What Impact does Artificial Intelligence have on Corporate Governance?

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Abstract

In recent years, the topic of 'digital transformation' has become a primary focus in the areas of business and research. Among digital technologies, the area attracting the most investment is artificial intelligence (AI). Research shows that AI can benefit corporate governance in a variety of ways.

In this article, we identify two academic streams on the topic and evaluate the existing literature. The first stream analyses AI-driven improvements in governance mechanisms such as boards of directors (BoD). The second stream explores the digital-driven organisational changes and broad governance adaptations necessary for AI improvements. We evaluate the evidence for AI implementation in improving and evolving traditional aspects of corporate governance.

The examined authors argue that digital technologies transform the nature of a firm, making it less based on traditional sources of authority. There is consensus that this environment calls for fundamental reconsideration of corporate governance and for the revision of regulatory models, moving towards decentralisation. Specific areas examined in these contexts include jobs automation, agency conflict, auditing processes, the selection of BoD members, compliance functions, data analytics, and capital allocation.

The examined research indicates that AI improves corporate governance and lowers agency cost by automating decision making using real-time big data analysis. However, while researchers propose multiple novel approaches to governance, practical implementation of those approaches or an empirical analysis of the results of such experiments is yet to occur.

Despite the consensus among researchers on the positive impact of AI for governance and implementations as making AI a part of BoD, open questions and skepticism persist. This is indicative of the immaturity of AI as a technology in terms of development and implementation, and as such there is ample scope for future research. We propose multiple areas within this article where opportunities exist for further insight within this burgeoning field.

JEL classification: G32, G34

Key words: corporate governance, artificial intelligence, digital transformation

Introduction

In recent years, the topic of 'digital transformation' has become a primary focus in the areas of business and research. Technologies such as blockchain and the 'internet of things' are transforming the way firms operate, creating what has been termed the 'fourth industrial revolution' [1]; [2]. Among digital technologies, the area attracting the most investment is artificial intelligence (AI) [3]. AI has been defined as "a technology that applies systems to machines so that machines can think like humans" [4]. The existing literature on this topic covers three types of AI (from basic to advanced): 1) Robotic process automation - the automation of basic human tasks such as creation of reports, etc. [5]; 2) Machine learning – the automation of decision-making, often without human intervention [6]; 3) AI approximating human behavior - so called artificial general intelligence or "strong" AI [7]; [8]. It is worth noting that the third type of AI is currently only at the theoretical stage. Companies have been applying robotic process automation for a long time [9], but AI in the machine learning area only became possible and relatively wide-spread with recent advances of technologies such as deep learning, image recognition, and cheaper computing [10]; [11]. Research shows that AI has the potential to transform corporate governance in a fundamental way. In this article, we identify two literature streams on the topic. The first analyses AI-driven improvements of governance mechanisms such as boards of directors (BoD). The second stream explores the organisational changes and broad governance adaptations necessary to adapt to AI and other improvements in digital technology.

The first literature stream examines the logic of jobs automation and its implementation. While robots are not yet expected to replace people in offices, there are opportunities and a several potential benefits from process automation that would benefit multiple stakeholders involved in corporate governance (shareholders, BoD, auditors, etc.) [12]. It is worth noting that at the foundation of any type of AI lies big data analysis, which by itself is already beneficial from a corporate governance perspective [13]; [14]. However, machine learning promises to make the biggest difference to corporate governance tools. Issa et al. show that employing AI features increases the accuracy of external auditing [15]. Multiple authors have demonstrated that it may allow the shareholders, the BoD, and auditors to move from systems of periodically reviewing data samples towards a systems of continuous analysis of all the data available about a firm in real time [16]; [17]. Other potential benefits of AI go beyond information processing. For example, Erel et al. demonstrate that machine-learning outperforms humans when selecting BoD members [18], and Cunningham and Stein argue that it helps with anomalies detection [19]. Wang et al. argue that machine learning helps identify risk factors and prevent corporate misbehaviour [20]. Bae argues that a more accurate prediction of financial distress can assist with the better decision making of CFO and boardroom and benefit investors [21]. An adjacent literature stream covers "algorithmic governance", which explores full decision-making automation [22]. However, to the best of our knowledge, this stream is yet to cover the corporate governance. There are of course AI skeptics. For example, Dignam argues that AI may aggravate such problems as discrimination, create problem such as liability attribution, and that it should be treated with caution [23]. Williams et al. go so far as to argue that algorithms may discriminate on the basis of "the data they lack", i.e. discrimination resulting from the omission of certain parameters fed into models, which makes it even harder to detect [24].

