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Stakeholder-accountability model for artificial intelligence projects

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Abstract

Aim/purpose – This research presents a conceptual stakeholder accountability model for mapping the project actors to the conduct for which they should be held accountable in artificial intelligence (AI) projects. AI projects differ from other projects in important ways, including in their capacity to inflict harm and impact human and civil rights on a global scale. The in-project decisions are high stakes, and it is critical who decides the system's features. Even well-designed AI systems can be deployed in ways that harm individuals, local communities, and society.

Design/methodology/approach – The present study uses a systematic literature review, accountability theory, and AI success factors to elaborate on the relationships between AI project actors and stakeholders. The literature review follows the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement process. Bovens' accountability model and AI success factors are employed as a basis for the coding framework in the thematic analysis. The study uses a web-based survey to collect data from respondents in the United States and Germany employing statistical analysis to assess public opinion on AI fairness, sustainability, and accountability.

Findings – The AI stakeholder accountability model specifies the complex relationships between 16 actors and 22 stakeholder forums using 78 AI success factors to define the conduct and the obligations and consequences that characterize those relationships. The survey analysis suggests that more than 80% of the public thinks AI development should be fair and sustainable, and it sees the government and development organizations as most accountable in this regard. There are some differences between the United States and Germany regarding fairness, sustainability, and accountability.

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Research implications/limitations – The results should benefit project managers and project sponsors in stakeholder identification and resource assignment. The definitions offer policy advisors insights for updating AI governance practices. The model presented here is conceptual and has not been validated using real-world projects.
Originality/value/contribution – The study adds context-specific information on AI to the project management literature. It defines project actors as moral agents and provides a model for mapping the accountability of project actors to stakeholder expectations and system impacts.

Keywords: accountability, artificial intelligence, algorithms, project management, ethics.
JEL Classification: C33, M15, O3, O32, O33, Q55.

1. Introduction

Artificial intelligence (AI) projects bring technologies, methods, and techniques from computing, communication, management, and sociology together to develop data-driven, algorithmic decision-making systems (Michalczyk et al., 2021). AI projects differ from other types of projects in ways that impact relationships between these projects and their stakeholders. AI systems may negatively impact individual human and civil rights and have adverse social and environmental impacts (Boyer & Veigl, 2015; Miao, 2018). This is especially the case when the systems do not allow human intervention in decision-making and action (Moser et al., 2022; OECD, 2019). However, many of the impacts of AI systems are not considered in existing information technology (IT) frameworks (Fazelpour & Lipton, 2020). Furthermore, in its treatment of AI, the project management literature predominately focuses on understanding and applying AI to project management practice (Foster, 1988; Fridgeirsson et al., 2021; Nemati et al., 2002; Ong & Uddin, 2020; Willems & Vanhoucke, 2015).

The differences between AI and other projects range from how data are sourced and manipulated to the consequences of in-project decisions. First, the environmental impacts and consequences of AI projects and systems are potentially global, affecting many individuals and local communities (Ryan & Stahl, 2021; Webb et al., 2018). Other types of IT projects or systems are geographically or organizationally bound. By contrast, AI systems can, for example, be integrated into digital platforms or devices (such as Facebook, Twitter, smartphones, and wearable devices) (Ryan & Stahl, 2021; Vesa & Tienari, 2020; Webb et al., 2018). Second, the value and quality of AI systems are based on the representativeness of the data used in their development. Those data, typically gathered from individuals and the public, may be incomplete, biased by past practices, or otherwise unavailable (Chasalow & Levy, 2021; Sambasivan et al., 2021). Third, there is an industry of temporary and contract workers responsible for labeling, annotating, or tagging training datasets; workers may be engaged through platforms such as Mechanical Turk (Moser et al., 2022). Those workers and users of datasets may be psychologically impacted by dealing with sensitive data (Munoko et al., 2020; Ryan & Stahl, 2021).

A fourth distinguishing feature of AI systems is the impact of their designers and developers; their bias, blind spots, and choices influence the systems and the consequences of those systems (Kasinidou et al., 2021; Manders-Huits, 2006; Martin, 2019). The methods selected for development, the system parameters chosen, and the clarity of the user interface designs are consequential. For example, some computing methods, such as artificial neural networks, produce complex, predictive models, the parameters of which may be hidden from or not be understood by their designers. The resulting systems can be black boxes that the end users do not understand and cannot explain or interpret (Cohen et al., 2014; Sambasivan et al., 2021).

Fifth, developing AI systems can have a profound environmental impact; training large models entails high energy consumption and carbon emissions (Bender et al., 2021; Ryan & Stahl, 2021). The final and most significant difference is that AI systems are "capable of inflicting (minor to serious or even lethal) harms as well, be it intentional/unintentional" (Wieringa, 2020, p. 1). In-project decisions in the AI arena are high stakes, and who decides the system's features is critical. Even well-designed AI systems can be deployed in ways that harm individuals, local communities, and society (Ryan & Stahl, 2021).

Scholars argue that the project teams implementing AI systems are moral agents accountable for the harms or benefits of developing or using their systems (Manders-Huits, 2006; Martin, 2019; Miller, 2022a). A moral agent is an actor who makes decisions but may not recognize that a moral issue is at stake in doing so (Jones, 1991). As Ryan and Stahl (2021, p. 71) argued that "developers are primarily responsible for the design and functionality of the AI, and when there is an error or harm, then the onus of responsibility often lies with them." Project participants need to be aware of and accountable for the harmful consequences of their activities (Ryan & Stahl, 2021). Assigning accountability is complicated, as many outcomes and impacts occur only months or years after the project's completion (Turner & Zolin, 2012). Wieringa (2020) evaluated algorithm accountability using the accountability theory of Bovens (2007). Wieringa (2020, p. 10) identified several risks that require further investigation, noting that it is "thus key to concretely specify the actors, their roles, level, and the part of the system for which they are responsible."

Stakeholders are "any group or individual who is affected by or can affect the achievement of an organization's objectives" (Freeman & McVea, 2001, p. 2). The project management literature describes multiple approaches to assessing how a project engages with and invests resources in stakeholders. The project management stakeholder literature includes studies in several contexts, including private-public partnerships, sustainability projects, mega-projects, and information technology projects (Di Maddaloni & Davis, 2018; Nguyen et al., 2019; De Schepper et al., 2014; Węgrzyn & Wojewnik-Filipkowska, 2022). Most studies only consider stakeholders as project beneficiaries rather than taking into account the project's impact on the stakeholders (Derakhshan et al., 2019). Furthermore, projects differ widely in terms of size, ownership, and external stakeholder concerns.

Adopting the view of Derry (2012) that all the interests of all stakeholders-community, environment, and business – should be considered, this study uses project success factors from Miller (2022a) to define the accountability relationships between the project actors and stakeholders of the AI systems. The present study addresses the following question:

Which project actors should be held to account for stakeholder expectations in AI projects and the impacts of AI systems?

The study uses Bovens' accountability theory as applied to AI by Wieringa (2020) and a systematic review of the literature to define the relationship between project actors and stakeholders. Public opinion of algorithmic accountability is confirmed using a web-based survey and quantitative analysis.

The remainder of the paper is structured as follows. Section 2 sets out the theoretical background, including a review of the literature on AI projects and project accountability. Then, Section 3 contains a description of the methodology, including the theoretical framework and process for data collection and analysis. Section 4 presents the findings, and these are discussed in Section 5 alongside the study's contributions and implications. Section 6 concludes, providing limitations and considerations for future research.

2. Theoretical background

This section provides the context for AI systems and projects, identifies the factors that differentiate these from other information systems, and addresses the relevance of accountability theory to this investigation.

2.1. Artificial intelligence systems

AI systems are machine-based systems that learn from data and use models and algorithms to make predictions and recommendations or influence decision-making (OECD, 2019). They are developed in data science projects and incorporate technologies, methods, and techniques from computing, communications, management, and sociology (Michalczyk et al., 2021). There are a variety of computer science methods used to develop AI systems, including natural language processing (NLP), machine learning (ML), and artificial neural networks (ANN) (Aggarwal & Kumar, 2018; Iqbal et al., 2017). NLP concerns the manipulation of human language. ML uses supervised and unsupervised methods to identify and model patterns and relationships in data, allowing the algorithm to make predictions. ANN are models trained on data to make predictions. Some methods result in complex predictive models with the parameters used to make inferences hidden in the model; this phenomenon is sometimes referred to as the ”black box AI problem” (Sambasivan et al., 2021).

AI project developments generate algorithms-defined, repeatable models based on data, processes, and assumptions – that are incorporated in a range of data-driven, algorithmic decision-making systems, such as autonomous vehicles, social media platforms, and weapons systems (Ryan & Stahl, 2021; Vesa & Tienari, 2020; Webb et al., 2018). The AI systems are considered black boxes when the end users cannot explain their functioning or interpret the results (Cohen et al., 2014).

The degree of human intervention in decision-making in AI systems varies according to its type and purpose and the method by which the algorithms are integrated into other systems or processes. Once deployed, some AI systems limit human intervention in decision-making or action. For example, robots or other artificial agents may carry out a complex series of actions without any need for human control or guidance (OECD, 2019).

Depending on the design and nature of the system, its implementation, use, or both, AI systems can impact human rights (Miao, 2018). For example, surveillance systems have the potential to access sensitive personal information in circumstances in which an individual’s right to privacy should be protected. Similarly, they can be used by state actors for systematic surveillance of citizens (Boyer & Veigl, 2015).

Following Miller (2022b), this study defines AI systems to include data-driven computer systems that incorporate algorithms that learn from data and defines algorithmic decision-making as the use of computerized systems for autonomous or human decision-making and problem-solving.

2.2. Artificial intelligence projects

Projects are temporary organizations or production functions embedded in a permanent organization (Müller et al., 2016). They exist for a limited time to produce deliverables or outputs that can be used. Thus, there is a need for resources to be shared between the project and the permanent organization to ensure the transfer of innovations and knowledge (Prado & Sapsed, 2016). Furthermore, the goals, expectations, and control of the permanent organization are relevant factors. Actions taken by the temporary organization affect the permanent organization and vice versa (Jacobsson & Hällgren, 2016).

The project management literature has predominately focused on understanding and applying AI to project management practice. AI has, as a result, been applied to many project operations, such as risk management, scheduling, and performance monitoring (Foster, 1988; Fridgeirsson et al., 2021; Nemati et al., 2002; Ong & Uddin, 2020; Willems & Vanhoucke, 2015). Like other domains, additional research is needed on AI in project management (Fridgeirsson et al., 2021). However, the literature on managing AI projects is sparse.

First, AI is a fundamental component of digital transformations of organizations, businesses, and customer-centric processes (Saurabh et al., 2021). Moreover, AI projects impact organizational business models and are expected to deliver benefits such as increased productivity, efficiency gains, and new revenue streams (Bonsón et al., 2021). The systems may introduce new job structures and patterns, eliminate certain jobs, or change the way of working (Rodrigues, 2020). An organization's ethical and value framework drives the AI system's business model and constitutes the practical guidelines and policies for the project's governance (Raji et al., 2020; Shneiderman, 2020).

There is a range of organizational structures for firms developing AI systems, including a single firm governing all aspects of the funding, development, and operations, independent firms governing each of these elements separately, large enterprises performing all functions, collaborations between enterprises, and supplier-vendor models (Simon, 2019). Several digital giants have invested in AI talent and applications to manage all aspects of algorithm development and usage (e.g., Amazon, Google, and Microsoft); see Simon (2019). Their AI systems are then deployed globally online using cloud platforms, e-commerce sites, social media, and search engines (Webb et al., 2018).

Several environmental factors affect AI projects and their stakeholders, including data and hardware; software; capital, and staffing; government policies, industry laws, and regulations; and emerging economies (Mir et al., 2020). On the one hand, projects are restricted by government policies, and on the other, liberal or outdated policies allow for intrusive or faulty algorithms.

Specifically, projects must recognize laws, regulations, and ordinances specific to handling data, creating and using algorithms, and the context-specific practices that may affect human rights and contractual or property rights of organizations (Rodrigues, 2020). For example, AI developers must observe the European Union's (EU) general data protection regulations (GDPR), AI laws and regulations of the EU and the United States (US), the Americans with Disabilities Act, the Fair Credit Reporting Act, the Health Insurance Portability and Accountability Act (HIPPA), the Children's Online Privacy Protection Act of 1998, and the German Network Enforcement Act (116th Congress (2019-2020), 2020; Büchi et al., 2020; European Commission, 2021; Rodrigues, 2020). However, weak technology policies and enforcement create situations when citizens have no agency or are forced to endure intrusive models with inadequate recourse to influence or contest their treatment (Sambasivan et al., 2021).

