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# Revealing the Impacting Factors for the Adoption of Federated Machine Learning in Organizations

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## Abstract

*The success of Machine Learning is driven by the ever-increasing wealth of digitized data. Still, a significant amount of the world's data is scattered and locked in data silos, which leaves its full potential and therefore economic value largely untapped. Federated Machine Learning is a novel model-to-data approach that enables the training of Machine Learning models on decentralized, potentially siloed data. Despite its potential, most Federated Machine Learning projects fail to actualize. The current literature lacks an understanding of the crucial factors for the adoption of Federated Machine Learning in organizations. We conducted an interview study with 13 experts from seven organizations to close this research gap. Specifically, we draw on the Technology-Organization-Environment framework and identified a total of 19 influencing factors. Thereby, we intend to facilitate managerial decision-making, aid practitioners in avoiding pitfalls, and thereby ease the successful implementation of Federated Machine Learning projects.*

**Keywords:** Federated Machine Learning, Technology Adoption, TOE Framework, Interview Study

## 1. Introduction

The ever-increasing wealth of digitized data powers the disruptive potential of Machine Learning (ML) and its immense economic impact. Even though vast amounts of data is freely available, extensive amounts of already generated data is scattered, stored, and locked up in decentralized devices and data silos. Accessing these data silos becomes more difficult with privacy concerns and legal regulations, which leaves the economic potential of the stored data largely untapped.

Federated Machine Learning (FedML) is a novel ML paradigm, with the promise to build prediction models on decentralized data without the need for direct data sharing (McMahan et al., 2016). Through its model-to-data approach, FedML enables the usage of siloed data without disclosing data to third parties. Therefore, FedML has the potential to overcome data silos, enable the usage of currently untapped data and thereby be the catalyst for novel application fields of ML. Despite its advantages, there are only a few production-level applications and most work on FedML comprises prototypes or simulations (Lo et al., 2021). Investigating the challenges, success factors, and influential factors for the adoption of FedML might offer valuable insights into the missing operationalization of FedML. A better understanding of these factors would also aid practitioners to implement FedML projects and thereby support its broader practical adoption.

In contrast to the literature on FedML, research on traditional, centralized Artificial Intelligence (AI) systems already provides relevant insights into the challenges and success factors of AI adoption. For example, research on AI adoption in the financial services industry recognized a lack of AI-related skills, missing top management support, market regulations, and complex implementation as the main challenges (Kruse et al., 2019). Similar studies in the manufacturing and production domain identified leadership support as a crucial success factor (Demlehner and Laumer, 2020). Besides, the complexity of an organization additionally hinders AI adoption in manufacturing firms (Chatterjee et al., 2021). Similar results have also been obtained for AI adoption in public organizations (Neumann et al., 2022).

Organizations that are relatively inexperienced in AI technologies depend on the initiatives of single

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employees or are able to successfully implement AI projects with the help of external partners (Bauer et al., 2020). However, top management support is essential to support the allocation of key resources. Once sufficient resources are available to develop AI solutions, the intra-organizational diffusion of AI may increase resistance due to conflicts between different in-house units (Neumann et al., 2022). Further studies confirm that organizational factors such as top management support and thereby organizational readiness are key factors in the adoption of AI in organizations (Alsheibani and Messom, 2019; Dora et al., 2022; Hamm and Klesel, 2021). For small and medium-sized enterprises, the lack of ML know-how poses an additional key challenge (Bauer et al., 2020).

However, FedML introduces another dimension of complexity. Due to its collaborative nature, we argue that FedML projects are additionally subject to collaboration-related challenges. Specifically addressing collaboration challenges in collaborative engineering projects is crucial to projects' efficiency and success (Diirr and Cappelli, 2018; Pauna et al., 2021). Since FedML works at the intersection of AI and collaborative project management, its influential factors for the adoption of FedML in organizations need to be investigated.

