existing ML models such as Markov models (MM), k-nearest neighbors (k-NNs), support vector machines (SVMs), Gaussian models (GMs), and more have computational limitations because of the centralized data processing. This makes it less efficient in terms of model sizes, high computational demands (Vashisth et al., 2021), power consumption, network bandwidth (Efron, B. 2020), and more.	FL makes informed decisions on spectrum allocation, user incentivization, security, and privacy (Lin et al., 2022; Wang et al., 2023) by training the model at the edge and minimizing data exchange, data sensitivity, and privacy.

IoT	Models like AdaBoost, CNN, Decision Tree, and Fuzzy face occasional failures due to centralized modeling and sometimes face security threats, scalability (Murugan et al., 2019), power consumption, latency, and more.	IoT carries sensitive data and transmitting that data to the central server can raise security issues (Liu et al., 2022). FL ensures in-house training and provides the raw data never leaves the device. Some IoT devices require real-time training. Federated Learning allows local device inference, enabling faster decision-making (Feng et al., 2022)—FL together with the GT model in cooperative working and making defensive strategies. IoT devices face intermittent connectivity and occasional failures, and FL is robust to this failure as it performs local training and reduces the impact of individual device unavailability.
Autonomous Vehicles	ML is already used in several aspects of technology, such as driver-assistance systems using methods like CNN, R-CNN, SVM, and Deep Reinforcement Learning (Cha et al., 2020). However, these models still face information leakage, centralized dependency, and real-time information.	Autonomous/intelligent vehicles generate a large amount of data, like real-time sensor data and location information, and hence preserving owners' privacy is crucial (Wu et al., 2022). FL performs edge computing on the vehicle or at the network edge, reducing dependency on the centralized cloud (Yamany et al., 2021). FL restricts the information communicated to corresponding patterns and sub-patterns (Qiao et al., 2022).
Healthcare	Existing Models have explainability, lack of quality data, and resource-sharing limitations, which causes less informed decision-making in healthcare sectors. Other than this, centralized data contains large volumes that take time to process (Nayyar et al., 2021; Abdullah et al., 2022). And sometimes causes ethical considerations.	FL-based methods such as FedStack architecture can model the vital signs of each client and bi-furcate them as per their physical activities to enhance the scope of the remote patient monitoring system (Shaik et al., 2022; Ghosh et al., 2023). FL enables large-scale collaborative research among medical data carriers by building robust clinical models with better generalizability and better health outcomes. FL, together with the help of the GT model, takes informed decision-making in the healthcare sector for healthcare resource allocation, health insurance mechanisms, healthcare policies, and regulations. Image classification is another healthcare sector area requiring proper data aggregation from multiple sources; hence, FL weighs each device model to its data distribution and provides fair and accurate model parameters (Shaik et al., 2022; Unal et al., 2021). FL-led image classification is performed across cloud servers, multiple edge nodes, and various clients.
Manufacturing	Manufacturing sites often consist of various resources such as suppliers, tools, past data, and production systems that require integration of all the processes. The existing ML model works on a centralized model in which failure in any section leads to the collapse of the complete system (Wuest et al., 2016).	The manufacturing sector deals with product designs, processes, and proprietary information; hence FL improves decision-making capabilities, optimizes operations, and drives innovation without sharing raw data. It ensures the successful integration of various manufacturing processes. FL optimizes the supply chain model by learning from diverse data sources like suppliers and distributors while maintaining privacy (Tang et al., 2023). It helps improve product quality and reduce defects and hence helps in monetary gain and accountability in real-time (Manimuthu et al., 2022).

Smart Construction	Existing Models, for example, deep learning, are widely used in safety, bridge inspection, and on-site operation monitoring. However, it lacks good data, and overfitting, and underfitting issues (Drgoňa et al., 2018).	FL plays a substantial role in smart city decision-making by enabling decentralized data preservation and fostering collaboration among various stakeholders (Tang et al., 2023). Data comes from multiple sources in smart city buildings, such as sensors, IoT devices, and citizen demand. These data are sensitive and decentralized across various entities, sectors, departments, and locations.
IS	IT sector works on a range of information, methods, and sources; hence it is prone to various kinds of malicious attacks, such as phishing and social engineering, to more complex states, such as denial of service attacks, ransomware, malware, DoS attacks, and more (Oliver, 1996). These attacks can hamper the organization by compromising sensitive data of the organization, its operations, and other economic losses. These imbalances affect the current ML system in information technologies.	Intrusion detection-based FL has a proper consensus technique to protect itself from viable attacks (Abdel-Basset et al., 2021). It is initiated to perform a consistent test set and decide whether a participant's data is eligible. FL checks the feature similarity between the source and the target classes (Zhao et al., 2023) and the similarity rate. The higher the similarities, the higher the attack rate.

4.3 FL-led decision leads to sustainable development (RQ3)

Based on this review, a decentralized data-driven model is a promising way to improve sustainable practices through predicting energy consumption, managing data shortage, detecting potential threats, privacy-preserving, intra-cluster or inter-cluster knowledge sharing, and customized trained models to boost performance. Sustainable economic and technological models help continuously assess and analyze the organizational vision, rationale, and corresponding frameworks that provide economic and technological sustainability in the long run. In Table 4, we presented what benefits FL can bring in terms of sustainability practices. FL empowers adaptation in a dynamic environment through feature learning in various contingencies. It promotes sustainable development and energy-efficient AI models to optimize energy consumption.

Table 4: Areas of Impact and their descriptions

Benefits and impacts	**Descriptions**	**Source**
Energy efficiency	FL builds real-time AI models that optimize energy consumption. FL analyses data from various sources and devices, identifies energy inefficiencies, and makes recommendations accordingly by adjusting energy usage patterns. This helps firms reduce energy wastage and lower carbon emissions, contributing to sustainable development goals.	Liu et al., 2022; Xie et al., 2022
Data privacy and security	FL ensures sensitive data remains on the local server and is not transmitted to a central server for the modeling. This process provides data privacy and security, essential for dealing with private information and building customer trust. FL safeguards privacy and builds company trust with customers, stakeholders, and regulatory bodies for fostering sustainable long-term relationships.	Li et al., 2022; Lau et al., 2021
Scalability and collaboration	FL ensures collaboration across various platforms and departments within the company. Each platform trains the model using local data by capturing unique characteristics and context. There is a decentralized local data training model without sharing the raw data, facilitating knowledge sharing, and enhancing the decision-making capabilities across the firms. It fosters a culture of innovation and sustainability in the data computation model.	Li et al., 2022; Lei et al., 2022

Adaptive optimization	FL-based AI models continuously learn and adapt to changing environments, allowing dynamic optimization of energy consumption patterns. When FL receives raw data, it analyzes emerging patterns and ensures the most efficient use of resources over time. Thus, FL adaptability improves energy consumption patterns and sustainability gains in the long run.	Shi et al., 2023; Zhao et al., 2023
Customization for local contexts	Different regions and communities have unique sustainability challenges. FL allows local stakeholders to train models using local data to incorporate local knowledge, cultural factors, or regulation. This local training model ensures sustainability solutions as per each community's-specific needs and situations and hence delivers appropriate intentions.	Liu et al., 2021
Continuous learning	FL reinforces continuous learning from the dynamic environment and adaptation. Models can be regularly upgraded using new data from distributed devices. This adaptation enables firms to acknowledge sustainability challenges and leverage real-time requirements for effective decision-making.	Li et al., 2022 (b); Chai et al., 2020; Chen et al., 2022

4.4 Challenges in using FL

Table 5 provides an overview of the primary challenges encountered when employing Federated Learning (FL). To enhance comprehension for future researchers investigating FL, we have sub-clustered these major challenges for a more detailed examination.

