Getting along with Frenemies: Enhancing Multi-competitor Coopetition Governance through Artificial Intelligence and Blockchain

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ABSTRACT: Collaborating with one competitor is difficult but collaborating with several competitors is a monumental challenge. However, multi-competitor coopetition, or cooperation between multiple competitors, is becoming increasingly common. This study examines how recent advancements in artificial intelligence (AI) and blockchain can enhance governance in innovation-oriented multi-competitor coopetition. Examining two coopetitive R&D consortia in pharmaceuticals and medical imaging, we find that a nascent form of AI called federated learning can improve the protection of proprietary and confidential data, thereby maintaining organisational boundaries and autonomy. The use of federated learning and blockchain increases transparency and accountability, which reduces information asymmetries and power differential inequities. Together, federated learning and blockchain decentralise governance and authority, reducing the tension between collective value creation and individual value appropriation inherent in coopetitive relationships, particularly those with multiple competitors. Finally, this study illustrates how emerging technologies challenge traditional assumptions about organisational boundaries, distributed innovation, and coopetition.

Keywords: innovation; coopetition; governance, artificial intelligence; machine learning; federated learning; blockchain

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1. Introduction

Getting along with competitors is not easy. Coopetition, or the simultaneous pursuit of competition and cooperation between firms (Bengtsson and Kock 2000; Brandenburger and Nalebuff 1996), balances collaboration for collective value creation with the individual participants' value capture goals. Coopetition examples include GE Healthcare and Intel Health IT collaborating to accelerate digital imaging, Samsung Electronics and Sony working together to develop and manufacture LCD TV screens (Gnyawali and Park 2011), Ford and GM jointly developing transmission technologies (Brandenburger and Nalebuff 2021), and Pfizer and BioNTech co-developing a COVID-19 vaccine. Coopetition has gained attention as an important strategy for organisations searching for ways to grow their competitive advantages through collaborative activities (Hoffman et al. 2018) because it can increase an organisation's performance and innovation (e.g. Ansari, Garud, and Kumaraswamy 2016; Bengtsson et al. 2016; Huang and Yu 2011), reduce research and development (R&D) costs, limit duplication of efforts, and increase the range of resources that a firm can access (Brandenburger and Nalebuff 2021). Coopetition can also enable participants to shape industry standards (Leiponen 2008; Carayannis and Gover 2002; Mathews 2002), pursue technological advancement (Gnyawali and Park 2011), and succeed in nascent industries (Hannah and Eisenhardt 2018). At the same time, coopetition is challenged by conflicting objectives and logics, and the risk of opportunism (e.g. Gnyawali and Park 2009; Gnyawali and Charleton 2018; Zeng and Chen 2003).

Multi-competitor coopetition, or collaboration among multiple competitors, is growing because of the potential individual and collective benefit from large scale collaborations and access to invaluable market-specific resources, knowledge, and expertise

(Czakon 2018; Salvato, Reuer, and Battigalli 2017). However, multi-competitor coopetition is considerably more complicated than dyadic coopetition because each additional partner adds complexity, communication challenges, and conflicting value appropriation goals (Czakon 2018; Fonti, Maoret, and Whitbred 2017; Rouyre and Fernandez 2019). Along with multiple competitors, multi-competitor coopetition such as R&D consortia (e.g. European EUREKA consortia), standards setting groups (e.g. SEMATECH), and innovation networks (e.g. National Industry Innovation Network) can involve dissimilar organisations including universities, government laboratories and agencies, and non-profit organisations that have a wider range of goals, resources, and logics than dyadic coopetition does (Fonti et al. 2017).[1] Furthermore, sharing resources and knowledge with more partners increases the potential for opportunism, free-riding, knowledge leakage, and spillovers that are more salient but difficult to identify (Das and Teng 2002; Rouyre and Fernandez 2019; Shan, Walker, and Kogut 1994). Thus, multi-competitor coopetition faces considerable challenges to success.

Multi-competitor coopetitive relationships that are created to exploit substantial amounts of data such as knowledge-intensive innovation coopetition face even more challenges. Data are valuable proprietary resources for many firms and their protection is paramount. Concerns regarding data privacy and security continue to grow as data breaches

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[1] Multi-competitor coopetition is defined as collaborative relationship among three or more competitors. Not all R&D consortia, alliances, standards groups, and innovation networks are coopetitive since they may not include multiple, if any, competitors. Similarly, multi-competitor coopetition includes three or more competitors, but may not be organised as consortia, standards setting groups, and innovation networks. Open innovation ecosystems include communities of firms united to use shared technology to create value (Chesbrough 2003; Vasudeva, Leiponen, and Jones 2020; Olk and West 2022), but this requires neither direct cooperation nor competition.

become commonplace. Consequently, throughout the world governments continue to implement enhanced regulations to strengthen data protection. Data transfer and sharing are restricted in many contexts such as health, medical, and financial industries. Even when data transfer is not restricted, organisations may be wary of sharing proprietary data that are critical to their competitive advantage. This makes coopetition with one other organisation challenging and with multiple organisations virtually inconceivable.

Nevertheless, multi-competitor coopetition, especially for R&D and innovation, is increasing (Chen, Dai, and Li 2019; Rouyre and Fernandez 2019; Frankort and Hagedoorn 2019). To mitigate some of the challenges associated with multi-competitor coopetition, firms have relied mainly on relational and transactional governance. However, it is not clear that these are effective in multi-competitor coopetition when the trust needed for relational governance is lacking and the increased risk of opportunism from collaborating with multiple competitors is not well managed through transactional governance. Furthermore, much of our theoretical understanding of coopetition governance derives from studying dyadic relationships. Work has started looking at the use of technology to support governance of distributed innovation (Lumineau, Wang, and Schilke 2021; Murray et al. 2021). However, little is known about how such technologies work for multi-competitor coopetition (Murray et al. 2021; Seidel 2018). Given the rise of multi-competitor coopetition, a better understanding of appropriate governance mechanisms is warranted.

This study investigates how two cases of multi-competitor coopetition use recent technological advancements to improve governance to overcome challenges inherent in such relationships. Specifically, we examine the adoption of a nascent type of AI machine learning (ML) called federated learning, and blockchain as governance mechanisms in two innovation-based multi-competitor coopetition consortia. Federated learning facilitates collaboration across multiple devices and organisations without directly sharing data

(Konecný et al. 2016; Li et al. 2019). We find that federated learning and blockchain enable the maintenance of individual competitive advantages and reduce risk, which may encourage firms to participate multi-competitor coopetition, even in settings where regulations prohibit data sharing. Furthermore, we find that the use of these technologies supports multi-competitor coopetition by preserving boundaries while accelerating learning and innovation. By improving transparency and accountability, federated learning and blockchain help to alleviate some structural challenges of coopetition such as power differentials, information asymmetry and trust. Together, these technologies decentralise governance resulting in a more robust and secure system. This technology-enabled decentralised governance model augments traditional governance to reduce the tensions inherent in coopetition, especially those heightened by collaborating with multiple competitors.

Our work contributes to the understanding of coopetition by examining how nascent technologies can change innovation dynamics among competitors. Instead of looking at how firms and organisations use AI for internal value creation through problem solving and product development (von Krogh 2019), this study provides insight into how AI can enable simultaneous individual and collective value creation. Much has been made in the popular press about the promise of AI and blockchain to improve innovation, increase profits, and eliminate costs; however, it is poorly understood in the management domain (von Krogh 2019; Lumineau et al. 2021; Murray et al. 2021). The use of federated learning by multi-competitor coopetition exemplifies how AI can 'enable a new approach to innovation itself' (Cockburn, Henderson, and Stern 2018, 6). Technology-enabled decentralised governance supports participation in risky or novel endeavours that would be untenable otherwise. Taken together, we provide insight into the potential for technology-enabled decentralised governance of coopetitive relationships.

2. Theoretical Background

2.1. Coopetition

Coopetition, or the simultaneous pursuit of competition and cooperation in interorganisational relationships (Bengtsson and Kock 2000, Brandenburger and Nalebuff 1996), has gained considerable attention as a viable strategy for firms to create value (Gnyawali and Charleton 2018), co-develop products, services, or innovations (Das and Teng 2000; Gulati and Singh 1998), set industry or technological standards (e.g. Carayannis and Gover 2002; Mathews 2002; Leiponen 2008; Teece 1992), or join forces against common threats (Browning, Beyer, and Shetler 1995). Coopetition can improve firms' access to resources and ability to learn (Bouncken and Fredrich 2016; Runge, Schwens, and Schulz 2021; Tripsas, Schrader, and Sobrero 1995), innovate and advance technologies (e.g. Ansari et al. 2016; Gnyawali and Park 2011; Huang and Yu 2011; Ritala and Hurmelinna-Laukkanen 2009), increase their competitiveness and performance (Lado, Boyd, and Hanlon 1997), and strengthen their ability to explore new opportunities (Bengtsson et al. 2016). In high-technology settings where innovation is critical, but expensive due to the resources required, coopetition is particularly attractive (Chen et al. 2019; Gnyawali and Park 2009). Coopetition includes strategic alliances, joint ventures, and consortia that simultaneously endeavour to enhance the ability of individual competitors to improve their market positions while supporting the collective success of joint activities (Hoffman et al. 2018).

