APPRAISE: a Governance Framework for Innovation with Artificial Intelligence Systems

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Abstract

As artificial intelligence (AI) systems increasingly impact society, the EU Artificial Intelligence Act (AIA) is the first legislative attempt to regulate AI systems. This paper proposes a governance framework for organizations innovating with AI systems. Building upon secondary research, the framework aims at driving a balance between four types of pressures that organizations, innovating with AI, experience, and thereby creating responsible value. These pressures encompass AI/technology, normative, value creation, and regulatory aspects. The framework is partially validated through primary research in two phases. In the first phase, a conceptual model is proposed that measures the extent to which organizational tasks result in AIA compliance, using elements from the AIA as mediators and strategic variables such as organization size, extent of outsourcing, and offshoring as moderators. 34 organizations in the Netherlands are surveyed to test the conceptual model. The average actual compliance score of the 34 participants is low, and most participants exaggerate their compliance. Organization size is found to have significant impact on AIA compliance. In phase 2, two case studies are conducted with the purpose of generating in-depth insights to validate the proposed framework. The case studies confirm the interplay of the four pressures on organizations innovating with AI, and furthermore substantiate the governance framework.

1 Introduction

The symbiosis between humans and AI is up for a new trial, fairness and discrimination, driven by ethical zeal (Bringas Colmenarejo et al. 2022) and legislative will (Mökander et al. 2022). The large-scale proliferation of AI systems within a relatively short span of time is accompanied by their uninterpretability and undesirable impact on society, which has become common knowledge (Angwin et al. 2016). From a market perspective, as competitors innovate with AI and potentially become market leaders (Marino, Lafuente, and Tebala 2023), organizations feel pressured to respond. To maintain their competitiveness, organizations strive to quickly adopt similar technologies (Oliveira and Martins 2008), resulting in higher productivity, improved quality of product offerings (Perifanis and Kitsios 2023), and even business model transformation at a strategic level (Edelman and Sharma 2024). With an urgency to redefine business models and in the absence of industry-wide norms, the work environment of a AI-developer is characterized by constant pressures to cut costs and deliver high quality systems, often prioritizing management interests over individual ethical considerations (Van den Bergh and Deschoolmeester 2010). As a result, organizations often creatively comply with pressure from regulations. (Waldman 2020) and (Kyi et al. 2023) reveal how legitimate interests under the GDPR are misused to justify deceptive design elements within websites. This paper characterizes these pressures as AI/technology-, normative-, value creation-, and regulatory pressures, describing them in sections 2, 3, 4, and 5. Organizations are known to perform balancing acts under such pressures (Winecoff and Watkins 2022).

Calls for responsible AI combining governance (Stahl 2022), and means of participation arise from diverse stakeholders - consumers (driven by discrimination/biasness concerns), philosophers and social activists (driven by ethical considerations), corporations (driven by responsibility objectives), and legislators aiming to protect fundamental rights of citizens (Rai 2022). These stakeholders may be operating independently, but at an organizational level the problem of AI governance is interconnected in their concerns. Assimilating insights generated form secondary research, section 6 presents the APPRAISE framework, validating it through an empirical research and two case studies presented in section 7. Finally, section 8 presents conclusions and directions for future research.

2 AI/Technology pressure

Withstanding the many trials and tribulations since its humble beginnings a century ago (Floridi 2020), AI and its applications are increasingly entrenching deeper and wider into our social fabric. In its earliest applications to solve business problems, the approach was mathematical and rule-driven. Later, the turn of the century witnessed the emergence of the widely-accepted predictive AI. More recently, this has led to the emergence of general purpose AI (GPAI). Both predictive AI and GPAI enable innovation in organizations in their own ways, albeit the former having the potential to have greater impact on the organization than the latter (Siegel 2024).

The relationship between an organization's ability to innovate and its financial viability has been investigated earlier (Bai and Tian 2020; Eisdorfer and Hsu 2011). With organizations increasing leveraging AI to discover new (functional) *requirements* and implement new improved business models (Lee et al. 2019), the consequence of not embracing AI is potentially fatal for organizations. In business model innovation, technology has traditionally been viewed as an external antecedent (Foss and Saebi 2017). Limiting AI to an external antecedent merely, grossly underestimates the comprehensive nature of its impact: AI strengthens the way other technologies perform, amplifying their added value, thereby transforming businesses and overall economic systems (Soni et al. 2020, 2018). The pressure to embrace AI reveals itself in a sense of urgency.

According to (Sachs 2023), "AI went through the whole hype cycle faster than any other technology". The speed at which an organization realizes innovation is essential to its viability due to costs and market relevance (Bai and Tian 2020). When innovating with AI, this also often necessitates interdepartmental exchanges (cross-border and/or cross-cultural), offshoring and collaboration, which need to be managed (Sarin and Mahajan 2001). Change management becomes challenging. The "considerable length of time" that Kotter (Kotter 1995) proposes is unrealistic, since the speed of innovations in AI is unprecedented (Tang et al. 2020). The cross-cultural/-border nature of AI innovations along with *technology complexity* makes organizational alignment challenging and time-consuming. It is this combination of urgency and challenges in change management that aggravates the AI/technology pressure. Under these circumstances, *leadership* plays a very important role in innovating successfully (Cho, Park, and Michel 2011). Parallels drawn from the global software engineering industry (Bhat, Gupta, and Murthy 2006), stress the importance of *coordination* to limit variations in development *processes* (Espinosa et al. 2007; Šmite, Moe, and Torkar 2008), reduce communication gaps (Bhat, Gupta, and Murthy 2006) and foster trust across boundaries and *interfaces* (Nguyen-Duc and Cruzes 2013).