The current literature lacks a structured overview of the factors which influence the adoption of collaborative AI paradigms, such as FedML. This work aims towards closing this research gap. Through an expert interview study, we aim to draw on the experiences and expertise of practitioners to investigate the motivations, challenges, and influential factors for the adoption of FedML. Through the structured overview of influential factors, we intend to guide managerial decision-making, help practitioners avoid pitfalls, overcome challenges and overcome risks at an early project stage. We aim to achieve this goal by answering the following research questions (RQs):

**RQ1**: What are the reasons for the adoption of FedML in organizations and the accompanying main challenges and risks?

**RQ2**: Which factors influence the practical adoption of FedML in organizations?

## 2. Theoretical Background

In the following, we will describe the theoretical background of FedML as well as the basis of technology adoption frameworks.

### 2.1. Federated Machine Learning

FedML is an innovative ML technique that enables the collaborative training of a joint ML model on distributed datasets without the need of sharing data. In traditional ML settings, the data is usually accumulated in a central location, where the ML model is subsequently trained. Hence, data owners need to share their data with a central server and thereby risk losing their Intellectual Property (IP). FedML counteracts this need of sharing datasets through a model-to-data approach.

First introduced by McMahan et al. (2016), FedML can be divided into four distinct steps. These steps are illustrated in Figure 1. The server initially chooses a global model which is suitable for the use case and underlying data structure. In this step, the initial global model can be pre-trained by the server. Secondly, the global model is distributed amongst all participating clients. Thirdly, each client trains the global model on its own local dataset and stores the resulting update gradient. Thereby, each client owns a customized version of the global model based on the clients' individual, local dataset. Lastly, each client sends their stored update gradients back to the server, which are collected and aggregated based on a pre-defined protocol. The aggregate of the individual update gradients is then used to update the global model. These steps can be repeated until a certain accuracy level is reached or until the accuracy converges.

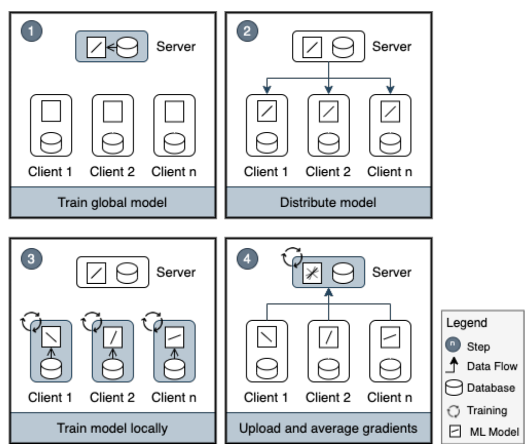


**Figure 1. Federated Machine Learning process.**

### 2.2. Technology Adoption Frameworks

The process of adopting innovative technologies in organizations has been a widely studied area within information systems and sparked a multitude of different technology adoption models. These models aim to identify, predict, and describe the variables that affect adoption behavior in institutions (Dube et al., 2020). Technology adoption frameworks can be classified by their adoption context and categorized into groups of models that aim to study the adoption behavior of groups, individuals, or organizations (Liu et al., 2008).

In this work, we investigate the organizational adoption of FedML and therefore focus on organizational-based technology adoption frameworks. Consequently, models and frameworks which focus on the individual or group level were not considered in our study. On an organizational level, the *Diffusion on Innovations (DOI)* (Rogers, 2003) theory and the *Technology-Organization-Environment (TOE)* (Tornatzky et al., 1990) framework are the two most prominent models to measure the organizational readiness and acceptable use of innovative technologies.

The TOE framework is consistent with the DOI theory. Both emphasize individual, internal, and external characteristics of the organization as influencing factors for the organization's innovativeness. Compared to DOI, TOE additionally considers environmental factors in the technology adoption of organizations. Therefore TOE is considered more complete to explain intra-firm innovation adoption (Oliveira and Martins, 2011). In summary, TOE enables a comprehensive understanding of innovative technology decisions by considering the aspects from a technological, organizational, and environmental perspective.

## 3. Research Methodology

To explore the influencing factors for the adoption of FedML in organizations, we followed a qualitative research approach by conducting semi-structured interviews and drawing on the experiences of experts. The following sections describe the study design, data collection, and data analysis of our research.

### 3.1. Study Design

To answer our RQs, we collected data through semi-structured interviews. First, we identified potential interviewees working with FedML either in business or applied research through pre-saved contacts of prior research, referrals, or top search results (e.g., via LinkedIn). We then contacted the identified experts either via email or direct message and scheduled the interview after a positive response. Prior to the scheduled interview, we presented the research purpose, content, and structure to allow for impromptu follow-up questions.