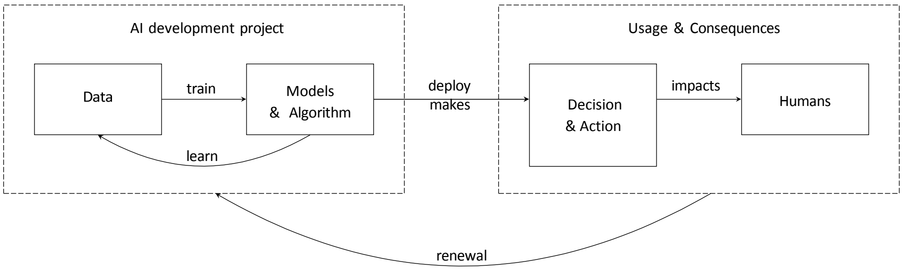
Data used in building AI systems are representative; that is, one set of data may stand for another (e.g., a sample for a population, an instance for a category) (Chasalow & Levy, 2021). Representativeness has a power and a value element based on who is included or excluded in the data. Data are not always reliable due to socioeconomic factors. For example, social infrastructure and systematic disparities can result in entire communities being missed or misrepresented in data (Sambasivan et al., 2021). Discriminatory practices may be reproduced where data are based on existing ones (Kasy & Abebe, 2021); for example, an extant understanding of "merit" may reinforce past practices and legitimize and perpetuate inequalities. Thus, data practices significantly impact AI projects and their stakeholders.

Finally, project actors must consider the impact of the application's quality on society, individuals, and the environment. This affects the choices, considerations, and trade-offs made in the design and implementation of the model, from managing the life cycle of data to addressing stakeholder bias, attitudes, perceptions, and expectations. Specifically, the age, education, role, and personal bias of stakeholders influence their perception of fairness and the extent to which they accept the outcomes produced by AI systems (Eslami et al., 2019). The collection and processing of personal data require informed consent. Workers interacting with and processing some types of sensitive data (e.g., pornography, hate speech, violence) may experience physical and psychological harm as a result (Munoko et al., 2020; Ryan & Stahl, 2021).

AI projects demand multi-disciplinary teams with specialized skills and knowledge to process data and accomplish the design and development of algorithms (Umar Bashir et al., 2020). Model developers may have blind spots that allow their biases or choices to intrude (Kasinidou et al., 2021). Furthermore, developers' expertise makes them the most capable and, in some cases, the only individuals who can enact changes to the project's design or algorithms (Manders-Huits, 2006; Martin, 2019). Finally, the model training involved in building AI systems may be energy-intense, using sufficient computing energy to generate carbon emissions with environmental impact (Bender et al., 2021; Ryan & Stahl, 2021).

Figure 1 shows a system boundary and process flow for the development and usage of an AI system. The algorithms and models are developed using data to learn. Once deployed, the system's output may impact people without the possibility of human intervention. The decisions, actions, and impacts are outside the project boundary. The system's performance and environment require monitoring to renew obsolete values and choices. See Miller (2022b) for details on AI project life cycles.

Figure 1. AI project flow



Source: Author's own elaboration.

2.3. Accountability

Accountability can only be determined relative to a particular task. Having accountability measures in place ensures a task is satisfactorily done; it requires an actor to take responsibility by accepting an obligation to perform a task satisfactorily, with transparent reporting on outcomes, corrective actions, or interactive controls (McGrath & Whitty, 2018; Rezania et al., 2019). There are multiple sources of accountability: legislative, organizational, contractual, administrative, legal, and informal (Bovens, 2007; McGrath & Whitty, 2018). In a hierarchical structure, responsibilities carried at one level may be converted into contractual accountability that can be transferred between levels. However, the responsibility for ensuring that a task is satisfactorily done, which is accountability, cannot be delegated (McGrath & Whitty, 2018).

The scope of accountability is defined by the obligations of project actors to stakeholders, as outlined in contracts, quality standards, processes, controls, or systems. Finally, there is mutual accountability between the stakeholders and the project. The project manager works within a defined project process and should proactively maintain the project's accountability and hold others to account (Rezania et al., 2019).

Stakeholders are "any group or individual who is affected by or can affect the achievement of an organization's objectives" (Freeman & McVea, 2001, p. 2). The stakeholder theory was first applied to strategic management as a way to manage group relationships strategically. Stakeholder actions can significantly impact whether or not a project can meet its objective (Nguyen et al., 2019). Derry (2012) suggested we challenge the firm's role and re-center the stakeholder model around our commons, defined broadly as our community and environment. We should think "about business as just one of many stakeholders whose needs must be balanced to maximize the sustainability of our environment and social well-being" (Derry, 2012, p. 263). This aligns with arguments from Mitchell et al. (1997), suggesting that managers should serve the legal and moral interests of legitimate stakeholders.

Several authors point to the complexities of assigning accountability for the outcomes produced by AI systems. The first point of discussion is the extent to which algorithmic designers and developers are responsible for decisions made using the systems they develop (Manders-Huits, 2006; Martin, 2019). Martin (2019) held both developers and their firms to account for the acts, bias, and influence of their technology. Miller (2022a) argued that "project team members are moral agents because they make decisions that may affect others (whether harmful or beneficial), even if they do not recognize that a moral issue is at stake. Hence, the systems they develop are artificial agents that should abide by the moral laws of society" (p. 85). However, assigning this accountability is complicated; defining who can be seen as a developer (Manders-Huits, 2006) or accounting for complex project environments involving collaborations between enterprises or through supplier–vendor models can be challenging.

A further debate concerns whether humans are responsible for AI decisions even when those decisions are delegated to systems by humans (Ryan & Stahl, 2021; Wieringa, 2020). This is a grey area in the interface between development and usage. Development processes can create a moral buffer where no one is accountable for a decision (Green & Chen, 2019). That is, neither the developers who develop the algorithms nor the human decision-makers who use them take responsibility for their social impact. Shaw et al. (2018) argued that machines are artificial agents that should not be held to a higher moral standard than humans.

A review framework and an algorithm accountability model are the approaches to clarify AI responsibilities. Cobbe et al. (2021) drew on administrative law to provide a systematic framework for the record-keeping of algorithm decision-making. They describe a documentation life cycle of commissioning, model building, decision-making, and investigation that involves managers, developers, and users. At each stage and with each step, the framework identifies records that provide transparent and targeted information that actors can present to various stakeholders. The study framework "offers a legally-grounded, holistic, systematic, and practical framework for making algorithmic systems meaningfully accountable" (Cobbe et al., 2021, p. 607).

Wieringa (2020) used Bovens' (2007) accountability model to assess accountability before, during, and after the development of an AI project. The study points to several risks and questions that remain around AI accountability. These concern issues such as the relationship between the phases of development and usage, the extent and content of actors' accountability, and determining who can be affected and who should be accountable for AI outcomes. Consequently, the study proposes a framework to "concretely specify the actors, their role, level and the part of the system for which they are responsible" (Wieringa, 2020, p. 10).

3. Methodology

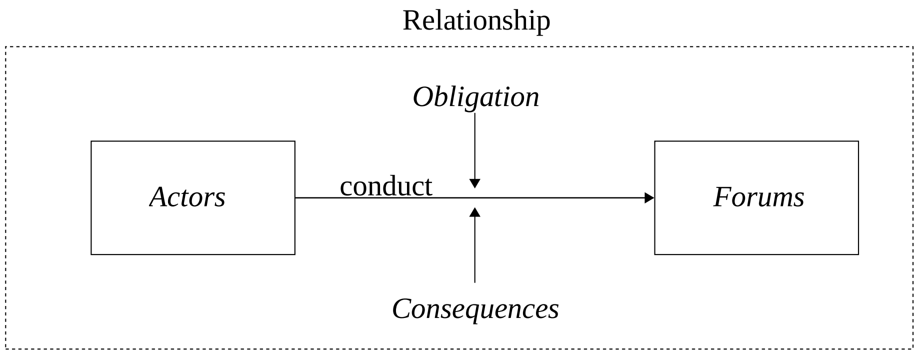
This study investigates the relationship of accountability between AI project participants and stakeholders. First, a model was designed through the theoretical lens of accountability theory. Data are collected using a systematic literature review before being analyzed and consolidated. The thematic analysis was conducted using Bovens' accountability model and a coding framework based on AI success factors. A web-based survey was used to gather public opinion on algorithmic accountability. In this section, we describe the theory underlying our analysis and our data collection process. This is followed by our analysis and, finally, our AI stakeholder-accountability model.

3.1. Theoretical framework

The theoretical framework for the AI stakeholder-accountability model builds on Bovens' accountability theory, as proposed by Wieringa (2020), and the AI success factors from Miller (2022a). According to the accountability theory: "Accountability is a relationship between an actor and a forum, in which the actor has an obligation to explain and to justify his or her conduct, the forum can pose questions and pass judgment, and the actor may face consequences" (Bovens, 2007, p. 450). The model was first developed as an instrument for a systematic multi-criteria assessment of public accountability. It is proposed as a yardstick of the effectiveness of governments in delivering on their organizational missions (Bovens et al., 2008).

Figure 2 depicts the use of the model for this study. Six of seven accountability elements are included: 1) actors, 2) forums, 3) obligations, 4) conduct, 5) consequences, and 6) relationships. The seventh element – justifying behavior – is specific to a project context and is thus excluded.

Figure 2. Relationship model for stakeholder–accountability



Source: Based on Bovens' (2007) accountability model.

The model was selected for four reasons. First, Wieringa (2020) used the model to provide insights into the risks and gaps in algorithm accountability and what is needed to respond to these. Wieringa (2020) proposed how the model can be used and expanded. Second, the model evaluates the relationship between stakeholders and a phenomenon and is relevant to assessing stakeholder relationships to AI projects. Third, it renders the relationship between the project and stakeholders transparent along multiple dimensions. Finally, it offers a method to connect all stakeholders – including internal, external, and governance stakeholders – to the project.

Within a project, success factors identify the circumstances, conditions, and events that must exist for the project to achieve its objectives (Ika, 2009). Success factors establish an accountability standard in the relationship between actors and forums. According to Davis (2017), accountability is itself an important project success factor, suggesting the need for clearly defined roles and responsibilities and transparent procedures. The study by Miller (2022a) identified the success factors for AI projects: "the deliverables, acts, or situations – success factors – necessary to avoid harm or ensure the benefits of an algorithm developed in projects" (Miller, 2022a, p. 70). The narrative descriptions accompanying the factors provide sufficient details to identify the relationship between the actors, stakeholders, and success factors. Furthermore, the context of the research was relevant to this study.

3.2. Systematic literature review

We undertook a systematic literature review to identify and collect data on AI stakeholders and their accountability relationships with AI projects. The review was pivotal in synthesizing existing knowledge in a structured and rigorous manner to construct the conceptual model. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement process was followed in conducting the literature review (Moher et al., 2010).

The details of the review are described in the following sections. Figure 3 depicts the flow of information in the systematic review. The process was conducted by a single researcher in 2021.

Bibliographic databases

The literature search included a keyword search for peer-reviewed articles in ProQuest, Emerald, ScienceDirect, IEEE Xplore, Emerald, ACM Digital Library, and Sage bibliographic databases. These databases were chosen as they together offer comprehensive coverage of the AI and project management literature. The databases cover many journals and are frequently updated with early versions of print publications and conference papers. In computer science, frontier research is mainly presented at conferences (Wang, 2018). The databases also include the leading project management journals: *Project Management Journal*, *International Journal of Project Management*, and *IEEE Transactions on Engineering Management* (Drouin et al., 2013). Finally, the "ACM Conference on Fairness, Accountability, and Transparency (ACM FAccT)" was identified as an important source for cross-disciplinary AI research (Miller, 2022a).

Search string

Multiple versions and iterations of the search string were used to search the titles of articles. The first search used the keyword “stakeholder” in combination with the term “algorithm.” This returned very few results. Subsequent searches emphasized the term “accountability” instead of “stakeholder,” and included ”AI” in addition to ”algorithm.” We also added frequently found keywords to make the results more meaningful. The final keywords with wildcards were as follows: accountabl*; and “machine learning,” “artificial intelligence,” AI, “big data,” algorithm*; and fair*, ethic*, moral*, success, transparency, or explainabl*.