3 Normative pressure

That technology leads to undesirable social effects is not new (Nye 2006). Yet, the concern today is maximi momenti for three reasons. First, history of discrimination stands to repeat itself, unprecedented in its global scale, its sweeping impact due to its pace and breadth and, its newly found cohort, uncontrolled AI systems. Second, blindfolded by its bountiful benefits the problem appears to have been underestimated; nevertheless, legislations by the EU are highly welcome steps in the right direction. Third, holding a creator of a self-learning system accountable for all its future actions is infeasible based on the Principle of Alternative Possibilities (Frankfurt 1969). As a result, anxious groups distancing themselves and unable to reap the benefits of these systems are increasingly common (Swant 2019). Participation of all stakeholders is important for responsible innovation (Jasanof 2016).

The complexity of defining the scope of AI and therefore what constitutes as an AI profession is immense (Gasser and Schmitt 2020), since its influence is felt across all sectors and contexts. On the one hand, this includes medical doctors and lawyers in traditional professions with high norms dosed through and advocated by their respective associations that oversee their professional standards. On the other hand, the amateurish, experimental nature of building machine learning models has resulted in its enormous popularity (Simonite 2018), which from a professional standards perspective has no fundament to build upon. Driven among others by corporate social responsibility, and creating internal *alignment*, organizations such as Google and Microsoft have formulated their own AI ethics and norms, whereas a professional association such as ACM has proposed an aspirational code of conduct that could be used to charter their own professional norms. The demarcation between ethics and norms is often unclear in these standards and in the absence of an industry-wide set of AI *ethics*, it often leads to employees protesting the lack of professional norms at work (Gent 2023).

The importance of ethics at an individual professional level in ensuring the responsible development of AI systems is presented by (Boddington 2017). Within ethics, concepts such as individual moral responsibility (IMR) and social dilemmas (SD) aid in comprehending the normative pressures faced by AI developers to act ethically and morally. IMR focuses on personal ethical decision-making (Beckers 2024), important mediators of which include freedom to act, causality, and culpability & moral sense (Rudy-Hiller 2022). SD involves conflicts between individual self-interest and collective well-being (Van Lange et al. 2013), implying the urge to strike balances between fulfilling societal responsibilities and safeguarding corporate and personal interests (Strümke, Slavkovik, and Madai 2022). In larger systems with high *technology complexity*, developers often struggle with IMR and SD. The absence of industry-wide professional norms and a deficit in collective moral responsibility imply that organizations must demonstrate *leadership* in stimulating the right *culture*. In doing so, they create the preconditions that enable IMR in their innovation teams, especially in cross-border global contexts. With increasing *technology complexity* and popularity of self-learning systems, it is essential that providers of AI-systems inspire ethical conduct, for example through stimulating IMR and harmonizing SD, since, it has been observed that organizations may unknowingly increase unethical behavior as a byproduct of their pursuit of high performance (Mitchell et al. 2018).

4 Value creation pressure

Transforming business models, especially through innovative *requirements* using predictive AI, involves strategic reviews in organizations aimed at developing strategic plans to capture value (Wamba 2022). Empirical research and subsequent insights into how such strategic plans involving AI create strategic value are limited in literature (Borges et al. 2021). Broadly speaking, AI-driven innovation adds value to organizations within three contexts (Bahoo, Cucculelli, and Qamar 2023): through process innovation (Ghahramani et al. 2020), improved decision making (Araujo et al. 2020), or product/ service innovation (Bhardwaj 2021). Typically, in the latter, functional *requirements*, defined within customer engagement processes, are passed onto model development professionals and software engineers within development processes. Post deployment, the AI systems go into maintenance processes, which in turn ensures the development, monitoring and their update. In realizing value within these three contexts, challenges that an organization encounters at different phases of its innovation roadmaps (Phaal et al. 2011) or strategic plans differ based on the organization's attributes.

Organization size and its surrounding economics in producing extraordinary returns on investment in innovation (generally-speaking) is extensively-researched (Gu and Lev 2011). To what extent size moderates AI innovation specifically, is a subject of research. Irrespective of their size, organizations exploit GPAI for enhancements and efficiency gains, whereas predictive AI creates possibilities for exploring new avenues (Siegel 2024). For larger organizations, this *exploitation/exploration* dilemma (Gu and Lev 1991) implies choosing between "ambidexterity" and "punctuated equilibrium" (Burgelman 2002). Despite the preference for ambidexterity (Mishra and Pani 2021), it is worthwhile to note that in organizational units, in which exploration is prevalent, the price of over-rigid processes is lack of innovation. *Coordinating* compliance and *requirements* objectives, which ultimately create value, within over-rigid *processes* across multiple organizational *interfaces* is challenging (Sadiq, Guido, and Kioumars 2007). The discussion is less relevant for small organizations, where the scope is narrower, where AI applications tend to be either exploited or explored, and where the steps in value-creation are shorter.