We based our questionnaire on the TOE framework since it provides a solid theoretical and empirically supported structure of the influencing factors for the organizational adoption of innovative technologies, such as FedML. Through leveraging the provided TOE structure, we deem to gather a holistic overview of the influential factors for the practical adoption of FedML in organizations.

In our study, we only included interviewees that had sufficient topic-related knowledge. For the semi-structured interviews, we followed the guidelines proposed by Myers and Newman (2007). Each interview was recorded, transcribed, and coded. The results were iteratively compared with the insights from previous interviews until we reached theoretical saturation, allowing us to close the interview study.

In total, we conducted interviews with 13 experts from seven different organizations. Table 1 provides a codified overview of our resulting sample, including the participants' relevant information, such as their position, organization, and experience in their current position. From hereon, we refer to the experts by their corresponding participant identifier (ID). The interviewee demographic indicates a large variety of ”voices” (Myers and Newman, 2007) and comprises a broad spectrum of backgrounds, job roles, and experience, thereby covering multiple viewpoints.

### 3.2. Data Collection

The interviews were conducted via videotelephony in February 2023, each with two participating researchers to ensure observer triangulation (Runeson and Höst, 2009). We presented a set of pre-defined questions to each interview partner. Each interview had the same outline, and the questions remained unchanged, however, due to the nature and flexibility of semi-structured interviews, slight variations regarding the order of questions or wording occurred. At the start of each interview, the research goal was recalled, and the interview structure was presented to alleviate misunderstandings before we proceeded to the interview questions. The interview guideline was developed based on the RQs and consisted of four different sections. The first section aimed to gather information about the participants' professional backgrounds and experiences with FedML projects. This was followed by general, open questions about their reason for adopting FedML as well as the encountered challenges and risks. Hence, the second section intends to address RQ1. The third section focused on the TOE factors as experienced by the interviewees and aimed towards RQ2. The final section investigated future directions and discussed

Table 1. Overview of expert interviews.

| ID | Position | Organization | Experience |
|---|---|---|---|
| I1 | Product Manager | Large software enterprise 1 | ≥10 years |
| I2 | Architect | Large software enterprise 1 | ≥5 years |
| I3 | Applied Researcher | Industrial software enterprise | ≥2 years |
| I4 | Development Expert | Large software enterprise 1 | ≥19 years |
| I5 | CEO and Founder | FedML Startup 1 | ≥3 years |
| I6 | Applied Researcher | Research center for AI security | ≥1 year |
| I7 | Senior Consultant and Project Lead | Large software enterprise 1 | ≥6 years |
| I8 | Customer Advisor | Large software enterprise 1 | ≥2 years |
| I9 | CEO and Founder | FedML startup 2 | ≥5 years |
| I10 | Product Manager | Large software enterprise 1 | ≥4 years |
| I11 | Researcher | Research center for software systems | ≥4 years |
| I12 | Solution Specialist and Product Manager | Large software enterprise 1 | ≥12 years |
| I13 | Research Manager | Large software enterprise 2 | ≥4 years |

possible tools that might help overcome challenges in an early project stage.

The results communicated in this work represent the findings of the first three sections. We plan to develop the discussed tool and publish the remaining empirical evidence in a separate work.

### 3.3. Data Analysis

The transcribed and recorded interviews were coded according to the guidelines of the *Reflexive Thematic Analysis* process (Braun et al., 2018). Consequently, we reviewed the conducted interviews and familiarized ourselves with the content of the collected data. We made notes on the initial insights of each interview and put the insights into the context of the overall data. Additionally, we assigned a unique ID to each expert and dismissed potentially sensitive information to ensure anonymity.

The transcripts were coded and analyzed with the help of MAXQDA2022[1]. Each interview was coded according to important features relevant to the RQs. New codes were created whenever new findings could not be assigned to an existing code category, which triggered a re-codification of the previously coded data. Hence, the final coding was created through multiple rounds of coding. The codes were examined and grouped into broader themes. These themes were thereafter named and analyzed in detail to validate if the themes accurately depict the transcript data. Emerging conflicts were discussed by the researchers and resolved by mutual consent. Finally, the interviews with the annotated transcripts and their themes were summarized and contextualized in relation to existing literature.