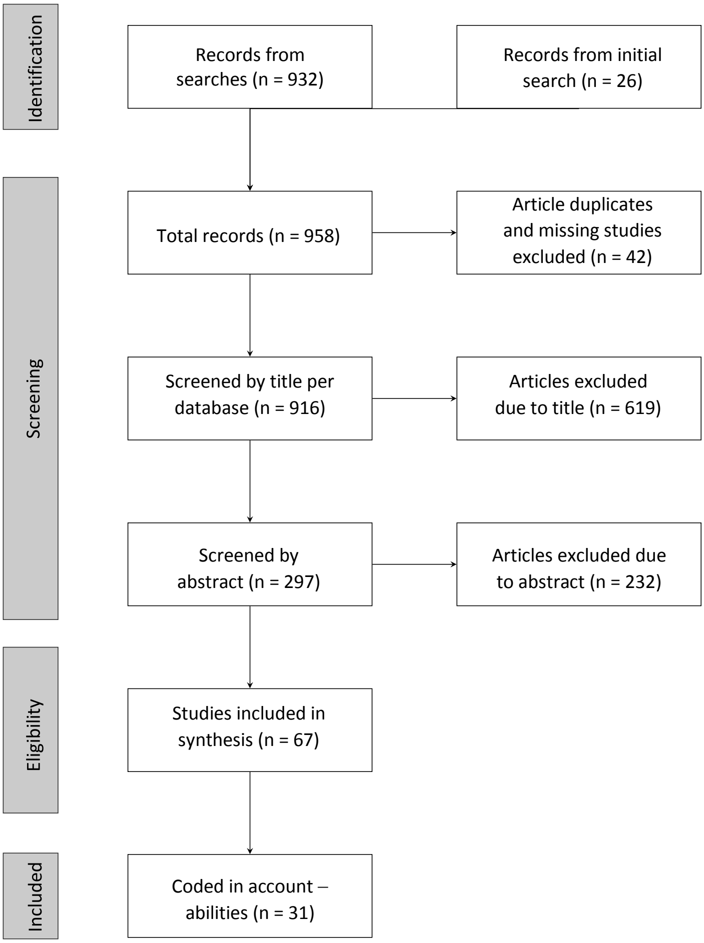
Inclusion and exclusion criteria

Articles were identified from the search results for peer-reviewed journal articles or conference papers in English; book reviews were excluded. Duplicate entries and entries with no documents available were removed. The articles identified during the initial search were retained throughout the process of analysis. The title, abstract, and full article text were reviewed step-wise to exclude or retain articles.

In total, the full texts of 67 articles were identified as relevant to the research. Most of the reviewed articles (82%) were published in the period since 2019, and many (39%) were conference papers. Less than 5% of the reviewed articles were published before 2016. Figure 3 shows the flow of information through the systematic review’s identification, screening, eligibility, and inclusion phases.

The references from the systematic literature review were used to identify stakeholders and map success factors and relationships according to the coding framework described in the thematic analysis section.

Figure 3. Flow of information through the four phases of systematic review



3.3. Quantitative survey

We used a web-based survey to collect public opinion data on accountability for fair and understandable algorithmic development. A two-stage process was used to develop a measurement instrument. Stage one included a content review; stage two consisted of a typographical and format review and adjustment of the text for clarity. The measurement instrument was in the English language. The survey data were collected in April 2021 using a SurveyMonkey audience panel for US respondents. SurveyMonkey is a global survey platform, and the SurveyMonkey audience is a proprietary panel of survey respondents.

In 2022, the framing of the survey questions was changed from evaluating algorithms as “just and moral” to evaluating them as “understandable.” This allowed us to avoid “just” being misinterpreted to mean legal, simplified the language, and enabled us to add a sustainability question. The revised survey was rerun in August 2022 for United States (US) and German audiences. There were 98 usable US responses and 50 German responses. The abandon rates were 8% and 22% and the margin of error was 10.1% and 14.1% for US and Germany, respectively.

The respondents provided their consent to participate, no personally identifiable data were collected, and they were not offered compensation. There were no mechanisms to prevent the same respondent from taking both the 2021 and 2022 surveys. The 2022 sample size was chosen to achieve a statistical power of .80 for a medium effect (Hair et al., 2014). This study uses the 2022 survey results to report public opinion on algorithmic accountability. The respondent demographics, provided in Table 1, were evenly distributed by gender and age.

Table 1. Demographic information for survey respondents

Variable	Demographic Category	Frequency			Percent (%)
		US	Germany	Total	
Gender	Male	49	26	75	51%
	Female	49	24	73	49%
Age	18-29 years	19	17	36	25%
	30-44 years	49	14	63	43%
	45-60 years	26	15	41	28%
	More than 60 years	4	4	8	5%
Education	Doctoral degree	8	2	10	7%
	Master’s degree	20	13	33	22%
	Bachelor’s degree	37	7	44	30%
	High school graduate or GED	16	17	33	22%
	Associate’s degree	16	10	26	18%
	Other	0	2	2	1%

Source: Author’s own elaboration.

The survey instrument included questions to derive accountability, fairness, and sustainability variables. For “accountability”, the measurement instrument uses a ranking question for five roles: software developer, developing organization, end users, the operating organization, and the government. The question in the 2022 survey was: *Who should be accountable for ensuring computer algorithms make fair and understandable decisions? Rank from most important (1) to least important (5).* The relative position of each role was assessed using a dummy variable created for the number of responses by rank from one to five.

"Fairness" was assessed using a seven-point Likert scale (1 = Not very important; 4 = Important; 7 = Extremely Important) in response to the question: *How important is it to you that computer algorithms make fair and understandable decisions?* "Sustainability" was assessed on a seven-point Likert scale (1 = Not very important; 4 = Important; 7 = Extremely Important) in response to the question: *How important is it to you that computer algorithms are developed sustainably (limit carbon emissions, conserve energy)?*

3.4. Thematic analysis

The thematic analysis and coding of the data were undertaken using NVivo 12 (Windows) software. The analysis involved a review of the 67 articles from the preceding stage to identify accountability relationships. The findings were incorporated into the model in an iterative process. Ultimately, a total of 31 articles were referenced to confirm the identified relationships. The following sections describe the coding framework used in constructing the model.

Stakeholders

Following the proposal in Derry (2012), we consider all stakeholders with a legal and moral interest in the project or its output. Internal stakeholders are the project actors, governance stakeholders are actors within the management structure of the developing organization, external stakeholders of the operating organization are seen as clients, and all other stakeholders are considered external. The stakeholders are either actors, forums or both.

We used the AI stakeholder list from Miller (2022b) for identifying actors and forums. The list was selected since it includes a comprehensive list of internal, external, and governance stakeholders for AI projects and systems. Furthermore, it includes individual team roles as described by the data-science job roles in Michalczyk et al. (2021). The complete list is shown in Table A.1 in the Appendix, and its usage is described in this section.

Actors

Actors are individuals or organizations assigned to three levels: individual, collective, and corporate. The hierarchical level of an actor in Bovens (2007) added no analytical value to the study and was excluded. In assigning roles to actors, we emphasized the identification of decision-makers to separate accountability from involvement. We further refined the roles to use project-specific terminology.

The project team was assigned further individual data-science job roles. The public collective was divided into individuals with a formal relationship to the developing or operating organization, the regulators, and the remaining public. The individuals are either external stakeholders with a formal data relationship (data subjects) or are affected by the decisions of the AI system (decision subjects).

Forums

A forum is a specific person or agency that is the principal to the actor. The forum must be able to ask questions and pass judgment on the actor (Bovens, 2007). This suggests a degree of subject-matter understanding on the part of the forum (Wieringa, 2020). Bovens (2007) described five types of forums: political, in a chain of principal-to-agent relationships; legal, based on a legal standard or precedent; administrative, for supervision or control; professional, for peer relationships or professional associations; and social, for direct and indirect client accounts and citizen accountability.

We followed the proposal in Wieringa (2020) with minor differences. Specifically, this study treats the regulator and courts as a legal forum, while Wieringa (2020) classifies them as administrative. The remaining entities, such as non-governmental organizations, journalists, the media, safety certifiers, accident investigators, and auditors, are classified in collectives as public actors or forums with social accountability.

Conduct

The conduct of the actor is what is evaluated by the forum. Bovens (2007) identified three types of conduct, i.e., financial, procedural, or product-related. We replaced the conduct types with the success categories, groups, and factors defined by Miller (2022a). This made the conduct types AI and project specific. Table A.2 in the Appendix sets out the success categories and groups; the success factors are also mapped in the supplemental tables.

Success categories for the conduct were extended by Bovens' types of conduct to include societal impact and ethical practices. Otherwise, broadly speaking, Bovens' financial conduct maps to the benefits and protection group, procedural conduct maps to project governance, and product type maps to product quality and usage qualities.

Obligations

An obligation is a vertical, horizontal, or diagonal relationship that defines the requirement that the actor informs the forum about their conduct. This obligation determines the forum's power over the actor. Vertical accountability is based on a hierarchical relationship, regulations, or laws. The diagonal relations are based upon a contractual relationship or formal agreements. With horizontal accountability, there is no formal accountability, and there is thus limited power to enforce compliance (Bovens, 2007). Thus, obligations exist within a power hierarchy, with vertical obligations being the most powerful, followed by diagonal and horizontal.

The obligation dimensions of the model are sensitive to the project's governance arrangements and subject matter. The project governance structure and the relationships between funding, development, and operations determine whether an obligation is vertical, diagonal, or horizontal. Governance structures can include individual firms performing parts of the projects, large enterprises, supplier–vendor models, and enterprise collaborations. Obligations may be time-sensitive and differ structurally. A client-to-supplier relationship would be diagonal, whereas an internally sourced project could be hierarchical. Once the project terminates, the obligation could become horizontal since all project agreements will have ceased. Thus, obligations are context and time-sensitive.

Consequences

A forum can impose formal or informal sanctions on an actor as a consequence of an infringement (Bovens, 2007). In general, formal consequences, such as fines or loss of profits identified in the algorithm or stakeholder literature, are in response to non-compliance with regulations and laws, infringements of intellectual property, and contractual disputes. Some consequences are situation-specific and too complicated to be generalized independent of the obligation. Thus, we added a code for context specificity.

Relationships

We use the mental accountability model from McGrath and Whitty (2018) to map actors and forums to success categories, groups, and factors. The accountable actor is liable for ensuring that the task is satisfactorily done or has approval responsibility toward a given forum. This method is consistent with viewing accountabilities as virtues that focus on the output product of the actors' behavior and the factors that induce accountable behavior (Brandsma, 2014).

We further consider the skill and knowledge required for an approver to carry out their responsibilities. As Martin (2019) argued, developers are uniquely positioned to understand the implications of the algorithms they create. However, the firms by whom they are employed are the actors who decide to sell the algorithms or put them into operation.

We assign accountability to the lowest hierarchical level where the appropriate knowledge resides and to the collectives to which the individuals belong. This decision was significant in framing the role of the project manager in the accountability landscape.

3.5. Quantitative analysis

SAS Studio Release 3.8 (Enterprise Edition) was used to perform statistical tests and checks. We performed quantitative checks for missing data and extreme responses (the same response for all questions), normality, homoscedasticity, and multicollinearity. There were no missing values or extreme responses, and the data met normality, homoscedasticity, and multicollinearity assumptions. The paired *t*-test was then used to compare the German and US means; the *t*-test was selected as it is relevant for comparing independent samples. The results are reported as Satterwaite statistic (*t*-value) for unequal variances, degrees of freedom (*df*), and probability (ρ). For any probability of less than 0.05, we reject the null hypothesis and determine that the means are significantly different (Hair et al., 2014).

The descriptive statistics, Pearson correlation coefficients, and *t*-test results are shown in in Tables A.3, A.4, and A.5 in the Appendix, respectively.

3.6. Validity and reliability

First, we ensured internal consistency by using theoretical models to conduct the literature search and produce the model. Second, we established the external validity by using the literature as a secondary source. Existing constructs were used where available, and variances in usage were explained. Deviations from the existing literature are documented in a manner that includes justifications for challenging the results. For the survey analysis, statistical checks ensured the validity and reliability of the data and the analysis.