The concurrent presence of competitive and cooperative dynamics in coopetition can lead to tensions from disparate motivations, norms, behaviours, and benefits (Ansari et al. 2016; Fernandez et al. 2018a; Gnyawali et al. 2016; Raza-Ullah 2018; Ritali and Hurmelinna-Laukkanen 2009). On one hand, *competition* entails the pursuit of capturing value and a superior market position, typically to the detriment of other firms in the market (Porter 1990). Competing firms preserve their market position by protecting assets and maintaining the

secrecy of intellectual property, knowledge, and routines that provide competitive advantages. On the other hand, *cooperation* is grounded in the idea that working together with shared goals can benefit both partners, outweighing any advantages of opportunism (Das and Teng 2000; Gulati and Singh 1998). Cooperation emphasizes common benefit through the sharing of resources, in contrast with private benefit through safeguarding in competition. Thus, coopetition must balance the disparate objectives and logics of competition and cooperation while reducing the potential for opportunistic behaviour (Lado et al. 1997). In innovation-based coopetition, the tension between competition and cooperation, specifically protecting and sharing knowledge, is a delicate and important issue (Fernandez and Chiambaretto 2016; Ritala et al. 2017). Coopetition's risk of unwanted knowledge spillovers or knowledge leakage can limit trust and encourage members to constrain their commitment and participation in such relationships (e.g. Bouncken and Kraus 2013; Li et al. 2012), thus reducing the potential benefits. As such, innovation-oriented coopetition necessitates a foundation of information management, knowledge sharing, and protection (Bouncken and Kraus 2013; Estrada 2018; Fernandez and Chiamabretto 2016).

Much of the work on coopetition has looked at dyadic inter-firm relationships, principally strategic alliances and partnerships (see Ryan-Charleton, Gnyawali, and Oliveira 2022; Czakon et al. 2020; and Child et al. 2019 for reviews). A more recent stream of research has started to consider multi-competitor coopetitive relationships or collaboration among three or more competitors (e.g. Chen et al. 2019; Hoffman et al. 2018; Salvato et al. 2017), which are becoming more prevalent (Frankort and Hagedoorn 2019). Multi-competitor coopetition endeavours include, but are not limited to, R&D consortia or networks (Chen et al. 2019; Czakon 2018; Madhavan, Gnyawali, and He 2004; Ritala et al. 2017), standards setting groups (Carayannis and Gover 2002; Leiponen 2008), innovation networks (Child et al. 2019), and open innovation ecosystems (Vasudeva et al. 2020; Olk and West

2020). In some circumstances, non-profit organisations, universities, government agencies, and institutions may be involved (Fonti et al. 2017). This can extend to an entire value network to include suppliers, customers, and complementing organisations (Czakon 2018; Lan, Liu, and Dong 2019).

Beyond the motivations to engage in dyadic coopetition such as reduced costs and access to resources, organisations sometimes enter multi-competitor coopetitive relationships to grow the collective resources through large-scale collaboration (Salvato et al. 2017), while emphasising the corresponding competitive advantage for their unique identity or brand (Sonenshein, Nault, and Obodaru 2017). Others enter multi-competitor coopetition to benefit from combining resources while reducing the value appropriated by competitors outside the relationship (Madhavan et al. 2004). Given the higher number of competitors, multi-competitor coopetition participants have more access to market-specific resources, knowledge, and expertise compared to those in dyadic coopetition (Czakon 2018), which can improve project innovation (Rouyre and Fernandez 2019).

Multi-competitor coopetition becomes increasingly complex and challenging with each additional partner that brings in its own value capture and appropriation goals, logics, and resources (Ansari et al. 2016; Czakon 2018; Fonti et al. 2017; Rouyre and Fernandez 2019; Ring, Doz, and Olk 2005). This balancing act can lead to a heightened risk of opportunism, as well as a higher potential for misbehaviour and misappropriation of value (Czakon et al. 2018; Ring et al. 2005), which can be difficult to identify (Rouyre and Fernandez 2019; Shan et al. 1994). As the number of competitor participants increases, the risk of knowledge leakages and free-riding also increases, leading to knowledge sharing-protecting tensions (Rouyre and Fernandez 2019). With more competitors, knowledge management issues become more salient due to both the opportunities and threats that are involved with managing numerous relationships (Das and Teng 2002; Li et al. 2012). Hence,

a firm that relies heavily on proprietary data as a competitive resource may be reluctant to participate in multi-competitor coopetition.

Knowledge-based multi-competitor coopetition can be subject to risks associated with partners' data infrastructure as well. Data privacy and security have become a worldwide concern of the utmost importance. Data breaches in which private or personal data are stolen or publicised occur regularly. Around the world, over 22 billion individual records were unintentionally or illegally released through over 4,000 data breaches in 2021 (Goddijn 2022). This figure does not include non-personal data such as proprietary databases and other intellectual property that are lost or stolen. These breaches have cost companies and individuals billions, if not trillions of dollars, both in data security and leak prevention efforts as well as repairing damages when data has been compromised. A partner with an unsecured communication infrastructure can open a firm to unnecessary risks.

In other cases, knowledge management is salient because data security and knowledge sharing are regulated. Governments around the world are implementing laws to strengthen data protection. In 2017, China implemented the Cyber Security Law to increase data protection. In 2018, the European Union implemented the General Data Protection Regulation (GDPR) to enhance data protection and individual privacy. The GDPR stipulates the 'right to be forgotten,' which means that an individual can request that their personal data be deleted. The United States currently does not have a comprehensive data security law but does have laws that apply to specific industries such as the Health Insurance Portability and Accountability Act (HIPAA) for medical information and the Code of Fair Information Practice for online transactions. These regulations influence how firms store, access, and analyse data. For example, the collection and integration or merging of personal data across databases are no longer allowed without user permission. Firms must consider data transfer and sharing restrictions and how they may change.

2.2. Coopetition Governance

Governance mechanisms provide some safeguards to help coopetition participants reconcile the tensions of simultaneous competition and cooperation, subsequently improving their chances for success (e.g. Hoffmann et al. 2018; Li et al. 2012). The most widely adopted governance models for coopetition are relational and transactional (Keller et al. 2021). Relational or relation-based governance is a set of informal mechanisms that rely on norms and agreed-upon processes based on social relationships and mutually held expectations about behaviour (e.g. Dyer and Singh 1998; Poppo and Zenger 2002; Granovetter 1985). Trust is perhaps the most prominent relational governance mechanism, but others include norms of cooperation, information exchange, solidarity, establishing teams, and joint decision making (e.g. Rai and Surana 2022; Rouyre and Fernandez 2019; Uzzi 1997). Relational governance is enforced through obligations, expected reciprocity, and self-reinforcement (Dyer and Singh 1998; Malhotra and Murnigham 2002; Poppo and Zenger 2002). In dyadic alliances, relational governance can promote exchange, cooperation, support, stability (Dyer and Singh 1998; Gulati and Singh 1998), and lower transaction costs from the reduced need for formal contracts and monitoring (Kale and Singh 2009), which can improve value creation (e.g. Zaheer, McEvily, and Perrone 1998; Dyer, Singh, and Hesterly 2018). Relational governance can also reduce opportunism (Hoetker and Mellewigt 2009) and improve collaboration (Woolthuis, Hillebrand, and Nooteboom 2005).

Relational governance suffers from multiple drawbacks. For relational governance to be effective, time and repeated interactions are required to develop trust (Das and Teng 2002; Dyer and Singh 1998; Poppo and Zenger 2002; Uzzi 1997). This process may not be possible with short-term relationships and can be costly in terms of time and other resources (Das and Teng 2002). Relational governance can suffer from opportunism when power structures are uneven (Dyer and Singh 1998). Furthermore, relational governance is less applicable to

multi-competitor coopetition because the increased number of competitor participants inhibits norm conformity and lowers trust. Indeed, some trust-building techniques used for dyadic coopetition like intention-based and capability-based mechanisms, have little impact on larger coopetitive relationships (Czakon and Czernek 2016). Thus, relational governance mechanisms may not be optimum for multi-competitor coopetition.

Transactional governance is a set of rules and regulations codified in legally binding agreements that govern interorganisational relationships. Transactional governance specifies the terms and conditions of each party's roles and responsibilities (e.g. Hagedoorn and Hesen 2007; Poppo and Zenger 2002; Reuer and Arino 2007) and describes enforcement and conflict resolution procedures, as well as incentives and penalties (Kale and Singh 2009; Mayer and Argyres 2004; Lumineau and Malhotra 2011). Much of the work on transactional governance is grounded in transaction cost economics such that the exchange of resources incurs transaction costs that should be minimised (Williamson 1981). Common transactional governance mechanisms include contracts, centralised project structures (Fernandez, Le Roy, and Chiambaretto 2018b; Rouyre and Fernandez 2019), capability overlap reduction (Bengtsson et al. 2016; Hoffman et al. 2018), administrative controls (Devarakonda and Reuer 2018; Bouncken, Fredrich, and Kraus 2020), scope limitations (Oxley and Sampson 2004), and leadership rotations (Davis and Eisenhardt 2011). Transactional governance does not require repeated interactions to build trust and, thus, can require less time to implement. The explicit parameters and processes involved in transactional governance can help reduce information asymmetry and power differentials (e.g. Kale and Singh 2009; Lumineau and Malhotra 2011; Poppo and Zenger 2002), control exchange hazards (Poppo and Zenger 2002; Weber and Mayer 2011), improve information exchange (Li et al. 2012; Mayer and Argyres 2004), enhance conflict resolution (Lumineau and Malhotra 2011), and decrease opportunism (e.g. Hoetker and Mellewigt 2009; Poppo and Zenger 2002; Williamson 2002).