[1]https://www.maxqda.com

## 4. Results

This section presents the summarized results of our interview study. We first address RQ1 by describing the experts' reasons to adopt FedML as well as the main challenges and risks from their experiences. The subsequent sections then answer RQ2 by presenting the identified technological, organizational, and environmental factors.

**Reasons of Adoption.** We identified three main reasons for adopting FedML, which will be described in more detail in the following. An overview of the aspects and interviewee references can be seen in Table 2.

*(1) Field of Application:* FedML can enable the development of novel use cases and applications that would not have been possible using traditional ML approaches. Furthermore, adopting FedML can improve the performance and capabilities of existing ML products by leveraging additional data from data silos, possibly leading to a competitive advantage.

*(2) Data Privacy:* The potential access to sensitive data and the need for protecting sensitive data also drive FedML adoption. The privacy-enhancing features of FedML help to mitigate privacy concerns by enabling local model training without sharing raw data. This can be particularly important for industries working with sensitive data, such as the healthcare or financial sector. The privacy-enhancing nature of FedML can foster trust between organizations, encouraging collaboration by eliminating the need to share data between organizations and preserving the IP on the data.

*(3) Efficiency:* The improved communication and computation efficiency also motivates FedML adoption. FedML can improve communication

**Table 2. Reasons of adoption and main challenges.**

| Category | Factors | Experts | #Experts (%) |
|---|---|---|---|
| Reasons of Adoption | Field of Application | I4, I5, I9, I10, I11, I13 | 6 (46.15%) |
| | Data Privacy | I1, I2, I4, I5, I6, I9, I11 | 7 (53.84%) |
| | Efficiency | I3, I5, I9, I10 | 4 (30.76%) |
| Challenges and Risks | Uncertainty, Risk Analysis, & Mitigation | I5, I12 | 2 (15.38%) |
| | Insufficient Management Support | I5, I7, I12 | 3 (23.07%) |
| | Novelty of Technology | I1, I2, I3, I5, I6, I8, I9, I10, I12, I11, I13 | 11 (84.61%) |
| | Collaboration | I1, I2, I4, I5, I6, I9, I10 | 7 (53.84%) |
| | Complex Implementation | I1, I3, I8, I9, I10, I13 | 6 (46.15%) |
| | ML Product | I2, I3, I6, I9, I13 | 5 (38.46%) |

efficiency by minimizing the need for raw data sharing and centralization, resulting in more efficient communication and reduced network overhead. This can be particularly beneficial for organizations with distributed data sources and limited bandwidth. In addition, FedML allows organizations to leverage external expertise and resources without sharing their data, making it an option for outsourcing ML tasks without compromising privacy and security. This also allows companies without sufficient ML in-house expertise to develop such applications.

**Challenges and Risks.** The interviewees mentioned a total of six main challenges and risks in the adoption of FedML. The list of main challenges and risks including interviewee references can be seen in Table 2.

*(1) Uncertainty, Risk Analysis and Mitigation:* Due to the novelty of FedML, organizations may face uncertainties and challenges related to privacy, security, and compliance. Mitigating these risks requires constant careful analysis and planning. This includes identifying potential risks, assessing their potential impact, and implementing appropriate mitigation measures.

*(2) Insufficient Management Support:* It can be difficult to secure sufficient financial support and investment for FedML initiatives and to gain strategic or tactical buy-in from key decision-makers. Overcoming this challenge may require advocating the value of FedML in terms of its potential impact on business operations, competitive advantage and digitization/data-first strategies.

*(3) Novelty of Technology:* As a relatively new approach, organizations may face challenges as first or early adopters of FedML. These challenges include complex compliance assessments, regulatory and standards uncertainties, and managing the rapid evolution of FedML. Organizations may need to invest in research, collaboration, and proactive monitoring of regulatory and technological developments to effectively address these challenges.