Driven by the need for speed (section 2) and possible competency gaps, arising from *technology complexity*, an organization's dilemma to *build* or *buy* AI models/systems, often results in (complete) parts of the development process being outsourced (Gerbert et al. 2018). Networked innovation outsourcing (Guan and Wang 2023) implies organizations also offshoring their development activities. To what extent the level of outsourcing and offshoring influences an organization's eventual success in innovating with AI is a subject of research. However, parallels may be drawn from software engineering (Nguyen-Duc and Cruzes 2013), in which the challenges of coordinating value across cross-border teams is researched. Examples of such challenges are communication across multiple *interfaces* (Piorkowski et al. 2021) and regulatory interpretation across cross-border teams. In essence, the urgency to produce investment returns amidst the rapid advancements of AI compels organizations to make strategic decisions (e.g., buy-versus-build, exploitation-versus-exploration) that have consequences at tactical levels.

5 Regulatory pressure through the AIA

Key technology-related legislative developments in the EU over the last decade include the widely acknowledged GDPR (Voigt and Von dem Bussche 2017) and the AIA (Parliament 2024). The GDPR aims at protecting the privacy of individuals, against a backdrop of by and large benevolent and bulging data processing, often facilitated by AI algorithms. The GDPR assists data controllers, processing personal data, in achieving compliance. Similarly, the AIA presents a conformity regime, in which accountability is directed to participants in the supply chain of algorithms, from conception to deployment and during their life cycle.

The European Commission proposed the AIA, which presents a conformity regime for regulating AI systems (Schuett 2023) and plays the role of a gatekeeper through ex-ante conformity assessments and associated penalties. Using a tiered risk-based approach, the AIA classifies a number of systems based on their *risk* profiles: prohibited AI practices, high-risk systems and GPAI models (with systemic risk). First, prohibited AI practices, among others, include AI systems that evaluate or classify natural persons based on their inferred personality characteristics that lead to their unfavourable treatment. Second, high-risk systems include, among others, AI systems that are intended as safety components of products and are required to undergo conformity assessments. Additionally, annex III of (Parliament 2024) provides a list of high-risk AI systems. Third, in the context of GPAI, the AIA distinguishes between GPAI models, GPAI systems and GPAI models with systemic risk. GPAI models refer to AI models trained on large amounts of data and capable of performing a wide variety of tasks. GPAI systems, built on these models and serving diverse purposes, are directly used or integrated as components of other systems. GPAI models pose systemic risk, for example, when they have negative effects on fundamental rights across the EU, with the effects propagating through to systems incorporating them. Deployers of AI systems incorporating models (systems) provided by suppliers must ensure *provider alignment* through *validating* their *compliance*.

The AIA addresses accountability in the supply chain and encompasses various standpoints, among others, prohibited practices, transparency obligations, governance, and compliance procedures across the supply chain of these systems. It sets out the legal requirements for high-risk AI systems, among others, in relation to *data and data governance*, *models*, *documentation* and recording keeping, transparency and provision of information to users, *monitoring*, human oversight, robustness, accuracy, *risk management*, *privacy* and (cyber) *security*. Articles 9 to 20 of Chapter 3 of the AIA elaborates on these legal requirements (Parliament 2024). For prohibited AI practices, demonstrating that a practice is not detrimental or unfavourable to natural persons or groups of natural persons implies obliging with many of the legal requirements for high-risk AI systems. Efficacy of the proposed AIA (Commissie 2021) and its economic cost have been questioned and criticized by some studies (Mueller 2021), which present an EU environment, that is potentially decoupled from the global AI market. The AIA exerts regulatory pressure on issues identified in earlier sections: *interfaces* arising out of *offshoring/outsourcing* that require additional *coordination* on AIA interpretation, *requirements* that require rebalancing *technology complexity*, compliance *risks* and economic returns, *processes* that need redesign, and more. Nevertheless, the increased interest in AI ethics across the wide range of stakeholders point to more efficient and effective regulatory frameworks in the future (Bringas Col-

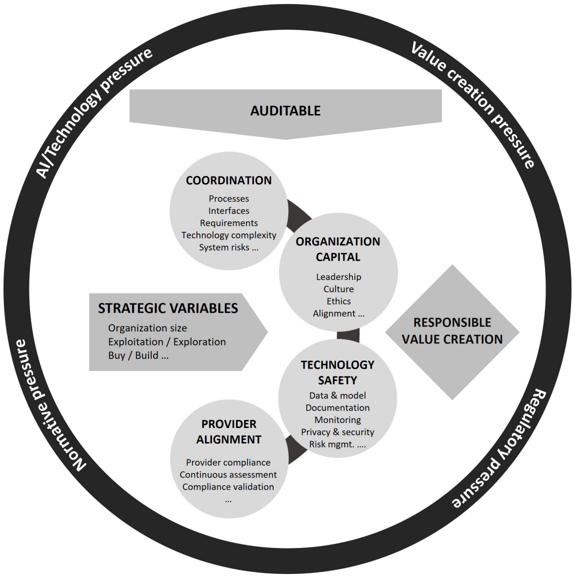

Figure 1: The APPRAISE framework

menarejo et al. 2022).

