A Design Toolbox for the Development of Collaborative Distributed Machine Learning Systems

David Jin^{*}, Niclas Kannengießer^{*†}, Sascha Rank^{*†}, Ali Sunyaev^{*†} *Karlsruhe Institute of Technology, Germany [†]KASTEL Security Research Labs, Germany

{david.jin, niclas.kannengiesser, sascha.rank, sunyaev}@kit.edu

Abstract-To leverage training data for the sufficient training of ML models from multiple parties in a confidentialitypreserving way, various collaborative distributed machine learning (CDML) system designs have been developed, for example, to perform assisted learning, federated learning, and split learning. CDML system designs show different traits, for example, high agent autonomy, machine learning (ML) model confidentiality, and fault tolerance. Facing a wide variety of CDML system designs with different traits, it is difficult for developers to design CDML systems with traits that match use case requirements in a targeted way. However, inappropriate CDML system designs may result in CDML systems failing their envisioned purposes. We developed a CDML design toolbox that can guide the development of CDML systems. Based on the CDML design toolbox, we present CDML system archetypes with distinct key traits that can support the design of CDML systems to meet use case requirements.

Index Terms—collaborative distributed machine learning (CDML), privacy-enhancing technologies (PETs), assisted learning, federated learning (FL), split learning, swarm learning, multi-agent systems (MAS).

I. INTRODUCTION

The training of machine learning (ML) models requires sufficient training data in terms of quantity and quality to make meaningful predictions with little generalization error. Sufficient training data is, however, seldom available from a single party (e.g., a bank or a hospital), which can prevent the adequate training of ML models [1]. Inadequate training of ML models can result in large generalization errors, rendering ML models ineffective [2].

To reduce generalization errors of ML models, developers request training data from multiple third parties. Training data retrievals from third parties are often subject to compliance, social, and technical challenges [3]–[5] that hinder the acquisition of sufficient training data. For example, strict data protection laws and regulations prohibit the disclosure of specific kinds of data, such as personal data by the General Data Protection Regulation of the European Union [6] and organizational data by the Healthcare Insurance Portability and Accountability Act of the USA [7]. From a social perspective, privacy behaviors of individuals restrict information flows to third parties based on personal preferences [8], preventing access to their training data. Insufficient computing resources inhibit the transfer of large data sets from data centers to developers in an acceptable time [3], [4]. To reduce generalization errors of ML models by using training data from multiple parties, an ML paradigm is required that solves those challenges.

Collaborative distributed ML (CDML) is an ML paradigm that can be implemented to overcome, in particular, compliance and technical challenges in using data from multiple parties to train ML models [9]-[14]. In CDML systems, such as federated learning systems [10], split learning systems [11], and swarm learning systems [14], each party operates at least one quasi-autonomous agent (referred to as agent in the following). Agents in CDML systems train (parts of) ML models on their local training data and self-controlled compute in a distributed manner. Agents only share their locally computed training results (interim results) with other agents, for example, gradients [15], activations [11], and (pseudo-)residuals [12]. Reconstructing training data from interim results is commonly difficult [9]. Using interim results received from other agents, agents improve their local (parts of) ML models. Following the CDML paradigm, parties can keep control over their training data, which can help solve compliance challenges. Moreover, CDML can help to solve technical challenges because large packages of training data are not transferred to single parties to train ML models, saving bandwidth. Moreover, computational resources for training ML models are distributed across multiple agents, which decreases the amount of computational resources a single party must possess to train ML models.

The potential of CDML to leverage large training data quantities in a confidentiality-preserving and resource-efficient way has sparked enormous interest in practice and research for various use cases with different requirements for CDML systems. For instance, effective next-word prediction in virtual smartphone keyboards requires language models to be trained on a large quantity of heterogeneous training data representative of future user inputs. To meet this requirement, CDML systems must be scalable to involve millions [16] or even billions of agents [10]. Another CDML use case is the prediction of financial risks in portfolio management [17], [18]. Financial institutions rely on ML models to predict investment risks in portfolio management. As customers pay for portfolio management, such ML models are core assets to financial institutions. To protect such core assets, CDML systems must enable collaborative training of ML models without disclosing ML models to competitors.

To meet different use case requirements, practice and research developed specialized CDML system designs. For instance, federated learning systems are scalable to engage billions of agents to train ML models for next-word prediction [19]. Assisted learning systems are unsuitable for this purpose due to the sequential processing of interim results [17]. Conversely, assisted learning seems to be suitable for training ML models for portfolio management because ML model confidentiality is protected in the learning process. Federated learning requires agents to disclose ML models and, thus, is unsuitable for use cases requiring ML model confidentiality. Developers need to understand how envisioned traits of CDML systems (e.g., high scalability, ML model confidentiality) can be achieved by designing CDML systems in a targeted manner.

The proliferation of a wide variety of specialized CDML system designs introduced a large number of design options (e.g., regarding the structure of interim results and the parts of ML models disclosed to other agents) that constitute the CDML system design space. Developers must select and combine design options from the CDML system design space to design CDML systems with traits that meet use case requirements (e.g., high scalability, ML model confidentiality, and high robustness of the training process). The targeted selection and combination of design options requires developers to thoroughly understand the CDML system design space and traits arising from the implementation of design options in CDML systems. An insufficient understanding of the CDML system design space can lead developers to select design options that can cause CDML systems to fail their purposes, for example, when ML models for portfolio management are inadvertently leaked in unsuitable training processes. However, literature on CDML systems is scattered, which is why the CDML system design space remains unclear and, thus, how envisioned key traits can be achieved through targeted CDML system designs. To support the targeted design of CDML systems suitable for use cases, we ask the following research questions:

RQ1: What does the CDML system design space look like? *RQ2:* What are the key traits of principal CDML system designs?

To answer our research questions, we applied a three-step research approach. First, we developed the CDML design toolbox, which is a conceptualization of the CDML system design space. The CDML design toolbox specifies the fundamentals of CDML systems (e.g., agent roles and their interactions) and design options for the customization of CDML systems (e.g., combinations of agent roles in single agents, communication paths between agents, and types of interim results). For the conceptualization, we analyzed literature on CDML and developed agent-based models in the schemes presented in the Gaia methodology [20]. These schemes are commonly used to develop agent-based models that can serve as blueprints for implementing distributed software systems, such as CDML systems. Then, we tested the validity of the CDML design toolbox by modeling CDML system designs using the CDML design toolbox. Second, we developed CDML archetypes based on commonalities and differences between the modeled CDML systems. Third, we reviewed publications on CDML system designs to extract key traits of the CDML archetypes.

This work has three principal contributions to practice and research. First, by presenting the CDML design toolbox, we offer a consolidated design knowledge base of CDML systems that introduces the main design commonalities of CDML systems and offers design options for the customization of CDML system designs to meet use case requirements. This consolidation of previously scattered design knowledge in agent-based models (e.g., the roles model, the interactions model) facilitates the application of the Gaia methodology for systematically designing custom CDML systems. Moreover, by presenting design options implemented in CDML system designs, the CDML design toolbox helps to compare CDML system designs systematically. Second, by showcasing CDML archetypes, we inform of combinations of design options commonly used in practice and research. The CDML archetypes can be refined to develop blueprints of CDML systems tailored to use cases using the CDML design toolbox, which facilitates designing CDML systems. Third, by presenting key traits of CDML archetypes, we support developers in understanding how design options can be leveraged to achieve specific key traits. By using the CDML archetypes and their key traits, developers are enabled to evaluate CDML system designs in their suitability for use cases before implementing the designs. Thereby, we support the targeted design of CDML systems for use cases.

The remainder of this work is structured into six sections. First, we explain the foundations of CDML, related research on CDML systems, and introduce basic concepts of multiagent systems (MAS). Second, we describe how we developed the CDML design toolbox, including a brief introduction to the Gaia methodology [20]. Moreover, we describe how we developed CDML archetypes using the CDML design toolbox and how we identified their key traits. Third, we present the CDML design toolbox. Fourth, we describe CDML archetypes and explain how different combinations of design options can lead to key traits of CDML systems. Fifth, we discuss our principal findings and describe the contributions and limitations of this work. Moreover, we give an outlook for future research directions. We conclude with a brief summary of this work and our personal takeaways.

II. BACKGROUND AND RELATED RESEARCH

A. Collaborative Distributed Machine Learning

CDML combines the ML approaches of collaborative ML (CML) and distributed ML (DML). Leveraging training data from various parties is the focus of CML [21]–[23]. In CML systems, training data from multiple parties is used in a centralized or siloed way. In centralized CML, agents send their local data to a central data server that various agents can access to train ML models using the shared training data. To preserve training data confidentiality, data may only be provided to the central data server in encrypted form. The used cryptographic techniques (e.g., homomorphic encryption [23], [24]) allow agents to train ML models on the encrypted data while the plain training data remains

confidential. However, the cryptographic techniques will likely lead the centrally controlled computing system to consume more resources for the ML model training [25]. Overall, agents in centralized CML depend on central data servers. Crashes of central data servers can lead such CML systems to failure.

Distributed ML was developed to accelerate the training of large ML models, such as deep learning models, by distributing training tasks to multiple agents that train (parts of) ML models in parallel. Distributed ML systems can train ML models in two ways [26]–[28]: data parallel and model parallel. In data parallel training, partitions of the entire training data set are passed to agents. Each agent trains the same ML model on individual subsets of the whole training data set. In model parallel training, each agent uses identical data but only trains a part of the ML model.

In preparation for DML, training data is usually gathered by a central party that sets up the DML system (e.g., in computing clusters). The central party then identically distributes the gathered training data across agents to achieve a uniform workload for each. Through the uniform workload distribution, idle times of agents are aimed to be low so that the ML model training is performed with high computational efficiency [26].

The training process in DML is often coordinated by a central server, called parameter server [29]–[31]. After the local training of the ML model, agents transmit their ML model updates to the parameter server. The parameter server stores ML model updates and offers the latest parameters to agents. Agents fetch the parameters to proceed with the local training of the ML model.

An alternative to using parameter servers in DML is allreduce [28], [32], [33]. In all-reduce, all agents have similar roles, thus executing identical tasks. The identical execution of tasks by all agents makes central parameter servers obsolete. Each agent aggregates training results and distributes them to other agents in the DML system. Any agent is notified about ML model updates to proceed with the local training of the latest version of ML models.

In summary, CML centers on the sharing and collaborative use of training data, while DML centers on performance improvements in training ML models. However, DML hardly contributes to overcoming the legal and social challenges related to leveraging training data from multiple parties in a confidentiality-preserving way.

The combination of principles of CML (e.g., leveraging training data from various parties) and DML (e.g., the distributed execution of ML tasks across multiple agents) forms the foundation for CDML. In CDML systems, trainer agents receive ML tasks from other agents and use local training data to accomplish ML tasks. ML tasks specify the objectives pursued with ML models (e.g., next-word prediction) and include information about the approach (e.g., what ML model architecture should be used). This approach can implement DML techniques, which can eventually speed up the training data is usually unknown to participants in the ML system, identical

distribution of training data, like in purely DML, is hard to achieve. Thus, the performance benefits targeted in DML systems may not be fully leveraged [34].