Some researchers exploring the topic of organisational change have argued that digital technologies transform the nature of a firm, making it less based on traditional sources of corporate authority [25]. Parker and Van Alstyne highlight the importance of platform-based business models such as Uber [26], while Fenwick and Vermeulen highlight that digital technologies change "who, what, when, and how people 'trust'" [27]. These researchers agree that this environment calls for fundamental reconsideration of corporate governance, making it much more decentralised, to reflect the changing nature of the business. There have also been calls to revise regulatory models accordingly. Luna et al. argue for the benefits of agile governance [28], while Ansell and Gash explore the topic of collaborative governance [29].

The rest of this article is structured as follows: in section 2, we briefly review AI technology and the types currently in use; in sections 3 and 4, we review the literature according to the two categories of impact of AI on corporate governance mentioned above; in section 5, we provide conclusions and discuss some of the most promising areas for future research.

Artificial Intelligence

Given the relative novelty of the technology, there is not yet a single universally accepted definition for artificial intelligence. Farrow defines AI in a relatively broad way as "computer science aiming to perform tasks that replicate human or animal intelligence and behaviour" [30]. Eliasy and Przychodzen define it a more technical way as an "algorithm that is capable of learning and thinking. Learning is defined as the ability to update the coefficients and parameters of an algorithm…" [31]. Multiple authors draw a line between 'weak' and 'strong' AI [32]; [23] [10]. Where 'weak' AI is defined as focused on narrow tasks while 'strong' AI is "functionally equivalent to a human's intellectual capabilities" [10]. As mentioned in the introduction, 'strong' or 'general' AI does not exist in practice [33]; [23] [10] and hence, we do not devote a separate section to it.

Despite the diversity of definitions, the one feature that finds its way to all the definitions of AI is the processing of data. This feature is so important that some researchers even call current AI models "overly dependent on big data" [34]. In this section of the article we first talk about big data as a foundation of any type of AI; we then talk about the types of AI mentioned above and conclude with a brief overview of so-called "explainable AI" which is a separate stream of literature.

Big data as a foundation of AI

As mentioned above, big data is the foundation of any type of AI. While there are multiple definitions of what big data is, a consensual definition is "the information asset characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into value" [35]. The technology by now can be considered as a rather mature one. There are numerous proprietary as well as open source solutions available for corporations to store, analyze and use big data in decision making. There are multiple studies demonstrating that the use of big data and advanced analytics are beneficial for many aspects of a firm's life across multiple industries and geographies [36]. Zhu shows that managers have less of an opportunity to trade on their private information for firms for which larger sets of alternative data are available, which is beneficial from the corporate governance perspective [37]. Multiple authors highlight the importance and benefits of big data analysis for auditing and accounting, which are very important corporate governance tools [38]; [39]. Cao, Chychyla and Stewart show how big data applications can improve the effectiveness of a financial statements audit [40], while Yoon et al. argue for the use of big data as complementary audit evidence [41]. Finally, Krahel and Titera call for a revision of accounting standards to include not only data representation, but also data creation and analysis [14].

Despite the benefits of big data usage, there are important limitations. Arguably the most important limitation involves the preservation of data confidentiality, especially where data is shared among multiple organisations. Van den Broek and van Veenstra show that organisations collaborating on the topic of big data tend to create a form of hierarchical governance arrangements when personal data and commercially sensitive data are used, although this hampers innovation [42]. Several authors bring an extra angle to the discussion by showing that less than 1% of world data is currently analysed, meaning that while there are already large volumes of data available for us, there is much more yet to come, and we can expect many more applications [43].