6 The APPRAISE framework

In defining AI governance, (Mäntymäki, Minkkinen, and Birkstedt 2022) combine ethical, organizational and technological aspects and position AI governance in the context of corporate- (Solomon 2020), IT- (Fernandes, Pereira, and Wiedenhoft 2022), and data governance (Vial 2023). Similar efforts by scholars include attempts to operationalize AI governance as "a variety of tools, solutions, and levers" (Butcher and Beridze 2019), intersubjectively recognized rules" (Gahnberg 2021), "practice of establishing and implementing policies"(Floridi 2018), and "structure of rules, practices, and processes" (Schneider, Abraham, and Meske 2020). The importance of ethical management of AI has been researched by other frameworks, e.g., within the EMMA framework (Brendel et al. 2021), in which managing AI ethics has been conceptualized as an interplay of managerial decisions, ethical considerations and environmental dimensions. These perspectives analyze insufficiently the context of AI innovation at organizations and often draw strong parallels with IT and/or Data governance. A major difference between AI and IT is the approach towards compliance: whereas in the latter, compliance has been driven by standards (Disterer 2013), models/metrics (Kan 2003), and organizational/cultural aspects (Mohammed et al 2023), the former has the superlative complexity of regulation, driven primarily by fundamental rights.

With the aim of creating a governance framework, the keywords (in italics) in sections 2, 3, 4 and 5 are assimilated, analyzed, structured and grouped together using Kaplan's strategy map and its four perspectives: financial, customer, internal, and learning & growth perspectives, with responsible value creation as the organizational goal. The aggregation of the keywords resulted in the creation of 4 modules: coordination, AI/technology safety, provider alignment and organization capital. These modules, along with their elements, and the four pressures presented earlier are exhibited in the Appraise governance framework for AI innovation in Figure 1. The organizational attributes (size, exploration/exploitation, build/buy), presented earlier in section 4, are depicted as strategic variables since these are strategic choices/consequences of organizations and affect the operationalization of AI governance. It is worthwhile noting that levels of offshoring/outsourcing are outcomes of the strategic variables.

6.1 Importance of auditability

Success of regulation efforts rely heavily on enforcement mechanisms, which differ based upon, e.g., the selected regulation strategy (Baldwin and Cave 1999). In a 'command and control' regulatory strategy, highly reflected in the AIA approach, a good balance between deterrence and compliance is essential to avoid 'creative compliance' and stimulate good dialogue and information exchange between notified bodies and providers of AI systems. The importance of audit is emphasized also from an ethical perspective (Rai 2022). Auditing the ethics of AI systems encompasses deontological and consequential ethics (Bringas Colmenarejo et al. 2022), one in which the consequential nature and process of developing an AI system needs to be audited along with the decision-making process at a provider (Finocchiaro 2023). This will not only ensure that the causal developmental process is robust, but also stimulate correctness, trustworthiness, and the right culture at providers. While ensuring quality of AI systems, the purpose of such an audit is three-fold: first, to raise the probability of both discovering and reporting a breach (DeAngelo 1981); second, a structured mechanism on the basis of which the past and present behavior of an organization can be offset against a set of requirements (Mökander et al. 2022), and, third, achieve a sustained homogeneous impact, which is yet to be observed under the GDPR (Peukert et al. 2022). Consequently, enforcement through audit would result in demonstrable compliance and good governance (DeAngelo 1981).

6.2 The modules

In subsequent paragraphs, the four modules of the APPRAISE framework, along with their elements, are substantiated in the context of the keywords identified in earlier sections.

Coordination: The importance of coordination from multiple perspectives, has been presented in sections 2 to 5. The typical product/service innovation context mentioned in section 4, requires alignment and coordination (e.g., of performance KPIs) across multiple functional interfaces: commercial professionals, model developers, software engineers and compliance professionals. Depending upon the level of offshoring/outsourcing and buy/build decisions, processes and interfaces will require additional coordination efforts. Additionally, the strategic variables in Figure 1 and the need for speed are often accompanied by greater technology complexity, and intricate requirements (functional, compliance, and otherwise), which impact the degree of required coordination. Furthermore, with complexer processes, increased number of interfaces, complex technology and requirements choices, system risks accumulate, which need to be coordinated. Audit KPIs for coordination is a topic of future research. However, parallels could be drawn from the software engineering industry (Bhat, Gupta, and Murthy 2006), in which audit KPIs measure process variations (Espinosa et al. 2007), and variations in development practices & styles (Šmite, Moe, and Torkar 2008).

Organization capital: The importance of organization capital is presented earlier through its elements, leadership, culture, and ethics in sections 2, 3, and 4. Alignment, essential for churning out faster and better innovations, is presented in section 3. Despite the pessimistic public tone towards auditing organization culture (Furnham and Gunter 1993), research on how these elements impact creativity & innovation and performance (Naranjo-Valencia, Jiménez-Jiménez, and Sanz-Valle 2016) are abundant and increasingly common practice (Tian et al. 2018). Additionally, as AI systems behave increasingly as black boxes, the role of ethics becomes more significant. In ensuring responsible valuee creation, leadership is expected to play an even greater role in stimulating the right culture and ethics, creating organizational alignment (across interfaces), and auditing these elements.

Technology safety: The elements of technology safety are a direct outcome of the AIA and presented in section 5. Increasing technology complexity leads to explainability challenges, which in turn poses safety risks. Technically assessing AI systems for explainability is of research interest today; for example when auditing binary classification models (Bhaumik and Dey 2023). Such studies propose technical audit frameworks aimed at multiple aspects including, fairness. Providers and deployers of prohibited AI practices and high-risk AI systems are required to demonstrate safety, privacy and security through audits.