Table 5: Identified clusters and sub-clusters

Clusters	Sub-clusters	References
Security	Adversarial attacks, malicious attacks, poisoning, bottlenecks, backdoor attacks	Lu et al., 2022; He et al., 2021; Taik et al., 2022
Expensive communication network	Massive devices, bandwidth requirements, gradient sharing	Fang et al., 2021; Zhang et al., 2023
Scalability	Huge edge clients, large model size, massive data, infrastructure, algorithms	Liu et al., 2022; Qayyum et al., 2022
Client selection	Accuracy, device, data distribution, convergence rate, communication capacity	Hei et al., 2020; Liu et al., 2021; Dong et al., 2020
Resource allocation	Fairness, tunable framework, optimal policy	Gu et al., 2022;
Statistical heterogeneity	Non-identically and independently distributed (non-IID) data, multiple outcomes,	Tian et al., 2021; Li et al., 2022; Hui et al., 2022
Data imbalance	Missing data sets, imbalanced datasets, data augmentation	Taik et al., 2022
Privacy	Differential privacy, raw data protection, data leakage, network traffic	Li et al., 2022; Lau et al., 2021; Lau et al., 2021
Algorithm and technical challenges	ML requirements, IoT constraints, and technologies, imbalanced datasets	Ali et al., 2021; Zhu et al., 2022

5 Discussion

This study aimed to explore three research questions. First, we used the TCCM framework to analyze the theme surrounding FL. To advocate this question, we presented the statistics of published journals, keywords networks, industries, used cases, theories, and methodologies applied. We found several emerging phenomena, such as the extensive use of GT for informed decisions (Liang et al., 2022). Within GT, two prominent theories, the Stackelberg game, widely used in operations and pricing strategies, and Evolutionary GT, utilized to model behaviour in repeated games among participating players. Also, FL research involves Forecasting theory to maximize accuracy, Graph theory for data visualization, and Expected utility theory for optimal resource allocation. Prospect theory frames decisions under uncertainty, directing participant behaviour in FL environments and offering efficient reward systems for FL participation. An analysis of industries and sectors focusing on FL research reveals that the technology sector leads in adopting FL for various aspects such as privacy and security, cyber-attack invasion, etc. Next the healthcare sector extensively employs FL for facial fatigue, health management, patient monitoring, and image reconstruction. The industrial sector leverages FL for travel time estimation, process optimization, and collision avoidance. FL finds applications in the oil and gas sector for emission trading, energy integration, pollution attack forecasting, and sustainable model building; last, FL benefits transportation and consumer goods management with time optimization, resource management, and edge computation. Features in FL research analyse the frequency and emerging trends, notably for security, privacy, and reliability due to its centralized advantage.

5.1 Research synthesis

Current study comprehensively synthesizes the emerging fundamental concepts in FL over the past six years, organizing them into themes for researchers to model their studies and choose appropriate methodologies from existing literature. It offers procedural guidance to create a smart industrial ecosystem using FL-enabled ML models for optimal performance and efficiency. The exploration contributes to the IS field by proposing an integrated framework (Figure 10) for decision-making, encompassing sustainability issues, barriers, and applicability, making this research more oriented towards techno-functional view. The techno-functional view based sustainable practices designs consists of an integration of functional and technological contemplation aimed at attaining efficient and sustainable results (Bostrom & Heinen,1977).

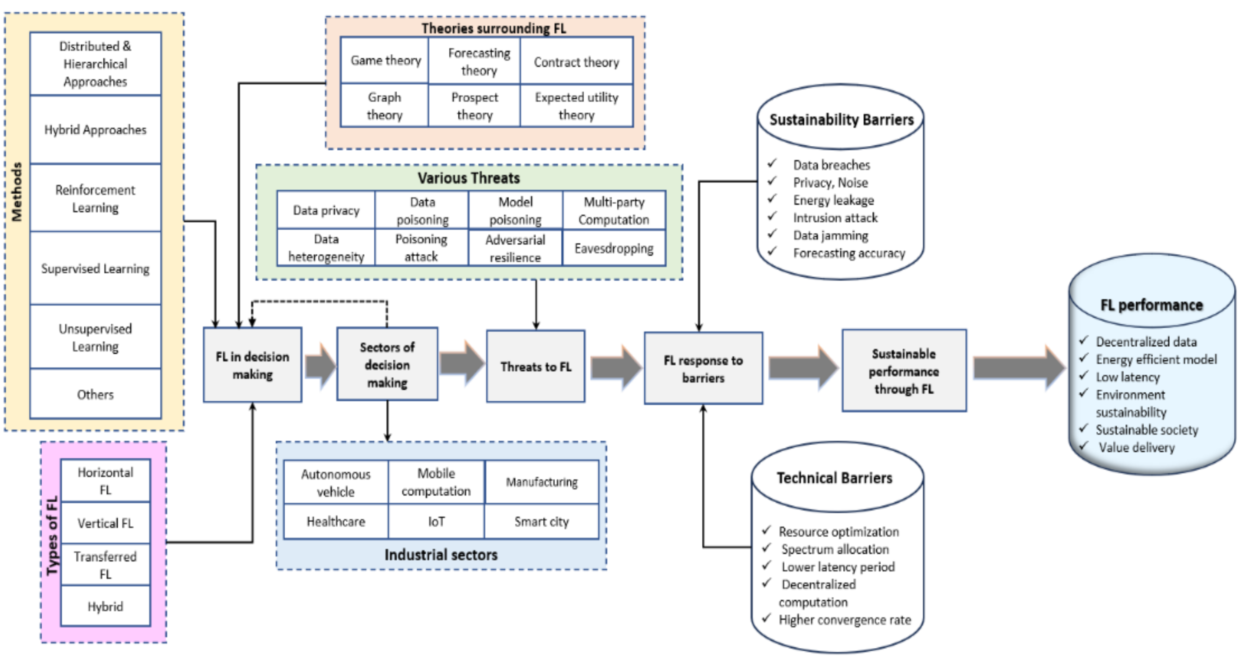


Figure 10. Summary of research findings concerning the FL-led sustainability model

The technical aspects of FL could be analyzed by the comparative analysis of ML methods combined with FL revealed two extensively used techniques in service delivery: Federated Deep Reinforcement Learning for effective model delivery and Blockchain-based FL for varied applications. Additionally, less common methods like Byzantine-robust FL, Chronos-induced FL, CoFED, and others are also found in research publications, which aid in the growth of FL in many different fields. (Zhang et al. 2022; Yuan et al. 2022)

Next, the functional components of FL embodied how FL-led decentralized data sharing improves decision-making. For this, we presented a comparative analysis of existing ML models and FL advantage in various sectors and explained how FL can be proven beneficial in analyzing untapped datasets and maintain security and privacy over the existing models (Kordzadeh & Ghasemaghaei, 2021; Wang et al., 2021a). In addition, the success of the FL system can be continuously tracked and evaluated by implementing key performance indicators (KPIs) for both the functionality and sustainability aspects. It is easier to spot areas of concern and make the required corrections when user and stakeholder feedback mechanisms are comprised.