B. Related Research on CDML

As one of the first CDML concepts, federated learning has established training data confidentiality and distributed computing as a fundamental goal pursued when applying the CDML paradigm [10], [16], [35]. Soon after its introduction, various shortcomings of federated learning became apparent. For example, federated learning systems have been shown to be inefficient due to high communication costs [9] and prone to performance bottlenecks caused by the use of a central parameter server [36]. From a security perspective, federated learning systems are prone to failures due to an adversarial central parameter server [9].

To tackle the shortcomings of federated learning, practice and research brought forth other CDML concepts, including swarm learning, split learning, and assisted learning. Like federated learning, swarm learning aims at the collaborative and distributed training of global ML models known to all parties involved in the training process. Other than federated learning systems, swarm learning systems rely on redundant agents orchestrating the training process in peerto-peer networks [14]. The redundant execution of tasks in swarm learning systems can make swarm learning systems more robust than federated learning systems [14]. However, the strong redundancies render swarm learning systems usually less resource-efficient and more complex compared to federated learning systems.

In split learning systems [11], agents only train parts of ML models defined by a so-called cut layer. Cut layers indicate the layers of neural networks where the complete neural network is split. Agents only receive the specifications of the cut layer as a kind of interface to input parameters for the training of the rest of the ML model. By only disclosing parts of ML models specified by cut layers, split learning helps to keep (at least parts of) ML models confidential. However, the gain in ML model confidentiality in split learning systems comes at the cost of the training performance of ML models compared to federated learning [37].

In assisted learning [12], the focus on preserving the confidentiality of training data is extended to ML models and even the purposes of ML models. In assisted learning, a user agent requests feedback on statistics relevant to training an ML model from service agents. Such feedback can include residuals of its own ML model. The user agent incorporates feedback received from service agents into its local ML model. This process can be executed repeatedly until the ML model reaches sufficient prediction performance. By enabling agents to decide which agents they want to assist, assisted learning can improve the autonomy of agents. However, the increased autonomy comes with coordination challenges, for example, how to assess the potential of agents to assist in a learning task and in which order agents interact [38].

Various design options for customizing CDML systems to meet use case requirements have been developed, such as federated learning systems with multiple hierarchical levels. In each hierarchical level, a preprocessing of previous training results is executed by aggregating a subset of training results. The global ML model is then computed from multiple aggregated training results [10]. Another design option for federated learning systems is to form subnetworks to deal with heterogeneous computational resources between trainer agents [39]. Agents with more computing resources (e.g., servers) execute training tasks that consume more computational resources than agents with only a few (e.g., smartphones).

Extant research has started to compare CDML systems to understand their commonalities and differences. Such comparisons are often based on benchmarks, for example, between systems of federated learning, split learning, and SplitFed learning [13] and between systems of federated learning, swarm learning, and decentralized federated learning [40]. CDML system benchmarks commonly offer valuable help in understanding likely CDML system behaviors, especially in terms of performance (e.g., convergence speed of ML models [13], communication cost [13] and prediction performance [40]). Such benchmarks can support practitioners in meeting performance requirements for CDML systems. However, benchmark results are only helpful at a limited scale to understand possible CDML system designs and their key traits, as they seldom explain how CDML system designs lead to different system behaviors. Moreover, benchmark studies only shed light on a few CDML system designs, leaving the entirety of the CDML system design space unknown.

Other works compare CDML system designs. Several design options for federated learning systems were revealed, describing different network topologies for communication (e.g., via central servers and peer-to-peer) and computational schedules [3], such as sequential training of ML models and parallel training synchronized by a central server. Key traits that originate from the different design options are discussed with a focus on confidentiality. Design differences between other CDML systems (e.g., assisted learning systems and split learning systems) remain unknown. In a comparison between federated learning systems, split learning systems, and SplitFed learning systems [13], key traits of those CDML systems are pointed out, with a focus on learning performance, resource consumption, ML model confidentiality, and training data confidentiality. Despite these valuable insights, several design options (e.g., regarding the network topology and computational schedules) and their influences on key traits of CDML systems remain unclear.

Since extant comparisons focus only on selected systems of a few CDML concepts, it is still hard to understand the entirety of the CDML system design space. To help developers design CDML systems that meet use case requirements, the CDML system design space must be understood, including the various CDML concepts, design options, and key traits of CDML system designs. This knowledge of the CDML system design space needs to become available in actionable form.

C. Multi-Agent Systems

The multi-agent system (MAS) concept [41] offers a theoretical lens to model systems based on agents (e.g., computing nodes) and their interactions in a specified environment [20], [42]. The MAS concept is widely used in computer science to model hardware systems and software systems, especially in the field of artificial intelligence (AI) systems [43], [44]. Since the MAS concept is established to develop blueprints of systems for their implementation [20], [45], [46], it seems to be adequate to represent the CDML system design space in a CDML design toolbox that helps to design, analyze, and advance CDML systems. In the following, we introduce the basic properties of the MAS concept relevant to this work. Important MAS properties are summarized in Table I.

 TABLE I

 MAS properties and corresponding characteristics relevant in this work (adapted from [42])

| Property | Description | Characteristic |
|-------------------|--|----------------|
| Cardinality | The number of objects and agents | Finite |
| | that are part of the MAS | Infinite |
| Coalition | The design of authority in the | Centralized |
| Control | MAS | Decentralized |
| Goal Structure | The number of goals in the MAS | Multiple |
| | The humber of goals in the MAS | Single |
| Interaction | | Competitive |
| | The way how agents work with other agents to achieve their goal(s) | Collaborative |
| | other agents to demote their gout(5) | Cooperative |
| Openness | The possibilities to enter and leave | Closed |
| Openness | the system | Open |
| Population | The presence of different types of | Heterogeneous |
| Diversity | agents | Homogeneous |

MASs are systems comprised of a population of agents. By design, MASs can limit the population to a finite number of agents or allow an infinite number of agents. Within MASs, agents can form groups, so-called coalitions. Coalitions can comprise entire MAS populations or population partitions. Agents can be part of multiple coalitions at the same time [20], [42]. We consider each CDML system as a coalition within a superordinate MAS. As agents can be part of multiple coalitions, agents can simultaneously participate in multiple CDML systems.

Coalitions can be controlled in a centralized or decentralized way. In centralized coalition control, a single or a few agents coordinate interactions between agents in the coalition, for example, in federated learning systems [16]. In decentralized coalition control, multiple or even all agents have equitable influences on the coordination of the coalition.

In coalitions, there are two common goal structures. Agents can pursue individual goals or common goals. Since agents can be part of multiple coalitions, agents can pursue multiple goals at the same time. For example, an agent may pursue an individual goal in one coalition (e.g., training its own ML model in an assisted learning system) and a common goal in another coalition (e.g., training a shared ML model in a swarm learning system). Agents can have different kinds of interaction to reach their goals in coalitions. They can act in a competitive, cooperative, and independent manner. When agents compete with each other, they need to fight for scarce resources to accomplish their tasks. Cooperative agents support each other in the accomplishment of common goals, where individual agents (or subgroups of agents) work on different tasks. In federated learning systems, for example, some agents only train ML models, while other agents aggregate interim training results [16], [47]. When agents collaborate, each agent is involved in each task to accomplish shared goals. Swarm learning systems are mostly collaborative, as most agents perform similar tasks in the ML model training [14].

MASs and coalitions can differ in their openness to allowing agents to join and leave arbitrarily. Closed MASs only allow specified agents to join. In some federated learning systems, only selected agents are permitted to join the coalitions [10]. Open MASs allow agents to join and leave arbitrarily, for example, in many peer-to-peer learning systems [48], [49].

Population diversity refers to the heterogeneity of agent types in a population. Agent types are sets of roles that are assigned to agents to specify their tasks in a coalition [20]. If many agents in a population have largely different agent types, the population is heterogeneous. For example, hierarchical federated learning systems comprise up to four different agent types that collaborate and execute different tasks in the training of ML models. If most agents have identical agent types, the population is homogeneous. Swarm learning systems, for example, can be considered homogeneous because all agents execute identical tasks in the training of ML models [14].

III. METHODS

We applied a three-step research approach to conceptualize the CDML design space (RQ1) and extract key traits of CDML systems originating from different designs (RQ2). First, we conceptualized CDML systems described in literature (Section III-A). Based on the conceptualization, we developed the CDML design toolbox. We modeled CDML systems using the CDML design toolbox to test its applicability. Second, we used the models of the CDML systems to develop CDML archetypes (Section III-B). Third, we extracted traits of CDML system designs from literature. We assigned the CDML system designs, including their traits, to the CDML archetypes and aggregated the traits to key traits (see Section III-C). In the following, we describe our methods in detail.

A. CDML Design Toolbox Development

To develop the CDML design toolbox, we adopted the Gaia methodology for agent-oriented modeling [20]. Using the structures of the five agent-based models presented in the Gaia methodology (see Section III-A1), we conceptualized CDML systems presented in the literature by applying open coding, axial coding, and selective coding [50] as described in Section III-A2. The literature analysis revealed design options for CDML systems (e.g., agent role distributions, optional communication paths, and structures of training processes). We tested and refined our coding in three iterations by classifying CDML systems into our coding (see Section III-A3).

1) The Gaia Methodology: One main purpose of the Gaia methodology is to support the development of agent-based models that can serve as blueprints for the implementation of software systems [20]. The Gaia methodology is constituted of an analysis stage and a design stage. In the analysis stage, a roles model and an interactions model are developed, enabling an abstract view of a system. This abstract view constitutes the concept level of the system description that enables an analysis of system structures. The roles model describes the tasks and basic processes, including the resources that agents can use. Roles essentially describe the functions that an agent performs within the system. Each role consists of four main aspects: responsibilities, permissions, activities, and protocols. Responsibilities define the functions an agent of a particular role needs to perform. An exemplary responsibility of an agent in the role of an updater in CDML systems could be the aggregation of ML models trained by other agents into a global ML model. Permissions describe which resources are available to agents with specific roles to fulfill their responsibilities. Exemplary resources for agents in the role of updater are information about the ML model to be trained and local training data. Activities are computations that agents perform locally without interaction with other agents. In the case of agents in the trainer role, local training of an ML model is an exemplary activity. Protocols as part of the roles model reference protocol definitions in the interactions model that describe how interactions between agents of specific roles are designed. For example, updater agents must interact with agents with the trainer role to retrieve interim training results and complete the training process.