Provider alignment: Working as microservices, AI models (systems), collaborating to deliver a seamless service, is increasingly common (Chunrong et al 2023). The AIA requires providers of such systems to be compliant and necessitates downstream organizations deploying such systems to demonstrate compliance (section 5). Deployers must oblige providers to provide the former with compliance validation of the latter's AI systems. For example, in the event of a deployer building a high-risk AI system on a GPAI system, the delpoyer must validate compliance of the GPAI system with its provider. The value-chain of a provider could comprise of multiple sub-providers, who may perform system updates at regular intervals or driven by specific events. In such a dynamic environment, managing risks continuously necessitates agreements between deployers and providers that facilitate an acceptable level of risk on behalf of the deployer. Formulating assessment frameworks helps a deployer manage and evaluate the compliance relationship with its providers.

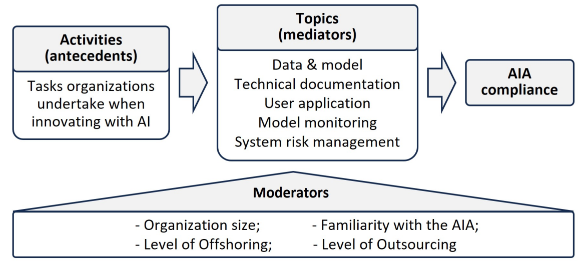

Figure 2: The conceptual model

7 Validating the framework

Validating the APPRAISE framework presented in Figure 1 is an extensive task. This paper attempts to substantiate parts of the framework through an empirical research presented in section 7.1 and two case studies presented in section 7.2. The empirical research studies the relationship between the strategic variables, technology safety and AIA compliance. The two case studies focus on coordination and organization capital, aiming to identify root causes emerging from the interplay among the four pressures.

7.1 Empirical research

Scope: Of the three contexts, within which AI systems add value to organizations (section 4), this empirical research is limited to organizations embracing AI for product/service innovation. The material scope of the empirical research is constrained by performing an analysis of the proposed AIA (Commissie 2021) and the JRC report of May 2023[1]; the purpose is to understand the implications of the AIA on functional requirements only and distinguish them from technical requirements. This distinction assumes that technical requirements serve as qualifiers to the AIA compliance of a system, whereas functional requirements, emanating from product/service innovation processes, could be implemented selecting from a wide range of algorithms varying in complexity/predictive power and depending upon an organization's risk appetite. This variability creates differentiation in the primary process of innovation between organizations. It is worthwhile mentioning that the choice of functional requirements (and therefore choice of algorithms) may have consequences on technical requirements. The analysis resulted in eight topics: data & data governance, technical documentation, user communication, human oversight, accuracy, monitoring, risk management, and quality management, all of which are included in the adopted AIA (Parliament 2024). Driven by the need for (a) structured communication during data collection, (b) ensuring overlap across topics (and eventually survey questions) is minimized, and (c) distinction between functional and technical requirements, the eight topics, are further narrowed down to five topics: data & model (DM), technical documentation (TD), user application (UA), model monitoring (MM), and risk management (RM).

[1] https://publications.jrc.ec.europa.eu/repository/handle/JRC132833

Topics	Questions
Data & model - Activity	When does your organization check suitability of data for the purpose of a system?
	How often does your organization recollect data when it is not suited for the purpose of a system?
	How often does your organization adjust data (e.g., append or delete features) when it is not representative of the purpose of a system?
	How often does your organization adjust data when it is found to contain errors?
	Has your organization noticed risks associated with using a dataset in the past 2 years?
	How often does your organization mitigate risks in a dataset?
	At which moment in the data gathering phase are actions taken to mitigate risks concerning a dataset?
	Which stakeholders do you involve in the process of risk mitigation?
	Does your organization train its employees on data and model bias?
	Which departments are trained on data and model bias?
	How often do you test model performance per demographic?
	How often are performance test results on demographics communicated with stakeholders?
	With which stakeholders are test results communicated?
	How often does it occur that a dataset misses data?
	How often does a data gap lead to an action, in which an existing dataset is adjusted, or new data is gathered to fix the data gap?
	With which stakeholders are data gaps communicated?
	How often does your organization reflect upon the acceptable level of model accuracy?
Data & model - Perception	My organization always ensures that data used for the purpose of a system is highly suitable.
	My organization always ensures that data used for a system's purpose is representative/free of errors.
	My organization identifies and mitigates risks associated with a dataset.
	My organization involves stakeholders in the process of risk mitigation.
	Professionals in my organization are aware that data can be biased.
	Professionals in my organization are aware that bias can occur within a model.
	Are these professionals, working on a project, aware of its customer demographics?
	Model performance on different demographics is tested and communicated all across the system development value chain.
	We are expected to follow a protocol if it comes out that a dataset misses data.
	Within my organization data gaps are communicated to different stakeholders.
	My organization has internally accepted levels of what a good accuracy is.
Technical documentation - Activity	Are there dedicated professional(s) for writing technical documentation (t.d.) in your organization?
	With which stakeholders is t.d. shared?
	T.d. of my organization is written for technical people only.
	There are guidelines within my organization to ensure completeness of t.d..
	How often is t.d. written?
	At which stage in the development process is t.d. written?
	How often are compliance requirements in relation to t.d. communicated with the development chain?
	With which stakeholders are compliance requirements in relation to t.d. communicated?
	Is someone in your organization trained to determine the compliance requirements of a t.d.?
	Are there guidelines for writing a t.d. within your organization?
	How often are guidelines for t.d. revised?
Technical documentation - Perception	T.d. is very detailed within my organization.
	The entire system development value chain is responsible for making t.d. of a system.
	T.d. is shared with the management of my organization.
	In my organization multiple departments understand the t.d..
	In my organization compliance requirements for t.d. are communicated across the development chain.
	My organization adheres to clear policies when writing t.d..