4. Findings

4.1. AI stakeholder-accountability model

Table 2 presents the consolidated results and represents the AI stakeholder-accountability model. It was constructed based on a review of the 67 articles identified; 31 articles provided the descriptive information used to define accountability relationships. The table elaborates on the specifications from Bovens' accountability model as shown in our theoretical framework in Figure 2. The actors and forums are responsible for a collective of multiple individual and organizational roles as specified in Table A.1 in the Appendix. The actors are answerable to the forums for their conduct. The conduct is defined by success groups, which roll up to success categories and down to success factors. The type of forum determines the nature of the relationship. The structure defines the obligations in the relationship and its consequences. The relationship between an actor and a forum is defined by success factors, obligations, and consequences. The research mapped 16 actors to 22 forums using 78 success factors as conduct and identified the obligations and consequences of the relationship.

A supplemental table is available to expand on the summary details provided in Table 2.

Table 2. AI stakeholder-accountabilities model

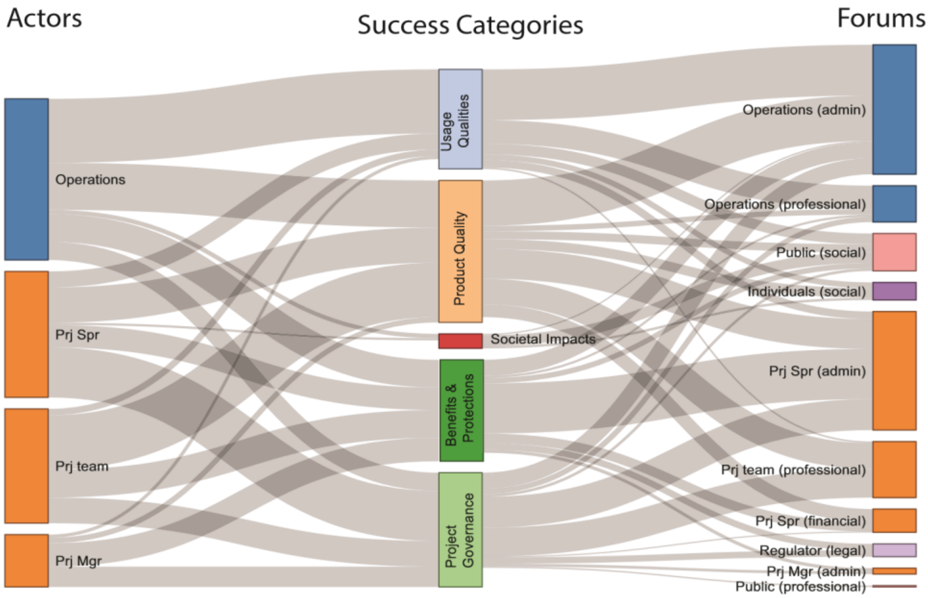
Actor	Forum & Type	Structure	Success Groups(s)
Operations	Individuals (social)	$D^{-}C$	DQ, IV, PP
		$H^{-}C$	DQ, PP
	Operations (admin)	$D^{-}F$	EP, FP, UC
		$V^{-}F$	DQ, EP, LP, PP, SC, UC
	Operations (professional)	$V^{-}F$	DQ, EP, FP, PP, STU, UC
	Prj Spr (admin)	$D^{-}F$	FB
	Public (professional)	$H^{-}C$	EP, IN
	Public (social)	$H^{-}C$	DQ, DS, FB, IN, IV, LP, MA, STU, SY, UI
	Regulator (legal)	$V^{-}F$	EP, LP
Prj Mgr	Prj Spr (admin)	$V^{-}F$	EP, FP, LP, PM, PP, SC, STU
	Prj team (professional)	$V^{-}F$	PM, TD
Prj Spr	Individuals (social)	$D^{-}C$	PP
	Operations (admin)	$D^{-}F$	DS, EP, IN, LP, MA, PM, STU, SY, TD, UC, UI
	Prj Mgr (admin)	$V^{-}F$	EP, FB, PM
	Prj Spr (admin)	$D^{-}F$	FB
	Prj Spr (financial)	$D^{-}F$	DS, FB, FP, IN, LP, MA, SC, TD, UI
	Prj team (professional)	$V^{-}F$	DS, EP, IN, PP
	Public (professional)	$H^{-}C$	EP
	Public (social)	$H^{-}C$	FP, IN, SY, TD, UI
	Regulator (legal)	$V^{-}F$	EP, LP, PM
Prj team	Prj Mgr (admin)	$V^{-}F$	FP
	Prj Spr (admin)	$V^{-}F$	EP, IN, LP, PM, PP, SC, STU, UC, UI
	Prj team (professional)	$V^{-}F$	DS, MA, PM, SC, TD, UC, UI

Notes: Structure is combined obligation (D – Diagonal, V – Vertical, H – Horizontal) and consequence (I – Informal, F – Formal, C – Context specific); Success Group(s): PM – Project Management, EP – Ethical Practices, IN – Investigation, DS – Source Data Qualities, TD – Training Data Qualities, MA – Model & Algorithm Qualities, UI – User Interface Qualities, SC – System Configuration, PP – Data & Privacy Protections, STU – System Transparency & Understandability, UC – Usage Controls, DQ – Decision Quality, FB – Financial Benefits, FP – Financial Protections, LP – Legal Protections, IV – Individual Protections, SY – Sustainability.

Source: Author's own elaboration.

Figure 4 provides a flow diagram tracing AI stakeholder accountabilities from actors through success categories to forums; the extent of the flow is determined by counting the number of relationships by success factors. It visualizes the relationship between actors, success, and forums. For example, it highlights that operations and project sponsors are the two actors accountable for the societal impacts success category; accountability for usage qualities, product quality, benefits and protections, and product governance is shared by all actors.

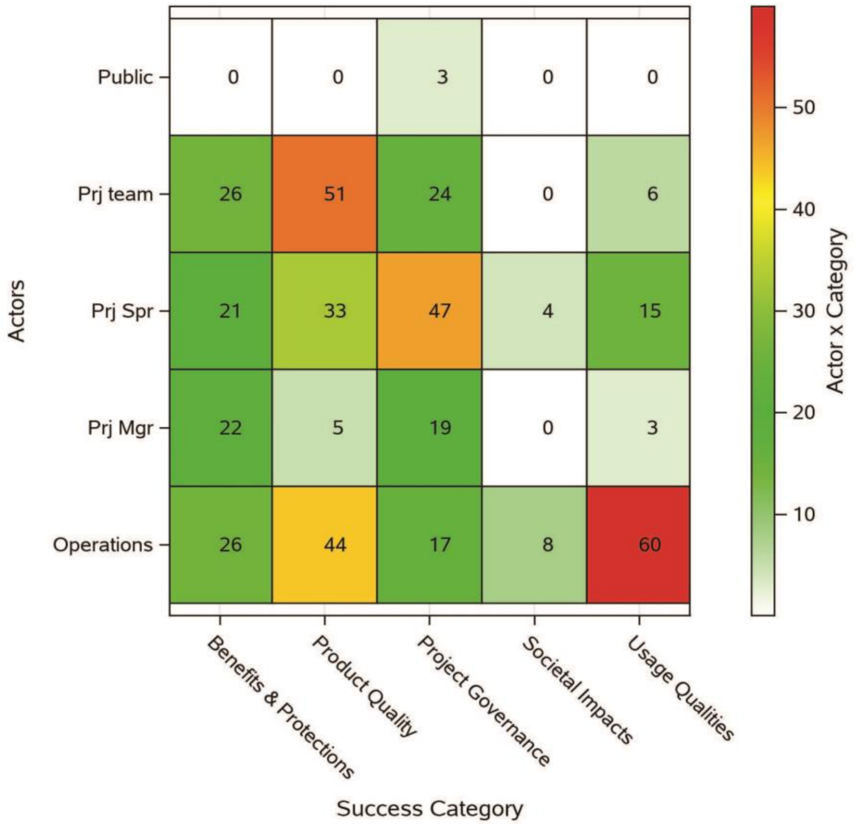
Figure 4. Sankey flow from actors through success categories to forums



Source: Author's own elaboration.

Figure 5 is a heatmap that visualizes and quantifies the relationships between actors and the success categories. The vertical axis represents the actors, the horizontal axis the success categories, and the squares indicate the actor's level of obligation for that success category by color and frequency. For example, public actors, specifically evaluators, can perform audits or certifications and deliver audit-finding records and certifications to the public or the operator. In summary, the operational actors were responsible for 67% of societal impacts, and the project sponsors the remaining 33%. Benefits and protections were evenly distributed at around 25% for each of the operations, the project manager, sponsor, and team actors. Responsibility for product quality was allocated between operations, the project sponsor, and the project team (a third each); operations bear the most accountability for operational qualities at 72%.

Figure 5. Heatmap of actors by success category

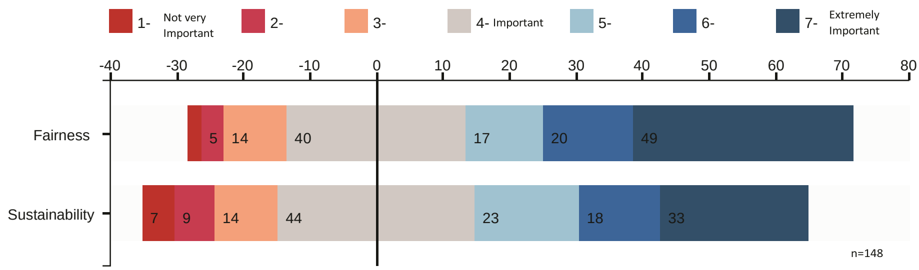


Source: Author's own elaboration.

4.2. Survey results

The survey assessed the public view on accountability and the importance of fair and sustainable algorithm development and usage. The opinion of survey respondents is measured by rank position for the accountability roles and the scale of the fairness and sustainability variables. In the 2022 survey, most survey respondents reported it was important that algorithms are fair and understandable (85%) and developed in a sustainable way (80%), as shown in Figure 6. In the comparison between Germany and the US, fairness (t = –5.19, ρ < .0001) and sustainability (t = –5.00, ρ < .0001) were significantly higher for the US. The statistics are shown in Table A.5 in the Appendix.

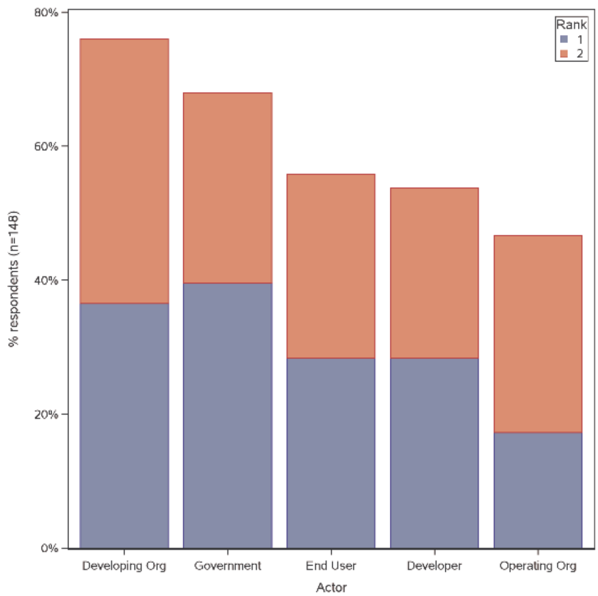
Figure 6. Public opinion on fairness and sustainability



Source: Author's own elaboration.

In terms of accountability, the ranking for the first position was the government (26%), development organizations (24%), individual developers (19%), end-users (19%), and operating organizations (11%). In the comparison, in Germany, the development organization was ranked in a higher position than in the US (t = 2.91, ρ = .0046) and the end-user was ranked higher for the US (t = –3.09, ρ = .0026). However, in comparing the combined first- and second-ranked positions, the developing organization moves to the first one, as shown in Figure 7. Nevertheless, in the combined comparison, there was no statistically significant difference between government and developer organizations or between Germany and the US regarding accountability.

Figure 7. Public opinion on who is accountable for AI impacts



Source: Author's own elaboration.

5. Discussion

The findings, based on an extensive literature review, highlight the relationships of accountability between the stakeholders of AI projects. The forums are the internal, governance, and external stakeholders that should hold the project actors to account. We establish the relationships between the project actors and the stakeholders using project success factors to address our research question: *What project actors should be held to account for stakeholders' expectations in AI projects and the impacts of AI systems?* We used a survey to understand public opinion on algorithm accountability.

5.1. Actor accountability conduct

There are both expected and unexpected patterns of accountability represented in the various tables and figures. Unsurprisingly, the operator is responsible for usage quality and the project team for product quality. However, the project sponsor and operator also bear significant responsibility for product quality. Furthermore, the project sponsor plays an important role in ensuring the usage qualities. The ethics literature emphasizes that the developer is responsible for ethical development; however, the operator's role is not frequently discussed. Thus, the study results bring some clarity to the issue of which actors share responsibility for ethical systems development (Manders-Huits, 2006; Wieringa, 2020).