Robotic Process Automation as the most basic form of AI

As discussed in the introduction, the largest portion of research on AI follows the logic of jobs automation. Hence, it comes as no surprise that the most basic type of AI application is the application of algorithms to automate routine human tasks, such as report creation (known as 'Robotic Process Automation'). As Mendling et al. point out "The so-called robots are software programs that interact with systems such as enterprise resource planning and customer relationship management systems [44]. The robots can gather data from systems and update them by imitating manual screen-based manipulations". This application is relatively basic. Crosman even calls it "the lowest-IQ form of AI" [45]. Hence, only a few authors acknowledge it as AI [45]; [46]. Yet, this type of AI has been a reliable source of value creation for many firms across variety of industries. Fersht and Slaby argue that robotic process automation is a threat to traditional low-cost outsourcing [5]. Acemoğlu and Restrepo show that robotic process automation helps to replace low-skill jobs, which creates a threat of increased unemployment [47]. Moffit et al. demonstrate the importance of robotics for auditing purposes [48]. Lacity et al. show the successes of studies of robotics implementation in the context of a utilities company [49]. Aguirre and Rodriguez demonstrate that robots help improve the productivity of both front and back-office functions, although other authors point out that robots do not necessarily decrease the duration of operations [50].

Machine learning — currently the most advanced form of AI

Machine learning in its various forms is currently the most advanced type of AI that exists in practice. Brynjolfsson and Mcafee state that "the most important general-purpose technology of our era is artificial intelligence, particularly machine learning (ML)" [51]. As Kibria et al. point out, the terms 'machine learning' and 'AI' are often used interchangeably [52]. Eliasy and Przychodzen define such learning as "the ability to update coefficients and parameters of an algorithm to enable it to recognise the pattern between input and output data" [31]. The difference from the previously described AI applications, then, is the ability of the model to "update itself", as opposed to following pre-defined values. Mullainathan and Spiess highlight that the "…fundamental insight behind [the machine learning] breakthroughs is as much statistical as computational" [53]. Machine learning has multiple applications, e.g. Lightbourne has shown that it can significantly lower the cost of financial advice, making it more accessible for the general public [54], and is now applied by the largest investment firms [55].

Within the universe of machine learning models, there is an important type known as 'deep learning'. "Deep learning, a new frontier in AI focusing on computational models (deep neural networks) for information representation, has the capacity to automatically extract features from unstructured or semi-structured data like images, speech, text, video, etc." [15]. As Jarrahi nicely summarises, deep learning allows machines "to learn from raw data itself and expand by integrating larger data sets" [11]. While deep learning is currently at the cutting edge of machine learning, it raises important ethical problems, the most obvious being the lack of ability to explain exactly what is happening within the model, which gives rise to the stream of literature on 'explainable AI' (see the section after the next one).

Explainable Artificial Intelligence

The subject of AI in general raises several ethical concerns [56]. As mentioned before, deep machine learning in particular creates an important question in terms of outcomes' explainability. As Arrieta et al. put it, "when decisions derived from such systems ultimately affect humans' lives (as in e.g. medicine, law or defense), there is an emerging need for understanding how such decisions are furnished by AI methods" [6]. This is so because the algorithm itself not only picks the sizes of the coefficients, but also the set of parameters that define the outcome. This feature gave rise to a stream of research dedicated to the questions of the 'explainability' of AI [57]; [58]; [32]. The authors contributing to the stream explore the ways to ensure that decisions made using AI do not suffer from biases and do not discriminate, e.g. against certain groups of people. The importance of this topic was confirmed by cases whereby an Amazon recruiting algorithm discriminates against female work candidates. This case became public and Amazon had to discontinue the algorithm [23].

Impact of AI on traditional corporate governance

While robots are not yet walking the corridors of offices and AI sitting on a board of directors remains a relatively new and rare phenomenon, there are several real and potential use cases of AI for corporate governance discussed in literature [59]; [60]. These use cases mostly follow the logic of jobs automation, which implies that a significant portion of jobs may soon be automated. Frey and Osborne predict that automation may replace 47% of today's jobs [61]. The general conclusion within this literature stream is that AI improves corporate governance and lowers the agency cost [27] by automating decision making using real-time big data analysis [62]. We see two buckets in the existing literature on the topic of corporate governance: first, a discussion on the role of AI for providing reliable information for shareholders and BoD primarily through improved audit, which is an important governance mechanism [63]; and second, the automation of certain BoD and management functions, including selecting BoD members. An adjacent literature stream covers "algorithmic governance" exploring benefits and issues of full decision-making automation through complex algorithms [22].