The interactions model specifies how agents with specific roles interact with each other in a purposeful way. Frequently recurring interactions between agents with other agents, objects, or the environment of the MAS are recorded as interaction patterns. Each interaction pattern is described in a protocol definition. Protocol definitions include six attributes: purpose, initiator, interactor, input, output, and processing. The purpose includes a textual description of the meaning of interaction, for example, "passing an ML model for its training". Interactions originate from an agent (i.e., an initiator) and are directed to an interaction partner (i.e., a responder). For interaction, the initiator prepares an input and issues the input into the interaction process. The output comprises the information received by the responder at the end of the interaction.

Based on the roles model and the interactions model, envisioned CDML systems can be detailed in the design stage of the Gaia methodology. The design stage centers on the development of an agent model, a service model, and an acquaintance model. These models form the design level of the system representation. In combination, the concept level and the design level form blueprints for the implementation of concrete software systems [20].

The agent model describes the agent types utilized by CDML systems. Agent types are combinations of roles. Moreover, the agent model describes instances of these agent types that will populate the CDML system. The service model describes the main services that are necessary to implement an agent role. The services that an agent can execute depend on its roles and corresponding activities and protocols. The acquaintance model describes communication paths between different agent types in the CDML system. The acquaintance model helps to identify communication bottlenecks that may arise during run-time.

Similar to the structure of the Gaia methodology, the CDML design toolbox comprises an abstract concept level and a more detailed design level. The concept level describes the general design of CDML systems, focusing on their commonalities (e.g., roles and interactions). On the design level, the CDML design toolbox describes design options to customize and differentiate CDML systems.

2) Conceptualization of CDML Systems: To develop the CDML design toolbox, we conceptualized CDML systems in three steps: *start set compilation, development of an initial version of the CDML design toolbox,* and *test and iterative refinement.* We describe the three steps in more detail in the following.

a) Start Set Compilation: For the development of the CDML design toolbox, we first compiled a start set constituted of publications on CDML systems. To systematize the search for potentially relevant publications, we specified the following inclusion criteria (see Table II): *English language, level of detail, topic fit,* and *uniqueness.* We excluded publications from the start set that did not meet all inclusion criteria.

After specifying the inclusion criteria, each author independently generated their own set of publications potentially relevant to developing the CDML design toolbox. We searched for publications that cover a large variety of CDML systems and offer detailed descriptions of CDML system designs. Then, we consolidated the independently generated sets of publications into a preliminary start set. The preliminary start set included peer-reviewed scientific publications and grey literature. Next, we applied the inclusion criteria to the publications in the preliminary start set (see Table II). We removed one publication from the preliminary set of relevant literature because it was a duplicate. Based on the full texts of the remaining 29 publications, we independently rated the relevance of each publication for the conceptualization as "relevant", "maybe relevant", and "irrelevant" based on the inclusion criteria (see Table II). Whenever we were at variance regarding the relevance of publications (e.g., when

TABLE II CRITERIA TO BE FULFILLED FOR THE INCLUSION OF PUBLICATIONS ON CDML SYSTEMS IN OUR LITERATURE ANALYSIS

| Name | Descriptions |
|------------------|---|
| English Language | The publication must be in English. |
| Level of Detail | The publication must present enough details to understand the design and functioning of CDML systems. |
| Topic Fit | The publication must describe at least one CDML system design. |
| Uniqueness | The publication must not be included in the set of relevant literature. |

one author felt the level of detail of a publication was sufficient and another author disagreed), we discussed the relevance of the publication in more detail until we concluded with unanimous decisions to include or exclude the publication from the preliminary start set. This relevance assessment led us to exclude 18 further publications from the preliminary start set. The final start set included eleven publications to be analyzed for the development of the initial version of the conceptualization.

b) Development of an Initial Version of the CDML Design Toolbox: We analyzed the publications in the start set by applying open, axial, and selective coding [50]. In open coding, we extracted aspects of CDML systems relevant to explain their designs and functioning. After coding the literature in the set of relevant publications, we iteratively refined our coding to achieve mutual exclusiveness between our codes and the exhaustiveness of our coding. For example, we merged the codes "client" and "device" into the code "trainer" and the codes "sendParameters" and "sendGradients" into the code "transmitInterimResult".

In axial coding, we extracted relationships between the codes developed in open coding. For example, we identified that the code "transmitInterimResult" can be implemented differently. We coded each implementation (e.g., "activations" and "gradients") and noted the relationship between "transmit-InterimResult" and "gradients".

In selective coding, we classified the extracted codes into coding schemes. The coding schemes correspond to five agentoriented models (i.e., the roles model, the interactions model, the agent model, the preliminary service model, and the acquaintance model) introduced in the Gaia methodology [20]. For example, we classified the code "trainer" as a role in the roles model and the code "transmitInterimResult" as a protocol in the interactions model.

After the analysis, we refined the coding to improve the mutual exclusiveness between codes and the exhaustiveness of our coding. For example, we abstracted the code "aggregator" to "updater" to include DCML systems in which the ML model is updated with and without aggregating interim results.

3) Test and Iterative Refinement: We gathered evidence for the external validity of our CDML design toolbox by testing whether CDML systems, which we did not use to develop our conceptualization, can be successfully modeled with our CDML design toolbox. To find CDML systems for testing the external validity of our conceptualization, we applied a backward search and a forward search to the set of relevant publications. We decided on the relevance of each publication collated in the backward and forward searches based on the previously used inclusion criteria (see Table II). If a publication met our inclusion criteria, we added the publication to our set of relevant literature.

We again applied open, axial, and selective coding to analyze the new relevant publications. Based on the coding, we classified the CDML systems into the preliminary CDML design toolbox comprised of the agent-based models of the Gaia methodology and the assigned codes.

When we recognized that a CDML system could not be classified into our conceptualization, we refined our con-

TABLE III

OVERVIEW OF OUR CONCEPTUALIZATION OF CDML SYSTEMS FOR THE DEVELOPMENT OF THE CDML DESIGN TOOLBOX PER ITERATION AND IN SUMMARY

| Category | Initial Conceptualization | Iteration 1 | Iteration 2 | Iteration 3 | Summary |
|--|------------------------------|----------------|----------------|--------------------------|---------------------|
| Number of Publications for the Validity Test | 10 | 5 (fs), 4 (bs) | 8 (fs), 1 (bs) | 5 (fs), 4 (bs) | 37 |
| Number of CDML Systems for the Validity Test | 13 | 5 (fs), 6 (bs) | 9 (fs), 1 (bs) | 5 (fs), 4 (bs) | 43 |
| CDML Systems Successfully Classified into Conceptualization | n.a. | 3 | 3 | 9 | 15 |
| CDML Systems Leading to Conceptualization Refinements | n.a. | 8 | 7 | 0 | 15 |
| | | | bs: backward s | earch fs: forward search | n.a.: not applicabl |

ceptualization accordingly and continued with the test and iterative refinement until we had analyzed all relevant CDML publications identified in the last round of backward and forward searches. When our conceptualization needed to be refined, we repeated this third step of our methods, "Test and Refinement". We executed this step three times (see Table III).

During the first iteration, we used four publications from the backward search and five publications from the forward search, presenting eleven CDML systems. When classifying the eleven CDML systems into our conceptualization, we recognized the need for refinements of the CDML design toolbox. For example, we added the role *coordinator* to map the sampling-service from the newly added gossip learning system [49].

During the second iteration, we included one publication from the backward search and eight publications from the forward search. When classifying the nine CDML systems presented in those publications into the conceptualization, we recognized the need to refine our CDML design toolbox. For example, we needed to add activities and protocols while also requiring a revision of existing definitions of activities and protocols. For instance, we added the protocol "assignInterimResultRecepient" and redefined the protocol 'SignalReadiness" so that agents with the roles *trainer* or *updater* can execute the protocol.

In the third iteration, we tested the conceptualization based on nine CDML systems presented in nine publications. We did not identify any further need to refine our concept and decided our concept to be final. Overall, the conceptualization was successfully tested on 43 CDML systems. 15 of these CDML systems required refinements of our conceptualization.

B. CDML Archetype Development

Since the concept level of the CDML design toolbox points out commonalities between CDML systems, we focused on the design level to identify CDML archetypes. The design level allows for the differentiation between CDML system designs. We developed an agent model, preliminary service model, and acquaintance model for each CDML system. Using these models, we analyzed the corresponding CDML system designs to identify similarities. Based on the identified similarities, we developed CDML archetypes. *a)* Agent Model: We started our analysis by examining role distributions in CDML systems to extract common agent types. To identify agent types and their distribution in CDML systems, we analyzed the agent models of the 43 CDML systems, which we previously used for testing the validity of the CDML design toolbox (see Section III-A2). We developed one agent model for each of the analyzed CDML systems. Next, we compared the individual models with each other to identify similarities and differences between the used agent types and their distribution in the corresponding CDML systems. Based on similarities between the agent models, we classified the 43 CDML systems into 18 groups of CDML systems. Each CDML system was assigned to exactly one group.

b) Preliminary Service Model: We analyzed the grouped CDML systems to reveal similarities in the design options implemented for activities and protocols. For example, CDML systems in a group all use the design option "only interim result definition" for the protocol provideMLTask. If CDML systems associated with different groups showed similar uses of design options, we merged these groups into candidate CDML archetypes. For example, we merged assisted learning systems with split learning systems because both systems use the design option "activations" for the protocol transmitInterimResult. Overall, we merged 18 groups of CDML systems into six candidate CDML archetypes.

c) Acquaintance Model and Main Processes: We analyzed the communication paths of the individual CDML systems using their acquaintance models. Whenever we observed similarities in acquaintance models of CDML systems associated with different groups, we merged the groups. After analyzing the acquaintance models, we merged our six candidate CDML archetypes into four final CDML archetypes (i.e., the confidentiality archetype, the control archetype, the flexibility archetype, and the robustness archetype). Overall, we assigned each of the 43 CDML systems to one of the four CDML archetypes.

C. Identification of Key Traits of CDML Archetypes

Using the set of relevant publications on CDML systems that we used to develop the CDML design toolbox (see Section III-A2), we performed open coding [50] to extract preliminary traits of CDML system (e.g., robustness against the participation of malicious agents) that authors point out to highlight strengths and weaknesses of CDML system designs. We noted the referenced CDML systems for all preliminary traits and noted explanations of how the trait originates from the CDML design in axial coding [50]. For example, the key trait "communication bottleneck" is referenced in several publications about federated learning systems. This trait originates from the reliability of federated learning systems on a central agent [40], [51], [52]. We added a description of whether the referenced CDML system has a strength or weakness in the respective trait. Our analysis revealed 132 codes representing preliminary traits of 43 CDML systems. Subsequently, we harmonized the preliminary traits in three iterations to ensure mutual exclusiveness and exhaustiveness of our coding [50]. For example, we aggregated the preliminary traits "does not rely on an orchestrator" and "no need to rely on a third party" to the trait "fault-tolerant". Our analysis revealed 38 traits of CDML systems.