The developing organization sponsors the project, establishes the project scope, and provides funding, strategic direction, and operational guidance. The organization's strategic goals are imposed on the project, and policies flow down from the organization to the project level (Derakhshan et al., 2019; Müller et al., 2014). The accountability model reflects this in focusing accountability on the project sponsor as the corporate agent.

The project manager is responsible for the project's outputs according to the scope of work agreed on with the project sponsor (Turner & Zolin, 2012; Zwikael & Meredith, 2018). The model shows that the project manager is responsible for record-keeping and managing the expectations and engagement of relevant stakeholders. The project manager is seen as able to manage the approval process but not as the party responsible for approval itself (Rezania et al., 2019). Thus, the project manager has far fewer responsibilities than anticipated.

The members of the project team are decision-makers and designers who directly influence the models, data, and trustworthiness of the system. The project team composition is context specific and determined by the scope of the project. The team may include members with various specializations depending on the type of technology, industry, and business function involved. In addition to responsibilities for product quality, the team is accountable for activities that secure the legal and financial benefits expected of the project sponsor. There is limited overlap between these responsibilities and the usage qualities; they are accountable for some quality controls, providing interpretable models, and supporting knowledge transfer with stakeholder-centric communications and onboarding procedures. Specifically, the team is responsible for avoiding the "black box AI problem;" that is, they must avoid building systems where even they do not understand how the model makes its inferences (Sambasivan et al., 2021).

The operating organization is the purchaser or consumer, including the end users and decision makers; the organization may have expectations and notions of success different from those of the end users. The organization is responsible for providing usage policies and practices, monitoring the systems and staff, and engaging with the end-users and decision subjects. System and staff monitoring assures that the system decision process has not become ineffective (Green & Chen, 2019). In addition to operations, the operators perform due diligence to ensure the system's appropriateness and quality. This accountability is reflected in their accountability for governance and product quality.

Figure 5 helps in visualizing several gaps in accountability. For example, the project team and project manager are not accountable for the post-project societal impacts. The project decisions on sustainability are considered in the benefits and protections success group; the project team shares some accountability there.

5.2. Accountability relationships

The accountability relationship is defined by the obligations the actors have to the forums and the consequences they face as a result of their conduct. The research highlights the bureaucratic nature of accountability in AI projects. We refer to the distinctions between responsibility and accountability in McGrath and Whitty (2018). Responsibility for ensuring that a task is satisfactorily completed is accountability that cannot be delegated. There are challenges and nuances of how and for what the project is accountable. Wieringa (2020) referred to the various actors as a problem of "many hands" and the forums as a problem of "many eyes." That is, for a given success category or group, there is a chain of actors involved and no guarantee that the responsible individual will be held accountable for the impacts of AI on external stakeholders. Accountability changes over time. Finally, the tensions between project success, ethics, internal controls, and compliance further complicate the issue of ensuring accountability (Müller et al., 2014; Scoleze Ferrer Paulo et al., 2020).

An illustrative example using the model in Table 2 is useful for exploring the complexities of these issues. AI systems may negatively affect individuals or the public based on product quality or use. The operating organization (actor) is accountable for many of the impacts on individuals (forum) and the public (forum), specifically decision quality (DQ) and privacy protections (PP). Meanwhile, the professional end users (forum) in the operations (actor) require system transparency and understandability (STU) in support of DQ. STU includes ensuring end-users have the specialized skill and knowledge to understand and use the system, providing avenues for problem reporting, and access to redress for incorrect decisions. However, features related to the quality of the system are development and design decisions; project team (actor) members are the parties that make these decisions. In this case, the project team is responsible for ensuring that the user interface (UI), model algorithm (MA), training data (TD), and system configuration (SC) have certain qualities, e.g., transparent, accurate, consistent, and interpretable models.

The operators (forum) may hold the project sponsors (actor) to account based on a contractual relationship (diagonal obligation) with formal consequences (loss of revenue, warranty costs). However, the project sponsor (forum) and project team (actor) relationship are context-specific and time-dependent. If the project has terminated, the team members may no longer be available. This process chain means the responsible persons may or may not be held accountable for impacts on the individuals (e.g., decision subjects) who have a relationship with the operators.

Of course, the mitigation of the AI system's risks is also shown in other aspects of the model. Operators and project sponsors may require (and project managers can coordinate) investigations (IN), for example, model risk assessments, impact assessments, and algorithm audit before handover to operations. Thus, individual actors could immediately be held responsible for risk assessment results. At this stage, opaque, non-interpretative, or other black box designs could be challenged.

An alternative structure for accountability could be to make individuals legally and professionally accountable for their work, as proposed by Mittelstadt (2019), who suggested licensing developers of AI systems. In the AI stakeholder-accountability model, such an approach would add vertical accountability with formal consequences from the project team to the operating organization or the decision subjects. The issue of accountability expiring after project termination could be addressed with this change.

Some industries are regulated, and some professionals are licensed, or both. Financial fines may be imposed for breaches in accountability. For example, the AI systems used in health care must comply with certain regulations. The users, potentially doctors and nurses, are licensed professionals. The argument in Mittelstadt (2019) suggested a similar model for high-risk AI systems.

The survey results also indicated that the public expects to hold the development organization and the government responsible for algorithmic fairness and understandability. This suggests that development organizations should insist on a rigorous accountability process in the development stage. These findings are consistent with other studies and proposed AI regulations. First, Kieslich et al. (2022) found empirical evidence in the German population that accountability is the most important ethical principle compared to explainability, fairness, security, accuracy, privacy, and machine autonomy. The German public expects a responsible party for AI development. Legal regulations are seen as effective countermeasures against discriminatory AI systems, and they are a way to enhance trust and acceptance of AI.

Next, the survey results are consistent with the proposed EU Artificial Intelligence Act that requires a risk assessment before operationalizing high-risk AI systems. However, even low-risk systems can be harmful, and AI systems are inappropriate for some business processes. For example, Stapleton et al. (2022) described several situations where AI systems harm families when used by the Child Protective Services organization in managing family situations; addressing such harms requires changes to the business models and low or nontechnical solutions. Neumann et al. (2022) identified misinformation as causing harm related to addictive habits, health care, democracy, climate change, and humanitarian crises. Thus, as presented in this study, the operational organization should not be left out of efforts to avoid or mitigate system harm.

The survey identified some cultural differences between the US and Germany in the perception of accountability. In the US, end users are held more accountable than the developing organization, and the opposite is the case for Germany. This difference is also reflected in views on regulations. The EU's AI regulation requires risk assessment before the operation of high-risk AI systems. The right to challenge algorithm decisions is embedded in the EU GDPR, which incorporates punitive penalties (European Commission, 2016, 2021). Currently, the US national legislative actions on AI are investigative, not punitive (116th Congress (2019-2020), 2020).

"AI systems *do* have agency, which – when unrecognized and unchecked – enables them to inform, guide, and steer human judgment in decision-making" (Moser et al., 2022, p. 150). Thus, the development organization is responsible for ensuring that the development process does not create a moral buffer where no one is accountable for the impacts of system usage on individuals and society (Moser et al., 2022; Singh et al., 2019). That is, the situation must be avoided in which neither the project team who develops the system nor the human decision-makers who use the system take responsibility for the social impact. The operating organization is the actor most able to decide on system use. Consequently, the accountability models show that the operating organization should be the most accountable to the public and society.

5.3. Practical implications

The AI stakeholder-accountability model could be useful as part of the project planning process for team assignment and stakeholder engagement. A project sponsor and manager could use the following steps in a planning exercise: 1) establish the goal for the project (scope definition document); 2) identify the stakeholders who could be harmed by or benefit from the system during its development or use, even months or years after the project has been completed (stakeholder identification); 3) identify the project deliverables, acts, or situations necessary to avoid harm or ensure the benefits from the development and usage of the system (success factors); 4) determine to whom the project owners or operators must answer should the system cause harm or damage (forums); 5) assign project responsibility, accountability, and risk mitigation activities accordingly (actors). For a generic AI project, the present model uses Miller (2022a) as a baseline to accomplish steps 2 through 5. Project managers and sponsors could adapt this conceptual model to project-specific situations.

The project manager and the project owner must consider governance processes that include operators and public advocacy groups. The model expands on AI usage that may occur after the project is completed. In this situation, the accountability shifts from the temporary project organization to one or more operational entities. Thus, project managers may have limited influence on future usage and operational processes. Nevertheless, those responsible for documentation, training, and awareness should strongly consider sharing resources, providing knowledge transfer and operational guidance, and establishing algorithm renewal processes (Jacobsson & Hällgren, 2016; Prado & Sapsed, 2016).

Not every aspect of the AI project is regulated, but many aspects of use are. Failure to address regulatory concerns can accrue financial, legal, and reputation costs to firms. Thus, the model provides some support in mitigating operational risks. The model also identifies gaps in accountability to society and individuals for algorithm development. Policy advisors should consider methods to create transparency in algorithm decision-making. This is especially the case when the project, operation, and technology platform organizations belong to the same legal structure.

Finally, the study provides some insights that firms can use to update their corporate governance practices and avoid potential ethical issues in AI projects. Müller et al. (2014) identified seven corporate governance practices that need strict and control-oriented governance at the corporate level to avoid ethical issues in temporary organizations. This study proposes additional practices that would be relevant to preventing temporary organizations from creating ethical or moral issues for the firm. They include:

– providing policies for acceptance of algorithm architecture decisions,
– creating procedures for algorithm transparency,
– establishing project teams' access to information on the definition and meaning of moral decision-making and the applicable laws and regulations, and
– establishing an ethical function that includes policies, training, and an ombudsman or a whistle-blower process for project team members to voice their concerns.

5.4. Theoretical implications

While stakeholder theory recognizes the power of stakeholders over the project, accountability theory recognizes the obligation of project actors to stakeholder forums. For example, external stakeholders such as investigative reporters and advocates have coercive power over the project and thus influence its direction. Conversely, accountability theory identifies which forum should hold the project to account and what the consequences are when there is a deficit. Thus, the stakeholder and accountability theories address opposite sides of the same coin: the impact stakeholders may have on the project, the responsibility of project actors to stakeholders, and the potential consequences of inaction. The AI stakeholder-accountability model is an example of applying the management-of-stakeholders and the management-for-stakeholders approaches. This is consistent with the assertion by Eskerod and Huemann (2013) that sustainable development requires that both be integrated into project stakeholder management.

The study builds on Wieringa's use of Bovens' accountability theory to define project success within AI. It applies the model for an industry-neutral but project-specific perspective. It answers the call to "concretely specify the actors, their role, level, and the part of the system for which they are responsible"

(Wieringa, 2020, p. 10). The research expands on the existing literature on the treatment of external stakeholders, adding to the project stakeholder and success literature. Thus, the research addresses multiple gaps in investigating different types of stakeholder relationships, as identified by Derakhshan et al. (2019).

6. Conclusions

This research presents a conceptual model of AI stakeholder accountability in projects. The model identifies the relationship between the actors and the forums to which they are accountable. It accounts for the different types of actors and forums and the accountabilities between parties. It sets out the deliverables, acts, or situations – success factors – necessary to avoid harm or ensure the benefits of an algorithm developed in projects. AI projects are complicated undertakings with many project actors and stakeholders.

The model confirms that members of the project team are moral agents; they make decisions that may benefit or harm others. However, it shows that the project team is not limited to the model developer; it also includes highly relevant actors in the developer and operating organizations. First and foremost, the scope established by the project sponsor is an essential artifact in designing AI systems. Arguably the operating organization, including the end users, is most accountable to the public. This gives them some power to influence the system's development. The public loses the power of influence when a single firm finances, develops, and operates the algorithmic system.

6.1. Limitations

Projects, and especially AI projects, are context-sensitive. The model presented is generic; adjusting and validating it in specific contexts is important. This research was based on a review of the secondary literature. Other methods, such as case studies, could extend and update the study and validate the findings. Furthermore, the results may be biased by the researcher's perspective.

The model in the present study is conceptual and has not been validated using real-world projects. Other methods, such as a survey instrument or a Delphi study with field experts, could be conducted to extend the study and validate the findings.

6.2. Future research

An additional opportunity for further research and expansion is to identify measurable criteria for some of the individual actors. There is significant discussion in the AI literature regarding ways to measure bias, inequality, and accuracy; specialists continue to consider these issues. However, from a project perspective, it would be interesting to understand how to evaluate the trade-offs needed during the projects and still meet all stakeholder requirements.