User application - Activity	With whom does your organization communicate accepted risks of the system? How often does your organization communicate accepted risks of the system with stakeholders? How does your organization estimate a model's risk on rights and discrimination? How often do you measure a model's risk on rights and discrimination? How often does your organization test that the customer understands what the model is predicting? How often does your organization perform user (e.g., customers) tests?
User application - Perception	My organization communicates accepted risks of the system with the user of the system. My organization has metrics to estimate a model's risk on rights and discrimination. My organization tests that the user of the system understands what the model is predicting.
Model monitoring - Activity	How many professionals in your organization are responsible for monitoring the AI systems? What type of qualifications do people who monitor the systems have? My organization has a dedicated employee, who is appropriately qualified, for monitoring systems. How often is model monitoring performed? How often are actions taken post monitoring? Post monitoring, how often do you check if model requirements are still met? What kind of actions do you take post monitoring, if the model does not meet requirements anymore?
Model monitoring - Perception	Are model monitoring and model development the responsibility of the same department? Models that learn after deployment are monitored to ensure that the model still meets requirements. My organization has clear quality standards to which a system must adhere.
System risk management - Activity	How many different employees are directly involved with managing risks of the model/ system? Which departments/professionals are involved in the risk management system? How often is the risk management system assessed? How often does your organization take a corrective action after a risk has been flagged? How often do you test that a corrective action has mitigated the risk? How often are flagged risks actually mitigated? How often are risks of the system communicated across stakeholders?
System risk management - Perception	My organization has established a risk management system. My organization assesses risk management at regular intervals. My organization coordinates risk mitigation across the entire development chain. My organization communicates risks of the system across all key stakeholders.
Moderator - Size	How many employees does your organization have?
Moderator - AIA knowledge	How would you rate your level of familiarity with the AIA? Have you received any training or guidance on the AIA?
Moderator – In-/Outsourcing	To what extent does your organization ”insource” and/or ”outsource” development of AI model?
Moderator – In-/Offshoring	To what extent does your organization develop AI models “inshore” and/or “offshore”?
AIA pressure	Do you believe that the AIA will have a significant impact on your organization's use of AI? How much of a priority does your organization currently place on complying with the AIA?

Table 1: List of survey questions/ statements

Conceptual model and questions: A conceptual model is developed (Figure 2), in which the five topics are depicted as mediators. The activities that organizations undertake within these topics are antecedents that contribute to the level of AIA compliance that these organizations demonstrate. Four moderators are selected: size, prior knowledge of the AIA and the extent to which organizations outsource or offshore their model development. The survey is developed and rolled out using Qualtrics between June and November 2023. Organizations in the Netherlands are targeted due to their geographical proximity and to avoid a too large variation in culture and ethics. To test the model, 76 closed questions, spread over these five topics, are formulated, which are presented in Table 1. A Likert scale is used to collect responses. Additionally, the questions are categorized as either "activities" or "perception". Of the 76 questions, 49 questions (activity questions) correspond to specific tasks that contribute to AIA compliance. The remaining 27 questions (perception questions) aim at identifying to what extent an organization supposes that it is compliant. The moderators account for five questions.

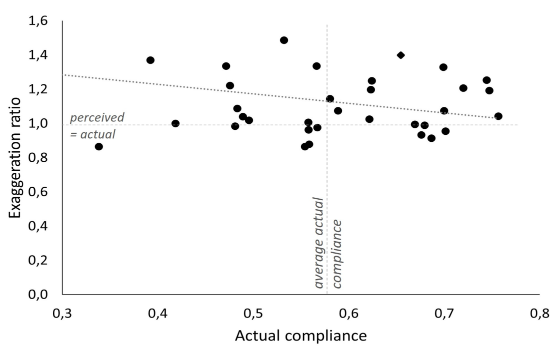

Figure 3: Do participants exaggerate their compliance?

Protocols: Networking is the primary method of sourcing respondents. Subsequent checks ensure that the selected organizations are proactively developing an AI-system for product/service innovation. Conscious effort is made to include large multinationals and startups in the survey. Senior participants, accountable for AI systems within their organization, are selected, rather than junior developers who concentrate on model/software development. Online interview is the preferred method of guiding respondents through the survey questions. The respondents are provided access to an online Qualtrics link, which they either filled-in on their own or are guided in a MS Teams environment. For the guided interviews, a minimum of 3 interviewers are scheduled for each interview. Responses to the survey is confidential.

Results: Actual compliance scores of participants are calculated based on their responses to the activity questions, whereas the perception questions are used to calculate perception of compliance score. All questions and topics have equal weightage in both scores. The responses within the Likert-scales are standardized in the range [0,1]. A yes/no, is converted to a 0/1 scale. In questions with multiple possible responses, points are allocated per response and the total points are standardized in the range [0,1] by dividing with the maximum possible points. This way the actual compliance scores and the perception of compliance scores for each participant could be calculated within each topic of the survey. An exaggeration score for each participant is calculated by taking the ratio of the perception of compliance and the actual compliance scores. Exaggeration ratios reflect the extent to which participants overstate their actual compliance level. Over a period of 6 months, 42 organizations responded, of which 34 successfully completed the survey. Since the 8 excluded organizations decided to take the survey on their own without assistance from the interviewers, their responses are deemed unreliable.