Next, we mapped the 38 traits to the CDML systems to their corresponding CDML archetypes. We evaluated which traits of individual CDML systems apply to all CDML systems assigned to corresponding CDML archetypes. We assigned the set of traits shared by all CDML systems associated with a CDML archetype to the corresponding CDML archetype as key traits. For example, we extracted the trait "not reliant on single agents" from literature on blockchain-based federated learning systems. To evaluate whether this trait also applies to all CDML systems of the robustness archetype, we analyzed the CDML systems of the robustness archetype (e.g., swarm learning) regarding their redundancy of agent types. Since all CDML system designs of the robustness archetype show a high redundancy of agent types, "not reliant on single agents" became a key trait of the robustness archetype. We repeated this process for all traits extracted from the literature analysis at the beginning of this step.

IV. THE CDML DESIGN TOOLBOX

Our CDML design toolbox comprises a concept level and a design level. The concept level (see Section IV-A) describes how CDML systems are designed in principle, including agent roles and agent interactions. Roles are assigned to agents in order to specify the activities and protocols to be executed by corresponding agents. After the role assignment, agents keep their roles until the coalition dissolves. Agents do not have to act in all their assigned roles simultaneously but in at least one role. The design level (see Section IV-B) includes design options that developers can use to design CDML systems. Exemplary design options encompass the assignment of agent types (i.e., combinations of roles) to agents in the CDML system and the definition of types of interim results to be transmitted between agents. The design options are presented in an agent model, a preliminary service model, and an acquaintance model. The agent model shows common combinations of agent types used in CDML systems. In the preliminary service model, we describe design options for implementing activities and protocols described in the roles model. The acquaintance model illustrates communication paths between these agent types in existing CDML systems.

To make the models incorporated in our CDML design toolbox tangible, we describe them along the principal CDML life cycle. The CDML life cycle incorporates three sequential phases each CDML system passes through: the initialization phase, the operation phase, and the dissolution phase. In the initialization phase, agents form and initialize a coalition that can become a CDML system. The initialization phase described in this paper focuses on the autonomous formation of CDML systems by agents in MASs. Alternatively, developers can manually initialize CDML systems. However, the manual setup of CDML systems is out of the scope of this work. In the operation phase, agents interact in order to train or execute ML models. In the dissolution phase, the agents end their collaboration and dissolve the CDML system. Because multiple CDML systems may be formed in a single MAS (e.g., in open MAS), these phases can be passed through in parallel. For simplicity, we describe these three phases using the example of the formation of a single coalition that becomes a CDML system and dissolves. We describe variants of the CDML system design (e.g., in terms of numbers of agents with specific roles) in Section IV-B.

A. Concept Level of the CDML Design Toolbox

The concept level of our CDML design toolbox incorporates a roles model and an interactions model. The roles model comprises role descriptions, activities of agents, and responsibilities. The interactions model includes protocols that specify interactions between agents.

a) Initialization Phase: In the initialization phase, agents form a coalition of at least two agents that aim to collaborate to accomplish an ML task. The formation of coalitions, which can become CDML systems, is triggered by a configurator agent. The configurator agent stores the CDML system specifications (activity: registerCoalition) about the purpose of envisioned CDML systems (i.e., the general prediction problem that ought to be addressed) and requirements for agents that are searched to join the coalition (e.g., in terms of the needed training data structure). The configurator agent defines (parts of) the initial ML model (activity: defineInitialMLModel) to be trained. Definitions of the (parts of) initial ML models are, for instance, the (first) layers of neural networks, a (sub-) set of parameters of linear regressions, activation functions, and the ML model architecture. Moreover, the configurator agent defines the structure and type of interim results (activity: defineInterimResult) to be transmitted between agents in the envisioned CDML system. Interim results are updates that are computed by agents based on local training data and the locally available (part of an) ML model. Then, the *configurator* agent registers the coalition (activity: registerCoalition) with a repository and starts an application process.

Agents fetch the CDML system specifications from the repository. Based on the CDML system specifications, agents decide whether to participate in the CDML system. Agents that decide to participate submit an application, including the roles they apply for, to the *configurator* agent (proto-col: applyForCoalition). Commonly, agents can apply for the roles *coordinator*, *selector*, *trainer*, and *updater*.

 TABLE IV

 Overview of Roles and corresponding activities and protocols in the CDML design toolbox

| Role | Description | Activities | Protocols | |
|--------------|---|--|---|--|
| Configurator | Approves agent applications for the coali- tion and defines the ML model and interim results to be transmitted in the coalition | registerCoalition, defineInitialMLModel, defineInterimResult, awaitApplications, decideOnApplication | applyForCoalition, informApplicant,provideMLTask | |
| Coordinator | Approves agent applications for the coali- tion and assigns communication paths among agents | awaitApplications, decideOnApplication | applyForCoalition, informApplicant, provideMLTask, assignInterimResultRecipient | |
| Selector | Chooses agents to train and update ML models | selectAgent | applyForCoalition, announceAgentSelection | |
| Trainer | Uses local data and computing resources under its control to update parameters of (parts of) ML models (e.g., to produce in- terim results) and transmits them to other agents in the coalition | awaitSelectionSignal, trainMLModel, | applyForCoalition, signalReadiness, transmitInterimResult | |
| Updater | Uses interim results received from other agents to compute updated parameters of (parts of) its ML model. | awaitSelectionSignal, awaitInterimResults, updateMLModel | applyForCoalition, signalReadiness, transmitInterimResult | |

The *configurator* agent iteratively checks for applications from agents (activity: awaitApplications). Upon application receipt, the *configurator* agent decides whether to accept or reject the agent for the CDML system (activity: decideOnApplication). Then, the *configurator* agent responds to the applying agent with an acceptance message or a rejection message (protocol: informApplicant).

When *trainer* and *updater* agents join the coalition, the *coordinator* agent assigns *trainer* agents to *updater* agents they will interact with in the operation phase and inform the respective agents about the assignment (protocol: assignInterimResultRecipient). The *trainer* agent sends its interim result to its assigned *updater* agent. The *updater* agent can return interim results to its assigned *trainer* agent(s) after updating (parts of) the ML model.

The *configurator* agent sends the ML task (protocol: provideMLTask) to agents in the coalition. ML tasks are a collection of information required to train and update ML models and can include the initial ML model definition and the interim result definition.

At the end of the initialization phase, at least two agents of the coalition must have been assigned the following roles to form a CDML system: *configurator*, *coordinator*, *selector*, *trainer*, and *updater*. Agents may have multiple roles. We describe common combinations of roles on the design level of the CDML design toolbox (see Section IV-B).

phase, After the initialization the coordinator agent handles applications of agents on behalf of the configurator agent, which executes the activities awaitApplications, decideOnApplication and the protocols applyForCoalition and informApplicant. The coordinator agents send the ML task to the accepted agents (protocol: provideMLTask). After the initialization of the CDML system, ML models can be trained and executed in the operation phase.

b) Operation Phase: In the operation phase, agents participate in the training and execution of ML models according to their assigned roles. At the beginning, the *trainer* agent and the *updater* agent signal their readiness to the *selector* agent (protocol: signalReadiness). Agents that have signaled their readiness iteratively check for triggers from the *selector* agent to execute activities and protocols required to collaboratively train and update ML models (activity: awaitSelectionSignal).

The selector agent selects trainer agents and updater agents (activity: selectAgent) to act in at least one of these roles. Then, the selector agent requests the selected agents to act in the corresponding roles (protocol: announceAgentSelection). Agents that are selected for the role trainer use their locally available (parts of the) ML model and local training data to compute interim results (activity: trainMLModel). The trainer agent sends its interim result to the updater agent (protocol: transmitInterimResult). The Updater agent waits until it receives interim results (activity: awaitInterimResults) and then uses the interim results received from *trainer* agents to compute a new version of the locally available (part of the) ML model (activity: updateMLModel). The execution order of training, updating, and transmitting interim results can vary between CDML systems (see Section IV-B). The procedure outlined in the operation phase is typically executed repeatedly. Protocols and activities may be executed in parallel or sequentially.

c) Dissolution Phase: In the dissolution phase, agents stop executing the processes described in the operation phase. This can be the case if agents decide that (parts of) the ML model(s) have been sufficiently trained or, in case that other agents are required to execute ML models, that they do not need to execute ML model anymore. When agents end their collaboration, the CDML system dissolves.

B. Design Level of the CDML Design Toolbox

While the concept level of the CDML design toolbox offers an abstract description CDML system designs, the design level can guide detailed specifications of concrete CDML system designs as follows. The first step in designing CDML systems entails the specification of an agent model (see Section IV-B1) that presents the assignment of agent types to agents. Agent types incorporate all roles that are simultaneously assigned to single agents. The CDML design toolbox offers a set of agent types commonly used in CDML systems in the agent model (see Section IV-B1). Second, developers need to tailor the activities and protocols associated with agent types to the requirements of the envisioned CDML system. In Section IV-B2, the CDML design toolbox offers a range of design options on how activities and protocols can be implemented to develop service models for CDML systems. Finally, the acquaintance model needs to specify communication paths between agents (see Section IV-B3). While some communication paths are integral to all CDML systems (e.g., trainer agents sending interim results to updater agents, see Section IV-B1), others are contingent on the characteristics of CDML systems (e.g., updater agents returning interim results to trainer agents). The CDML design toolbox introduces communication paths necessary to operate CDML systems successfully. This list comprises necessary and optional communication paths and helps developers consider communication efficiency and communication bottlenecks when designing CDML systems.

In the following, we describe the three models (i.e., the agent model, the preliminary service model, and the acquaintance model) that can be utilized to develop CDML systems.

1) Agent Model: Agent types are a combination of roles identified in the roles model that can serve as a blueprint to implement agents in CDML systems. Following the concept level of the CDML design toolbox (see Section IV-A), CDML systems require at least two agents with agent types that in combination comprise the following roles: configurator, coordinator, selector, trainer, and updater. These roles can be assigned to agents in seven combinations (see Table V), each combination forming an individual agent type. Identical agent types can be assigned to multiple agents, for example, to increase redundancies in the processing of ML tasks [14] or to distribute workload in the processing of ML tasks [10]. First, the Tra agent type only comprises the role trainer. Agents of the Tra agent type only train the ML model without updating it with interim results from other agents. The Tra agent type is utilized in CDML systems with only one training round [53].

Second, the *CooSel* agent type comprises the roles *coordinator* and *selector*. This agent type is utilized in CDML systems with a peer-to-peer structure. If agent selection and the assignment of *trainer* agents to *updater* agents follow a sophisticated rule (e.g., unbiased peer-to-peer sampling service [54]), *CooSel* agents can be implemented that only focus on the selection and assignment of agents [49], [55].

Third, the *TraUpd* agent type combines the roles *trainer* and *updater*. The *TraUpd* agent type is implemented in many CDML systems since it combines the two main roles accounting for training ML models. *TraUpd* agents can train

ML models but can include interim results into their local ML models [35], [47], [56].