AI for providing reliable information for shareholders and BoD

At the core of the principal-agent conflict lies information asymmetry between the shareholders and the management of a firm [64]. Management may manipulate the data demonstrated to the shareholders seeking its own private interests [12]. One mechanism applied to establish the required level of trust in the financial data is the hiring of external audit firms, which verify the accuracy of the financial statements [65]; [66]. This situation is suboptimal from several points of view. First, it makes BoD and shareholders wait for a quarterly report to appear to get a glimpse of their firm's operations [12]. Second, it focuses audit firms on a relatively routine process of manual raw data verification instead of focusing on more relevant services, such as assurance of information systems, etc. [67]; [68]; [69]. Moreover, Beisland et al.; Hope et al.; Francis and Wang show that audit quality remains an important concern for all stakeholders involved in the process [65]; [66]; [70]. Manita et al. point out some problems with current external audit processes that prevent audit from being a useful tool for the improvement of decision making. A major challenge is that it provides analysis of historical data and not of the forward looking information, which produces absolutely standardized results. These results do not satisfy the needs of all the potential decision makers [12]. Research shows that AI applications can potentially solve, or at least mitigate this situation.

As discussed above, big data is the foundation of any type of AI, and using data from various sources discussed above is beneficial from the corporate governance point of view. At the very minimum, these additional data sources should be used as a complementary evidence [41]. Manita et al. argue that even within a firm, data is increasingly generated automatically and stored in secure systems that allow very limited opportunities for manipulation [12]. Providing this data to shareholders would dramatically reduce information asymmetry and hence improve the governance of the firm. However, despite being generally beneficial, big data proliferation leads to a situation when information asymmetry changes its nature. Now governing bodies such as BoD need not only to get as much data as possible and ensure that the management-provided data is reliable - they also have to navigate the increasingly-complicated data landscape, adding an extra layer of challenge [71].

Several researchers (see e.g. [48] for detailed review) show that robotic process automation, as the most basic form of AI, is beneficial for audit firms that automate a bulk of tasks, while also increasing the output accuracy and focusing on more value-adding jobs [15]. However, the changes discussed above would require a significant adaptation of audit firms' business models and focus. Manita et al. argue that digitisation of audit firms may allow firms to check not only the historical, but also current information, which further limits the opportunities of management to manipulate information [12]. Krahel and Tiera argue that audit firms should spend time on data analysis rather on data collection [14]. Kim et al. show instruments for the analysis of big data, including identifying and eliminating redundant data [72].

While providing shareholders with more accurate and timely data is already an important step toward improving the corporate governance, machine learning application opportunities discussed in literature extend even further. Several authors argue that machine processing creates opportunity for audit firms to switch from reviewing sample documents to reviewing full data sets, thus creating so called continuous auditing, and enabling BoD and shareholders to access the data in real time, and not having to wait for the regular reports [16]; [73]; [40].

As we see, application of big data and AI has real benefits from the corporate governance point of view. But for these benefits to fully materialise, industry participants and regulators will need to adapt. Several researchers call for revision of accounting standards to include not only data representation, but also data creation and analysis [14]. It is important to note that large audit firms readily embrace the AI opportunities by investing in technologies such as IBM Watson, etc. [74].

While the promise of reduced principal-agent conflict seems clear, the actual consequences are yet to be researched empirically. Questions remain to be satisfactorily answered, including for example, do firms applying AI experience more or less conflict in the organisation, or do those firms have better corporate governance.

AI for minimising agency costs by decisions' automation

One of the root causes of the principal-agent conflict is a passive investor base, resulting from the dispersed ownership status of firms [75]. This root cause leads to two important consequences: 1) shareholders hire directors (and most notably independent directors) to represent their interests in the BoD; 2) BoD establishes rules and procedures to ensure that management does not abuse its power [18]; [76]. Research shows that AI and advanced big data analytics can bring significant improvements to both the aforementioned situations, and hence improve corporate governance and mitigate the principal-agent conflict. However, since both situations are relatively advanced in terms of development, we only see machine learning applications as appropriate tools to address them.