Transactional governance is not without drawbacks. The most significant is that these mechanisms are designed by humans who are limited by bounded rationality (Williamson 1981), which leads to incomplete contracts (Gnyawali and Park 2011; Luo 2002, 2006). To be effective, such transactional mechanisms require insight into how a relationship will evolve, which is difficult at its outset (Bouncken and Fredrich 2016; Oxley and Sampson 2004). Even the best contracts cannot anticipate every eventuality. This incompleteness can lead to opportunism when partners seek to exploit imperfections and ambiguity (e.g. Luo 2006; Woolthuis et al. 2005). Also, transactional governance tends to be inflexible since contract terms are set out in advance and can be difficult to change (Faems et al. 2008; Mayer and Argyres 2004), which can inhibit innovation (Clauss and Kesting 2017; Dyer and Hatch, 2006; Mayer, Xing, and Mondal, 2022). Such flaws can trigger interorganisational misunderstandings such as signalling a lack of trust (e.g. Poppo and Zenger 2002) that can lead to conflict (Cao and Lumineau 2015). Also, the enforcement can be costly and difficult (Oxley and Sampson 2004; Cao and Lumineau 2015). Thus, transactional governance alone is unlikely to be sufficient for smooth multi-competitor coopetitive relationships.

Work has started to explore the use of blockchain technology as a governance mechanism (e.g. Leiponen, Thomas, and Wang, 2022; Lumineau et al. 2021; Malhotra, O'Neill, and Stowell 2022; Murray et al. 2021). Blockchain is a decentralised digital ledger or immutable database that stores transactions or tracks assets (see Murray et al. 2021 for an overview). Blockchain was introduced as the enabling technology behind Bitcoin in 2008, although its development dates to the 1990s (Nakamoto 2008; Lumineau et al. 2021). More recently, blockchain has been adopted in a range of applications from digital currency and voting to supply chain monitoring, online gaming, and NFT marketplaces (e.g. Sultanik et al. 2022; Vergne 2020).

Blockchain works by bundling groups of verified transactions into blocks. When there

are enough transactions to fill a block, the block is closed, given an identifying tag called a hash, and permanently added to the ledger of existing blocks. Blocks are encrypted and cannot be changed. Any new information or transaction must be added in a new block. Authority is shared such that all participants approve new blocks (Malhotra et al. 2022). Verification of transactions or asset ownership is easier because it does not need to occur through a third-party. Since the ledger is shared across a peer-to-peer network and is visible to everyone, transparency is heightened, which helps to establish trust (e.g. Chen and Bellavitis 2020). Blockchain can improve efficiencies, reduce transaction costs, and lower risk (Lumineau et al. 2020; Malhotra et al. 2022; Murray et al. 2021). Blockchain is being used as governance when it is employed as a 'self-contained and autonomous system of formal rule' (Lumineau et al. 2021, 506). As an internal governance mechanism, blockchain can mitigate agency costs that arise from employing external governance providers (Murray et al. 2021). Rules are automatically enforced in blockchain governance, in contrast with obligation and expected future benefit enforcement in relational governance and costly legal enforcement in transactional governance (Lumineau et al. 2021). In this way, blockchain governance is distinct from transactional and relational governance (Lumineau et al. 2021).

While widely heralded as the high-tech alternative to the reliance on intermediaries for financial transactions, there are several challenges associated with blockchain. Although decentralisation is considered one of its main benefits, decentralisation itself is not a technological feature, but derives from organisation norms and governance such as protocol and system development, updates, and transaction verification (Halaburda and Mueller-Block 2020; Sultanik et al. 2022). Common blockchains are associated with a set of privileged entities that can alter semantics and change past blocks (Sultanik et al. 2022). In fact, to retain control over strategic design elements, such as how transactions are conducted, firms need to centralise part of blockchain technology (Cennamo, Marchesi, Meyer 2020). Although

blockchain was designed to eliminate the need for trust between the involved parties, trust in the underlying infrastructure is still required. Furthermore, the security of a blockchain depends on software and hardware security, which can be outdated or flawed, jeopardizing its integrity. Few, if any, penalties exist for misuse or exploitation of design weaknesses. Thus, there are limits to the ability of blockchain to govern beyond automation (Leiponen et al. 2022) and further mechanisms are necessary to effectively manage relationships.

Using multiple governance models together can the bolster performance of interorganisational relationships (e.g. Cao and Lumineau 2015; Gast et al. 2019; Poppo and Zenger 2002; Ryall and Sampson 2009). Both relational and transactional governance mechanisms are important for basic research and pre-commercial applied research Arranz and de Arroyabe (2007), while relational governance is more useful for acquiring tacit knowledge and transactional governance is more useful for explicit knowledge acquisition (Li, Poppo, and Zhou 2010). Gast and colleagues (2019) found that firms balanced their knowledge sharing and protection needs by using both formal and informal governance practices. However, using relational and transactional governance simultaneously and successfully is heavily dependent on partner, institutional, and industrial characteristics such as network scope, legal frameworks, and knowledge intensity, respectively (Abdi and Aulakh 2012; Li et al. 2010; Rai and Surana 2022). For example, environmental uncertainty supports a substitutive effect for relational and transactional governance while behavioural uncertainty supports a complementary effect in international relationships (Abdi and Aulakh 2012).

Recent work has explored alternative governance models. Digital technology has enabled distributed innovation in online and open communities (e.g. Chesbrough 2003; Faraj, Pachidi, and Sayegh 2018; von Hippel and von Krough 2003), which can promote the sharing and integrating of heterogeneous knowledge resources temporarily across participants (Yoo et al. 2012). Although coopetitive relationships tend to be more closed and longer lasting than

distributed innovation, recent technological advancements may be able to facilitate innovation across multiple parties in coopetitive relationships. With regards to owner-complementor relationships, work has examined decentralised governance in digital platforms in which rights and control are shared between the infrastructure owner and its users (e.g. Chen, Richter, and Patel 2021; Malhotra et al. 2022; Vergne 2020). Governance decentralisation facilitates the engagement of participants, which can result in enhanced welfare (Chen et al. 2021), but disperse power and inhibit consensus (Wareham, Fox, and Giner 2014). The balance of how much control and power is shared among participants is delicate; governance decentralisation has an inverted U-shaped relationship with digital platform performance and can slow decision making (Chen et al. 2021).

Overall, governance mechanisms are only marginally successful and can even inhibit positive outcomes of coopetition. For example, Ritala and Hurmelinna-Laukkanen (2009) propose that coopetition that attempts to avoid opportunism risk through governance mechanisms restricting knowledge transfer reduce the anticipated benefits from R&D coopetitive relationships. Indeed, interorganisational relationships tend to fail when coordination costs outweigh the benefits (Park and Ungson 2001), particularly when trust is lacking (e.g. Czakon and Czernek 2016; Faems et al. 2008; Krishnan, Martin, and Noorderhaven 2006). Thus, for coopetition to work, careful consideration of governance mechanisms is paramount.

Much of our understanding of governance efficacy is based on studies of dyadic relationships such as alliances. However, mechanisms effective for helping to forge dyadic relationships may not be effective in multi-competitor coopetitive relationships. The behaviours of multi-competitor coopetition participants are more difficult to observe than they are in dyadic relationships, which increases coordination costs (Li et al. 2012; Zeng and Chen 2003). This limitation reduces the ability to enforce collective norms and free rider-

reducing sanctions (Das and Teng 2002). In the case of R&D consortia, pre-partnership social relationships can provide a foundation of initial understanding that facilitates collaboration (Ring et al. 2005), however, these relationships tend to have weak governance structures that can fail to deter opportunism (Agarwal, Croson, and Mahoney 2010; Fonti et al. 2017; McCarter, Mahoney, and Northcraft 2011). In multi-competitor coopetition, trust is lower and information asymmetry and uncertainty are higher than in dyadic coopetition or non-coopetitive consortia, which suggests that transactional governance is a better fit than relational governance (Yami and Nemah 2014). At the same time, transactional governance is still limited by the designers' bounded rationality which may be amplified when the complexity of the relationship increases. Furthermore, little is known about the implementation of blockchain or other nascent technologies as governance mechanisms for multi-competitor coopetition. This study empirically examines the adoption of nascent technologies in two separate innovation-based multi-competitor coopetition consortia.

3. Research Setting and Methods

To understand how nascent technologies can influence coopetition governance, this study made use of two extreme cases in which the phenomenon of interest was clearly observable (Eisenhardt 1989; Bechky and Okhuysen 2011). In-depth case studies are useful when the phenomenon, such as multi-competitor coopetition, is not well understood (Ritala and Hurmelinna-Laukkanen 2009). Multiple case studies allow for cross-case analysis of patterns, similarities, and differences upon which to build or elaborate theory (Eisenhardt 1989; Eisenhardt and Graebner 2007). We found three multi-competitor coopetitive relationships using nascent artificial intelligence (AI) techniques for innovation. For this study, we selected two coopetitive relationships among over 30 organisations that offered the highest data availability and access: Machine Learning Ledger Orchestration for Drug Discovery (MELLODDY) and the London Medical Imaging and Artificial Intelligence Centre for Value

Based Healthcare (AI4VBH).[2] MELLODDY and AI4VBH include multiple competitors involved in their focal industries – pharmaceuticals and medical imaging, respectively – as well as a wide range of participants. Table 1 summarises the two coopetition cases.