Fourth, the *ConTraUpd* agent type combines the roles *configurator*, *trainer*, and *updater*. The *ConTraUpd* agent type is mainly used in split learning systems and assisted learning systems. The *configurator* role is required since agents in these CDML systems define their own ML model [11], [12].

Fifth, the *ConCooSelUpd* agent type combines the roles *configurator*, *coordinator*, *selector*, and *updater*. *Con-CooSelUpd* agents primarily operate central servers in federated learning systems [35], [47].

Sixth, the *CooSelTraUpd* agent type combines the roles *coordinator*, *selector*, *trainer*, and *updater*. This agent type has a high degree of autonomy as it can execute all activities and protocols except those with the *configurator* role. The *CooSelTraUpd* agent type is used in CDML systems to create a high level of redundancy [14], [57], [58].

Seventh, the *ConCooSelTraUpd* agent type combines the roles *configurator*, *coordinator*, *selector*, *trainer*, and *updater*. This agent type is assigned to central agents in federated learning (e.g., [59]) that train ML models or a single agent that initiates the ML model to be trained in peer-to-peer-based CDML systems (e.g., the BraintTorrent system [48] and the gossip learning systems [49]).

TABLE V OVERVIEW OF AGENT TYPES IN CDML SYSTEMS

| | Agent Roles | | | | |
|-----------------|--------------|--------------|--------------|--------------|--------------|
| Agent Type | Configurator | Coordinator | Selector | Trainer | Updater |
| Tra | | | | \checkmark | |
| CooSel | | \checkmark | \checkmark | | |
| TraUpd | | | | \checkmark | \checkmark |
| ConTraUpd | \checkmark | | | \checkmark | \checkmark |
| ConCooSelUpd | \checkmark | \checkmark | \checkmark | | \checkmark |
| CooSelTraUpd | | \checkmark | \checkmark | \checkmark | \checkmark |
| ConCooSelTraUpd | \checkmark | \checkmark | \checkmark | \checkmark | \checkmark |

2) Preliminary Service Model: The key activities and protocols introduced at the concept level of the CDML design toolbox (see Table IV) can be implemented based on various design options. It is important to note that the following descriptions do not represent a complete service model [20]. Complete service models are usually highly context-dependent and, thus, out of scope for this work. The following descriptions of design options for the key activities and protocols are intended as a foundation for developing detailed service models.

a) Activities: We identified 12 design options for five key activities. The activity awaitApplications has two design options. First, the agent population awaits agent applications to join the coalition "only during the initialization phase". Applications are ignored when the CDML system is already initialized. For example, in most variants of split learning systems [11], the ML model layers to be trained need to be assigned to agents during the initialization phase, which prevents agents from joining after the initialization phase. Second, the agent population accepts applications "always" [14]. This allows agents to join the CDML system arbitrarily.

The activity selectAgent has three design options. First, agents can be selected for a role "based on votes from other agents" in the CDML system. The *selector* collects the votes of other agents and decides which agents should execute which activities and protocols; for example, all agents in the CDML system can vote on which agent activates the *updater* role and executes the updating of the ML model (activity: updateMLModel) [14]). Second, agents can be selected "based on agent attributes", for example, based on the size of agents' datasets [53]. Third, agents can be selected "randomly" to activate a role and execute corresponding activities and protocols [48], [60].

The activity awaitInterimResults has two design options. To maintain liveness in CDML systems, the waiting time of agents for interim results can be "response-bound" or "time-bound". If the waiting time of the agents is "responsebound" [61], the *updater* agent waits for a specified number of interim results before updating the ML model with the interim results received. "Response-bound" waiting for interim results can decrease the liveness of CDML systems if set too high; for example, when an agent with the role *updater* awaits interim results from all trainer agent, but on trainer agent may have crashed, the updater agent may theoretically wait infinitely. "Time-bound" waiting tackles this issue [10]. If the waiting time exceeds a specified time bound, the updater agent updates the ML model with all interim results received during the waiting period. However, "time-bound" waiting may lead the updater agent to ignore interim results received too late.

The activity updateMLModel has two design options. First, *updater* agents can perform "batched updates" [52], [53], [57], [62]. In "batched updates", *updater* agents use a set of interim results received from *trainer* agents to update their ML model at one time. Second, *updater* agents can perform "individual updates" to separately update the ML model for each interim result received from a *trainer* agent or an *updater* agent [11], [61].

The activity trainMLModel has three design options. First, trainer agents can "train two complete ML models". In this case, *trainer* agents compute two separate ML models. A local ML model that learns representations of the training data and a global ML model that is trained on the local ML model instead of the raw training data. An advantage of this approach is that the local ML model can protect confidential attributes from the global ML model, thus improving training data confidentiality. Moreover, the communication efficiency can be improved because the global ML model requires fewer parameters due to the local ML model learning being the foundation for the global ML model [63], [64]. Second, trainer agents can "train one complete ML model". A complete ML model refers to the entire set of parameters comprising the ML model. In most CDML systems, *trainer* agents store and train one complete ML model [16], [47]. Third, trainer agents can "train a part of an ML model". A part of an ML model refers to a subset of ML model parameters. Exemplary parts

of ML models are layers of a neural network or a subset of coefficients of linear regression. Training only a part of an ML model has two main advantages. First, *trainer* agents require less storage and computing resources. Second, due to *trainer* agents only having access to a part of the ML model, the complete ML model can remain confidential [11], [12].

b) Protocols: We identified nine design options for three key protocols. We identified two design options for the protocol provideMLTask. First, the agent with the role *configurator* can provide "only interim result definitions" to other agents in the CDML system. The agent with the role *configurator* only provides the interface between agents (e.g., exchange parameters or gradients). The exact ML model to be used remains unknown to other agents (e.g., in terms of the ML model architecture and its hyperparameters) [12]. Second, the *configurator* agent provides both the interim result definition and initial ML model definition (e.g., [10], [35]).

The protocol announceAgentSelection has two design options. First, the *selector* agent can announce which agent should activate which role [10], [49]. Second, the *selector* agent can announce what agents should activate which role and announce the training sample IDs that should be trained [12].

There are five design options for the protocol transmitInterimResult. First, agents can transmit "parameter values" [19], [65]. Parameter values refer to a set of variables or weights that the ML model learns from the training data and that determine how the ML model makes predictions based on the input data. Second, agents can transmit "gradients" [35], [61]. Gradients refer to the directional slopes or change rates of a mathematical function. Third, agents can transmit "activations with labels" [11], [66]. We refer to activations as intermediate outputs of an ML model for a given input. When the ML model is presented with input data, it propagates the data through its layers, applies the learned parameters (weights and biases), and produces an output. We refer to the output as "activations" if it is not the final output of the ML model. If the output is from the final layer / includes all parameter values of the ML model, we call the outputs predictions. Fourth, agents can transmit "activations without labels" [11], [66]. Fifth, agents can transmit "(pseudo-)residuals" [12]. Residuals refer to the differences between the actual target values and the predicted values generated by an ML model. Pseudo-residuals can be considered intermediate residuals and are often used in boosting algorithms.

3) Acquaintance Model: Several communication paths between agents are required for the functioning of CDML systems. Some of those communication paths are indispensable in every CDML system; other communication paths only appear in some CDML systems. Based on our concept level of CDML systems (see Section IV-A), we describe indispensable communication paths and optional communication paths (design options) in the following. Since communication paths differ between the lifecycle phases of CDML systems, we describe the communication paths for each phase separately.

a) Initialization Phase: The configurator agent must have a bidirectional communication path to all other

agents for two purposes: first, to participate in the coalition application process (protocols: applyForCoalition, informApplicant); second, to provide them with the ML task definition (protocol: provideMLTask).

The *coordinator* agent must have a unidirectional communication path to the *trainer* agent to inform the agent to which *updater* agent they should send their interim results (protocol: assignInterimResultRecipient). This communication path allows for more flexibility by enabling sub-coalitions that form around *updater* agents [10], [19], [67].

The *coordinator* agent may have a unidirectional communication path to the *updater* agents. Via such a communication path, the *coordinator* agent can inform the *updater* agents to which *updater* agents they should send intermediate results (protocol: assignInterimResultRecipient). This communication path can be used for a hierarchically organized CDML system, in which *updater* agents communicate with each other to improve their local ML model without using local training data [10], [19], [67].

b) Operation Phase: The selector agents must have a bidirectional communication path to the *trainer* agent and the *updater* agent. This communication path enables the *selector* agent to receive signals that these agents are ready to participate in the training (protocol: signalReadiness) and to inform these agents that they are selected for the training (protocol: announceAgentSelection).

The *trainer* agent must have a unidirectional communication path to the *updater* agent to send it interim results (protocol: transmitInterimResult).

The *coordinator* agent can have a bidirectional communication path to all other agent roles if applications can be received and processed after the initialization phase. In this case, the *coordinator* agent take over handling the applications from the *configurator* agent (protocols: applyForCoalition, informApplicant). Because agents can apply and be admitted to a CDML system after the initialization phase, this communication path enables the CDML system to address issues in the agent population during the operation phase. For example, if it becomes clear during the operation phase that the training data is insufficient, more *trainer* agents can be admitted to the CDML system.

The *updater* agent can have unidirectional or bidirectional communication paths with an other *updater* agent to exchange information about their ML model update (e.g., [10], [19]). This communication path allows for hierarchical structures with more than one *updater* agent.

The *trainer* agent can have bidirectional communication paths to the *updater* agent, for example, to send and receive interim results (protocol: transmitInterimResult). Such bidirectional communication paths are common in CDML systems. In some CDML systems (e.g., one-shot federated learning [53]), the *trainer* agent sends interim training results to the *updater* agent without receiving interim results in return [53].

c) Dissolution Phase: During the dissolution phase, the communication paths between agents are dissolved. Agents that have stored a local ML model can keep it and use it to make predictions on their own.

V. CDML ARCHETYPES

We developed four CDML archetypes that reflect CDML system designs common in practice and research: the confidentiality archetype, the control archetype, the flexibility archetype, and the robustness archetype. The CDML archetypes are distinguished by their agent models, acquaintance models, and principal functioning, including preliminary service models. Table VI gives an overview of the four CDML archetypes we describe in detail in the following. The coalition-forming phase is outside the scope of the archetype descriptions because developers can set up CDML systems that correspond to the CDML archetypes. For each CDML archetype, we highlight common design variants.

A. Confidentiality Archetype

The confidentiality archetype is suitable for use cases in which agents want to preserve the confidentiality of ML models, ML tasks, and training data. Agents only store parts of ML models. The full architectures of ML models trained in the confidentiality archetype are not disclosed. Thus, no agent has access to the global ML model. Instead, the global ML model is distributed across several agents, which only store parts of it. ML models are not synchronized coalition-wide during ML model training and for ML model inference. Exemplary CDML systems of the confidentiality archetype are split learning [11], [66], [70], assisted learning [12], [68], gradient assisted learning [17], SplitFed learning [37], FDML [71], hierarchical SplitFed learning [19], and FedLite [72].