*(4) Collaboration:* FedML may be applied in collaborative settings with multiple organizations, which may present challenges for managing, coordinating, and achieving critical mass for effective training. To overcome this challenge, organizations may need to establish robust mechanisms for managing responsibilities, suitable communication channels, and ownership frameworks.

*(5) Complex Implementation:* Deploying and managing FedML systems can involve a significant effort to overcome complex technical challenges. Organizations need to carefully plan and execute technical implementation to ensure the effective adoption of FedML, potentially even across company borders.

*(6) ML Product:* The stochastic nature of FedML leads to challenges in managing expectations, evaluating performance, and ensuring reliable results. In addition, organizations may face privacy concerns as FedML involves local model training but does not eliminate privacy concerns.

## 4.1. Technological Factors

We identified a total of nine technological factors, which can be grouped into four categories. The following presents the categories with the identified factors. Table 3 provides an overview of these factors with references to the interviewees.

**Data Considerations.** Ensuring high-quality data, sufficient data volume, and data interoperability are critical factors to consider when assessing the feasibility and suitability of adopting FedML in a specific use case.

*(1) Data Quality:* Sufficient data quality is an essential foundation for the implementation of FedML and has a significant impact on the performance and reliability of the resulting models. Organizations

Table 3. Identified technological, organizational and environmental factors.

| | Category | Factors | Experts | #Experts (%) |
|---|---|---|---|---|
| Technology | Data Considerations | Data Quality | I1, I2, I3, I5, I6, I8, I9, I10, I11, I13 | 10 (76.92%) |
| | | Data Volume and Accessibility | I1, I2, I3, I5, I6 | 5 (38.46%) |
| | | Data Interoperability | I1, I2, I3, I5, I6, I8, I9, I10, I11, I13 | 10 (76.92%) |
| | System Interoperability | FedML System | I3, I5, I13 | 3 (23.07%) |
| | | Data Integration | I1, I5 | 2 (15.38%) |
| | Infrastructure | Compatibility and Accessibility | I1, I5, I9, I13 | 4 (40.76%) |
| | | Computational Power | I5, I8, I9, I13 | 4 (30.76%) |
| | Orchestration | Versioning | I1, I2, I9 | 3 (23.07%) |
| | | Pipelines | I3, I8, I9, I10, I13 | 5 (38.46%) |
| Organization | Organizational Readiness | Management Support | I1, I5, I6, I9, I10, I11, I12, I13 | 8 (61.53%) |
| | | Knowledge and Expertise | I3, I5, I6, I7, I10, I11, I13 | 7 (53.84%) |
| | Federation Considerations | Collaboration Management | I1, I2, I3, I4, I5, I6, I7, I8, I9, I10, I11, I12 | 13 (100%) |
| | | Co-Creation Management | I1, I9, I13 | 3 (23.07%) |
| | | IP Management | I1, I7, I10, I11, I13 | 5 (38.46%) |
| Environment | Legal Regulations | Cartell Office | I6 | 1 (7.69%) |
| | | Data Privacy | I3, I9, I11, I12, I13 | 5 (38.46%) |
| | | Legal Clarity and Unambiguity | I1, I2, I5, I6, I9, I11, I12, I13 | 8 (61.53%) |
| | External Pressure | Market Competition | I6, I10 | 2 (15.38%) |
| | | Regulatory Enforcement | I10 | 1 (7.69%) |

need to consider various aspects of data quality, such as completeness, timeliness, and consistency. Data cleaning may be required to ensure high data quality, which is costly and may outweigh the resulting benefits.

*(2) Data Volume and Accessibility:* An adequate volume of data is essential for the training of accurate and reliable models. Sufficient data availability is a prerequisite for every FedML use case. The availability and accessibility of the data volume, potentially across data silos, is a critical factor for the adoption of FedML. Additional to the training process, organizations also need to ensure that they can also provide an appropriate data sample for the initial feasibility study.

*(3) Data Interoperability:* The data structure and statistical distribution must provide an interoperable basis. For that, organizations need to assess whether the data is homogeneous or can be homogenized. Standardized semantics and industry protocols can help to ensure data interoperability.

**System Interoperability.** System interoperability is crucial for the seamless training of a joint ML model across multiple clients. It is crucial that the FedML system is implemented appropriately on each side and that the local data storages are integrated and accessible.