MELLODDY is a research consortium launched in 2019. It is comprised 17 participants across nine countries: ten pharmaceutical companies, four small and medium-sized firms, two universities, and a non-profit organisation. Some of the largest world's pharmaceutical firms participate including Amgen, Astellas, AstraZeneca, Bayer, Boehringer Ingelheim, GlaxoSmithKline, Institut de Recherches Servier, Janssen Pharmaceutical, Merck KGaA, and Novartis. These firms directly and fiercely compete with one another across multiple pharmaceutical categories. The technological infrastructure is developed by NVIDIA, Iktos, Kubermatic, Owkin, and the Substra Foundation. MELLODDY is attempting to leverage data from all pharmaceutical participants to streamline drug discovery and testing.

King's College London (KCL) was founded in 1829 as the fourth oldest university in England. In 2018, the university created a coopetitive relationship with NVIDIA; two other universities, Imperial College, and Queen Mary University of London; and four hospitals: King's College Hospital, Guy's and St Thomas, South London and Maudsley, and Barts Health. The goal of the coopetition was to improve radiology diagnostics. The success of the initial consortium led to an expanded consortium, AI4VBH, led by KCL and Guy's and Thomas' Hospital, and brings together ten technology firms that compete in the design and implementation of AI software across industries: Ainostics, Brainminer, Cydar Medical, IBM, Innersight Labs, Kheiron, Mirada Medical, NetApp, NVIDIA, and Perspectum Diagnostics. The technological infrastructure is being developed by six firms specialising in various medical and healthcare technologies including Biotronics 3D, GlaxoSmithKline,

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[2] The third potential case was not included since it is primarily a university research initiative.

Ixico, Mellanox Technologies, Owkin, and Seimens. The consortium focuses on using distributed data from its university and hospital partners to improve diagnostics. Since hospitals compete for patients, they can be considered competitors as well. The new consortium was launched in February of 2019.

------ Insert Table 1 about here ------

3.1. Data

We use several sources of archival data to develop the case studies of MELLODDY and AI4VBH, summarised in Table 2. Both consortia provided documentation regarding the structure and implementation of their projects including technical management plans, participant agreements, and white papers. Further technology-related data were collected from publicly available and private sources including patents, company white papers, conference proceedings, and scientific journal articles. [3] Coopetition-related data were collected from company, university, and consortium documentation; funding institution records; and government reports. Additional sources included industry reports, press releases, news, and social media. Given the highly sensitive nature of the relationships and the non-disclosure agreements signed by participants, contributors were reluctant to go on record since the consortia had a small number of participants and anonymity would be limited, even when identifying information was removed. We were able to interview six MELLODDY participants and three AI4VBH participants, all of whom held coordinating or executive-level positions in the consortiums. To reduce the potential influence of reporting bias from the

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[3] Examples of archival data sources include The Lancet, Nature, IEEE, Drug Discovery Today, Neural Information Processing Systems Conference, Journal of Machine Learning Research, International Conference on Learning Representations, Annual ACM Symposium, European Patent Office, and United States Patent Office

documents' authors (Yin 2017), we critically assessed the types of audience to which the documents were addressed in our analysis. Interviews and emails with coopetition participants clarified the themes that emerged from archival data analysis. Overall, 3,000 pages of archival data from over 200 sources were collected and analysed. Using a wide range of data sources enabled triangulation and strengthened data validation (Denzin 1989).

------ Insert Tables 2 and 3 about here ------

3.2. Analysis

This study used the grounded theory approach to data analysis (Bechky and Okhuysen 2011). Data analysis took place in several iterative stages. After identifying appropriate research sites, we created extensive profiles of each including the innovations being developed and the nature of the collaborations. Each organisation that participated in the coopetition was also profiled. Together, these profiles provided insight into the diversity of organisations and their roles in each case. Next, we built a timeline of the development and use of technology in the coopetitive relationships. This step enabled us to write individual case studies for each coopetition. We sought clarification by sharing these cases with key personnel in the coopetition and obtaining feedback, revising the case as appropriate. We analysed the chronologies using cross-case techniques (Eisenhardt 1989; Miles, Huberman, and Saldana 2019). We found that many of the developments were taking place simultaneously, which provided an interesting contrast.

We also immersed ourselves in data on the technology to establish how the technology worked and how it could be implemented. Patents, technical reports, and white papers provided much of the data for this step. We wrote a non-technical summary of the technologies used. We obtained feedback from participants about the validity of our analysis.

After building foundational cases for each coopetition, we advanced to understanding their governance structures and mechanisms. Informed by research on coopetition,

governance, multi-competitor inter-organisational relationships, and R&D consortia, we re-analysed the data by axial coding with Atlas.ti software. We iteratively analysed data and revisited theory to develop insight into coopetition dynamics. Several first-order categories emerged: the technology and its influence; value creation, value capture, the relationship structure, perceived benefits, challenges, and risks. Next, we re-examined the data in light of these categories and found two themes of governance challenges: maintaining and building individual competitive advantages while minimising coopetition risk and structural and inter-participant dynamics. Together, we developed the data structure displayed in Table 3. We also continually re-reviewed the data to confirm or disconfirm tentative conclusions (Miles et al. 2019) and discussed the findings with coopetition participants. These steps increased the reliability of the resulting findings and our confidence in them.

4. Findings

The following details MELLODDY and AI4VBH and their adoption of nascent technologies to augment traditional governance mechanisms. We found that both consortia use federated learning, a type of AI ML, and blockchain technology to overcome knowledge and data sharing challenges inherent in innovation coopetition as well as to comply with regulations related to data privacy. First, we describe federated learning to provide an overview of how it works and its applications. Next, we discuss how the consortia are integrating these technologies into their governance design to enable learning and innovation across multiple competitors at scales implausible when using traditional governance mechanisms.

4.1. Technology Background - AI, ML, and Federated Learning

AI is an area of computer science that enables machines to perform functions that would ordinarily require human intelligence such as processing information, recognising patterns, making decisions based on historical or real-time data, and drawing conclusions. A simple form of AI is a program that uses decision trees with multiple, sequential rules for action. As

a general-purpose technology, AI is used across many industries and applications such as speech recognition, chatbots, and inventory management. However, the results of using AI are limited by the quality of the algorithms, or the rules or procedures to analyse data, and the data itself. If an algorithm is biased, the resulting models will be biased. Likewise, if data are flawed, the output will be useless.

Machine learning (ML) is a type of AI that develops models by iteratively applying algorithms to data (Lavecchia 2019), depicted on the left side of Figure 1. A simple example is the prediction of a house price using data on other relevant houses such as previous sales prices, lot size, number of bedrooms, age, and the like. A programmer would determine an algorithm that would be applied to, or trained on, housing data to produce a model that could predict a house price, the output in Figure 1. Algorithm training is a process in which the initial algorithm is repeatedly applied to the data to determine the optimum mathematical weights of the parameters based on the relationship between the variables identified, much like the analysis of statistical data. After multiple iterations of training, a refined output model is provided that can be applied to new data to provide a prediction. Critical to the validity of the algorithms are individuals with domain expertise who ensure the minimisation of bias (Choudhury, Starr, and Agarwal 2020; Taddy 2018).

In traditional ML, both the data and algorithms are located on the owner's computer. Thus, ML can result in a duplication of efforts and resources when different firms work on similar predictions based on their own algorithms and data. Collaborative ML involves the integration of multiple data sources, as depicted on the right side of Figure 1. In collaborative ML, resources are shared and duplication of efforts are reduced because data are aggregated in a centralised system where algorithms are trained and models are developed. Accordingly, the entity in control of the centralised system also controls the aggregated data, model development, and final output.

There are several challenges associated with co-locating data from multiple sources, which can inhibit collaboration. First, the process of transferring data can take a long time if the dataset is large. Second, the process of transferring data can introduce errors into the data that are difficult to identify. Third, datasets to be merged must be available in similar formats, which can require additional processing time and programming effort. Fourth, the resulting dataset will be larger than the separate ones, which can make it expensive to store and process. Fifth, should a participant want to leave the system, their data must be separated from the aggregated dataset, which can be a complicated and challenging process itself. Sixth, transferring data means that the original owners are vulnerable to the actions and control of the centralised system's owner. These are just a few of the most prominent complications that ML system designers must consider.

------ Insert Figures 1 and 2 about here ------

Introduced by researchers at the University of Edinburg and Google in 2016 (Konecný et al. 2016), federated learning is a type of ML that enables collaboration across multiple organisations without co-locating data in one centralised system. Instead, federated learning allows data to remain on individual devices. Figure 2 summarises the federated learning process. First, initial algorithms are generated by participants and collected by an aggregator, which has shared ownership and often is supported by a third party. The algorithms are distributed across the consortia to participating organisations (e.g. firms, universities, research labs, etc.) that train the algorithms on their local data, generating models. These individual models are sent back to the aggregator that develops a global model. This process repeats until the model is optimised. Thus, federated learning enables collaboration and decentralised innovation without the need to share data, which overcomes many of the data ownership and privacy concerns associated with knowledge-intensive coopetition (Li et al. 2019). Federated learning also eliminates the need to transfer or share

the data with the server, which can be expensive and compromise data integrity, and the larger amounts of data and iterative nature increases the overall learning for participants. At any point, participants can leave or join without compromising the system.