1) Agent Model: The confidentiality archetype comprises the agent types *ConCooSelUpd* and*ConTraUpd*. In its basic configuration, the confidentiality archetype comprises one *ConCooSelUpd* agent and at least one *ConTraUpd* agent.

2) Acquaintance Model: In the confidentiality archetype, the ConCooSelUpd agent can communicate with all Con-TraUpd agents on bidirectional communication paths (see Figure 1). ConTraUpd agents do not communicate with each other directly.



Fig. 1. Exemplary acquaintance model of the confidentiality archetype

3) Principal Functioning: In the initialization phase, the ConCooSelUpd agent configures its local part of the ML model and defines the interim results to be transmitted (activities: defineInitialMLModel, defineInterimResult). Local parts of the ML model can be specific layers of a neural network in split learning [11] or just parts of a layer of a neural network in vertical split learning [11] and assisted learning [12]. Examples of interim results include activations of a particular layer of a neural network (e.g., referred to as the cut layer in split learning) [11] or (pseudo-)residuals [17]. The ConCooSelUpd

TABLE VI OVERVIEW OF CDML ARCHETYPES AND THEIR DESIGNS

| | CDML Archetypes | Confidentiality Archetype | Control Archetype | Flexibility Archetype | Robustness Archetype |
|----------------------------------|--|---|--|--|--|
| | Exemplary CDML Systems | Assisted learning sys- tems [12], [68], Split learning systems [11], [66], SplitFed learning systems [37] | Variants of federated learning systems [10], [35], [39], [51]–[53], [59], [61], [63] | Gossiplearningsystems[49],Decentralizedfederatedlearningsystems[40],[62],[62],[64],BrainTorrentsystems[48] | Swarm learning sys- tems [14], Blockchain- based federated learn- ing systems [57], [60], [65] |
| ns Br | Hierarchy | Strong | Strong | Weak | Weak |
| Distinguishing Design Options | Agent Types and their Number of Occurences | ConTraUpd $(1 \leq)$, ConCooSelUpd (1) | TraUpd (1 \leq), ConCooSelUpd (1) | ConCooSelTraUpd (1 \leq), CooSelTraUpd (1 \leq) | ConCooSelTraUpd (1), CooSelTraUpd (1 \leq) |
| | Coalition-wide ML Model Synchronization | No | Yes | No | Yes |
| | awaitApplications | Only during the initial- ization phase, Always | Only during the initial- ization phase, Always | Only during the initializa- tion phase, Always | Only during the initial- ization phase, Always |
| Design Options for Activities | awaitInterimResults | Waiting for a time- threshold, Waiting for a response-threshold | Waiting for a time- threshold, Waiting for a response-threshold | Waiting for a time- threshold, Waiting for a response-threshold | Waiting for a time- threshold, Waiting for a response-threshold |
| | selectAgent | Based on agent attributes, Randomly | Based on agent attributes, Randomly | Based on agent attributes, Randomly | Based on agent votes from other agents |
| | trainMLModel | Train a part of the ML model | Train a part of the ML model, Train one com- plete ML model, Train two complete ML models | Train one complete ML model, Train two com- plete ML models | Train one complete ML model |
| | updateMLModel | Batched update, Individ- ual update | Batched update, Individ- ual update | Batched update, Individ- ual update | Batched update |
| Design Options for Protocols | announceAgentSelection | Role and training sample IDs | Only role | Only role | Only role |
| | provideMLTask | Provide only interim re- sult definition | Provide ML model defi- nition and interim result definition | Provide ML model defi- nition and interim result definition | Provide ML model def- inition and interim re- sult definition |
| | transmitInterimResult | Activations with labels, Activations without la- bels, (Pseudo-)Residu- als, Gradients | Gradients, Parameter val- ues | Gradients, Parameter values | Gradients, Parameter values |

agent then provides *ConTraUpd* agents with the interim result definition (protocol: provideMLTask; design option: provide only interim result definition). After receiving the interim result definition, *ConTraUpd* agents individually set up their local parts of the ML model following the interim results definition. For example, the ConTraUpd agents in split learning systems set up the layers of a neural network from the input layer to the cut layer. The number of outputs of the cut layer is set depending on the interim results definition.

The operation phase starts with the *ConTraUpd* agents signaling their readiness to the *ConCooSelUpd* agent (protocol: signalReadiness) to participate in the subsequent training round. Then, *ConTraUpd* agents wait for a response (activity: awaitSelectionSignal). The ConCooSelUpd agent decides which *ConTraUpd*

agents to select for the next training round (activity: selectAgent). For example, this selection can be made based on agent attributes or randomly. After the selection, the ConCooSelUpd agent announces its decision to the Con-TraUpd agents (protocol: announceAgentSelection). Selected ConTraUpd agents train their parts of the ML model (activity: trainMLModel; design option: train a part of the ML model) and transmit their interim results to the ConCooSelUpd agent (protocol: transmitInterimResult; design option: activations with labels, (pseudo-) residuals). The *ConCooSelUpd* agent waits for incoming interim results (protocol: awaitInterimResults). The ConCooSelUpd agent uses the interim results to update (and train) its local (part of the) ML model (activities: trainMLModel, updateMLModel). Depending on the implementation, the *ConCooSelUpd* agent then transmits another interim result back to the *ConTraUpd* agents (protocol: transmitInterResult; design option: gradients). *ConTraUpd* agents use it to update their local part of the ML model. The *ConCooSelUpd* agent decides how often this process is repeated.

4) Key Traits: The confidentiality archetype relies on a strongly hierarchical agent organization and does not have a coalition-wide synchronization of ML models. The missing synchronization of ML models among agents leads to the fact that ML models can be kept confidential. The main trait of the confidentiality archetype is that confidentiality entails training data confidentiality and the ML model confidentiality because agents only have access to parts of the ML model. Next to enabling ML model confidentiality, The confidentiality archetype can be very computation efficient since agents only have to store and compute a part of the ML model, which can be potentially very large [11], [72]. The confidentiality archetype requires fewer training rounds than the control archetype and converges quickly [11], [66]. The confidentiality archetype has high communication costs due to the ML model partitioning and the communication of both activations and gradients [72]. Some CDML systems that correspond to the confidentiality archetype, such as split learning systems (e.g., [11]), can have high idle times of trainer agents since the trainer agents only interact with the updater agents sequentially [37]. Other CDML systems, such as SplitFed learning systems, address this issue by combining elements of split learning and federated learning and, thus, can reduce the idle times [37]. As no agent has access to the entire ML model, the coalition (or a subset of it) is required to make ML model inferences. Therefore, the coalition can only be resolved when the ML model is not used anymore.

5) Variants of the Confidentiality Archetype:

a) U-Shaped Split Learning [11]: U-shaped split learning systems can be used to train neural networks. A selected ConTraUpd agent executes the forward propagation up to a specific layer (i.e., the first cut layer) and only transmits activations to the ConCooSelUpd agent (protocol: transmitInterimResults; design option: activations without labels). The ConCooSelUpd continues the forward propagation up to the second cut layer and transmits activations back to the ConTraUpd agent. The ConTraUpd agent completes the forward propagation, starts the backpropagation, and transmits the gradients of the second cut layer to the ConCooSelUpd agent (protocol: transmitInterimResults; design option: gradients). Using these gradients, the ConCooSelUpd agent continues the backpropagation to the first cut layer and transmits the gradients of the first cut layer to the ConTraUpd agent. The ConTraUpd agent executes the backpropagation for the remaining layers and, thus, completes a training round.

B. Control Archetype

The control archetype is suitable for use cases in which one agent should have control over the DCML system. The control archetype incorporates a hierarchical communication structure with an agent on the top level that controls the training process. The agent on top receives all interim results and synchronizes the training process by deciding on the global ML model to be trained in each training round. Exemplary CDML systems of the control archetype implement variants of federated learning [10], [35], [61], [63], including one-shot federated learning [53], semiFL [59], heteroFL [39], and hierarchical federated learning [51], [52].

1) Agent Model: CDML systems belonging to the control archetype comprise the agent types *ConCooSelUpd* and *TraUpd*. The control archetype comprises one *ConCooSelUpd* agent and at least one *TraUpd* agent.

2) Acquaintance Model: The acquaintance model of the control archetype has the structure of a tree (see Figure 2). Agents can bidirectionally communicate in a strictly hierarchical manner along the vertexes of the tree. In its basic form, there are two hierarchical levels (e.g., [10]): a root ConCooSelUpd agent forms the top level of the hierarchy. At least one TraUpd agent resides on the bottom level of the hierarchy. There can be additional levels between the top level and the bottom level (e.g., [51], [52]). The inner nodes of the tree are ConCooSelUpd agents, whereas TraUpd agents represent the leaves.

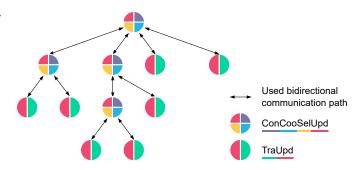


Fig. 2. Exemplary acquaintance model of the control archetype

3) Principal Functioning: In the initialization phase, the ConCooSelUpd agent on the top level of the hierarchy defines the initial ML model and interim results (activities: defineInitialMLModel, defineInterimResult). Suppose there are additional ConCooSelUpd agents on lower levels of the acquaintance model. In that case, the initial ML model and interim result definition are propagated to these agents by executing the protocol provideMLTask (design option: ML model definition and interim result definition). ConCooSelUpd agents on lower levels of the acquaintance model can only forward parts of the ML model (i.e., sub-models) to their child nodes. Thus, each ConCooSelUpd agent can individually define the initial ML model and interim results for its descendants (activities: defineInitialMLModel, defineInterimResult).