*(1) FedML System:* Each participating organization either needs to have the expertise and resources to implement their part of the FedML system, or use an existing FedML platform. Additionally, it needs to be ensured that the system can be enrolled across all clients.

*(2) Data Integration:* To run the FedML algorithm, data sources need to be integrated. Organizations need to make the data sources accessible so that the FedML system can train on the data sources locally. These data integration tasks must ensure that at each client's side the data from different sources can be combined and used for training in the FedML system.

**Infrastructure.** The infrastructure for the FedML process is crucial. This includes compatibility with existing infrastructure and ensuring sufficient computing power. Assessing the compatibility of the FedML system with the existing infrastructure on each client's side and evaluating the availability of sufficient computing resources are essential factors to consider in order to ensure a successful implementation of FedML.

*(1) Compatibility and Accessibility:* This relates to the compatibility of the FedML system with the existing IT infrastructure of each client. Organizations must ensure that the FedML system and its components can be implemented within existing infrastructure, including network architecture, hardware, and software. The FedML system may require internet access to enable communication and coordination between the distributed parties. Hence, organizations must ensure that the required connectivity and access are available. Compatibility also includes the integration of FedML with existing IT systems, such as data storage,

processing, and authentication mechanisms.

*(2) Computational Power:* The available computing power required for FedML training needs to be sufficient and depends on several factors, such as the role of the participant (client or aggregator), the specific FedML system, the size and complexity of the ML models, and the amount of data to be trained on. Organizations need to be able to assess whether their existing computational resources are sufficient to support the computational requirements of FedML deployment, or whether additional resources need to be allocated.

**Orchestration.** This category relates to the deployment of the FedML model including the versioning, training automation, and deployment. Adopting appropriate versioning practices and implementing robust training pipelines with automation can help ensure proper coordination and alignment of ML models between parties in a FedML system.

*(1) Versioning:* Model versioning is critical for managing changes and updates to the ML models used in FedML systems. Organizations need to implement appropriate versioning procedures and mechanisms to ensure accountability and that the FedML models are updated, tracked, and managed efficiently.

*(2) Pipelines:* The Pipelines and automated processes are critical for orchestrating the training process across distributed clients and coordinating gradient exchange, model synchronization, and model serving. Pipeline automation can help streamline the FedML deployment process and reduce manual effort to ensure efficient and scalable training operations.

### 4.2. Organizational Factors

The organizational factors are divided into two categories with a total of five factors, whereas the federation consideration is only applicable if the project includes a collaboration of different organizations. An overview of these factors with references to the interviewees is provided in Table 3.

**Organizational Readiness.** The readiness and resources of an organization to adopt emerging technologies and innovative ideas are critical. Organizations need to ensure that there is adequate management support, including awareness, understanding, and willingness to invest in AI projects. Secondly, they need to assess internal knowledge and data science expertise to ensure the successful adoption and implementation in the organization.

*(1) Management Support:* The level of awareness, understanding, and support by management for the adoption of emerging technologies such as FedML is an important success factor. It includes the management's understanding of the potential of FedML in addressing business challenges, willingness to invest in AI projects, and overall mindset and openness to new technologies. Investments in ML projects are difficult to implement without risk aversion due to the lack of predictability of the outcome. Management support is critical to driving organizational change, providing the necessary resources, and creating a culture that is supportive of innovative ideas. Factors such as company size, risk aversion, and strategic focus on data-driven processes additionally influence organizational readiness.

*(2) Knowledge and Expertise:* The successful implementation of FedML systems also depends on the knowledge and experience of ML (and FedML) of an organization. It includes the organization's existing capabilities and resources for ML projects, digitization maturity, and overall readiness to implement emerging technologies such as FedML. Organizations need to provide internal capabilities and expertise for data science projects, ML model development, data infrastructure, and other necessary resources for their tasks. This factor heavily depends on the role of the participant and the degree of automation within the project. The lack of internal skills could be compensated through the acquisition of external knowledge.

**Federation Considerations.** If the project is implemented within a setting with different participating organizations, additional challenges arise. These influencing factors relevant to the federated setting include the effective management of collaboration, co-creation, and IP. Organizations need to carefully manage the collaboration between the participants as this is critical to the establishment of the collaboration, the feasibility of the project, and finally the successful implementation of FedML in the use case.