Federated learning is not without challenges. As with all AI, the performance of federated learning is limited by the quality of the algorithms, the data on which the models are trained, and the system capabilities (Humbeck et al. 2021). Poor partner data negate any gains from using federated learning. Also, for federated learning to succeed, there must be agreement on the workflow process — how models will be run, in what time frame, and how outcomes will be reported and integrated. Thus, federated learning requires agreement not only on common goals, but also on the mechanics and logistics of innovation.

4.2. Case Findings

While all coopetition has challenges, two overarching themes emerged from the cases as challenges most salient to the consortia's governance: balancing the unique risks and rewards of multi-competitor coopetition and managing complex structural and inter-participant dynamics. We next present the specifics of how MELLODDY and AI4VBH are incorporating federated learning and blockchain and provide illustrative evidence of how these nascent technologies can influence coopetition governance to address these challenges.

4.2.1 Governance Challenge 1: Balancing Multi-competitor Coopetition Risks and Rewards

One of the most pressing challenges of coopetition with multiple partners is the protection of an organisation's competitive advantage. In multi-competitor innovation coopetition, this challenge is particularly salient in terms of safeguarding firm resources and preventing knowledge leakage while sharing information necessary for the coopetition's success (Rouyre and Fernandez 2019). Traditionally, coopetition participants benefit from access to a larger, more diverse pool of resources shared across competitors. However, when knowledge

is critical to a firm's competitive advantage, it is challenging to reconcile the benefits of multi-competitor coopetition with the heightened risks of weakening one's competitive advantage (Oxley and Sampson 2004).

MELLODDY was developed to reconcile this tension. Pharmaceutical firms' annotated chemical databases are a quintessential proprietary resource in that they are highly valuable, rare, inimitable, and non-substitutable (Barney 1991), created over decades of expensive R&D (Burki 2019). Indeed, moving a new drug from concept to market requires an average of 10 and 15 years and $2.5 billion in costs (DiMasi, Grabowski, and Hansen 2016; Burki 2019). Though technology has advanced, the cost of developing pharmaceuticals continues to increase. Collaboration in the pharmaceutical industry is a well-established source of cost reduction and value creation (see Olk and West 2022); however, it tends to occur across organisations with vertical complementarities, not with competitors (e.g. Rothaermel and Deeds 2004; Schilling 2009). Because of this, Colm Carroll, scientific project director at the Innovative Medicines Initiative, argued that, 'The value of pharmaceutical databases [has] not been fully realised' (Burki 2019, 2382). This is unfortunate because pharmaceuticals influence people's health and well-being throughout the world. Given the value of data for pharmaceutical firms, and the costs of innovation, the industry has strong incentives for multi-competitor coopetition. However, the threat of opportunism and misappropriation make proprietary data aggregation unfeasible. Multi-competitor coopetition in the pharmaceutical industry defies convention. For MELLODDY to succeed, they had to mitigate the risks associated with sharing proprietary resources.

To accomplish collaboration among pharmaceutical competitors, MELLODDY relies on federated learning to enable value creation without sharing proprietary resources. Typically, AI requires a large volume of data for effective modelling. In industries where data is highly sensitive or proprietary and cannot be shared or transferred, traditional AI

techniques are limited, even with strict transactional governance. Federated learning enables MELLODDY to overcome this limitation by training models remotely. Algorithms are sent to the aggregator that disperses these to partners where they are applied to a subset of their local databases. Then the trained models are securely transmitted using blockchain to the dispatcher where they are consolidated. Mathieu Galtier, project coordinator for Owkin, the firm developing MELLODDY's ML infrastructure, stated that federated learning is vital for collaboration among the pharmaceutical participants since they 'can waive all limitations linked to data sharing' (Lansdowne and Mackenzie 2019). Federated learning reduces the likelihood of knowledge leakage and maintains organisational boundaries. Galtier elaborated: 'The data is never put at risk. The data sits in its own GPU server, while the algorithms travel from one to the other for training' (Rhodes 2019 1). One interviewed project manager confirmed that without FL, the project would not have been possible since the competitors did not trust one another enough to share data. Thus federated learning allows firms to remain autonomous helping to maintain their competitive advantage while creating value using others' resources and supporting collective value creation.

Data sovereignty is another challenge for coopetition since data and its use are subject to national and international laws and regulations that restrict the ability of organisations to share many types of data (Savona 2020; Treleaven, Smietanka, and Pithadia 2022). AI4VBH applies AI to patient medical data to improve diagnostic accuracy. Patient confidentiality is mandated by regulations around the world, including in the United Kingdom and United States, making data security paramount for AI4VBH. Since patient health, medical history, and demographic data are important for testing and improving the algorithms, decisions regarding access to such data must be handled carefully. Anonymised data from consenting patients can be aggregated under current regulations, but the anonymization process can eliminate data such as demographics that can be useful for model optimisation. The AI4VBH

consortium enlisted federated learning to ensure that confidential patient information was not compromised. In fact, the clinical data does not leave the hospitals or research facilities, and only models are shared among organisations. Federated learning enables models to train on databases at hospitals and health facilities that include demographic data that traditionally would be lost if aggregated, without compromising patient confidentiality. Only with this assurance were hospitals willing to participate, paralleling the initial reluctance of potential MELLODDY participants and their requirement of federated learning. Participants also were persuaded to join because the 'predictive models developed from patient data are representative and unbiased because they will be trained on the widest possible population of patient data,' as stated by Dr. Sebastien Ourselin from King's College London (Owkin 2019). Thus, federated learning maintains confidentiality and complies with government data privacy requirements while maximising data quality.

Both MELLODDY and AI4VBH use blockchain technology to enhance transparency by maintaining records of trainings and interactions, thus preserving traceability of operations. In MELLODDY, after a model is trained on a subset of a company's data, the updated model is transmitted using blockchain so that individual data contributions are not identifiable, thereby reducing the ability of competitors to reverse engineer information about others' proprietary data (executive interviewee). Similarly, when the models travel among AI4VBH participants, each obtains the blockchain ledger to ensure the integrity of the models while maintaining patient privacy and operating within government regulations. This double protection from using both federated learning and blockchain provides participants and regulators with confidence that the likelihood of misappropriation and knowledge leakage are minimised, facilitating contribution by participants who may otherwise be unwilling or unable to be involved.

In summary, federated learning and blockchain have enabled MELLODDY and

AI4VBH to balance the risks of compromising one's competitive advantage, knowledge leakage, and reverse engineering of data while enhancing transparency, maintaining data sovereignty, maximizing data value, and complying with regulations.

4.2.2. Governance Challenge 2: Managing Complex Structural and Inter-participant Dynamics

Multi-competitor coopetition must also contend with structural issues such as power, control, trust, and free riding. For example, innovation-oriented multi-competitor coopetition can be both strengthened and limited by the large amount of data involved because they require more sophisticated computing devices and expertise. When data are combined, the organisation controlling the centralised data may become more powerful because they are contributing resources and expertise in addition to holding the aggregated data. Federated learning and blockchain help to overcome such structural challenges by reducing the reliance on centralised technology and knowledge, increasing transparency, encouraging trust development through repeated interactions, and facilitating consortium membership change.

Medical imaging and pharmaceutical data are prime examples of settings in which data centralisation is a strength and liability. Medical imaging files are large and their analysis requires extensive memory capacity and powerful computing processors, both of which are expensive. Researchers using AI have been able to improve the efficiency of diagnoses based on medical images (Annarumma et al. 2019); however, these techniques have been successful only on databases at one location, not across locations. And, as mentioned, aggregating data opens the possibility of data corruption that would render the results worthless. In medical imaging, individual hospitals can hold millions of image records. Indeed, the Guy's and St Thomas' NHS Foundation Trust alone holds over five million images (KCL 2019). AI4VBH uses federated learning and decentralised model testing to distribute the workload and resource needs across the consortium. Since the data

are not shared, no single entity needs run models on databases larger than their own. Each partner shoulders part of the analysis burden by testing models on their own data. Models are securely transferred using blockchain. Pharmaceutical coopetition is similarly challenged by substantial amounts of data. Chemical libraries of major pharmaceutical companies contain millions of molecules with hundreds of millions of data points on their activity (David et al. 2019; Kogej et al. 2013), making data computation difficult, even with the latest technology. Each pharmaceutical participant in MELLODDY has such a proprietary database. Collectively, the consortium has access to over a billion data points regarding the effects of more than ten million molecules (Innovative Medicines Initiative 2019). Federated learning provides a mechanism by which the consortium can reduce their hardware needs and spending while maintaining data quality, maximising returns, and eliminating data centralisation. In both cases, no one participant has uneven power due to the coopetition's structure.

Distributing workloads across participants also helps reduce structural power differentials stemming from resource imbalances (Pfeffer and Salancik 1978). Using federated learning, the burden of training models is distributed across partners, which helps enable the inclusion of both larger and smaller organisations that typically may not have the resources to participate. AI4VBH distributes model training to eliminate centralized control of high-powered machines and aggregated data, which reducing system costs (Ingham 2019). To further reduce power differentials, MELLODDY requires that models are trained on similarly sized database subsets so 'all the pharmas contribute the same thing' (MELLODDY executive), which helps to reduce potential free riding. Hugo Ceulemans, scientific director at Janssen Pharmaceutica, stated, 'For participating pharma companies, one advantage of consortium membership is that they are at liberty to use whatever prediction results emerge'

(Borfitz 2019). Federated learning guarantees control of both the data and the innovations that emerge.