In the operation phase, *TraUpd* agents execute the *signal-Readiness* protocol to signal their availability to participate in a training round to their respective parent *ConCooSelUpd* agent. Then, *TraUpd* agents wait for a selection signal (activity: awaitSelectionSignal). *ConCooSelUpd* agents decide which of their child *ConCooSelUpd* and *TraUpd* agents to include in a training round. Once a sufficient number of

child agents have signaled their readiness to a ConCooSelUpd agent, it signals its readiness to its parent agent and waits for a selection signal (activity: awaitSelectionSignal). This process is repeated recursively throughout the hierarchy until it reaches the root ConCooSelUpd agent. Then, the root ConCooSelUpd agent selects (a subset of) its subordinate agents to participate in the upcoming training round (activity: selectAgent; design option: based on agent attributes or randomly) and announces its selection to its child agents (protocol: announceAgentSelection). Afterward, it transmits the current version of the ML model, or a part thereof, to selected child agents (protocol: transmitInterimResult; design option: gradients or parameter values) and waits for interim results (activity: awaitInterimResult; design option: waiting for a time-threshold or waiting for a response-threshold). This selection process is repeated recursively by descendant ConCooSelUpd agents until it reaches the leaf TraUpd agents. The TraUpd agents update their local ML model based on the interim result received (activity: updateMLModel; design option: batched update) and train it using local training data and selfcontrolled compute (activity: trainMLModel; design option: train one complete ML model or train a part of the ML model). After training is completed, TraUpd agents initiate the transmitInterimResult protocol (design option: gradients or parameter values) with their respective parent ConCooSelUpd agent as the responder. The parent ConCooSelUpd agent waits until a defined threshold is reached (activity: awaitInterimResult; design option: waiting for a time-threshold or waiting for a response-threshold) and update their (part of the) ML model based on the interim results received (activity: updateMLModel; design option: batched update). Each ConCooSelUpd agent can decide how often to repeat this training procedure with its descendants. When the desired number of training rounds is completed, ConCooSelUpd agents send the updated (part of the) ML model to their parent nodes (protocol: transmitInterimResult; design option: gradients or parameter values). Once the threshold of the root ConCooSelUpd agent is reached, a coalition-wide training round is completed.

The procedure described for the operation phase is repeatedly executed until the dissolution phase is initiated by the root *ConCooSelUpd* agent.

4) Key Traits: The control archetype implements a strongly hierarchical organizational structure of agents and requires the coalition-wide synchronization of ML models. The combination of these traits leads to organizational structures in which a small fraction of all agents wield the predominant control over the CDML system. The control archetype is suitable for use cases with strict hierarchies where one or a few agents should keep control over the CDML system. The control archetype relies on only one root *ConCooSelUpd* agent. If the one *updater* agent crashes, the whole CDML system crashes [48], [49], [52]. Thus, the control archetype is not crashfault tolerant. The use of multiple *updater* agents assigned to multiple layers of the hierarchy of the control archetype

can make the system tolerant to crashes of single updater agents [19], [52]. If one *updater* agent crashes, *updater* agents can take the load in aggregating interim results of the crashed one. However, this redistribution of load to fewer updater agents can drastically reduce the overall performance of the control archetype. The control archetype can be prone to performance bottlenecks due to a few central agents having to execute numerous computationally intensive activities and protocols [52], [53]. Such performance bottlenecks include computation [40] (i.e., during updating) and communication [40], [51] (i.e., sending and receiving interim results). Regarding the predictive performance of the ML model trained collaboratively, the control archetype usually performs better than the confidentiality archetype (e.g., [37]). The ML model usually converges faster than in CDML systems of the flexibility archetype (e.g., [9]). The coalition can be dissolved after training because the coalition is not required to make ML model inferences.

5) Variants of the Control Archetype:

a) TraUpd Agents as Tra Agents [53]: TraUpd agents lose their updater role and become Tra agents. In this variant, the interim results are only transmitted from Tra agents to ConCooSelUpd agents. No interim results are transmitted back to Tra agents. Tra agents do not update their local ML models.

b) ConCooSelUpd Agents as ConCooSelTraUpd Agents [59]: ConCooSelUpd agents gain the trainer role and become ConCooSelTraUpd agents. In these systems, the agents on higher levels of the hierarchy possess training data on their own and use it to train (parts of) the ML model themselves (e.g., [59]). ConCooSelTraUpd agents train the ML model (activity: trainMLModel; design option: train one complete ML model or train a part of the ML model) while waiting for interim results of subordinate agents in the hierarchy.

c) TraUpd Agents Train Two Complete ML Models [63]: TraUpd agents train two complete ML models locally (activity: trainMLModel; design option: train two complete ML models). TraUpd agents train one ML model on local data. The second ML model is trained on the first ML model. Only the gradients or parameter values resulting from the training of the second ML model are transmitted to the superordinate agent.

C. Flexibility Archetype

The flexibility archetype is suitable for use cases with communication topologies that can change at run-time [40]. The flexibility archetype offers a high degree of agent autonomy. Agents can arbitrarily join and leave the flexibility archetype without impeding the functioning of the CDML system [40]. In its basic variant, agents can select agents they want to collaborate with. Moreover, agents can decide if and when they execute activities (e.g., trainMLModel or updateMLModel) and protocols (e.g., signalReadiness or transmitInterimResult). The flexibility archetype is weakly hierarchically organized. ML models are not synchronized coalition-wide during ML model training. Exemplary CDML systems of the flexibility archetype implement gossip learning [49], BrainTorrent [48], and decentralized federated learning [40], [62], [64], [69].

1) Agent Model: The flexibility archetype comprises the agent types ConCooSelTraUpd and CooSelTraUpd. In its basic configuration, the flexibility archetype comprises one Con-CooSelTraUpd agent and at least one CooSelTraUpd agent.

2) Acquaintance Model: To participate in the training, agents must establish a bidirectional communication path to at least one other agent. (see Figure 3). Other agents include ConCooSelTraUpd agents and CooSelTraUpd agents. Agents decide with which agents they interact on an equitable basis.

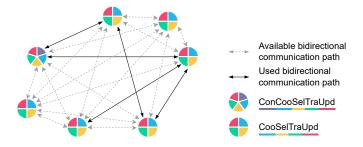


Fig. 3. Acquaintance model of the flexibility archetype for an exemplary training round

3) Principal Functioning: In the initialization phase, the ConCooSelTraUpd agent first defines the ML model (activity: defineInitialMLModel) and interim results (activity: defineInterimResult). The ConCooSelTraUpd agent distributes the ML model and the interim result definition to other agents in the CDML system (protocol: provideMLTask; design option: provide initial ML model definition and interim result definition). Agents can join at any time (protocol: applyForCoalition; design option: always).

In the operation phase, each ConCooSelTraUpd and CooSel-TraUpd agents train the ML model locally using local training data and self-controlled computing resources. Afterward, each agent signals its readiness to activate its updater role for the upcoming training round (protocol: signalReadiness) and waits for other agents to signal their readiness (activity: awaitAgentReadiness). Then, at least one agent that signals its readiness is selected (activity: selectAgent) to receive the interim results. Agents are usually selected randomly (design option: randomly, but can also be selected in a targeted manner (design option: based on agent attributes. The selection is announced to the selected agent (protocol: announceAgentSelection). Agents that are selected to activate the role updater wait (activity: awaitInterimResult) until they receive the interim results from other agents using the protocol transmitInterimResult (design option: gradients or parameter values). Lastly, the selected agents use the interim results of other agents to update their local ML model (activity: updateMLModel). The update can entail several interim results (design option: batched update) or only one interim result from another agent (design option: individual update).

This process is repeated until the dissolution phase is initiated. The flexibility archetype dissolves when no agents engage in collaborative training anymore.

4) Key Traits: The flexibility archetype is weakly hierarchical and agents store different states of ML models. ML models are not synchronized coalition-wide. Agents have a high degree of autonomy and can individually decide when to train collaboratively and with whom. Moreover, agents can individually decide to activate roles and execute activities and protocols, which leads to agents having little idle time [48].

The flexibility archetype can handle agent crashes better than the control archetype [49]. An agent dropping out of the system may temporarily reduce the performance of the flexibility archetype, but because a new agent can be easily integrated into the training process due to the lack of rules, the flexibility archetype can recover from the agent dropout [9]. Because agents can largely operate independently of each other, no single agent is vital for the proper functioning of the CDML system. If agents are redundant, agents can theoretically be replaced. However, this may not always be possible because the flexibility archetype does not require redundant agents.

The flexibility archetype is not robust against malicious agents. Malicious agents are agents that tamper with training processes and manipulate collaboratively trained ML models [9]. Malicious agents can obfuscate their identities by arbitrarily joining and dropping out of the CDML system and arbitrarily switching their collaboration partners. Such obfuscation can facilitate the engagement of agents in performing malicious activities without detection (e.g., because reputation systems may not be applicable [42]). Moreover, even when malicious agents are identified, it is hard to punish them because rules (e.g., agents that act maliciously are forced to leave the system) are hardly enforceable in the flexibility archetype. The coalition can be dissolved after ML model training because the CDML system is not required to make ML model inferences.

5) Variants of the Flexibility Archetype:

a) Additional CooSel Agent [49]: There can be a dedicated CooSel agent (e.g., [49]). The remaining agents lose the selector role and become ConCooTraUpd and ConTraUpd agents. In each training round, the CooSel agent selects a subset of the ConCooTraUpd and CooTraUpd agents to function as the updater (activity: selectAgent; design option: randomly) and assigns each of the remaining agents to one of the agents selected as an updater. Each agent then sends its interim result to the agent it was assigned to (protocol: transmitInterimResult; design option: gradients or parameter values).

D. Robustness Archetype

The robustness archetype is suitable for use cases in which agents may inadvertently drop-out of the coalition during ML model training (e.g., due to crashes or network failures) because a large fraction of agents is redundant and, thus, can replace each other. The robustness archetype is weakly hierarchically organized and performs coalition-wide synchronization of the ML model. Exemplary CDML systems of the robustness archetype are swarm learning system [14] and other blockchain-based CDML systems [57], [65].

1) Agent Model: The robustness archetype comprises the agent types ConCooSelTraUpd and CooSelTraUpd. In its basic configuration, the robustness archetype comprises one Con-CooSelTraUpd agent and at least one CooSelTraUpd agent.

2) Acquaintance Model: As illustrated in Figure 4, there can be bidirectional communication paths between all agents in the system. This includes both agents of the type Con-CooSelTraUpd and CooSelTraUpd.

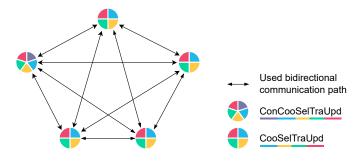


Fig. 4. Exemplary acquaintance model of the robustness archetype

3) Principal Functioning: In the initialization phase of the robustness archetype, the ConCooSelTraUpd agent defines the ML model and interim results and distributes corresponding definitions to other agents in the coalition (protocol: provideMLTask; design option: provide ML model definition and interim result definition). There must always be at least one CooSelTraUpd agent and one ConCooSelTraUpd agent to redundantly execute the roles coordinator, selector, trainer, and updater. Additional CooSelTraUpd agents can join at any time (protocol: applyForCoalition; design option: always).

In the operation phase, ConCooSelTraUpd and CooSel-TraUpd agents broadcast their readiness to activate their roles updater and trainer for the training in the robustness archetype (protocol: signalReadiness). All agents that received the broadcast individually decide whether the ConCooSelTraUpd or CooSelTraUpd agent should activate the trainer and updater role (activity: selectAgent). Agents broadcast their individual decisions to all agents in the robustness archetype. The final selection of trainer and updater is made through a consensus mechanism (design option: based on votes from other agents). Next, ConCooSelTraUpd and CooSelTraUpd agents start training the ML model using their locally available training data and compute (activity: trainMLModel; design option: train a complete ML Model). All selected agents receive identical interim results from agents that trained their ML model (protocol: transmitInterimResult; design option: gradients or parameter values). All agents use the identical interim results to update the ML model (activity: updateMLModel). For the update, all selected *updater* agents use the results of from all other agents (design option: batched update). All agents, which computed ML model updates, broadcast their new interim results to all agents in the system (protocol: transmitInterimResult).