The last question investigated how decisions based on FL underline drivers of sustainability. Sustainable performance stems from diverse, realistic markets and incorporation of various operations, and making informed decisions (Wang et al., 2021a; Schoormann et al., 2023). Given our final objective of exploring combined FL-led strategies and their advantages regarding sustainability, we found some articles discussing the sustainability aspects of FL in several ways, and we have presented them in Table 3. In Figure 10, the final model leading to sustainability is illustrated. The work aims to synthesize several interdisciplinary elements that touch upon FL performance. We have presented factors such as challenges, methods, and typologies, demonstrating FL's information processing and decision-making capabilities. The following discussion is structured around the connections, as shown in Figure 10. Rather than being causal, these connections should be viewed as associative. We classified the whole process into three steps, which involve the specification of methods & typologies, threats & attributes, and barriers while building the model for sustainability.

First, implementing the FL requires analyzing existing methods and typologies employed by existing industries (Liu et al., 2021; Yuan et al., 2022). This can help upcoming and related industries to map existing technologies with their precinct to pre-determine the efficiency of the model in terms of privacy, data heterogeneity & complexity, and extensive model building. In the next step we presented threat that FL needs to address for efficient model building in terms of decentralized computation, data confidentiality, data access rights, robustness, cross-silos management, and cryptographic modeling to perform real-time modeling (Li et al., 2022; Lau et al., 2021; Liu et al., 2022).

Third, the model presents barriers to existing ML models due to diverse data sources and privacy protocols, which can be superintend using FL. We have classified all barriers into two categories, such as sustainability barriers (data breaching, noise, energy leakage, forecasting accuracy) and technical barriers (resource optimization, lower latency, decentralized computation, spectrum allocation, and more) that pose significant threats to network operations' coordination and synchronization. We showed that efficient internal modeling and sector synchronization leads to achieving an energy-efficient model and delivering sustainable performance in the long run using IS technology (Dedrick, 2010).

The imitation presents the technical importance of FL to overcome barriers in existing ML models such as challenges from diverse data sources, privacy protocols and ensuring secure and efficient coordination and synchronization of network operations. Given model enables researchers to map FL-related factors with respect to their own requirements and deliver optimize performance for better sustainable performance.

5.2 Future research directions

For identify gaps in the existing literature and what questions remain unanswered we considered limitations or shortcomings in previous studies that suggest areas for further investigation. Hence, we developed future research directions that can address these gaps (Suriadi et al., 2014; Paul and Criado, 2020; Snyder, 2019). Based on our analysis, we foresee the following areas of research to emerge over time.

- Research surrounding fairness, accountability, and transparency is yet to be explored in the existing literature on FL. This area could potentially see growth, given the nature of its importance for sustainable development.

- How can enterprises employ FL models for decision-making to enhance consumer privacy? What methodologies can be employed to quantify this privacy preservation during the utilization of FL by corporations?
- To achieve scalability in enterprises, how might FL assist researchers and industry experts in comprehending extensive decentralized datasets for orchestrating operations, generating insights, and catering to customer requisites?
- How can FL tools expedite decentralized decision-making across marketing, business, and sociocultural endeavours to attain sustainability goals within firms?
- How does the influence of FL manifest in augmenting creativity and problem-solving across diverse sectors, contributing to organizational flexibility, and what are the associated merits and demerits?
- How can FL both amplify and address ethical concerns concerning data privacy, bias mitigation, and accountability maintenance in the distributed computing paradigm?
- What are the potential disruptive consequences of implementing FL, encompassing the loss of internal data, proprietary knowledge, and trade secrets? How can practitioners establish apt governance protocols to oversee FL initiatives and avert unforeseen ramifications arising from its integration into business landscapes?
- How do FL models impact societal ethics, cultural predispositions, and user well-being in an era dominated by data-driven paradigms and localization focused services?
- How should regulatory frameworks be devised to mitigate cybersecurity vulnerabilities posed by FL models? What strategies can corporations and society adopt to navigate privacy challenges while upholding access to copious volumes of high-quality data?
- What role can FL assume within the agricultural and banking domains as a presiding tool for decision-making?
- In what manner does FL facilitate organizations in imparting adaptability to their operational workflows through an iterative learning mechanism?
- Also, A distributed ML paradigm called "gossip learning" is based on the idea of social network gossip (Hegedűs et al., 2021). Gossip learning can be explored, which can be better than the existing model, which requires no server for merging data from different locations. With gossip learning, nodes in a network can interact with one another decentralized to learn a model collectively, as opposed to depending on a central server to oversee the learning process.
- FL-based learning can be used to investigate the difficulty of striking a balance between the capabilities of generative AI and protecting data privacy. It can assist in improving data privacy, knowledge sharing, and model generalization which is also inexpensive.

5.3 Practical implications

Overall, the output of the FL process mapping led to helps in fetching the following knowledge:

- A comprehensive overview of key sectors of the industries and their integration with various FL models is presented and dictates sustainability competitiveness in the long run.
- The critical technical threats are emphasized while doing decentralized computations.
- Critical data understanding of the framework enables efficient model building and tracking of the process till the end of operations.

Our model has highlighted the various threats in the FL model implementations and revealed the model for driving sustainability out of it. Properly analyzing the model in the standardized formats is the first step towards FL implementation in the various sectors. Investigating the underlying model of FL can help make informed operational decisions and foster sustainability.

5.4 Limitations

In this review, we only considered the keyword "Federated learning" to find the papers on FL, while some papers might have used the word "collaborative learning" or "distributed learning." Hence those articles are not considered in this review. Technical subjects like FL often span multiple disciplines, and researchers may not be experts in all relevant fields. This can result in a limited understanding of certain aspects of literature. The primary focus of the study was on IS research. Although we have extended the scope of this literature review by including game theory component, background mechanism of FL working, aiming to make the analysis more comprehensive, the conclusion might get impacted as this study may not fully encompass all the relevant aspects of the game theory and technicalities of FL working model.