Federated learning also reduces the challenge of controlling data in silos. In healthcare, clinical data are typically separated due to confidentiality rules. Managers who must maintain compliance with the regulatory 'right to be forgotten' tend to favour data silos so that an individual's data can be disaggregated and removed upon request, a monumental task should data be aggregated. With federated learning, clinical data does not leave the AI4VBH institutions and sensitive patient information is not shared. Each participant trains the models on their own siloed data, including demographic data that is essential for model optimisation. The data remain siloed and each participant learns from confidential data with federated learning as a way to 'function between them' (project executive). The ability to improve diagnostic models on secure data from multiple sources encourages collaboration among clinics, hospitals, healthcare institutions, and research centres since control is not relinquished. In contrast to enhanced interdependencies typically seen in R&D interfirm relationships (Hagedoorn, Link, and Vonortas 2000), the use of nascent technologies enables firms to reduce dependencies on one another and maintain organisational boundaries.

Control was also a factor for MELLODDY in another way. One of the initial catalysts for the MELLODDY project was that in traditional interorganisational innovation relationships, partner data was aggregated by a broker or intermediary who would have control of that data and any potential gains (project manager interview). This was untenable for the pharmaceutical participants who recognised the possible upside of collaborating with competitors but were unwilling to relinquish control of their data let alone potential value to a third party. MELLODDY was designed to operate without a central authority such that, by using blockchain, all partners approved model training transactions, enhancing transparency and reducing the risk of opportunism.

Multi-competitor coopetition often lacks long-term relationships and trust among partners that are required for relational governance to be effective. Federated learning facilitates repeated interactions among participants who may lack prior relationships with their competitors and may therefore be cautious. This was the case with MELLODDY where many participants had not worked with each other. In a short time, mutual trust increased as partners honoured their commitments and saw benefits emerge from participation (project executive). Thus, federated learning acts as a mechanism to build trust through transparency and mutual benefit. Likewise, optimising the number of competitor partners is a concern. Initial MELLODDY participants believed that they needed at least six participants to make the project worthwhile since a smaller group would be able to make only incremental gains (MELLODDY manager). In contrast to size concerns of many alliances, MELLODDY designers believed that the bigger the group, the bigger the overlaps, which would reduce security holes, improve protection, and reduce the likelihood uneven gains and opportunism. They discovered that federated learning provided the infrastructure to coordinate a large group of participants, enhancing both individual and collective innovation.

Both MELLODDY and AI4VBH incorporate blockchain in their federated learning architectures to further reduce power differentials. In MELLODDY and AI4VBH, participants can see when models are trained in their respective consortium and the sequence of training. Blockchain helps to mitigate challenges related to the difficulty of observing partner behaviour in coopetition (Li et al. 2012; Zeng and Chen 2003). The visibility of transactions to all parties further reduces the likelihood of opportunistic behaviour.

Multi-competitor coopetitive relationships are fragile. Once started, coopetitive relationships typically are closed to new participants because add participants can be difficult logistically. Likewise, losing a partner prematurely can reduce or eliminate benefits to remaining participants. Using federated learning, participants can join or leave the

consortium at any time. Should a partner leave, the remaining partners would no longer be able to train models on the former partner's data; however, the existing models would have already benefited from previous training rounds. To reduce the potential for reverse engineering in which a participant compares the output of an algorithm before and after a participant leaves, MELLODDY required that changes in membership must include three firms (executive interview). Thus, federated learning and blockchain strengthen the structure of multi-competitor coopetition and reduces the need for additional governance structures.

Rotating leadership among participants in collaborations can help alternate decision control, reduce opportunism and support innovation (Davis and Eisenhardt 2011). At MELLODDY and AI4VBH, federated learning enabled a shared leadership model instead that decentralised authority to further mitigate the risks of competitive and opportunistic behaviour. R&D coopetition often struggles with governance (Das and Teng 2002; Salvato et al. 2017) and their inherent complexity can make shared leadership unfeasible. Thus, federated learning facilitates an alternative, more streamlined governance model, less focused on resource exchange and more focused on improving firm and collective value creation. Incorporating this nascent technology into the coopetition design transforms the relationship and enhances its ability to succeed. AI4VBH has successfully obtained additional funding to expand its network and develop technology for a wider range of diagnoses and treatments. The consortium plans to analyse longitudinal data following patients through their treatments to offering predictive guidance for hospitals to optimise resources. MELLODDY found that in three years, they were able to build a secure platform that improved the predictive performance of collaboratively trained models over single partner models for all participants.

5. Discussion and Conclusion

In this study, we examined two extreme cases of multi-competitor coopetition to provide some insight into how nascent technologies can mitigate some of the challenges inherent in

coopetition governance such as competitive advantage compromise, opportunism, knowledge leaks, alliance collapse, and power differentials. Work regarding the efficacy of existing governance models has indicated mixed results (Agarwal et al. 2010; Fonti et al. 2017; McCarter et al. 2011; Ritala and Hurmelinna-Laukkanen 2009). Thus, an alternative governance model is needed to encourage participation in such risky endeavours and support their overall success. The findings show how MELLODDY and AI4VBH used federated learning and blockchain as decentralised governance that supports both individual firm and collective value creation by transforming how participants interact and reducing some of the risks of multi-competitor coopetition. Federated learning and blockchain can facilitate innovation on multiple proprietary or regulated datasets increasing the value created overall, further improving the likelihood that the coopetition will succeed. Table 4 compares this technology-enabled decentralised governance model facilitated by federated learning and blockchain to traditional transactional and relational governance.

------ Insert Table 4 about here ------

One of the major findings of this study is the demonstration that federated learning and blockchain can decentralise authority and preserve organisational boundaries and autonomy, helping to protect a participant's competitive advantage. Federated learning reduces the risk of opportunism and knowledge leakage by protecting proprietary intellectual property on which the coopetitive relationship is based and allowing it to remain within the control of its owner. Multi-competitor coopetition is designed to utilise the range of resources across participating competitors; however, the risk of knowledge leakage is often too great to overcome. Improving the ability of coopetition participants to benefit from industry-relevant resources without the threat of compromising their own advantage may increase the chances that partners will engage and benefit from the relationship. Thus, federated learning reduces the risks associated with traditional innovation-oriented coopetition such as knowledge

leakage (Khanna et al. 1998; Oxley and Sampson 2004) and decreases the need for trust. Neither transactional nor relational governance mechanisms adequately address this concern.

Federated learning and blockchain help to address other challenges in multi-competitor coopetition. Federated learning reduces the influence of power differentials because an individual firm's intellectual property is not vulnerable to centralisation. Blockchain decentralises authority by requiring all transactions to be accepted by all parties (Malhotra et al. 2022; Vergne 2020), which heightens insight into partner transactions and behaviour, and reduces information asymmetries and the subsequent power differentials that can result. Together, federated learning and blockchain increases transparency and accountability, further reducing the need for trust when developing a coopetitive relationship. This safeguard lessens the likelihood that misunderstanding in the implementation of a contract will lead to diminished trust and conflict, a risk associated with transactional governance (e.g. Cao and Lumineau 2015; Poppo and Zenger 2002). In contrast to one-time dyadic transactional governance mechanisms, federated learning encourages repeat transactions that helps build trust among partners over time. Federated learning and blockchain do not replace transactional or relational governance, but rather provide decentralised governance mechanisms that can mitigate challenges not alleviated by traditional governance.

Federated learning and blockchain are not perfect and many challenges remain for their wider adoption (e.g. Hallock et al. 2021; Sultanik et al. 2022). Federated learning requires considerable ex-anti costs to build the system. For example, data must be homogeneous in coding and structure, which requires coordination and resources to validate alignment. The first phase of MELLODDY was to align the databases and ensure that models could be trained across the consortium, a process that took a year to complete. Also, partners could unintentionally train models on flawed data or deliberately use poor data, resulting in

faulty models. If bad data are used for competitive projects, the resulting models could damage a firm's competitive advantage or worse, threaten patient health. Thus, some trust is still required in decentralised governance.

The security infrastructure of federated learning and blockchain technology is paramount. Networks using federated learning or blockchain are only as secure as the least secure partner. Weaknesses expose all participants to the risk of internal or external entities gaining access to intellectual property. Using federated learning and blockchain together mitigates some of the drawbacks associated with individual security, but not all. Multi-competitor coopetition participants must trust in the overarching design of the technology infrastructure, but caution is prudent since these are designed by humans. Similar to a deficiency in transactional governance mechanisms, bounded rationality limits the ability of the system designers to plan for all eventualities (Lumineau et al. 2021). Errors and oversights may occur in the design or implementation of federated learning or blockchain, or both (e.g. Malhotra et al. 2022). Partners with differing levels of cybersecurity can expose the entire consortia to attacks. Federated learning can be subject to other privacy-related risks such as model stealing and reverse engineering of models or data (Goncalves, Bessa, and Pinson 2021). Applying blockchain to federated learning helps to secure the process and preserve intellectual property protection, but to a limited extent. Attackers could exploit flaws in the design of the federated learning platform or the blockchain communications to obtain insight into data or models (Diechmann and Goller 2021). Blockchain tends to be inflexible, with decision-making criteria established when the protocol is developed, which can be problematic if changes are needed (Murray et al. 2021; Malhotra et al. 2022). MELLODDY and AI4VBH have attempted to reduce these threats by employing external auditors and internal assessments to review the platform for flaws and weaknesses. Overall, federated learning and blockchain technology tend to improve overall security for participants in

knowledge-sharing coopetition, but they also introduce some new ones, as described.