This process is repeated until the start of the dissolution phase. The dissolution phase starts when no agents engage in the collaborative training anymore.

4) Key Traits: The robustness archetype is weakly hierarchical and is designed to train global ML models that are synchronized coalition-wide. Both of these traits culminate in CDML systems where agent types are redundantly assigned to agents. Agents process and store data of the global ML model redundantly, increasing the robustness of CDML systems. The robustness archetype uses a fully connected communication network [40]. Due to the high redundancy of agents, except the agent with the role configurator, the robustness archetype does not rely on single agents. This design prevents the robustness archetype from failing if some agents drop-out of the CDML system [57], for example, due to crashes and network failures. The robustness archetype allows for the replacement of updater agents after each training round. Agents in the robustness archetype usually require large computational resources, for example, to compute ML model updates based on interim results from all other agents in the CDML system [40]. The coalition can be dissolved after training since the coalition is not required to make ML model inferences.

5) Variants of the Robustness Archetype:

a) A subset of agents activates the updater role per training round [14], [57]: Interim results are transmitted to and stored by all agents, but only a subset of agents activate their udater role. From all ConCooSelTraUpd and CooSelTraUpd agents that signal their readiness (protocol: signalReadiness), not all agents are selected (activity: selectAgent; design options: based on agent attributes, based on votes from other agents, or randomly) to activate their updater role in every training round. In some cases, only one agent is selected [14].

VI. DISCUSSION

A. Principal Findings

In this study, we present a CDML design toolbox, including a concept level and a design level. The concept level of the CDML design toolbox includes five roles (i.e., configurator, coordinator, selector, trainer, and updater), ten activities (e.g., updateMLModel), and seven protocols (e.g., transmitInterimResult) inherent to CDML systems. On the design level, the CDML design toolbox includes design options to customize CDML systems. For example, the roles trainer and updater can be combined into the agent type TraUpd. We present seven agent types and seven mandatory communication paths between these agent types. For example, agents with the role updater can have communication paths among each other. Moreover, the CDML design toolbox presents design options for activities and protocols. Based on common combinations of design options, we present four principal CDML archetypes (i.e., the confidentiality archetype, control archetype, flexibility archetype, and robustness archetype) and their key traits.

The design level of the CDML design toolbox shows different implementations of roles, activities, and protocols in CDML systems that we describe as design options. Different combinations of design options can lead to different CDML systems. Our results show how CDML systems can be grouped and differentiated on the basis of common combinations of design options and resulting key traits. We observed significant similarities among CDML systems studied by research communities with limited overlap. It turns out that split learning systems and assisted learning systems implement similar design options; for example, they comprise only *ConCooSelUpd* and *ConTraUpd* agents. Moreover, swarm learning systems have similar design options. For example, both implement the agent types *ConCooSelTraUpd* and *CooSelTraUpd* but differ regarding the number of agents with an active *updater* role each training round.

The presented CDML archetypes and their key traits show that no one-size-fits-all CDML system can be used for every use case. Developers must carefully assess the suitability of CDML systems based on their designs and different traits. For instance, the redundant distribution of roles in swarm learning enhances robustness. However, in use cases where most agents have limited resources, mandating that all agents perform all roles may result in the failure of the CDML system because agents may be assigned roles that exceed their resource capacities. Conversely, the redundancy in distributing agent roles can be better suited for use cases characterized by frequent agent drop-outs. Therefore, the careful assessment of CDML system suitability for use case requirements is mandatory to operate CDML systems successfully.

In the agent model (see Section IV-B1), we present the agent types that we identified in the analyzed publications. The presented agent types represent a subset of the possible combinations of agent roles. For example, we did not identify a *Con* agent or an *Upd* agent even though the implementation of such agents could be possible as long as all roles are distributed to agents in CDML systems. CDML systems that assign each agent only one role could also have new traits, including agents requiring fewer resources, that might be useful in many use cases. Because of the theoretical availability of more agent types and combinations of design options, more CDML system designs with different traits may become available in the future.

B. Contributions to Practice and Research

With this study, we contribute to practice and research in three principal ways. First, by presenting the CDML design toolbox, we offer a consolidated design knowledge base of previously scattered design knowledge of CDML systems. Since the comparison of differences between CDML system designs has focused on a few design aspects (e.g., the training process), the CDML design toolbox enables systematic comparisons between CDML system designs covering a broad set of design options. The agent-based models on the concept level (i.e., the roles model and interactions model) of the CDML design toolbox present the main design commonalities of CDML systems (e.g., the use of specific agent roles and the principal training process). The three agent-based models on the design level (i.e., agent model, service model, and acquaintance model) can guide the systematic comparison between CDML system designs and the customization of CDML system designs to meet use case requirements. Moreover, the developed agent-based models can facilitate the application of the Gaia methodology for developing custom CDML system designs.

Second, by showcasing CDML archetypes, we offer starting points for the combination of design options to develop CDML system designs. The archetypes inform of combinations of design options commonly used in practice and research. The CDML archetypes can be customized by using the design options presented in the CDML design toolbox to develop blueprints of CDML systems. Thereby, in combination, the CDML archetypes and the CDML design toolbox offer actionable help in guiding the design of CDML systems.

Third, by presenting key traits of CDML archetypes, we support developers in deciding on combinations of design options to meet use case requirements. The key traits of CDML archetypes enable developers to choose the most fitting CDML archetype for use cases. Using the selected CDML archetype as a starting point, developers can use the CDML design toolbox and customize the archetype to show additional required traits. By executing this process, developers can evaluate CDML system designs in their suitability for use cases prior to implementing the designs.

C. Limitations

For the development of the CDML design toolbox, the CDML archetypes, and the identification of key traits, we analyzed publications and CDML systems that we deemed to be representative of the CDML field. With our selection of publications and CDML systems for analysis, we aimed to cover the large spectrum of different CDML system designs. However, the number of publications and CDML systems significantly increased in the past years, making it impossible to incorporate all publications. The CDML design toolbox may not cover all CDML system designs.

To conceptualize CDML systems, we strove to extract and understand their key design aspects (e.g., activities, processes, and roles), requiring the resolution of ambiguities, and to set extracted key aspects in relationships (e.g., roles and responsibilities). Although well-suited to conduct such research, qualitative research is inherently prone to subjective biases, for example, because publications are individually interpreted depending on personal conceptions. Despite our efforts to reduce such biases (e.g., through feedback on our results from ML experts), we cannot guarantee that we have completely eliminated them.

The analyzed publications focus on the core training process [11], [40], [48], [49], [53]. Other system components required to operate CDML systems are mostly neglected. By triangulating descriptions of CDML systems based on our coding and intense discussions with ML experts, we aimed to complete fragmented descriptions of CDML systems. Still, the CDML design toolbox may lack aspects not specifically mentioned in the analyzed publications. Similarly, a significant number

of the examined publications lacked sufficient detail in their descriptions of permissions of roles, activities, and protocols. This hindered us in describing permissions associated with agent roles at the concept level and impeded the development of a complete service model. Instead, we developed a preliminary service model that describes how activities and protocols can be implemented.

D. Future Research

This work presents a wide range of CDML system designs that address the different requirements of use cases. We noticed that research on CDML systems remains predominantly theoretical, with only a few real-world implementations of CDML systems (e.g., [16]). To gain a more comprehensive understanding of the advantages and limitations of CDML systems in various use cases, future research should prioritize empirical investigations of practical implementations of CDML systems. This research should place particular emphasis on real-world implications, encompassing socio-technical aspects such as human perception and acceptance. The CDML design toolbox offers a foundation for knowledge transfers within the CDML community (e.g., to develop new CDML systems) and across multiple disciplines. In the following, we describe three areas for knowledge transfer that may be particularly interesting for improving CDML systems in future research.

a) Hyperparameter Optimization: Automated hyperparameter optimization (HPO) has become very important in the development of ML models for manifold purposes [73], such as to improve ML model performance and decrease necessary computations in the training of ML models. For most automated HPO methods, such as Bayesian optimization [74]–[76], the availability of complete training data sets is assumed. This assumption lies at odds with decentralized training data management in CDML systems. Extant automated HPO methods are hardly applicable to CDML systems, which may result in under-optimized ML models trained in CDML systems [73]. The CDML design toolbox can serve as a foundation for future research to identify challenges in performing HPO in CDML systems with different designs and develop corresponding solutions.

b) Data Confidentiality: The exchange of interim results instead of training data does not guarantee training data confidentiality per se [77]. To protect training data confidentiality, the combination of CDML and other privacy-enhancing technologies (PETs), such as differential privacy and homomorphic encryption, has become promising [56], [78]. Future research should develop guidelines for how to combine the CDML paradigm with other PETs reasonably.

c) Robustness: Agents may pursue individual goals in CDML systems. However, ensuring the accurate alignment between individual agent goals and the overarching goal of the CDML system is critical. Misalignment can have detrimental consequences, such as the introduction of the free-rider problem [79] and incentivizing agents to poison training data or ML models [80]–[82]. The free-rider problem is characterized by agents that provide subpar data while being able to improve their ML model from interim results received from other

agents. Integrating robustness measures from diverse fields into CDML systems, such as financial incentives in economics and normative principles in sociology for agent behavior coordination [42], [82]–[84], could enhance the robustness of CDML systems against challenges, such as anticipating malicious actions of agents in CDML systems. Future research should extend the CDML design toolbox to include design options that improve the robustness of CDML systems and protect ML model training from malicious agent activity.

VII. CONCLUSION

This work presents a CDML design toolbox that can be used to guide developers in the development of CDML system designs. Leveraging the CDML design toolbox, we developed four CDML archetypes with different key traits that can guide developers in the design of CDML systems.

The CDML design toolbox is envisioned to offer a foundation for developers to design CDML systems suitable for use cases. With our presentation of design options, we aim to accelerate the design process and develop novel CDML systems that can cover an even wider range of use cases.

During our investigation, we recognized the substantial expansion of the CDML design space through contributions from practice and research. Following federated learning systems, alternative CDML systems, such as split learning systems, assisted learning systems, and gossip learning systems, have moved into the focus of practice and research.

We hope that the CDML design toolbox will support the targeted design of CDML systems suitable for use cases (e.g., by facilitating the use of the Gaia method [20]) so that training of ML models on sufficient training data becomes easier for developers. Owing to the considerable attention that CDML systems have garnered in practice and research and the emergence of novel CDML concepts beyond federated learning, we encourage the advancement of the CDML design toolbox in the future.

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