6 Conclusion

Working around the theme of FL can help build transparency, economics, and traceability while implementing the FL model for future researchers. While making FL led decision requires understanding the various themes surrounding the FL implementation process, data integration, process modeling, and incorporating suitable methodology are the most pertinent value-delivering methods while implementing the FL model. Our findings can help researchers with queries surrounding FL themes and context and provide a business roadmap for capturing a sustainable value chain delivery model underpinning interrelated processes. The proposed unified framework encapsulates critical factors that need to be analyzed across various hierarchies of the FL model as a basis for successful FL implementations.

References

Abdel-Basset, M., Moustafa, N., Hawash, H., Razzak, I., Sallam, K. M., & Elkomy, O. M. (2021). Federated intrusion detection in blockchain-based smart transportation systems. *IEEE Transactions on Intelligent Transportation Systems*, *23*(3), 2523-2537.

Abdullah, A. A., Hassan, M. M., & Mustafa, Y. T. (2022). A review on bayesian deep learning in healthcare: Applications and challenges. *IEEE Access*, *10*, 36538-36562.

Al-Abiad, M. S., & Hossain, M. J. (2022). Coordinated Scheduling and Decentralized Federated Learning Using Conflict Clustering Graphs in Fog-Assisted IoD Networks. *IEEE Transactions on Vehicular Technology*, *72*(3), 3455-3472.

Ali, M., Karimipour, H., & Tariq, M. (2021). Integration of blockchain and federated learning for Internet of Things: Recent advances and future challenges. *Computers & Security*, *108*, 102355.

Aljaafari, N., Nazzal, M., Sawalmeh, A. H., Khreishah, A., Anan, M., Algosaibi, A., ... & Vizcarra, C. P. (2022). Investigating the Factors Impacting Adversarial Attack and Defense Performances in Federated Learning. *IEEE Transactions on Engineering Management, 1-14*. 10.1109/TEM.2022.3155353

Bostrom, R. P., & Heinen, J. S. (1977). MIS problems and failures: A socio-technical perspective. Part I: The causes. *MIS quarterly*, 1(3), 17-32.

Brisimi, T. S., Chen, R., Mela, T., Olshevsky, A., Paschalidis, I. C., & Shi, W. (2018). Federated learning of predictive models from federated electronic health records. *International journal of medical informatics*, *112*, 59-67.

Cha, J., Kim, K. S., & Lee, S. (2020). Hierarchical auxiliary learning. *Machine Learning: Science and Technology*, *1*(4), 045002.

Chai, H., Leng, S., Chen, Y., & Zhang, K. (2020). A hierarchical blockchain-enabled federated learning algorithm for knowledge sharing in internet of vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *22*(7), 3975-3986.

Chen, D., Hong, C. S., Zha, Y., Zhang, Y., Liu, X., & Han, Z. (2021). FedSVRG based communication efficient scheme for federated learning in MEC networks. *IEEE Transactions on Vehicular Technology*, *70*(7), 7300-7304.

Chen, H., Fu, C., & Hu, C. (2022). An efficient and secure recommendation system based on federated matrix factorization in digital economy. *Personal and Ubiquitous Computing*, 1-12.

Chen, Q., Wang, Z., Zhang, W., & Lin, X. (2023). PPT: A privacy-preserving global model training protocol for federated learning in P2P networks. *Computers & Security*, *124*, 102966.

Chen, M., Zhang, W., Yuan, Z., Jia, Y., & Chen, H. (2022). Federated knowledge graph completion via embedding-contrastive learning. *Knowledge-Based Systems*, *252*, 109459.

Chen, Z., Li, J., Cheng, L., & Liu, X. (2023). Federated-WDCGAN: A federated smart meter data sharing framework for privacy preservation. Generalizing intrusion detection for heterogeneous networks: A stacked-unsupervised federated learning approach. *Computers & Security*, *127*, 103106.

Chopra, I. P., Jebarajakirthy, C., Acharyya, M., Saha, R., Maseeh, H. I., & Nahar, S. (2023). A systematic literature review on network marketing: What do we know and where should we be heading?. *Industrial Marketing Management*, 113, 180-201.

Dedrick, J. (2010). Green IS: Concepts and issues for information systems research. *Communications of the Association for Information Systems*, 27(1), 11.

Dong, Y., Chen, X., Shen, L., & Wang, D. (2020). Eastfly: Efficient and secure ternary federated learning. *Computers & Security*, *94*, 101824.

Drgoňa, J., Picard, D., Kvasnica, M., & Helsen, L. (2018). Approximate model predictive building control via machine learning. *Applied Energy*, *218*, 199-216.

Efron, B. (2020). Prediction, estimation, and attribution. *International Statistical Review*, *88*, S28-S59.

Eseryel, U. Y., Wei, K., & Crowston, K. (2020). Decision-making processes in community-based free/libre open source software-development teams with internal governance: An extension to decision-making theory. *Communications of the Association for Information Systems*, *46(1), 20.*

Fan, J., Furger, A., & Xiu, D. (2016). Incorporating global industrial classification standard into portfolio allocation: A simple factor-based large covariance matrix estimator with high-frequency data. *Journal of Business & Economic Statistics*, 34(4), 489-503.

Fang, C., Guo, Y., Hu, Y., Ma, B., Feng, L., & Yin, A. (2021). Privacy-preserving and communication-efficient federated learning in internet of things. *Computers & Security*, *103*, 102199.

Fantacci, R., & Picano, B. (2020). When network slicing meets prospect theory: A service provider revenue maximization framework. *IEEE Transactions on Vehicular Technology*, *69*(3), 3179-3189.

Feng, S., Li, B., Yu, H., Liu, Y., & Yang, Q. (2022). Semi-Supervised Federated Heterogeneous Transfer Learning. *Knowledge-Based Systems*, *252*, 109384.

Fernández, J. D., Menci, S. P., Lee, C. M., Rieger, A., & Fridgen, G. (2022). Privacy-preserving federated learning for residential short-term load forecasting. *Applied energy*, *326*, 119915.

Friha, O., Ferrag, M. A., Benbouzid, M., Berghout, T., Kantarci, B., & Choo, K. K. R. (2023). 2DF-IDS: Decentralized and differentially private federated learning-based intrusion detection system for industrial IoT. *Computers & Security*, *127*, 103097.

Ibitoye, O., Shafiq, M. O., & Matrawy, A. (2022). Differentially private self-normalizing neural networks for adversarial robustness in federated learning. *Computers & Security*, *116*, 102631.

Ghosh, K., Deokar, A. V., & Sen, S. (2023). Impact of Using Online Health Management Tools on Patient Perception of Healthcare Quality: A Multiple Chronic Conditions and Generational Perspective. *Communications of the Association for Information Systems, 52(1), 34.*

Guo, J., Luo, Y., & Li, K. (2017). An adaptive hierarchical trajectory following control approach of autonomous four-wheel independent drive electric vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *19*(8), 2482-2492.

Gu, X., Tianqing, Z., Li, J., Zhang, T., Ren, W., & Choo, K. K. R. (2022). Privacy, accuracy, and model fairness trade-offs in federated learning. *Computers & Security*, *122*, 102907.