In terms of ex-post coordination, the implementation of federated learning-blockchain governance is expensive and requires considerable highly skilled human resources. Federated learning requires communication among nodes (participants), and poor network and communications infrastructure can slow transmission to the point where model training is inefficient (Treleaven et al. 2022). Each layer of blockchain cryptography adds to the data processing and communications requirements. In addition to slowing the training process and creating bottlenecks, this can immobilise organisational resources that could be deployed elsewhere. While incredible innovations have been accomplished for both MELLODDY and AI4VBH, it is not clear yet if the immediate benefits outweigh the costs or that all participants benefit. Over time, as the technologies are refined and adopted, costs will decrease and may become more affordable in relation to expected gains.

The ability to access the resources of other organisations that can improve an organisation's ability to capture value is an attractive incentive to join a coopetition. However, the need to maintain one's market position and competitive advantage may overshadow the perceived benefits of coopetition (Fonti et al. 2017). Emerging technologies such as federated learning are moderating these motivations such that the amount of value that an organisation can capture from coopetition may increase, while the risks of devaluing one's market position decrease. Technology-enabled decentralised governance may be needed to encourage participation in risky or novel endeavours.

5.1 Boundary Conditions

Federated learning and blockchain help balance the competition-collaboration tension inherent in coopetition. Situations in which data ownership and intellectual property are valuable for both individual participants and the collective collaboration are perhaps the most appropriate for federated learning. It is particularly well positioned to benefit situations where

proprietary data are digital. When the data are organised using common industrial standards, federated learning and other nascent technologies may enable cross-border, cross-industry, and cross-regulation relationships better than previous generations of technologies.

Likewise, laws regarding patient confidentiality, individual privacy, intellectual property, and AI are different around the globe and change frequently. Cross-border coopetition, in which the variety of regulations and standards is high, requires adhering to the strictest guidelines, not the lowest common denominator. Technologies that enable the control of data provide organisations with tools to comply with varying regulations. As such, federated learning may be particularly appropriate for situations where laws, regulations, or standards differ or are in flux. Indeed, federated learning, blockchain, and other nascent technologies may enable relationships among organisations that were not deemed possible in the past, given formidable legal and competitive pressures.

Patient confidentiality is not the only data concern constraining multi-competitor coopetition. The GDPR'S 'right to be forgotten,' requires procedures and processes to enable personal data deletion upon request. This means that all relevant data across individual and merged databases must be identified and eliminated. This task is incredibly difficult, if not impossible, when databases are consolidated. Since data are not aggregated when using federated learning, organisations can more easily fulfil requests to be removed from a database. By working *with* instead of *around* regulations, federated learning and blockchain build opportunities for organisations to work together. Leveraging decentralised governance techniques, multi-competitor coopetition participants in different industries may create and capture new value by contributing important data in new ways.

This study focused on large innovation-oriented, multi-competitor coopetition and the findings are not generalisable to all coopetition relationships. Although model training takes place at individual firms, the computing power required is substantial and impractical for

small-to-medium-sized firms. As the cost of computing power decreases, this limitation may make the findings of this study more generalisable. When this study was started, very few coopetitive relationships had adopting federated learning or blockchain. More recently, federated learning is being used for text prediction, advertisement selection, and medical applications (Kerkouche, Acs, and Castellucci 2020) including Healthchain, the Health Utility Network, Intel and the University of Pennsylvania, COVID-19 Open AI Consortium, and the Kidney Center Association. The adoption of blockchain across industries is staggering. It is likely that technologies beyond federated learning and blockchain are emerging that will improve decentralised governance further.

The use of federated learning and blockchain may provide insight into coopetition that is not based on digital resources. For example, the findings suggest that coopetition participants value safeguards that maintain boundaries. Further development of technologies to support coopetition should consider the protection of non-digital resources in both value creation and value appropriation activities to encourage participation. Likewise, emerging technologies may be able to enhance the ability of competitors to create value beyond their industries. For example, medical databases may contain demographic and health information that can support innovation in public policy, urban planning, or education. Currently, such data are closed off from analysis. Technologies such as federated learning that enable models to learn on remote, confidential data, while maintaining privacy and abiding by regulations, could have invaluable benefits for society.

5.2. Limitations and Opportunities for Further Research

This study has limitations that should be addressed. First, the research design of comparative case studies is based mainly on archival data. An analysis of archival of data can be biased by the researcher' objectives, rationalization, or social desirability (Yin 2017). We attempted to mitigate this risk by using a wide range of sources from disparate organisations including

those involved and not involved in the consortia. Patents and research studies on the technologies were especially useful for providing specific, objective data regarding use and implementation. Also, executives from both cases provided feedback on our analysis. Nevertheless, the reliance on archival data may have limited the findings of the study.

AI is a burgeoning field. Indeed, few AI system designers understand how to design a comprehensive ML system, let alone one capable of federated learning. Throughout the world, fewer than 150 patents had been granted for federated learning by the end of 2021. The specialised nature of the technology may limit its development. In fact, the adoption of federated learning may be slow or fail altogether. Although research has shown that federated learning outperforms other types of ML (Smith et al. 2017; Zhuo et al. 2019), little research has replicated these findings. There are also trade-offs among the competing goals of robustness, privacy, efficiency, and model accuracy (Kerkouche et al. 2020). It is not clear that using federated learning will provide outcomes greatly different from existing ways of organising. Many questions remain and research evaluating the ability of federated learning, blockchain, and new technologies to improve governance will help advance our understanding of coopetition.

5.3. Conclusion

Multi-competitor coopetition is growing (Chen et al. 2019; Frankort and Hagedoorn 2019; Rouyre and Fernandez 2019). Tools that support the success of such relationships will benefit not only the participants, but also the industries that interact with these entities as well as stakeholders. In terms of improving medical imaging diagnostics and pharmaceutical development, millions, if not billions of people may be affected. This study takes a step toward shedding light on these important tools. Given the role that multi-competitor coopetition may play in solving grand global challenges, and the need to understand data as fundamental resources, we hope that this research sparks further inquiry into this field.

Nascent technologies are challenging our traditional view of coopetition governance by providing new tools to mitigate challenges. The balance of competition and collaboration in coopetition implies a level of interorganisational interaction and agreement. Previous work emphasised using relational or transactional governance, or both (e.g. Cao and Lumineau 2015; Poppo and Zenger 2002), to navigate the dynamics of such interactions, making them beneficial for all involved, or at least not harmful. However, federated learning and blockchain remove a level of interaction because the decentralisation of authority and decision-making reduces the need to interact. In fact, one could conceive of a federated learning-blockchain facilitated relationship in which the participants do not interact or may not even know each other. This decentralisation holds the potential to democratise research and innovation beyond open innovation and other inclusive techniques. We believe that decentralised governance indicates the tip of the iceberg for opportunities to improve our understanding of how interorganisational relationships are designed and implemented.

Disclosure statement

No potential conflict of interest was reported by the author.

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Table 1. Summary of Cases.

	MELLODDY	AIC4VBH
Started	2018	2018
Launched	July 2019	February 2019
Industry	Pharmaceuticals	Health care
Innovation	Drug discovery	Medical diagnostics
Main Challenge	Collaboration with proprietary data protection	Patient data privacy concerns and regulation
Data Owners	Pharmaceutical companies	Hospitals
Database Type	Proprietary	Proprietary and regulated
Data Type	Annotated chemicals	Medical imaging
Competitors	Pharmaceuticals: Amgen, Astellas, AstraZeneca, Bayer, Boehringer Ingelheim, GlaxoSmithKline, Institut de Recherches Servier, Janssen Pharmaceutical, Merck KGaA, Novartis	Hospitals: King's College, Guy's and St Thomas, South London and Maudsley, Barts Health Artificial Intelligence: Ainostics, Brainminer, Cydar Medical, IBM, Innersight Labs, Kheiron, Mirada Medical, NetApp, NVIDIA, Perspectum Diagnostics
Infrastructure Participants	Iktos, Kubermatic, NVIDIA, Owkin, Substra Foundation (Labelia Labs)	Biotronics 3D, GlaxoSmithKline, Ixico, Mellanox Technologies, Owkin, Seimens
Universities	Budapest University of Technology and Economics and Katholieke Universiteit (Catholic University of Leuven)	King's College London, Imperial College, and Queen Mary University of London
Countries	Belgium, France, Germany, Hungary, Netherlands, Sweden, Switzerland, U.K., U.S.	U.K. and U.S.

Table 2. Summary of Data.

Data type	Examples of Data Sources	Count	Pages
Scientific journals	IEEE, Journal of Machine Learning Research, Nature, Science, Genomics Proteomics Bioinformatics, Drug Discovery Today, Genes, Oncotarget	40+	500+
Patents	European Patent Office and United States Patent Office	97	2000+
Company white papers	NVIDIA, Owkin, MELLODY, Google	20+	200+
Company blogs and press releases	Astellas, Google, Janssen, KCL, MELLODDY, NVIDIA, Owkin	20+	150+
Conference proceedings	Neural Information Processing Systems, Journal of Machine Learning Research: Workshop, Knowledge Discovery and Data Mining, International Conference on Learning Representations, Annual ACM Symposium, International Workshop on Machine Learning in Medical Imaging	15	250+
News articles	BioNow, CandEN, FierceBiotech, TechnologyNetworks, TICPharma,	20	50+
Total			3000+

Table 3. Data Structure.