The process of selecting BoD members is a complicated one, involving not only selection, but also election of the directors. The selection of BoD members is among the most common causes for conflict at shareholder meetings [77]. Erel et al. show that machine learning outperforms humans in selecting BoD members [18]. The authors construct several machine learning algorithms to select the directors for a large set of firms and predict which directors would perform better in a firm. The support of shareholders on the next director election is used as a proxy variable for analysing directors' performance and show that the directors selected using AI algorithms perform better. The authors analyse which characteristics of directors are overrated in human analysis. As they put it, "the algorithm is saying exactly what institutional shareholders have been saying for a long time: that directors who are not old friends of management and come from different backgrounds are more likely to monitor management". However, the authors also note that algorithms should be used as an aid, not as a replacement for a human judgement. Despite the proposed advantages, to the best of our knowledge, this process is yet to be applied in practice.

Following a similar research pattern, Hernandez-Perdomo et al. propose a machine-learning solution for the assessment of a firm's corporate governance, picking the best performing firms as measured by RoA [78].

In theory, there is no reason why a firm would limit itself only to machine-learning-based directors selection. There are at least two instances, when a firm "hired" AI as a BoD member. In one case it was a Hong Kong-based investment fund [60] and an earlier case, it was Finnish software company Tieto [27]. However, since the evidence remains rather anecdotal, the success of these measures remains to be researched. More concretely, it is not clear whether this improves a firm's performance or even if shareholders appreciate such an initiative.

However, the potential benefits of AI expand beyond the BoD. Several researchers argue that automated data processing can potentially improve decision making and prevent management from abusing its power. At the very minimum, AI can improve the quality of internal reporting, including raising the quality of audit as discussed above [13], and can aid in anomalies detection [19].

However, the benefits go farther than that. Wang et al. argue that machine learning helps identify risk factors and prevent corporate misbehavior [20]. By using the random forest algorithm (a popular machine learning tool) in the context of the Chinese construction industry, Wang et al. detect 11 parameters related to corporate governance linked to corporate illegal activities. This instrument, authors argue, may be beneficial for investors as well as regulators to take proactive measures against such firms. Hajek and Henriques follow a similar pattern and suggest several machine learning methods for corporate fraud detection [79]. Pai et al. develop a model that helps detect potential corporate fraud, assisting auditors and ultimately, investors [80].

Kiron and Unruh expand the logic of using the predictive abilities of AI and argue that in the age of AI the BoD can improve their work by continuously monitoring firms' management by way of creating an AI-based monitoring system that identifies events that trigger alerts to the board throughout the year [81].

AI applications expand beyond monitoring activities by the BoD to improvement and automation of certain managerial decisions. Bae argues that AI may be a useful tool for the prediction of financial distress [21]. The authors construct an algorithm that allows them to predict the firms that are likely to face financial distress. This tool, they argue, can assist with better decision making by the CFO and boardroom, and ultimately benefit investors.

Libert et al. argue that AI has multiple uses in a boardroom, e.g. for tracking and suggesting optimal capital allocation in R&D by comparing the actions of a firm to its competitors; for scanning the market for new competitors by reviewing the press releases; and for analysing the internal communications to assess the corporate morale to improve the operational decision-making [71]. Authors propose three steps to take a full advantage of AI in corporate governance that are similar to the steps taken in the medical industry that has many successful AI use cases: 1) build what authors call the "corporate genome", i.e. the dataset that encompasses the information on many firms, linking it to corporate performance; 2) quantify an individual company to assess its competitiveness and trajectory; 3) use AI to recommend a course of action to improve the organisation's performance.