Hauschild, A. C., Lemanczyk, M., Matschinske, J., Frisch, T., Zolotareva, O., Holzinger, A., ... & Heider, D. (2022). Federated Random Forests can improve local performance of predictive models for various healthcare applications. *Bioinformatics*, *38*(8), 2278-2286.

He, C., Xiao, B., Chen, X., Xu, Q., & Lin, J. (2021). Federated learning intellectual capital platform. *Personal and Ubiquitous Computing*, 1-12.

Hegedűs, I., Danner, G., & Jelasity, M. (2021). Decentralized learning works: An empirical comparison of gossip learning and federated learning. *Journal of Parallel and Distributed Computing, 148, 109-124.*

Hei, X., Yin, X., Wang, Y., Ren, J., & Zhu, L. (2020). A trusted feature aggregator federated learning for distributed malicious attack detection. *Computers & Security*, *99*, 102033.

Hui, Y., Zhao, G., Li, C., Cheng, N., Yin, Z., Luan, T. H., & Xiao, X. (2022). Digital twins enabled on-demand matching for multi-task federated learning in hetvnets. *IEEE Transactions on Vehicular Technology*, *72*(2), 2352-2364.

Jebarajakirthy**,** C., Maseeh, H. I., Morshed, Z., Shankar, A., Arli, D., & Pentecost, R. (2021). Mobile advertising: A systematic literature review and future research agenda. *International Journal of Consumer Studies*, 45(6), 1258-1291.

Kamei, S., & Taghipour, S. (2023). A comparison study of centralized and decentralized federated learning approaches utilizing the transformer architecture for estimating remaining useful life. *Reliability Engineering & System Safety*, *233*, 109130.

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production*, 134120.

Kordzadeh, N., & Ghasemaghaei, M. (2022). Algorithmic bias: review, synthesis, and future research directions. *European Journal of Information Systems*, *31*(3), 388-409.

Kreps, D. M. (1989). Nash equilibrium. In *Game Theory* (pp. 167-177). London: Palgrave Macmillan UK.

Kumar, P., Hollebeek, L. D., Kar, A. K., & Kukk, J. (2023). Charting the intellectual structure of customer experience research. *Marketing Intelligence & Planning, 41(1), 31-47.*

Kumar, S., Kar, A. K., & Ilavarasan, P. V. (2021). Applications of text mining in services management: A systematic literature review. *International Journal of Information Management Data Insights*, *1*(1), 100008.

Lau, H., Tsang, Y. P., Nakandala, D., & Lee, C. K. (2021). Risk quantification in cold chain management: a federated learning-enabled multi-criteria decision-making methodology. *Industrial Management & Data Systems*, *121*(7), 1684-1703.

Lee, H., Kim, J., Ahn, S., Hussain, R., Cho, S., & Son, J. (2021). Digestive neural networks: A novel defense strategy against inference attacks in federated learning. *Computers & Security*, *109*, 102378.

Liang, F., Yang, Q., Liu, R., Wang, J., Sato, K., & Guo, J. (2022). Semi-synchronous federated learning protocol with dynamic aggregation in Internet of Vehicles. *IEEE Transactions on Vehicular Technology*, *71*(5), 4677-4691.

Lopez, V. G., Lewis, F. L., Liu, M., Wan, Y., Nageshrao, S., & Filev, D. (2022). Game-theoretic lane-changing decision making and payoff learning for autonomous vehicles. *IEEE Transactions on Vehicular Technology*, *71*(4), 3609-3620.

Li, F., Shen, B., Guo, J., Lam, K. Y., Wei, G., & Wang, L. (2022(b)). Dynamic spectrum access for internet-of-things based on federated deep reinforcement learning. *IEEE Transactions on Vehicular Technology*, *71*(7), 7952-7956.

Li, D., Luo, Z., & Cao, B. (2022(a). Blockchain-based federated learning methodologies in smart environments. *Cluster Computing*, *25*(4), 2585-2599.

Li, B., Jiang, Y., Pei, Q., Li, T., Liu, L., & Lu, R. (2022). Feel: Federated end-to-end learning with non-iid data for vehicular ad hoc networks. *IEEE Transactions on Intelligent Transportation Systems*, *23*(9), 16728-16740.

Li, C., Zhang, Y., & Luo, Y. (2022). A federated learning-based edge caching approach for mobile edge computing-enabled intelligent connected vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 24(3), 3360-3369.

Li, P., Zhong, Y., Zhang, C., Wu, Y., & Yu, R. (2022). FedRelay: Federated Relay Learning for 6G Mobile Edge Intelligence. *IEEE Transactions on Vehicular Technology*, *72*(4), 5125-5138.

Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated learning: Challenges, methods, and future directions. *IEEE signal processing magazine, 37(3), 50-60.*

Liu, J., Xu, H., Wang, L., Xu, Y., Qian, C., Huang, J., & Huang, H. (2021). Adaptive asynchronous federated learning in resource-constrained edge computing. *IEEE Transactions on Mobile Computing, 22(2), 674-690*

Li, Y., Guo, Y., Alazab, M., Chen, S., Shen, C., & Yu, K. (2022). Joint optimal quantization and aggregation of federated learning scheme in VANETs. *IEEE Transactions on Intelligent Transportation Systems*, *23*(10), 19852-19863 (a).

Liang, F., Yang, Q., Liu, R., Wang, J., Sato, K., & Guo, J. (2022). Semi-synchronous federated learning protocol with dynamic aggregation in Internet of Vehicles. *IEEE Transactions on Vehicular Technology*, *71*(5), 4677-4691.

Lei, M., Li, Q., Ge, X., & Pandharipande, A. (2022). Partially Collaborative Edge Caching Based on Federated Deep Reinforcement Learning. *IEEE Transactions on Vehicular Technology*, *72*(1), 1389-1394.

Lim, W. Y. B., Ng, J. S., Xiong, Z., Jin, J., Zhang, Y., Niyato, D., ... & Miao, C. (2021). Decentralized edge intelligence: A dynamic resource allocation framework for hierarchical federated learning. *IEEE Transactions on Parallel and Distributed Systems*, *33*(3), 536-550.

Lin, W. T., Chen, G., & Huang, Y. (2022). Incentive edge-based federated learning for false data injection attack detection on power grid state estimation: A novel mechanism design approach. *Applied Energy*, *314*, 118828.

Liu, L., Xi, Z., Zhu, K., Wang, R., & Hossain, E. (2022). Mobile Charging Station Placements in Internet of Electric Vehicles: A Federated Learning Approach. *IEEE Transactions on Intelligent Transportation Systems*, *23*(12), 24561-24577.

Liu, S., Yu, J., Deng, X., & Wan, S. (2021). FedCPF: An efficient-communication federated learning approach for vehicular edge computing in 6G communication networks. *IEEE Transactions on Intelligent Transportation Systems*, *23*(2), 1616-1629.