The model provides some additional options for investigating accountability using other theories, such as those focused on the economics of transaction costs and resource-based theories. The AI stakeholder-accountability model could be used to analyze the transaction costs for collaboration between the project and external stakeholders in alternative governance models. Similarly, using resource theory, the model could be used to assess and challenge the value source in AI projects.

An additional quantitative analysis could be conducted to compare the public views in different geographical regions on algorithm accountability. This is a particularly promising area of research, given the different regulatory approaches and social practices already identified between the US and Europe.

Disclosure statement

No potential conflict of interest was reported by the author.

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Supplement

The supplemental tables are provided after the references.

Appendices

Table A.1. Stakeholder classification as actors and forums

Stakeholder	Actor Type	Forum Nature	Collective	Corporate
Prj owner	individual	admin	Prj Spr	Dev org
Prj funder	individual	financial	Prj Spr	Dev org
Prj / Prog mgrs	individual	admin	Prj Mgr	Dev org
Prj team	collective	professional	Prj team	Dev org
Data scientist	individual	professional	Prj team	Dev org
Data engineer	individual	professional	Prj team	Dev org
Architects	individual	professional	Prj team	Dev org
Software dev	individual	professional	Prj team	Dev org
Business users	individual	professional	Prj team	Dev org
Data analyst	individual	professional	Prj team	Dev org
Operate org	corporate	admin	Operations	Operate org
Platform owners	corporate	admin	Operations	Operate org
End users	individual	professional	Operations	Operate org
Model mtn	individual	professional	Operations	Operate org
Data custodian	individual	professional	Operations	Operate org
Decision subj	individual	social	Individuals	Public
Data subj	individual	social	Individuals	Public
Public	collective	social	Public	Public
Advocates	collective	social	Public	Public
Local community	collective	social	Public	Public
Regulators	collective	legal	Regulator	Public
Evaluators	collective	professional	Public	Public

Legend: Dev – Developer, Indv – Individuals, Mgr – Manager, Mtn – Maintainer, Prj – Project, Prog – Program, Ops – Operations, Org – Organization, Spr – Sponsor, Subj – Subject.

Source: Adapted from Miller (2022b).

Table A.2. Success groups and categories

Success Categories		Success Groups	
Code	Category	Code	Group
PG	Project Governance	PM	Project Management
		EP	Ethical Practices
		IN	Investigation
PQ	Product Quality	DS	Source Data Qualities
		TD	Training Data Qualities
		MA	Model & Algorithm Qualities
		UI	User Interface Qualities
		SC	System Configuration
		PP	Data & Privacy Protections
UQ	Usage Qualities	STU	System Transparency & Understandability
		UC	Usage Controls
		DQ	Decision Quality
BP	Benefits & Protections	FB	Financial Benefits
		FP	Financial Protections
		LP	Legal Protections
SI	Societal Impacts	IV	Individual Protections
		SY	Sustainability

Source: Miller (2022a).

Table A.3. Descriptive statistics by survey group

Demographic	N	Variable	Mean	SD
2022 – US	98	Developer	2.95	1.33
		Dev Org	2.51	1.34
		Government	2.93	1.53
		End User	3.47	1.47
		Ops Org	3.14	1.24
		Fairness	4.70	1.34
		Sustainability	4.27	1.50
2022 – Germany	50	Developer	2.96	1.29
		Dev Org	3.24	1.49
		Government	2.74	1.43
		End User	2.70	1.42
		Ops Org	3.36	1.38
		Fairness	3.52	1.30
		Sustainability	3.22	1.02

Legend: Dev – Developer, N – Number observations, Ops – Operations, Org – Organization, SD – Standard deviation.

Source: Author' own elaboration.

Table A.4. Pearson correlation coefficients (N = 148)

	Dev	Gov	Ops Org	End User	Dev Org	Fairness
Developer						
Government	–0.22**					
User Org	–0.32***	–0.21**				
End User	–0.29***	–0.28***	–0.17*			
Dev Org	–0.10	–0.36***	–0.20*	–0.34***		
Fairness	–0.11	0.04	0.02	0.18*	–0.15	
Sustainability	–0.04	0.10	−0.00	0.02	–0.09	0.60***

Significance: *** p < .0001, ** p < .01, * p < .05.

Legend: Dev – Developer, Gov – Government, Ops – Operations, Org – Organization.

Source: Author's own elaboration.

Table A.5. Two sample *t*-test and statistics (N = 148)

Variable	Satterthwaite			United States		Germany	
	df	*t*-value	P	Mean	SE	Mean	SE
Developer	101.58	0.05	0.9614	2.95	0.13	2.96	0.18
Dev Org	89.99	2.91	0.0046	2.51	0.14	3.24	0.21
End User	101.73	–3.09	0.0026	3.47	0.15	2.70	0.20
Ops Org	89.594	0.94	0.3514	3.14	0.12	3.36	0.20
Government	105.44	–0.74	0.4601	2.93	0.16	2.74	0.20
Fairness	101.71	–5.19	0.0000	4.70	0.14	3.52	0.18
Sustainability	134.68	–5.00	0.0000	4.27	0.15	3.22	0.14

Legend: Dev – Developer, Gov – Government, Ops – Operations, Org – Organization; df – degrees of freedom, t-value – Satterthwaite unequal variance, P – Significance, SE – Standard error.

Source: Author's own elaboration.

References

116th Congress (2019-2020). (2020). National Artificial Intelligence Initiative Act of 2020 (H.R. 6216). https://www.congress.gov/bill/116th-congress/house-bill/6216/all-actions

Aggarwal, J., & Kumar, S. (2018). A survey on artificial intelligence. *International Journal of Research in Engineering, Science and Management, 1*(12), 244-245. https://doi.org/10.31224/osf.io/47a85

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In *FAccT 2021: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610-623). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445922

Bonsón, E., Lavorato, D., Lamboglia, R., & Mancini, D. (2021). Artificial intelligence activities and ethical approaches in leading listed companies in the European Union. *International Journal of Accounting Information Systems, 43*, 100535. https://doi.org/10.1016/j.accinf.2021.100535

Bovens, M. (2007). Analysing and assessing accountability: A conceptual framework. *European Law Journal, 13*(4), 447-468. https://doi.org/10.1111/j.1468-0386.2007.00378.x

Bovens, M., Schillemans, T., & Hart, P. T. (2008). Does public accountability work? An assessment tool. *Public Administration, 86*(1), 225-242. https://doi.org/10.1111/j.1467-9299.2008.00716.x

Boyer, M., & Veigl, S. (2015, July 15-17). *Privacy preserving video surveillance infrastructure with particular regard to modular video analytics*. 6th International Conference on Imaging for Crime Prevention and Detection (ICDP-15), Queen Mary University, London, UK. https://doi.org/10.1049/ic.2015.0120

Brandsma, G. J. (2014). Quantitative analysis. In M. Bovens, R. E. Goodin, & T. Schillemans (Eds.), *The Oxford handbook of public accountability* (pp. 143-158). Oxford University Press, https://books.google.pl/books?hl=th&lr=&id=pip8AwAAQBAJ&oi=fnd&pg=PA143&ots=ksisAB5c4P&sig=keACNkGzRMWSOIvEL6DChCcuILI&redir_esc=y#v=onepage&q&f=false

Büchi, M., Fosch-Villaronga, E., Lutz, C., Tamò-Larrieux, A., Velidi, S., & Viljoen, S. (2020). The chilling effects of algorithmic profiling: Mapping the issues. *Computer Law & Security Review, 36*, 1-15. https://doi.org/10.1016/j.clsr.2019.105367

Chasalow, K., & Levy, K. (2021, March 3-10). Representativeness in statistics, politics, and machine learning. In *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, Virtual Event* (pp. 77-89). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445872

Cobbe, J., Lee, M. S. A., & Singh, J. (2021). Reviewable automated decision-making: A framework for accountable algorithmic systems. In *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 598-609). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445921

Cohen, I. G., Amarasingham, R., Shah, A., Xie, B., & Lo, B. (2014). The legal and ethical concerns that arise from using complex predictive analytics in health care. *Health Affairs, 33*(7), 1139-1147. https://doi.org/10.1377/hlthaff.2014.0048

Davis, K. (2017). An empirical investigation into different stakeholder groups perception of project success. *International Journal of Project Management, 35*(4), 604-617. https://doi.org/10.1016/j.ijproman.2017.02.004

Derakhshan, R., Turner, R., & Mancini, M. (2019). Project governance and stakeholders: A literature review. *International Journal of Project Management, 37*(1), 98-116. https://doi.org/10.1016/j.ijproman.2018.10.007

Derry, R. (2012). Reclaiming marginalized stakeholders. *Journal of Business Ethics, 111*(2), 253-264. https://doi.org/10.1007/s10551-012-1205-x

Drouin, N., Müller, R., & Sankaran, S. (Eds.). (2013). *Novel approaches to organizational project management research: Translational and transformational* (Advances in Organization Studies). Copenhagen Business School Press.

Eskerod, P., & Huemann, M. (2013). Sustainable development and project stakeholder management: What standards say. *International Journal of Managing Projects in Business, 6*(1), 36-50. https://doi.org/10.1108/17538371311291017

Eslami, M., Vaccaro, K., Lee, M. K., On, A. E. B., Gilbert, E., & Karahalios, K. (2019). User attitudes towards algorithmic opacity and transparency in online reviewing platforms. In *CHI 2019: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Paper No. 494; pp. 1-14). Association for Computing Machinery. https://doi.org/10.1145/3290605.3300724

European Commission. (2016). *General Data Protection Regulation*. http://data.europa.eu/eli/reg/2016/679/2016-05-04

European Commission. (2021). *Proposal for a Regulation laying down harmonised rules on artificial intelligence*. Artificial Intelligence Act. https://digital-strategy.ec.europa.eu/en/library/proposal-regulation-laying-down-harmonised-rules-artificial-intelligence

Fazelpour, S., & Lipton, Z. C. (2020, February 7-8). Algorithmic fairness from a non-ideal perspective. In *AIES '20: Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 57-63). Association for Computing Machinery. https://doi.org/10.1145/3375627.3375828

Foster, A. T. (1988). Artificial intelligence in project management. *Cost Engineering, 30*(6), 21-24, https://www.proquest.com/docview/220438981?parentSessionId=I8SQEhpH7AcGNcfFU8HssXBnBvL7Xpi51WHxR3MtqCA%3D

Freeman, R. E., & McVea, J. (2001). *A stakeholder approach to strategic management* (Working Paper, No. 01-02). Darden Graduate School of Business Administration, University of Virginia. https://doi.org/10.2139/ssrn.263511

Fridgeirsson, T. V., Ingason, H. T., Jonasson, H. I., & Jonsdottir, H. (2021). An authoritative study on the near future effect of artificial intelligence on project management knowledge areas. *Sustainability, 13*(4), 2345. https://doi.org/10.3390/su13042345

Green, B., & Chen, Y. (2019). Disparate interactions: An algorithm-in-the-loop analysis of fairness in risk assessments. In *FAT* '19: Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 90-99). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287563

Hair, J. F. J., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.). Pearson College Division.