Despite the positive attitude, there are of course AI skeptics. Dignam argues that AI may aggravate problems such as discrimination, creates problems of liability attribution, and should be treated with caution [23]. The author proceeds to argue that the current perception of AI is too heavily biased by science fiction, and the general public may not fully understand the realities, including the nature of the firms dominating the corporate and technical space. Yet, Kleinberg et al. and Sunstein argue that algorithms, if applied properly, may help minimise discrimination resulting from the application of human judgement [82]; [83]. Lightbourne brings another angle to the discussion by raising the question of whether AI algorithms will fulfill its fiduciary duties in a similar way a human would [54].

Montes and Goertzel share similar concerns and point out that "AI is currently dominated by an oligopoly of centralised mega-corporations who focus on the interests of their stakeholders" [84]. They further argue that this situation is negative for smaller businesses with less capital and may be harmful for humanity overall in the longer run.

Algorithmic governance as a next stage of governance automation

Research on the topic of AI applications for decision making expands beyond the corporate governance use cases discussed above. As noted earlier, a very important feature of big data is the lack of opportunity for a human to analyse it in a comprehensive way. Hence, society will have to rely on algorithms to work with ever-increasing amounts of data. What is important is that people do not always have a full understanding of the inner works of the algorithms that impact their lives. As shown in several works [85]; [86]; [87], this may be beneficial or problematic for society at large. Researchers working in the field of algorithmic governance aim to ensure that society benefits from the emerging opportunities [22]. As Katzenbach puts it, "algorithmic governance is a form of social ordering that relies on coordination between actors, is based on rules and incorporates particularly complex computer based epistemic procedures" [88]. To the best of our knowledge, this field is yet to explicitly cover the topic of corporate governance. However, going forward, this promises to be an important topic.

Organisational change driven by AI and other digital technologies

Researchers working in the area of organisational change argue that digital technologies transform the nature of a firm. Fenwick and Vermeulen highlight that digital technologies change "who, what, when, and how people 'trust'" [27]. These changes in turn require changes in corporate governance requirements, mechanisms and regulations.

Several authors argue that one of the key changes in the nature of the business driven by the emerging technologies is the rising importance of platform business models [25]; [26]; [89]; [90]; [91]; [92]. While there are multiple theories as to what exactly constitutes a platform business model and what features it has, arguably a good general definition is a firm that enables direct interactions between two or more distinct sides, where each side is affiliated with the platform; those sides retain control over the key terms of the interaction, as opposed to the intermediary taking control of those terms [90]. Parker and Van Alstyne show platform-organised technology firms (the most well-known are Apple, Amazon, Google, and Facebook) rank among the largest in terms of market capitalisation globally [26]. The authors explore the microeconomic features of such firms. Authors show that these firms face important trade-offs such as the degree of openness they apply, i.e. how long a firm retains rights to the innovations before opening it for other developers to build on. Using the Cobb–Douglas function, authors show that opening the code earlier and creating profits via royalties may be more profitable than keeping the code closed.

Fenwick, McCahery, and Vermeulen argue that there is no doubt that the platform model is replacing traditional economic theories based on organisations, firms, and markets [25]. These authors argue that the traditional corporate governance mechanisms are designed for the 'old' type of hierarchical organisations whose sole purpose is benefiting shareholders as opposed to a broader set of stakeholders involved in platform business models. Authors highlight that a narrow focus on shareholders' benefits is suboptimal in the long run, as it creates an environment in which conservative decision-making is prioritised. Authors conclude that traditional governance is not optimal for the new type of platform organisation. They outline three strategies that make platform-based firms successful: 1) leveraging current and near-future digital technologies to create more 'community-driven' forms of organisation; 2) building an 'open and accessible platform culture'; and 3) facilitating the creation, curation, and consumption of meaningful 'content'. To make these strategies work, authors point out, much more open communications and governance are required.

Fenwick and Vermeulen show that there are two ways of implementing the new emerging technologies to the 'old' world of corporations [27]. The more basic one is the 'retrofitting' of a technology, i.e. using AI or blockchain to achieve cost savings of a traditional firm. Authors show that while this approach is relatively straightforward and clearly has its advantages, it definitely does not allow us to realise the full potential of the emerging technologies. Fenwick and Vermeulen argue that data-driven decision making, made possible by AI, may not fit the traditional model of corporate governance based on 'people and accountability'. It requires what the authors call "community-driven corporate governance", which would allow a broader group of people to make decisions without a central authority.