Liu, Y., Zhang, X., Zhao, Y., He, Y., Yu, S., & Zhu, K. (2022). Chronos: Accelerating Federated Learning With Resource Aware Training Volume Tuning at Network Edges. *IEEE Transactions on Vehicular Technology*, *72*(3), 3889-3903.

Lu, S., Li, R., Liu, W., & Chen, X. (2022). Defense against backdoor attack in federated learning. *Computers & Security*, *121*, 102819.

Liu, T., Zhou, H., Li, J., Shu, F., & Han, Z. (2022). Uplink and Downlink Decoupled 5G/B5G Vehicular Networks: A Federated Learning Assisted Client Selection Method. *IEEE Transactions on Vehicular Technology*, *72*(2), 2280-2292.

Li, Y., Guo, Y., Alazab, M., Chen, S., Shen, C., & Yu, K. (2022). Joint optimal quantization and aggregation of federated learning scheme in VANETs. *IEEE Transactions on Intelligent Transportation Systems*, *23*(10), 19852-19863.

Li, Y., Wang, R., Li, Y., Zhang, M., & Long, C. (2023). Wind power forecasting considering data privacy protection: A federated deep reinforcement learning approach. *Applied Energy*, *329*, 120291.

Liu, H., Zhang, S., Zhang, P., Zhou, X., Shao, X., Pu, G., & Zhang, Y. (2021). Blockchain and federated learning for collaborative intrusion detection in vehicular edge computing. *IEEE Transactions on Vehicular Technology*, *70*(6), 6073-6084.

Manimuthu, A., Venkatesh, V. G., Shi, Y., Sreedharan, V. R., & Koh, S. L. (2022). Design and development of automobile assembly model using federated artificial intelligence with smart contract. *International Journal of Production Research*, *60*(1), 111-135.

Ma, X., Jiang, Q., Shojafar, M., Alazab, M., Kumar, S., & Kumari, S. (2022). DisBezant: secure and robust federated learning against byzantine attack in IoT-enabled MTS. *IEEE Transactions on Intelligent Transportation Systems*, *24*(2), 2492-2502.

Martínez-López, F. J., Merigó, J. M., Gázquez-Abad, J. C., & Ruiz-Real, J. L. (2020). Industrial marketing management: Bibliometric overview since its foundation. *Industrial Marketing Management*, 84, 19-38.

Mehmood, K. K., Kim, C. H., Khan, S. U., & Haider, Z. M. (2018). Unified planning of wind generators and switched capacitor banks: A multiagent clustering-based distributed approach. *IEEE Transactions on Power Systems*, *33*(6), 6978-6988.

Montazeri, M., Kebriaei, H., Araabi, B. N., Kang, J., & Niyato, D. (2022). Distributed mechanism design in continuous space for federated learning over vehicular networks. *IEEE Transactions on Vehicular Technology*, *72*(4), 4196-4206.

Murugan, B. S., Elhoseny, M., Shankar, K., & Uthayakumar, J. (2019). Region-based scalable smart system for anomaly detection in pedestrian walkways. *Computers & Electrical Engineering*, *75*, 146-160.

Nayyar, A., Gadhavi, L., & Zaman, N. (2021). Machine learning in healthcare: review, opportunities and challenges. *Machine Learning and the Internet of Medical Things in Healthcare*, 23-45.

Nisan, N., Roughgarden, T., Tardos, E., & Vazirani, V. V. (Eds.). (2007). *Algorithmic game theory*. Cambridge University Press.

Oliver, J. R. (1996). A machine-learning approach to automated negotiation and prospects for electronic commerce. *Journal of management information systems*, *13*(3), 83-112.

Qiao, C., Qiu, J., Tan, Z., Min, G., Zomaya, A. Y., & Tian, Z. (2022). Evaluation mechanism for decentralized collaborative pattern learning in heterogeneous vehicular networks. *IEEE Transactions on Intelligent Transportation Systems*, 24(11), 13123-13132

Pham, Q. V., Zeng, M., Ruby, R., Huynh-The, T., & Hwang, W. J. (2021). UAV communications for sustainable federated learning. *IEEE Transactions on Vehicular Technology*, *70*(4), 3944-3948.

Park, S. H., & Lee, H. (2022). Completion time minimization of fog-RAN-assisted federated learning with rate-splitting transmission. *IEEE Transactions on Vehicular Technology*, *71*(9), 10209-10214.

Paul, J., & Rosado-Serrano, A. (2019). Gradual internationalization vs born-global international new venture models: A review and research agenda. *International Marketing Review*, 36(6), 830–858. https://doi.org/10.1108/IMR-10-2018-0280

Paul, J., & Criado, A. R. (2020). The art of writing literature review: What do we know and what do we need to know?. *International business review*, 29(4), 101717.

Qayyum, A., Janjua, M. U., & Qadir, J. (2022). Making federated learning robust to adversarial attacks by learning data and model association. *Computers & Security*, *121*, 102827.

Qiu, D., Xue, J., Zhang, T., Wang, J., & Sun, M. (2023). Federated reinforcement learning for smart building joint peer-to-peer energy and carbon allowance trading. *Applied Energy*, *333*, 120526.

Qiao, C., Qiu, J., Tan, Z., Min, G., Zomaya, A. Y., & Tian, Z. (2022). Evaluation Mechanism for Decentralized Collaborative Pattern Learning in Heterogeneous Vehicular Networks. *IEEE Transactions on Intelligent Transportation Systems*.

Rezazadeh, F., Zanzi, L., Devoti, F., Chergui, H., Costa-Pérez, X., & Verikoukis, C. (2022). On the Specialization of FDRL Agents for Scalable and Distributed 6G RAN Slicing Orchestration. *IEEE Transactions on Vehicular Technology*, *72*(3), 3473-3487.

Schoormann, T., Strobel, G., Möller, F., Petrik, D., & Zschech, P. (2023). Artificial Intelligence for Sustainability—A Systematic Review of Information Systems Literature. *Communications of the Association for Information Systems*, 52(1), 8.

Shaik, T., Tao, X., Higgins, N., Gururajan, R., Li, Y., Zhou, X., & Acharya, U. R. (2022). Fedstack: Personalized activity monitoring using stacked federated learning. *Knowledge-Based Systems*, *257*, 109929.

Sharma, H., Kumar, N., & Tekchandani, R. (2022). Mitigating Jamming Attack in 5G Heterogeneous Networks: A Federated Deep Reinforcement Learning Approach. *IEEE Transactions on Vehicular Technology*, *72*(2), 2439-2452.

Singh, V., Chen, S. S., Singhania, M., Nanavati, B., & Gupta, A. (2022). How are reinforcement learning and deep learning algorithms used for big data based decision making in financial industries–A review and research agenda. International Journal of Information Management Data Insights, 2(2), 100094.

Shi, N., & Kontar, R. A. (2023). Personalized federated learning via domain adaptation with an application to distributed 3D printing. *Technometrics*, 1-12.

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of business research*, 104, 333-339.