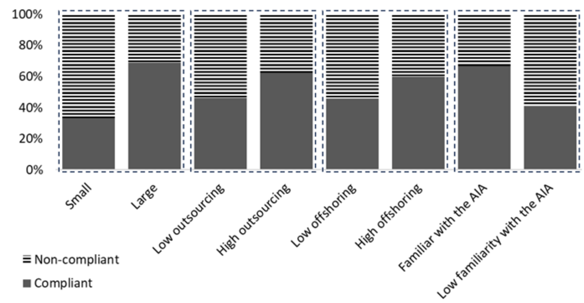

Figure 4: Effect of moderators on actual compliance

Organizations exaggerate their actual compliance: Figure 3 depicts exaggeration ratios versus actual compliance scores. The average actual compliance score (0.57) is quite low and about 80% of the participants exaggerate their compliance. Among the topics, the lowest average actual compliance score is observed in MM (0.51), whereas the other four topics have similar scores (0.60). The average perception of compliance scores range between 0.57 (TD) and 0.77 (DM). Participants exaggerate the least in TD and the most in DM.

Moderators, esp. organization size, affect actual compliance: The percentage of participants demonstrating actual compliance per moderator is depicted in Figure 4. The sample mean of actual compliance of 0.57 (sample median = 0.56) is chosen as a decision boundary for classifying compliance/non-compliance. At a significance level of 95%, with a test statistic of χ^2 = 3.841, it is concluded that size and actual compliance are not independent of each other. This implies that smaller organizations demonstrate lower compliance. For the other three moderators, it is not possible to conduct chi-square tests of independence, as the minimum number of elements is not always 5. Nevertheless, in Figure 4 it is observed that level of familiarity with the AIA has stronger influence on compliance than effects of insourcing/outsourcing and onshoring/offshoring.

Small organizations have a lower internal priority to comply with the AIA: In Figure 4, it is concluded that

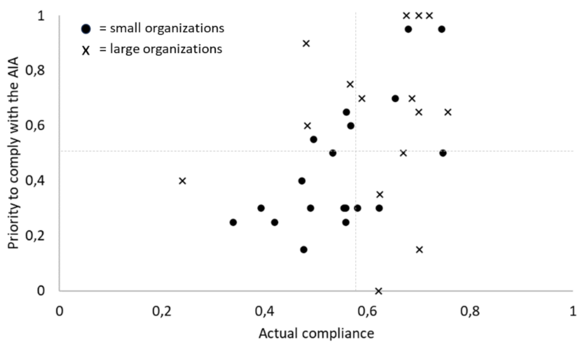

Figure 5: Regulatory pressure

size of an organization has a moderating effect on its actual compliance. Additionally, in Figure 5, it is observed that small organizations tend to have a lower priority to comply. It seems as if larger organizations endure more regulatory pressure and therefore, they have a higher internal priority to comply with the AIA. At a significance level of 90%, with a test statistic of χ^2 = 2.982, it is observed that the priority to comply with the AIA and actual compliance are not independent of each other. This implies that low actual compliance of small organizations is related to their lower internal priority to comply.

7.2 Validation case studies

Based on the results of the empirical research, case studies are conducted in December 2023 with two participants – a global leader in capital goods and home appliances (referred to as "Firm 1" below) and a startup focusing on developing AI systems for educational institutions (referred to as "Firm 2 below"). The two organizations are very different in the moderators. Firm 1 is global, with a good mix of insourcing/outsourcing and onshoring/offshoring in their innovation processes, and recognized for high internal priority towards compliance. Firm 2 is a small local startup developing innovative AI systems for the education industry only. The purpose of both studies is to further validate the APPRAISE framework.

Firm 1: The actual compliance score of Firm 1 is 0.75 and the exaggeration ratio is 1.04, indicating that Firm 1 hardly exaggerates its compliance. Its actual compliance scores in DM, TD, UA, MM, and RM are .79, .78, .89, .34 and .93, respectively. Given Firm 1's large size, the scope is restricted to one product group acquired by it a year ago. Subsequent paragraphs refer to this group Firm1a. Key insights are summarized as challenges Firm 1a encounters within requirements specification, organization capital, and processes.

Requirements specification challenges: At Firm 1a, internal communication on the AIA is informal and tacit. The model development team is aware of the AIA and is speculative about its potential implications. The speculation is a result of the team's individual best-effort towards compliance driven by SD and IMR, and concerns that the AIA could have significant impact on them. Furthermore, in the absence of training, formal guidelines, and procedures, also reflected in the survey response, model developers doubt if requirements incorporated in their AI systems, eventually comply with compliance requirements. The key challenge that Firm 1a faces is lack of internal alignment. This is driven by a combination of inadequate AIA competency in the team, individual ethical perceptions and lack of AIA compliance processes. This results in business value and compliance requirements often pitted against each other.