First Order Codes	Second Order Codes	Themes
Silo data challenge	Technology	**Governance Challenge 1: Balancing Risk and Rewards of Multi-competitor Coopetition**
Big data / volume		
Collocation of data		
Remote training		
Blockchain traceability		
Security of proprietary data	Value Creation	
Data sovereignty		
Privacy concerns		
Maintenance of firm boundaries		
Knowledge leakage		
Value of collaboration		
Improved products	Value Capture	
Enhanced competitive advantage		
Use of algorithms		
Output ownership		
Hardware capacity limits	Technology	**Governance Challenge 2: Structural and Inter-participant Dynamics**
System cost		
Inherent trust		
Blockchain transparency		
Workload distribution		
Data access	Structural Benefits	
Data volume		
Regulations compliant		
High quality inputs		
Leverage external resources		
Distributed authority		
Data compatibility	Challenges and Risks	
Power differentials		
Data control		
Faulty data security protocols		
Traditionally centralised		
Participant fluctuations		

Table 4. Comparison of Multi-competitor Coopetition Governance Models.

	Transactional	**Relational**	**Technology-enabled Decentralised**
Summary	A set of rules and regulations codified in legally binding agreements	A set of informal mechanisms that rely on norms and agreed-upon processes based on social relationships	Governance based on distributed participation aided by technology
Main Mechanisms	- Incentives and penalties for behavior - Explicit terms and conditions of each party's roles and responsibilities - Precise processes for conflict resolution	- Mutually held expectations about behaviour - Trust and relational norms - Norms of cooperation, information exchange, and solidarity	- Technological control of interaction; blockchain - Ex-anti design and continued interactions build trust - Explicit rules of engagement
- Examples	Contracts, centralised project structures; capabilities overlap reduction; leadership rotation	Expected value of future relationships; team establishment; joint decision-making	Project-based design of innovation-based coopetition
Enforcement	Legal action, sanctions, penalties, forfeiture of the value, third-party	Obligations, expected reciprocity, and self-enforcement	Removal of participant
Application	- Presence of asset specificity, measurement difficulty, uncertainty, and limited trust - Effective when potential incentives can shape behavior - Stronger for explicit knowledge transfer	- Long-term relationships is setting with high uncertainty - Knowledge-intensive settings - Stronger for tacit knowledge transfer	- High risk of valuable proprietary asset compromise - Innovation driven coopetition with several participants - Stronger for learning without knowledge transfer
Advantages	- Can reduce information asymmetry, power differentials, transaction costs, and opportunism - Helps control exchange hazards, improve coordination, information exchange, and conflict resolution - Requires less time than relational governance	- Relational norms reduce likelihood of opportunism - Promote exchange, cooperation, and stability - Lower transaction costs and mitigate exchange hazards	- Access to valuable competitors' resources while value created is controlled by contributor - Technology can reduce communication and coordination costs - Can mitigate knowledge leaks, alliance collapse, and power differentials - Enable distributed innovation - Enhanced transparency reduces likelihood of opportunism, free riders

Table 4. Comparison of Multi-competitor Coopetition Governance Models. - continued

	Transactional	**Relational**	**Technology-enabled Decentralised**
Limitations	- Limited by bounded rationality - Incomplete contracts can lead to opportunism - Inflexible - Interpretation issues can lead to conflict - Costly design and difficult enforcement, especially with more participants - Can signal lack of trust	- Time and repeated interactions are required to develop trust - Not applicable for short term relationships - Increasing participants inhibits norm conformity and trust - Costly (time and resources) - Trust-building techniques for dyadic coopetition may not be applicable for larger relationships	- Limited to digital resources (s.a. data) - Difficult when data organisation is not standardized - Risk of flawed data eliminating gains - Underlying technology is nascent - Ex-anti coordination costs (i.e. design) may outweigh potential value creation
Coordination Costs	Remain high throughout	Relational norms minimise formal contracts and monitoring costs	Ex-anti design reduces ex-post enforcement costs
Ex-anti	- Negotiation costs - Contract design - Incentive alignment	- Time for relationship building - Establishment of norms	- System design and data management - Coordination and negotiation costs
Ex-post	- Continued coordination and monitoring - Enforcement and regulation	- Reciprocity and continued relationships	- Technology maintenance
Illustrative Works	Abdi and Aulakh 2012; Devarakonda and Reuer 2018; Fernandez et al. 2018b; Hagedoorn and Hesen 2007; Kale and Singh 2009; Luo 2002; Lumineau and Malhotra 2011; Mayer and Argyres 2004; Poppo and Zenger 2002; Reuer and Arino 2007; Ryall and Sampson 2009; Weber and Mayer 2011; Williamson 1981	Czakon and Czernek 2016; Das and Teng 2002; Dyer and Singh 1998; Dyer et al. 2018; Granovetter 1985; Gulati and Singh 1998; Hoetker and Mellewigt 2009; Liu et al. 2009; Malhotra and Murnigham 2002; Poppo and Zenger 2002; Rouyre and Fernandez 2019; Uzzi 1997; Woolthuis et al. 2005; Zaheer et al. 1998	Hybrid governance: Chen et al. 2021; Lumineau et al. 2021; Malhotra et al. 2022; Murray et al. 2021; Vergne 2020

Figure 1. Machine Learning and Collaborative Machine Learning Processes.

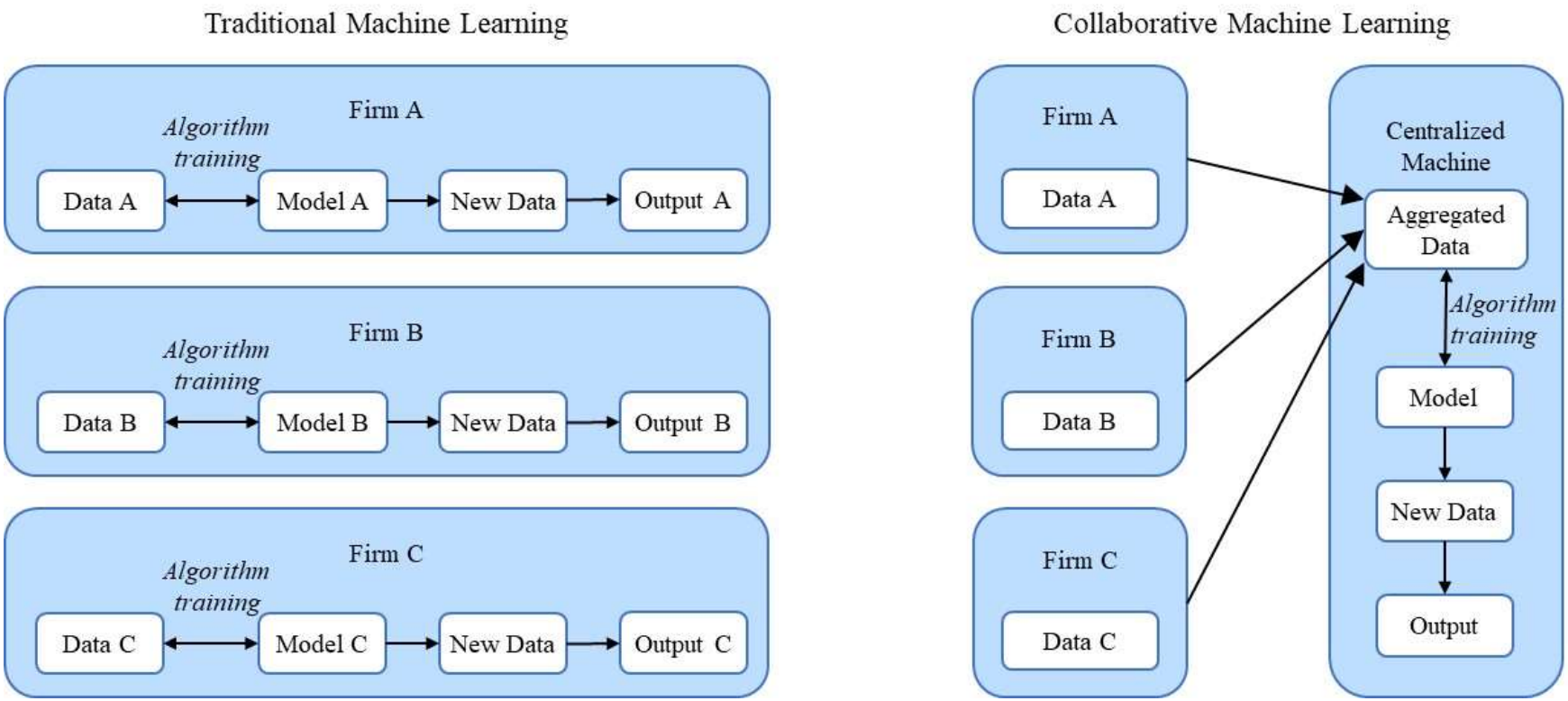

Figure 2. The Federated Learning Process.