Suriadi, S., Weiß, B., Winkelmann, A., ter Hofstede, A. H., Adams, M., Conforti, R., ... & Wynn, M. (2014). Current research in risk-aware business process management—overview, comparison, and gap analysis. *Communications of the Association for Information Systems*, 34(1), 52.

Taik, A., Mlika, Z., & Cherkaoui, S. (2022). Clustered vehicular federated learning: Process and optimization. *IEEE Transactions on Intelligent Transportation Systems*, *23*(12), 25371-25383.

Tian, P., Chen, Z., Yu, W., & Liao, W. (2021). Towards asynchronous federated learning based threat detection: A DC-Adam approach. *Computers & Security*, *108*, 102344.

Tian, Z., Gao, X., Su, S., Qiu, J., Du, X., & Guizani, M. (2019). Evaluating reputation management schemes of internet of vehicles based on evolutionary game theory. *IEEE Transactions on Vehicular Technology*, *68*(6), 5971-5980.

Tian, Y., Govindan, K., & Zhu, Q. (2014). A system dynamics model based on evolutionary game theory for green supply chain management diffusion among Chinese manufacturers. *Journal of Cleaner Production*, *80*, 96-105.

Turedi, S., & Zhu, H. (2019). How to generate more value from IT: The interplay of it investment, decision making structure, and senior management involvement in IT governance. *Communications of the Association for Information Systems*, 44(1), 26.

Unal, D., Hammoudeh, M., Khan, M. A., Abuarqoub, A., Epiphaniou, G., & Hamila, R. (2021). Integration of federated machine learning and blockchain for the provision of secure big data analytics for Internet of Things. *Computers & Security*, *109*, 102393.

Wakolbinger, T., Fabian, F., & Kettinger, W. J. (2013). IT-enabled interorganizational information sharing under co-opetition in disasters: A game-theoretic framework. *Communications of the Association for Information Systems,* 33(1), 5.

Wang, K. Y., Ting, I. H., & Wu, H. J. (2013). Discovering interest groups for marketing in virtual communities: An integrated approach. *Journal of Business Research*, 66(9), 1360-1366.

Wang, X., Garg, S., Lin, H., Kaddoum, G., Hu, J., & Hassan, M. M. (2021) (a). Heterogeneous blockchain and ai-driven hierarchical trust evaluation for 5G-enabled intelligent transportation systems. *IEEE Transactions on Intelligent Transportation Systems*. 10.1109/TITS.2021.3129417

Wang, X., Liu, W., Lin, H., Hu, J., Kaur, K., & Hossain, M. S. (2022) (b). AI-empowered trajectory anomaly detection for intelligent transportation systems: A hierarchical federated learning approach. *IEEE Transactions on Intelligent Transportation Systems*, *24*(4), 4631-4640.

Wu, C., Yoshinaga, T., Ji, Y., & Zhang, Y. (2018). Computational intelligence inspired data delivery for vehicle-to-roadside communications. *IEEE Transactions on Vehicular Technology*, *67*(12), 12038-12048.

Wu, G., Li, J., Ning, Z., Wang, Y., & Li, B. (2022). Federated Learning Enabled Credit Priority Task Processing for Transportation Big Data. *IEEE Transactions on Intelligent Transportation Systems*. 10.1109/TITS.2022.3210405

Wuest, T., Weimer, D., Irgens, C., & Thoben, K. D. (2016). Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research*, *4*(1), 23-45.

Vashisth, S., Dhall, I., & Aggarwal, G. (2021). Design and analysis of quantum powered support vector machines for malignant breast cancer diagnosis. *Journal of Intelligent Systems*, *30*(1), 998-1013.

Xia, M., Jin, D., & Chen, J. (2022). Short-term traffic flow prediction based on graph convolutional networks and federated learning. *IEEE Transactions on Intelligent Transportation Systems*, *24*(1), 1191-1203.

Xiao, H., Zhao, J., Pei, Q., Feng, J., Liu, L., & Shi, W. (2021). Vehicle selection and resource optimization for federated learning in vehicular edge computing. *IEEE Transactions on Intelligent Transportation Systems*, 23(8), 11073-11087.

Xie, K., Zhang, Z., Li, B., Kang, J., Niyato, D., Xie, S., & Wu, Y. (2022). Efficient federated learning with spike neural networks for traffic sign recognition. *IEEE Transactions on Vehicular Technology*, *71*(9), 9980-9992.

Xu, B., Xia, W., Wen, W., Liu, P., Zhao, H., & Zhu, H. (2021). Adaptive hierarchical federated learning over wireless networks. *IEEE Transactions on Vehicular Technology*, *71*(2), 2070-2083.

Xu, J., Jin, Y., Du, W., & Gu, S. (2021). A federated data-driven evolutionary algorithm. *Knowledge-based systems*, *233*, 107532.

Yamany, W., Moustafa, N., & Turnbull, B. (2021). Oqfl: An optimized quantum-based federated learning framework for defending against adversarial attacks in intelligent transportation systems. *IEEE Transactions on Intelligent Transportation Systems*. 10.1109/TITS.2021.3130906

Yang, E., Huang, Y., Liang, F., Pan, W., & Ming, Z. (2021). FCMF: Federated collective matrix factorization for heterogeneous collaborative filtering. *Knowledge-Based Systems*, *220*, 106946.

Yang, M., Qian, H., Wang, X., Zhou, Y., & Zhu, H. (2021). Client selection for federated learning with label noise. *IEEE Transactions on Vehicular Technology*, *71*(2), 2193-2197.

Yu, Y., Chu, F., & Chen, H. (2009). A Stackelberg game and its improvement in a VMI system with a manufacturing vendor. *European Journal of Operational Research*, *192*(3), 929-948.

Yu, M., & Hong, S. H. (2016). Supply–demand balancing for power management in smart grid: A Stackelberg game approach. *Applied energy*, *164*, 702-710.

Yuan, X., Chen, J., Yang, J., Zhang, N., Yang, T., Han, T., & Taherkordi, A. (2022). Fedstn: Graph representation driven federated learning for edge computing enabled urban traffic flow prediction. *IEEE Transactions on Intelligent Transportation Systems,* 8738 - 8748.

Zeng, R., Zeng, C., Wang, X., Li, B., & Chu, X. (2022). Incentive Mechanisms in Federated Learning and A Game-Theoretical Approach. *IEEE Network*, *36*(6), 229-235.

Zhao, K., Hu, J., Shao, H., & Hu, J. (2023). Federated multi-source domain adversarial adaptation framework for machinery fault diagnosis with data privacy. *Reliability Engineering & System Safety*, *236*, 109246.

Zhou, H., Zheng, Y., Huang, H., Shu, J., & Jia, X. (2023). Toward Robust Hierarchical Federated Learning in Internet of Vehicles. *IEEE Transactions on Intelligent Transportation Systems*. 10.1109/TITS.2023.3243003

Zhao, Y., Zhang, J., & Cao, Y. (2023). Manipulating vulnerability: Poisoning attacks and countermeasures in federated cloud–edge–client learning for image classification. *Knowledge-Based Systems*, *259*, 110072

Zhang, C., Li, M., & Wu, D. (2022). Federated Multidomain Learning With Graph Ensemble Autoencoder GMM for Emotion Recognition. *IEEE Transactions on Intelligent Transportation Systems*.