*(1) Collaboration Management:* This factor concerns the management of collaboration between different participants in a FedML environment. Collaboration in FedML can be complex and difficult due to factors such as establishing collaboration, withdrawing from collaboration, and finding and selecting appropriate partners for the use case. The distribution and management of tasks and responsibilities among uneven participants can increase the complexity. Incentive mechanisms may be needed to encourage active participation and collaboration among participants in a FedML environment. Effective collaboration management is critical to the success of a FedML implementation, and organizations need to carefully plan and manage collaboration processes to

ensure smooth and efficient operation.

*(2) Co-Creation Management:* In collaborative settings, the co-creation challenges involve the joint creation and ownership of the FedML model among all collaborators and stakeholders. This may include defining model ownership, data/model contributions, and sharing of results. Co-creation management may also involve defining roles and responsibilities, model usage policies, and governance mechanisms.

*(3) IP Management:* IP management includes issues related to the ownership, use, and protection of the IP. Organizations must carefully define and agree on the ownership and use of IP among participants, which may include legal agreements, contracts, and policies.

### 4.3. Environmental Factors

We identified two categories with a total of five environmental factors, which will be described in the subsequent paragraphs. All environmental factors and interviewee references can be seen in Table 3.

**Legal Regulations.** FedML projects in general and especially in collaborative settings need to consider legal regulations to be compliant. These regulations include antitrust compliance, data protection regulations, and ensuring clarity and unambiguity in the legal landscape. Companies need to carefully review and comply with the relevant legal requirements to ensure legally compliant implementation of FedML in their specific use cases and ultimately to be able to use the FedML model. The fast development and emergence of legal regulations which are relevant to AI applications and collaborative projects need to be carefully observed.

*(1) Cartel Office:* In collaborative settings, it needs to be determined whether cooperation with all participants is permissible under local antitrust or competition authority regulations. Depending on the jurisdiction and specific use case, the collaboration between participants may be subject to competition laws and regulations.

*(2) Data Privacy:* Considering legal regulations regarding data privacy is crucial, especially in projects with sensitive data. The type and sensitivity of used data, as well as the jurisdiction in which the FedML system operates, can have significant implications for legal compliance requirements. Organizations must carefully evaluate and understand the privacy implications of using data in a FedML environment, including potential risks associated with data sharing, data use, and privacy. Compliance with data protection regulations, such as the GDPR in the European Union, may be required, and organizations should ensure that all data processing within the project is compliant with relevant regulations.

*(3) Clarity and Unambiguity:* Legal clarity and unambiguity are complicated topics given the fast pace of FedML's technological advances and the developments of laws. This can lead to uncertainty regarding the legal framework and applicable laws, which is even more complex given the high variability depending on the specific use case. Keeping up to date with the regulations and guidelines is important for regulatory compliance, and currently, there are no certifications or legal frameworks for FedML systems yet.

**External Pressure.** FedML projects are subject to external factors such as market competition or regulatory enforcement. Organizations must assess and respond to these external pressures by considering the potential benefits, risks, and available resources to make well-informed technology selection decisions about FedML adoption in their specific context.

*(1) Market Competition:* The pressure to collaborate with other organizations influences the development of FedML projects. Organizations may be pressured to engage in collaborations to remain competitive, gain access to sufficient data sources, and generate collective insights. Collaborations may also be needed to meet regulatory requirements, such as transparency along the supply chain in the example of the CO2 footprint.

*(2) Regulatory Enforcement:* The development of FedML systems may be affected by regulatory enforcement or regulatory changes. For example, in certain industries or jurisdictions, privacy-enhancing technologies such as FedML may be required by law to protect sensitive data. As a result, organizations may be forced to allocate additional budgets for implementing privacy-enhancing solutions.