The discussion around the need for a change in governance expands beyond the field of corporate governance. Multiple researchers show that the current environment calls for a fundamental reconsideration of governance, making it more decentralised, and to revise regulatory models accordingly. This field is called collaborative governance. Ansell and Gash provide a comprehensive review [29]. Authors show that collaborative governance is a concept, and an alternative to adversarial and managerial modes of policymaking and implementation. It brings "public and private stakeholders together in collective forums with public agencies to engage in consensus-oriented decision making." Ansell and Gash identify parameters influencing the success of collaborative governance implementation. Examples of such parameters are a "prior history of conflict or cooperation, the incentives for stakeholders to participate, power and resources imbalances", etc. Additionally, the authors show factors crucial within the collaborative process: face-to-face dialogue, trust building, etc. Authors conclude that collaboration is most successful when "forums focus on 'small wins' that deepen trust, commitment, and shared understanding". However, the governance examples discussed by the authors do not include the field of corporate governance, which would be a very promising study.

Luna et al. bring another angle to the discussion of adjustments of corporate governance [28]. Authors look for opportunities to implement agile methodology in the corporate governance setting. Agile software development is a proven way to improve the process of software development and authors argue that the principles of the agile manifesto, such as "individuals and interactions over processes and tools" may be beneficial for corporate governance [93]. Authors conduct this research in the context of information and communication technology governance, which is a subset of corporate governance focusing on information technology (IT) and its performance systems and risk management. The authors conduct a comprehensive review of concepts of the principles of the 'Manifesto for Agile Software Development' [93] and the 'Critical Success Factors of Projects of implementation and improvement of Governance in ICT'. After identifying these principles, the authors conduct a survey of professionals in the field to show that both sets of principles are highly beneficial for each other and hence may be applied as a joined "agile governance" mode. While the conclusion is no doubt a very important one, the study is limited to ICT governance and not corporate governance in general, which would be a very important extension of the research.

As we have seen, emerging digital technologies pose fundamental questions of the basic principles of firms operations, making firms more open and decentralised. This creates the need for a review of traditional corporate governance mechanisms designed for traditional hierarchical business structures. While researchers propose multiple novel approaches to governance, to the best of our knowledge, there are yet to be practical implementations of those approaches or an empirical analysis of the results of such experiments, which creates an opportunity for future research.

Conclusion

As we have seen, AI in its various forms poses a great promise for improvement of corporate governance as we know it. Big data, as a foundation of any AI application is by itself already beneficial, as it may mitigate the instances of the typical principal-agent conflict. Process automation through the use of robotics may improve the quality of data available for shareholders, and hence empower them to make better decisions and decrease the disproportionate power of management. Machine learning techniques may automate or at least improve a significant part of the decision-making process, including the selection of BoD members, as well as helping to detect corporate misconduct. Importantly, AI creates an opportunity to transition from sporadic monitoring from the BoD and shareholders to continuous monitoring of management. At the same time, management would also benefit from AI through better information processing, and hence would be able to act in the best interest of the shareholders. Automation, of course, should be taken seriously and without rush, as more complex forms of AI create a spectrum of challenges involving the ability of people to understand how the decisions are made (hence, the explainable AI trend).

We have also seen that AI together with other emerging digital technologies changes the nature of business and firms. Firms are becoming more decentralised and inclusive of the interests of stakeholders beyond shareholders and management. This fundamental change creates a need for a broader "corporate governance overhaul". New proposed approaches to governance are more inclusive, and community- and consensus-based.

Despite the relative consensus among researchers on the positive impact of AI for governance and implementations as making AI a part of BoD, there are still multiple open questions. Do AI-exploring firms have better corporate governance and weaker levels of principal-agent conflict? Do shareholders appreciate it, i.e., does investment in AI make the shareholders friendlier or more hostile towards a firm's management? Do firms exploring alternative corporate governance benefit from it? What type of AI application is the best from the corporate governance point of view? What is the best way to proceed with AI implementation? These questions remain to be researched going forward and provide ample material for practical and academic evaluation.

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