Ika, L. A. (2009). Project success as a topic in project management journals. *Project Management Journal, 40*(4), 6-19. https://doi.org/10.1002/pmj.20137

Iqbal, R., Doctor, F., More, B., Mahmud, S., & Yousuf, U. (2017). Big data analytics and computational intelligence for cyber-physical systems: Recent trends and state of the art applications. *Future Generation Computer Systems, 105*, 766-778. https://doi.org/10.1016/j.future.2017.10.021

Jacobsson, M., & Hällgren, M. (2016). Impromptu teams in a temporary organization: On their nature and role. *International Journal of Project Management, 34*(4), 584-596. https://doi.org/10.1016/j.ijproman.2016.02.001

Jones, T. M. (1991). Ethical decision making by individuals in organizations: An issue-contingent model. *Academy of Management Review, 16*(2), 366-395. https://doi.org/10.5465/amr.1991.4278958

Kasinidou, M., Kleanthous, S., Barlas, P., & Otterbacher, J. (2021). I agree with the decision, but they didn't deserve this: Future developers' perception of fairness in algorithmic decisions. In *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 690-700). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445931

Kasy, M., & Abebe, R. (2021). Fairness, equality, and power in algorithmic decision-making. In *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 576-586). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445919

Kieslich, K., Keller, B., & Starke, C. (2022). Artificial intelligence ethics by design. Evaluating public perception on the importance of ethical design principles of artificial intelligence. *Big Data & Society, 9*(1). https://doi.org/10.1177/20539517221092956

Di Maddaloni, F., & Davis, K. (2018). Project manager's perception of the local communities' stakeholder in megaprojects. An empirical investigation in the UK. *International Journal of Project Management, 36*(3), 542-565. https://doi.org/10.1016/j.ijproman.2017.11.003

Manders-Huits, N. (2006). Moral responsibility and IT for human enhancement. In *SAC 2006: Proceedings of the 2006 ACM Symposium on Applied Computing* (Vol. 1, pp. 267-271). Association for Computing Machinery. https://doi.org/10.1145/1141277.1141340

Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics, 160*(4), 835-850. https://doi.org/10.1007/s10551-018-3921-3

McGrath, S. K., & Whitty, S. J. (2018). Accountability and responsibility defined. *International Journal of Managing Projects in Business, 11*(3), 687-707. https://doi.org/10.1108/IJMPB-06-2017-0058

Miao, Z. (2018). Investigation on human rights ethics in artificial intelligence researches with library literature analysis method. *The Electronic Library, 37*(5), 914-926. https://doi.org/10.1108/EL-04-2019-0089

Michalczyk, S., Nadj, M., Mädche, A., & Gröger, C. (2021, June 14-16). *Demystifying job roles in data science: A text mining approach*. Twenty-Ninth European Conference on Information Systems (ECIS 2021), Marrakesh, Morocco|A Virtual AIS Conference, 1622. https://aisel.aisnet.org/ecis2021_rp/115/

Miller, G. J. (2022a). Artificial intelligence project success factors – beyond the ethical principles. In E. Ziemba & W. Chmielarz (Eds.), *FedCSIS-AIST 2021/ISM 2021: Information technology for management: Business and social issues.* (Lecture Notes in Business Information Processing; Vol. 442; pp. 65-96). Springer International Publishing. https://doi.org/10.1007/978-3-030-98997-2_4

Miller, G. J. (2022b). Stakeholder roles in artificial intelligence projects. *Project Leadership and Society, 3*, 100068. https://doi.org/10.1016/j.plas.2022.100068

Mitchell, R. K., Agle, B. R., & Wood, D. J. (1997). Toward a theory of stakeholder identification and salience: Defining the principle of who and what really counts. *Academy of Management Review, 22*(4), 853-886. https://doi.org/10.5465/amr.1997.9711022105

Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence, 1*(11), 501-507. https://doi.org/10.1038/s42256-019-0114-4

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & The PRISMA Group (2010). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *International Journal of Surgery, 8*(5), 336-341. https://doi.org/10.1016/j.ijsu.2010.02.007

Moser, C., den Hond, F., & Lindebaum, D. (2022). Morality in the age of artificially intelligent algorithms. *Academy of Management Learning & Education, 21*(1), 139-155. https://doi.org/10.5465/amle.2020.0287

Müller, R., Turner, R., Andersen, E. S., Shao, J., & Kvalnes, Ø. (2014). Ethics, trust, and governance in temporary organizations. *Project Management Journal, 45*(4), 39-54. https://doi.org/10.1002/pmj.21432

Müller, R., Turner, R. J., Andersen, E. S., Shao, J., & Kvalnes, Ø. (2016). Governance and ethics in temporary organizations: The mediating role of corporate governance. *Project Management Journal, 47*(6), 7-23. https://eprints.whiterose.ac.uk/161389/

Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. *Journal of Business Ethics, 167*(2), 209-234. https://doi.org/10.1007/s10551-019-04407-1

Nemati, H. R., Todd, D. W., & Brown, P. D. (2002). A hybrid intelligent system to facilitate information system project management activities. *Project Management Journal, 33*(3), 42-52. https://doi.org/10.1177/875697280203300306

Neumann, T., De-Arteaga, M., & Fazelpour, S. (2022). Justice in misinformation detection systems: An analysis of algorithms, stakeholders, and potential harms. In *FAccT '22: 2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1504-1515). Association for Computing Machinery. https://doi.org/10.1145/3531146.3533205

Nguyen, T. H. D., Chileshe, N., Rameezdeen, R., & Wood, A. (2019). External stakeholder strategic actions in projects: A multi-case study. *International Journal of Project Management, 37*(1), 176-191. https://doi.org/10.1016/j.ijproman.2018.12.001

OECD. (2019). *Artificial intelligence in society*. https://doi.org/10.1787/eedfee77-en

Ong, S., & Uddin, S. (2020). Data science and artificial intelligence in project management: The past, present and future. *The Journal of Modern Project Management, 7*(4), 04. https://journalmodernpm.com/manuscript/index.php/jmpm/article/view/JMPM02202/376

Prado, P., & Sapsed, J. (2016). The anthropophagic organization: How innovations transcend the temporary in a project-based organization. *Organization Studies, 37*(12), 1793-1818. https://doi.org/10.1177/0170840616655491

Raji, I. D., Smart, A., White, R. N., Mitchell, M., Gebru, T., Hutchinson, B., Smith-Loud, J., Theron, D., & Barnes, P. (2020). Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing. In *FAT* '20: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 33-44). Association for Computing Machinery. https://doi.org/10.1145/3351095.3372873

Rezania, D., Baker, R., & Nixon, A. (2019). Exploring project managers' accountability. *International Journal of Managing Projects in Business, 12*(4), 919-937. https://doi.org/10.1108/IJMPB-03-2018-0037

Rodrigues, R. (2020). Legal and human rights issues of AI: Gaps, challenges and vulnerabilities. *Journal of Responsible Technology, 4*, 100005. https://doi.org/10.1016/j.jrt.2020.100005

Ryan, M., & Stahl, B. C. (2021). Artificial intelligence ethics guidelines for developers and users: Clarifying their content and normative implications. *Journal of Information, Communication and Ethics in Society, 19*(1), 61-86. https://doi.org/10.1108/JICES-12-2019-0138

Sambasivan, N., Arnesen, E., Hutchinson, B., Doshi, T., & Prabhakaran, V. (2021, March 3-10). Re-imagining algorithmic fairness in India and beyond. In *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, Virtual Event* (pp. 315-328). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445896

Saurabh, K., Arora, R., Rani, N., Mishra, D., & Ramkumar, M. (2021). AI led ethical digital transformation: Framework, research and managerial implications. *Journal of Information, Communication and Ethics in Society, 20*(2), 229-256. https://doi.org/10.1108/JICES-02-2021-0020

De Schepper, S., Dooms, M., & Haezendonck, E. (2014). Stakeholder dynamics and responsibilities in public-private partnerships: A mixed experience. *International Journal of Project Management, 32*(7), 1210-1222. https://doi.org/10.1016/j.ijproman.2014.01.006

Scoleze Ferrer, P. S., Araujo Galvão G. D., & Monteiro de Carvalho, M. (2020). Tensions between compliance, internal controls and ethics in the domain of project governance. *International Journal of Managing Projects in Business, 13*(4), 845-865. https://doi.org/10.1108/IJMPB-07-2019-0171

Shaw, N. P., Stöckel, A., Orr, R. W., Lidbetter, T. F., & Cohen, R. (2018). Towards provably moral AI agents in bottom-up learning frameworks. In *AIES 2018: Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 271-277). Association for Computing Machinery. https://doi.org/10.1145/3278721.3278728

Shneiderman, B. (2020). Bridging the gap between ethics and practice: Guidelines for reliable, safe, and trustworthy human-centered AI systems. *ACM Transactions on Interactive Intelligent Systems, 10*(4), 1-31. https://doi.org/10.1145/3419764

Simon, J. P. (2019). Artificial intelligence: Scope, players, markets and geography. *Digital Policy, Regulation and Governance, 21*(3), 208-237. https://doi.org/10.1108/DPRG-08-2018-0039

Singh, J., Cobbe, J., & Norval, C. (2019). Decision provenance: Harnessing data flow for accountable systems. *IEEE Access, 7,* 6562-6574. https://doi.org/10.1109/ACCESS.2018.2887201

Stapleton, L., Lee, M. H., Qing, D., Wright, M., Chouldechova, A., Holstein, K., Wu, Z. S., & Zhu, H. (2022). Imagining new futures beyond predictive systems in child welfare: A qualitative study with impacted stakeholders. In *FAccT '22: 2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1162-1177). Association for Computing Machinery. https://doi.org/10.1145/3531146.3533177

Turner, R. J., & Zolin, R. (2012). Forecasting success on large projects: Developing reliable scales to predict multiple perspectives by multiple stakeholders over multiple time frames. *Project Management Journal, 43*(5), 87-99. https://doi.org/10.1002/pmj.21289

Mir, U. B., Sharma, S., Kar, A. K., & Gupta, M. P. (2020). Critical success factors for integrating artificial intelligence and robotics. *Digital Policy, Regulation and Governance, 22*(4), 307-331. https://doi.org/10.1108/DPRG-03-2020-0032

Vesa, M., & Tienari, J. (2020). Artificial intelligence and rationalized unaccountability: Ideology of the elites? *Organization, 29*(6), 1133-1145. https://doi.org/10.1177/1350508420963872

Wang, Q. (2018). A bibliometric model for identifying emerging research topics. *Journal of the Association for Information Science and Technology, 69*(2), 290-304. https://doi.org/10.1002/asi.23930

Webb, H., Koene, A., Patel, M., & Perez Vallejos, E. (2018, July 18-20). Multi-stakeholder dialogue for policy recommendations on algorithmic fairness. In *SMSociety '18: Proceedings of the 9th International Conference on Social Media and Society* (pp. 395-399). Association for Computing Machinery. https://doi.org/10.1145/3217804.3217952

Węgrzyn, J., & Wojewnik-Filipkowska, A. (2022). Stakeholder analysis and their attitude towards PPP success. *Sustainability, 14*(3), 1570. https://doi.org/10.3390/su14031570

Wieringa, M. (2020). What to account for when accounting for algorithms: A systematic literature review on algorithmic accountability. In *FAT* '20: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 1-18). Association for Computing Machinery. https://doi.org/10.1145/3351095.3372833

Willems, L. L., & Vanhoucke, M. (2015). Classification of articles and journals on project control and earned value management. *International Journal of Project Management, 33*(7), 1610-1634. https://doi.org/10.1016/j.ijproman.2015.06.003

Zwikael, O., & Meredith, J. R. (2018). Who's who in the project zoo? The ten core project roles. *International Journal of Operations & Production Management, 38*(2), 474-492. https://doi.org/10.1108/IJOPM-05-2017-0274

Supplement

Table 1. AI Stakeholder Accountability – Project Governance (PG)

Ref(s)	Success Group	Success Factor(s)	Actor Collective	Actor Role(s)	Structure	Forum & Type
1	*2*	*3*	*4*	*5*	*6*	*7*
[1], [2], [3], [4]	Project Management (PM)	Community engagement, Disclosure records, Diverse working environment, Model risk assessment, Procurement records, Recordkeeping, Responsibility assignment matrix, Risk assessment records, Scope definition document, Standards and guidelines	Prj Mgr	Prj / Prog mgrs	V-F	Prj Spr (admin)
		Disclosure records, Model risk assessment, Procurement records, Recordkeeping, Responsibility assignment matrix, Risk assessment records, Scope definition document, Standards and guidelines	Prj Spr	Prj owner	V-F	Regulator (legal)
		Model risk assessment	Prj team	Prj team	V-F	Prj Spr (admin)
		Procurement records, Scope definition document	Prj Spr	Prj owner	V-F	Prj Mgr (admin)
		Scope definition document	Prj Mgr	Prj / Prog mgrs	V-F	Prj team (professional)
			Prj Spr	Prj owner	D-F	Operations (admin)
		Standards and guidelines	Prj team	Architects, Business users, Data analyst, Data engineer, Data scientist, Prj team, Software dev	V-F	Prj team (professional)
[5], [6], [7]	Investigation (IN)	Algorithm auditing	Prj Spr	Prj owner	D-F	Prj Spr (financial)
		Algorithm auditing, Algorithm impact assessment, Audit finding records, Audit response records, Certification	Prj Spr	Prj owner	D-F	Operations (admin)
		Algorithm auditing, Audit response records	Prj team	Prj team	V-F	Prj Spr (admin)
		Algorithm auditing, Audit response records, Certification	Operations	Operate org	H-C	Public (professional)
		Algorithm impact assessment	Operations	Operate org	H-C	Public (social)
			Prj Spr	Prj owner	H-C	Public (social)

Table 1 cont.