Resource challenges: Despite being a preferred employer, Firm 1a's resource challenges are representative of the contemporary short tenure of data professionals in the industry. Even at its inshore location, majority of its data professionals are foreign nationals with an average tenure of less than 2 years. These professionals leave Firm 1a for jobs as data professionals elsewhere, driven by better employment terms and conditions. This poses three challenges. First, providing training under these high-churn circumstances is infeasible. Second, frequent handovers put strain on the quality/continuity of projects. Lastly, the different nationalities and cultural backgrounds within the same team, result in sub-optimal alignment on ethical issues. This is worsened by the absence of repositories at Firm1a aimed at managing compliance and the lack of a single point of contact on compliance & ethical issues related to AI systems. Nevertheless, Firm 1 have these installed in other product groups.

Process challenges: Being a global leader in engineering, Firm 1 conducts its operations through well-documented processes that comply to relevant ISO standards. From the perspective of business process maturity, it is at least an optimized enterprise. It is not surprising therefore that it scored high on TD, UA, and RM. However, when it comes to processes that govern, describe and support MM, Firm 1a does not quite resemble Firm 1. This has to do with two challenges that Firm 1 confronts. Firstly, the drive to AI is driven by acquisitions. Integration of the acquisitions are often intentionally delayed, which leads to postponed roll-out of Firm 1's organization-wide processes at Firm 1a, which operates siloed. This impacts MM disproportionately since Firm 1's attention post-merger lies on value-capture through synergies, thereby overshadowing the monitoring of legacy models for (continued) compliance. Secondly, and probably more importantly, Firm 1 has no established AI compliance processes in Firm 1a. Individual best-efforts at AIA compliance in Firm 1a often leads to disrupted workflows and drop in productivity. The model team is concerned how highly-anticipated AIA compliance processes and procedures will affect their own productivity and the current explorative nature of innovation.

The compliance concerns at Firm 1a are driven by normative pressures from compliance developments in other parts of Firm 1 and adjacent legislations such as GDPR. Despite Firm 1's global reputation, it has prioritized value-creation by deciding to secure the value of the acquisition through non-integration. The case study provided very valuable insight into how Firm 1 balances the four pressures.

Firm 2: Firm 2's actual compliance score is 0.57 and the exaggeration ratio is 1.34, indicating that Firm 2 has highly exaggerated its compliance. Its actual compliance score is .46, .59, .61, .51 and .70 in DM, TD, UA, MM, and RM. As with Firm 1, these observations are used to initiate the validation discussion. The single-mindedness and need for speed in demonstrating innovative AI products results in basic tasks of building a compliant AI-system being neglected, which substantiates the low actual compliance score in DM. The financial and AI/technology pressures often result in Firm 2 developing AI systems with students studying AI, who in their DIY approach, heavily prioritize prediction accuracy over explainability. This could result in Firm 2's AI-systems being brought to the market without prior consideration of the harmful effects of the system. The "compromise" attitude towards compliance is noticeable in TD and MM. In TD, it undertakes all tasks inherent to TD, however these activities are not done sufficiently enough to demonstrate compliance. In MM, a very similar trend is observed.

As a startup with a very modest organization, Firm 2's employees are expected to be multi-functional, be willing to learn new skills, and deal with a broader range of activities as compared to Firm 1. Management's focus is primarily on meeting budget goals and fulfilling product commitments rather than prioritizing compliance. 'Avoidance' and 'compromise' as partial compliance strategies (Baldwin and Cave 1999) and creative compliance are observed during the discussion, for example in TD and MM. The model development team incorporates compliance in Firm 2's products without any well-defined processes, dedicated resources and oversight. Firm 2 is steered more by AI/technology and financial pressures than by regulatory ones.

8 Conclusion and next steps

This paper identifies four pressures - AI/technology, value creation, regulatory and normative - which organizations embracing AI for innovation endure to varying extents. Their reactions to these pressures differ based on their size, familiarity with regulation (AIA), and strategic choices they make regarding build/buy and exploration/exploitation dilemmas. The level of outsourcing and offshoring of an innovation process is an outcome of these strategic choices, which among others, impact an organization's ability to create value responsibly. The importance of audit in this context is also presented. By intertwining these themes, the paper introduces the APPRAISE governance framework for organization's embracing AI for product/service innovation. The framework bridges the gap between an organization's strategic variables and responsible value creation, using auditability as a yardstick for assessing itself.

To validate the framework, insights from empirical research with 34 organizations and 2 case studies in the Netherlands are presented. These insights validate how mix of the strategic variables and the four pressures affect AIA compliance. In the empirical study, the average actual compliance score has been low and most participants have exaggerated their compliance. Smaller organizations have demonstrated lower actual compliance. An organization's actual compliance is (also) dependent on the internal priority that it has placed on complying with the AIA and smaller companies tend to place lesser priority on compliance. The effects of offshoring and outsourcing, although indicative, have not provided statistically significant results. The case studies provide insights on how organizations, performing balancing acts among the four pressures, creatively or partially comply. These insights and the importance of homogeneity (e.g., across small and large organizations) in achieving compliance necessitate audit as an enforcement mechanism.

In developing and validating the framework, the focus has been on providing structure to the governance challenges that organizations innovating with AI encounter. Quite a few areas require further research to improve reliability of the insights in this paper and generate additional insights, for example the moderating influence of outsourcing and offshoring, and the combined effects of the moderators. This would improve understanding on how these moderators play roles in AIA compliance. Moreover, the four modules presented in the framework need comprehensive research, especially concerning auditability. This is anticipated to provide detailed assessment frameworks, which organizations could eventually use for self-evaluation.

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