Zhang, C., Xie, Y., Bai, H., Yu, B., Li, W., & Gao, Y. (2021). A survey on federated learning. *Knowledge-Based Systems*, *216*, 106775.

Zhang, H., & Hanzo, L. (2020). Federated learning assisted multi-UAV networks. *IEEE Transactions on Vehicular Technology*, *69*(11), 14104-14109.

Zhang, Z., Tianqing, Z., Ren, W., Xiong, P., & Choo, K. K. R. (2023). Preserving data privacy in federated learning through large gradient pruning. *Computers & Security*, *125*, 103039.

Zhu, J., Dong, H., Zheng, W., Li, S., Huang, Y., & Xi, L. (2022). Review and prospect of data-driven techniques for load forecasting in integrated energy systems. *Applied Energy*, *321*, 119269.

Zhu, Y., Liu, Y., James, J. Q., & Yuan, X. (2021). Semi-supervised federated learning for travel mode identification from GPS trajectories. *IEEE Transactions on Intelligent Transportation Systems*, *23*(3), 2380-2391.

About the Authors

Shweta Kumari Choudhary is a research scholar at the department of management studies (DMS) Indian Institute of Technology (IIT) Delhi. Prior to this she worked as a research associate in “digital technologies and tourism in the ICPS CoE” and project sponsored by the Ministry of Science and Technology. Education-wise, she has completed her graduation in Engineering and master’s in management and business administration. Her professional interests focus on research areas like artificial intelligence, social media, tourism, and sustainability. She serves as a reviewer for journals like the International Journal of Information Management Data Insights and the Global Journal of Flexible Systems Management. She has published her research in journals like the Journal of Cleaner Production and Decision.

Arpan Kumar Kar is full Professor of Information Systems in Indian Institute of Technology Delhi, India where he holds the AS Gupta Endowed Chair Professorship. He has a joint appointment in the Department of Management Studies and School of Artificial Intelligence. He works in the interface of use, impact, and governance of emerging technologies like artificial intelligence, digital platforms, social media, blockchain and metaverse, often using computationally intensive empirical methods. He has authored over 200 publications and edited 14 books, of which over 75 publications are in ABDC A, ABS 3 and WoS Q1 level journals, and 15 are A* publications. He is the Editor in Chief of International Journal of Information Management Data Insights, published by Elsevier. He has been a Guest Editor for journals like JAIS, DSS, IMM, IJIM, ISF, ECR, AJIS, etc. He is an Associate Editor for CAIS, JCIS and GJFSM, which are all ABDC A level journals. He received the Research Excellence Award by Clarivate Analytics for highest individual Web of Science citations from 2015-2020 in India. He received the BK Birla Distinguished Researcher Award based on the count of ABDC A*/ABS 4 level publications between 2014 - 2019 in India. He is the recipient of the Best Seller Award from Ivey / Harvard in 2020 for the 5-year sales of his authored case on social media analytics.

Yogesh K. Dwivedi is a Professor of Digital Marketing and Innovation, Founding Director of the Emerging Markets Research Centre (EMaRC) and Co-Director of Research at the School of Management, Swansea University, Wales, UK. Professor Dwivedi is also currently leading the International Journal of Information Management as its Editor-in-Chief. His research interests are at the interface of Information Systems (IS) and Marketing, focusing on issues related to consumer adoption and diffusion of emerging digital innovations, digital government, and digital and social media marketing particularly in the context of emerging markets. Professor Dwivedi has published more than 300 articles in a range of leading academic journals and conferences that are widely cited (more than 18 thousand times as per Google Scholar). Professor Dwivedi is an Associate Editor of the Journal of Business Research, European Journal of Marketing, Government Information Quarterly and International Journal of Electronic Government Research, and Senior Editor of the Journal of Electronic Commerce Research.

Appendix A

A.1 Comparative judgment from management or IS research perspective.

Theory	Major area of focus	Application in Federated Learning (FL)	Key Insights and Considerations	References
Game theory	Decentralized operations and coordination, leader-follower model, and their significant applications in hierarchical decision-making. -Determines how player strategies evolve, adapt, and change repeated games in FL to illustrate participant behaviour.	- Stackelberg game theory: Utilized for coordinating communications between companies and users, optimizing data orders, and decentralized operations. - Evolutionary GT: Mimics FL participants' actions as players in a recurring game, improving the ML model and encouraging collaboration and concurrence.	-The Stackelberg Game sheds light on the best pricing and demand tactics in FL. - Evolutionary GT fosters device collaboration and assists in understanding the dynamics of FL algorithms.	Yu et al., 2009; Yu & Hong, 2016; Tian et al., 2014; Lim et al., 2021
Forecasting theory	Permits data pooling in FL while preserving security and privacy, which increases the forecasting model's accuracy.	By extracting data while preserving security and privacy, FL improves the precision of forecasting models. Patterns in sales, inventory, and website traffic can be determined in FL through time series analysis. In FL, regression analysis anticipates results according to the demands of the market.	The complementary functions of forecasting theory and FL in AI. In industries like supply chain forecasting, FL enhances accuracy by leveraging data from multiple organizations.	Fernández et al., 2022
Contract theory	Incentivizes organizations to participate in FL through optimal contracts, addresses asymmetric information issues	- Incentivizes FL participation through contracts offering rewards for data leveraging or model enhancement. - Contracts in FL task allocation considers incomplete information about private data. - Provides mechanisms under asymmetric information, incentivizing data owners to join FL tasks and report information truthfully.	Employing a structure based on contract theory, FL enables an ideal layout of contracts that address insufficient data. Data owners are urged to participate in strengthening FL models through incentives.	Fernández et al., 2022; Montazeri et al., 2022
Expected utility theory	Using decision theory, respondents' behaviors in FL are influenced by predicting individual preferences in	Forecasts individual preferences in FL decision-making with unanticipated outcomes. It explains resource utilization decisions	Explains the decision-making process behind respondents' distribution of resources (like	Fantacci & Picano, 2020

	unpredictable results.	made for training processes, leading participants' actions in FL.	network bandwidth) and their participation in FL training. It emphasizes the utility and payoff of participants in advising the establishment of effective and efficient FL systems.	
Prospect theory	An effective incentive system for fostering FL participation and distribution of resources is that respondents take risks when they advocate to gain and are cautious when they are at risk.	Allows FL participants to reach decision in midst of ambiguity by setting potential rewards and expenses in setting. When it comes to benefits, individuals are prudent, but when it pertains to damage, they can take the risk.	Emphasizes decision-making in FL on expenses (e.g., computational resources) and possible benefits (e.g., increased model accuracy). Provides reward initiatives that are aligned with the criteria used for reference of the participants.	Fantacci & Picano, 2020