## 5. Discussion

Through an expert interview study with 13 participants from seven organizations, we investigated the factors influencing the adoption of FedML in organizations. We identified three main reasons for adopting FedML in organizations and a total of six main challenges of practitioners, which are summarized in Table 2. Additionally, we identified a total of 19 factors that impact the adoption of FedML in organizations and summarized our findings in Table 3. We can sum up the results of our RQs as follows:

**RQ1**: *What are the reasons for the adoption of FedML in organizations and the accompanying main* *challenges and risks?*

The main motivation for the usage of FedML revolved around the need to protect sensitive data and thereby its potential to enable the usage of sensitive data. The possibility of using sensitive data enables the training of ML algorithms on currently untapped data. A larger amount of training data yields the possibility to train more sophisticated ML algorithms for complex problem statements, which could not be solved with the current amount of available data. Therefore, the stated motivational driver to use sensitive data and the motivation to tackle novel fields of application are closely interrelated but still differ in the underlying motivation. The results suggest that a better-performing ML model and the increase of training data volume are perceived as more beneficial than improving the communicational and computational efficiency of FedML. However, some experts (I4, I5, I9, I10, I11) were driven by a combination of motivational factors.

As for the challenges and risks, most experts experienced challenges due to the novelty of the technology due to complex compliance assessments, as well as regulatory and standards uncertainties. Additionally, the first and early adopters need to come up with novel business cases, which impedes the allocation of budget and management support for FedML projects. Besides, the experts encountered challenges regarding the collaboration and the complex technical implementation of FedML.

**RQ2:** *Which factors influence the practical adoption of FedML in organizations?*

We structured the identified factors according to the TOE framework. The most relevant technological factors were aspects regarding data quality and data interoperability. On the organizational side, all experts unanimously agreed that collaboration management is a crucial impacting factor for the adoption of FedML in organizations. This is followed by factors regarding organizational readiness, especially management support as well as knowledge and expertise. The most relevant environmental factors comprised aspects around legal regulations, especially around missing legal clarity. The most relevant TOE factors concur with the identified challenges and risks, which further validates the significance of these aspects.

**Contribution.** The results of this study contribute to research on the adoption of emerging technologies in organizations. We complement current information systems literature by investigating the influencing factors of FedML adoption. Through systemizing and presenting the influencing factors of its practical adoption, we intend to provide structured insights into the complex processes of implementing FedML projects. We hope that our insights aid management-oriented as well as technology-oriented audiences in the planning and development process. By knowing the crucial factors for the adoption of FedML, we help to avoid pitfalls, overcome challenges and counteract risks at an early stage. Overall, we intend to facilitate the process of adopting FedML in organizations and thereby help unlock novel fields of applications in the ML domain. In addition, our study provides a basis for further research on challenges and success factors for collaborative AI projects.

**Limitations.** There are multiple limitations to our work. FedML is an emerging technology and the influencing factors might change with a broader adoption of the technology. More factors might arise and some might be alleviated through the emergence of best practices or changed business understanding towards FedML. Due to its novelty, we were only able to interview first and early adopters, mainly consisting of larger enterprises, research institutes, or start-ups. Middle-sized enterprises were sparsely represented in the interviewee demographic and their experiences might have altered the outcome of our study. Moreover, our study is based on the experiences and expertise of 13 interview participants. Even though we reached theoretical saturation which terminated our interview study, more data from a bigger and more diverse set of interviewees with more perspectives might enrich our results. We encourage researchers and practitioners to further validate our findings in practice, and complement our proposed list of influencing factors.

## 6. Conclusion

In this paper, we presented a systematized set of critical factors that influence the adoption of FedML in organizations. Through an expert interview study with 13 participants from seven organizations, we identified a total of 19 influencing factors. Additionally, we presented the reasons for the adoption of FedML as well as the main challenges and risks, which were encountered by the interviewed experts. The critical factors with the most occurrences comprised aspects regarding collaboration management, data quality, data interoperability, organizational readiness, and the lack of legal clarity. Due to the novelty of FedML, these factors might change. A broader practical adoption will spark best practices and a change in the business understanding of FedML, which can impact the landscape of influential factors. We encourage researchers to further extend and improve the list of influencing factors by applying it to various application domains or verifying it in case studies. We hope that our study provides a thorough understanding of the critical factors in the adoption of FedML, aids managerial decision-making, and that it can be used as a basis for further understanding of the challenges and success factors of collaborative AI projects.


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