1	2	3	4	5	6	7
		Audit finding records	Prj Spr	Prj owner	V-F	Prj team (professional)
			Public	Evaluators	H-C	Operations (admin)
		Audit finding records, Certification	Public	Evaluators	H-C	Public (social)
Ref(s)	Success Group	Success Factor(s)	Actor Collective	Actor Role(s)	Structure	Forum & Type
[8]	Ethical Practices (EP)	Ethics policies	Operations	Operate org	D-F	Operations (admin)
		Ethics policies, Ethics training, Ombudsman			H-C	Public (professional)
					V-F	Regulator (legal)
			Prj Spr	Prj owner	D-F	Operations (admin)
					H-C	Public (professional)
					V-F	Regulator (legal)
			Operations	Operate org	V-F	Operations (professional)
			Prj Spr	Prj owner	V-F	Prj Mgr (admin)
						Prj team (professional)
		Ethics policies, Professional membership	Operations	End users, Model mtn	V-F	Operations (admin)
			Prj Mgr	Prj / Prog mgrs	V-F	Prj Spr (admin)
			Prj team	Architects, Business users, Data analyst, Data engineer, Data scientist, Prj team, Software dev	V-F	Prj Spr (admin)

Notes: Structure is combined Obligation (D – Diagonal, V – Vertical, H – Horizontal) and Consequence (I – Informal, F – Formal, C – Context specific).

Abbreviations: AI – artificial intelligence, Dev – developer, Mgr – Manager, Mgt – management, Mtn – maintainer, Org – organization, Prj – project, Spr – Sponsor, Sys – system.

Table 2. AI Stakeholder Accountability – Product Quality (PQ)

Ref(s)	Success Group	Success Factor(s)	Actor Collective	Actor Role(s)	Structure	Forum & Type
1	*2*	*3*	*4*	*5*	*6*	*7*
[9], [1], [10], [10], [11]	Training Data Qualities (TD)	Data quality and relevance, Equitable representation	Prj Spr	Prj owner	D-F	Prj Spr (financial)
		Data quality and relevance, Equitable representation, Model training records	Prj team	Data scientist	V-F	Prj team (professional)
		Equitable representation	Prj Spr	Prj owner	D-F	Operations (admin)
					H-C	Public (social)
		Equitable representation, Interaction safety	Prj Mgr	Prj / Prog mgrs	V-F	Prj team (professional)
[1], [12], [2], [13], [14]	Models & Algorithms Qualities (MA)	Accuracy, Algorithm transparency, Auditability, Consistency, Equitable treatment, Interpretability	Prj Spr	Prj owner	D-F	Prj Spr (financial)
		Accuracy, Algorithm transparency, Auditability, Consistency, Equitable treatment, Interpretability, Model validation, Model validation records	Prj team	Data scientist	V-F	Prj team (professional)
		Algorithm transparency	Operations	Operate org	H-C	Public (social)
			Prj Spr	Prj owner	D-F	Operations (admin)
[1], [15], [16]	System Configuration (SC)	Security safeguards	Prj Mgr	Prj / Prog mgrs	V-F	Prj Spr (admin)
			Prj team	Architects, Business users, Data analyst, Data engineer, Data scientist, Prj team, Software dev	V-F	Prj Spr (admin)
		Security safeguards, System and architecture quality, Technical deployment records, Technical logging, Versioning and metadata	Operations	End users, Model mtn, Platform owners	V-F	Operations (admin)
			Prj team	Architects	V-F	Prj team (professional)
		Security safeguards, System and architecture quality, Technical logging, Versioning and metadata	Prj Spr	Prj owner	D-F	Prj Spr (financial)
[17], [18]	User Interface Qualities (UI)	Equitable accessibility	Prj Spr	Prj owner	H-C	Public (social)
		Equitable accessibility, Front-end transparency	Operations	Operate org	H-C	Public (social)

Table 2 cont.

1	2	3	4	5	6	7
		Equitable accessibility, Front-end transparency, Human intervention	Prj Spr	Prj owner	D-F	Prj Spr (financial)
			Prj team	Software dev	V-F	Prj team (professional)
		Front-end transparency, Human intervention	Prj Spr	Prj owner	D-F	Operations (admin)
		Human intervention	Prj team	Prj team	V-F	Prj Spr (admin)
Ref(s)	Success Group	Success Factor(s)	Actor Collective	Actor Role(s)	Structure	Forum & Type
[2], [19]	Source Data Qualities (DS)	Data accessibility	Prj Spr	Prj owner	V-F	Prj team (professional)
		Data accessibility, Data collection records, Data transparency	Prj team	Data engineer	V-F	Prj team (professional)
		Data transparency	Operations	Operate org	H-C	Public (social)
			Prj Spr	Prj owner	D-F	Operations (admin) Prj Spr (financial)
[2], [20], [21]	Data & Privacy Protections (PP)	Confidentiality	Operations	End users	H-C	Individuals (social)
		Confidentiality, Data anonymization, Data encryption, Data governance, Informed consent, Personal data controls, Privacy safeguards	Operations	Data custodian, End users, Model mtn	V-F	Operations (admin)
			Prj team	Architects, Business users, Data analyst, Data engineer, Data scientist, Prj team, Software dev	V-F	Prj Spr (admin)
		Confidentiality, Informed consent, Personal data controls	Operations	Operate org	D-C	Individuals (social)
		Data governance, Data retention policy	Operations	Operate org	V-F	Operations (professional)
			Prj Spr	Prj owner	V-F	Prj team (professional)
		Informed consent, Personal data controls	Prj Spr	Prj owner	D-C	Individuals (social)
		Privacy safeguards	Prj Mgr	Prj / Prog mgrs	V-F	Prj Spr (admin)

Notes: Structure is combined Obligation (D – Diagonal, V – Vertical, H – Horizontal) and Consequence (I – Informal, F – Formal, C – Context specific).

Abbreviations: AI – artificial intelligence, Dev – developer, Mgr – Manager, Mgt – management, Mtn – maintainer, Org – organization, Prj – project, Spr – Sponsor, Sys – system.

Table 3. AI Stakeholder Accountability – Usage Qualities (UQ)

Ref(s)	Success Group	Success Factor(s)	Actor Collective	Actor Role(s)	Structure	Forum & Type
[1], [22], [23], [24], [25]	Usage controls (UC)	Algorithm renewal process	Prj team	Data scientist	V-F	Prj Spr (admin)
		Algorithm renewal process, Complaint process, Consequence records, Process deployment records, Quality controls, Staff monitoring, System monitoring, Usage records	Operations	End users, Model mtn, Operate org, Platform owners	V-F	Operations (admin)
		Algorithm renewal process, Quality controls, System monitoring	Prj Spr	Prj owner	D-F	Operations (admin)
		Complaint process, Quality controls	Operations	Operate org	D-F	Operations (admin)
					V-F	Operations (professional)
		Quality controls, System monitoring	Prj team	Software dev	V-F	Prj team (professional)
[17], [26], [11], [27], [28], [16]	System Transparency & Under-standability (STU)	Choices, Interaction safety – usage, Interpretable models, Onboarding procedures, Problem reporting, Specialized skills and knowledge-usage, Stakeholder-centric communication	Operations	Operate org	V-F	Operations (professional)
		Interpretable models, Onboarding procedures, Problem reporting, Stakeholder-centric communication	Operations	Operate org	H-C	Public (social)
			Prj Spr	Prj owner	D-F	Operations (admin)
		Interpretable models, Onboarding procedures, Stakeholder-centric communication	Prj Mgr	Prj / Prog mgrs	V-F	Prj Spr (admin)
			Prj team	Prj team	V-F	Prj Spr (admin)
[2], [20]	Decision Quality (DQ)	Access and redress, Awareness	Operations	Operate org	H-C	Public (social)
		Access and redress, Awareness, Decision accountability, Privacy and confidentiality	Operations	Operate org	D-C	Individuals (social)
		Access and redress, Decision accountability	Operations	Operate org	V-F	Operations (professional)
		Awareness, Privacy and confidentiality	Operations	End users	H-C	Individuals (social)
		Decision accountability, Privacy and confidentiality	Operations	End users, Operate org	V-F	Operations (admin)

Notes: Structure is combined Obligation (D – Diagonal, V – Vertical, H – Horizontal) and Consequence (I – Informal, F – Formal, C – Context specific).

Abbreviations: AI – artificial intelligence, Dev – developer, Mgr – Manager, Mgt – management, Mtn – maintainer, Org – organization, Prj – project, Spr – Sponsor, Sys – system.

Table 4. AI Stakeholder Accountability – Benefits & Protections (BP)

Ref(s)	Success Group	Success Factor(s)	Actor Collective	Actor Role(s)	Structure	Forum & Type
[29], [30], [31], [20]	Financial Protections (FP)	Cost efficiency	Operations	Operate org	V-F	Operations (professional)
		Cost efficiency, Energy costs, Environmental impacts, Intellectual property protection, Project efficiency	Prj Mgr	Prj / Prog mgrs	V-F	Prj Spr (admin)
			Prj Spr	Prj owner	D-F	Prj Spr (financial)
			Prj team	Prj team	V-F	Prj Mgr (admin)
		Energy costs, Environmental impacts	Operations	Operate org	D-F	Operations (admin)
		Environmental impacts	Prj Spr	Prj owner	H-C	Public (social)
[25]	Financial Benefits (FB)	Financial gains, Intellectual property rights, Licensing or service fees	Prj Spr	Prj owner	D-F	Prj Spr (financial)
		Financial gains, Licensing or service fees	Operations	Operate org	H-C	Public (social)
		Investment funds	Prj Spr	Prj funder	D-F	Prj Spr (admin)
				Prj owner	V-F	Prj Mgr (admin)
		Licensing or service fees	Operations	Operate org	D-F	Prj Spr (admin)
[20]	Legal Protections (LP)	Legal safeguards, Regulatory and legal compliance	Operations	End users, Model mtn, Platform owners	V-F	Operations (admin)
			Prj Mgr	Prj / Prog mgrs	V-F	Prj Spr (admin)
			Prj Spr	Prj owner	D-F	Prj Spr (financial)
			Prj team	Architects, Business users, Data analyst, Data engineer, Data scientist, Prj team, Software dev	V-F	Prj Spr (admin)
		Regulatory and legal compliance	Operations	Operate org	H-C	Public (social)
				Operate org, Platform owners	V-F	Regulator (legal)
			Prj Spr	Prj owner	D-F	Operations (admin)
					V-F	Regulator (legal)

Notes: Structure is combined Obligation (D – Diagonal, V – Vertical, H – Horizontal) and Consequence (I – Informal, F – Formal, C – Context specific).

Abbreviations: AI – artificial intelligence, Dev – developer, Mgr – Manager, Mgt – management, Mtn – maintainer, Org – organization, Prj – project, Spr – Sponsor, Sys – system.

Table 5. AI Stakeholder Accountability – Societal Impacts (SI)

Ref(s)	Success Group	Success Factor(s)	Actor Collective	Actor Role(s)	Structure	Forum & Type
[29]	Sustainability (SY)	Environmental sustainability	Operations	Operate org	H-C	Public (social)
			Prj Spr	Prj owner	D-F	Operations (admin)
					H-C	Public (social)
[20]	Individual Protections (IV)	Civil rights and liberties protections	Operations	Operate org	D-C	Individuals (social)
					H-C	Public (social)

Notes: Structure is combined Obligation (D – Diagonal, V – Vertical, H – Horizontal) and Consequence (I – Informal, F – Formal, C – Context specific).

Abbreviations: AI – artificial intelligence, Dev – developer, Mgr – Manager, Mgt – management, Mtn – maintainer, Org – organization, Prj – project, Spr – Sponsor, Sys – system.

Bibliography

[1] Cobbe, J., Lee, M. S. A., & Singh, J. (2021). Reviewable automated decision-making: A framework for accountable algorithmic systems. In *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 598-609). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445921

[2] Bertino, E., Kundu, A., & Sura, Z. (2019). Data transparency with blockchain and AI ethics. *Journal of Data and Information Quality, 11*(4), 1-8. https://doi.org/10.1145/3312750

[3] Ryan, M., & Stahl, B. C. (2021). Artificial intelligence ethics guidelines for developers and users: Clarifying their content and normative implications," *Journal of Information, Communication and Ethics in Society, 19*(1), 61-86. https://doi.org/10.1108/JICES-12-2019-0138

[4] Unceta, I., Nin, J., & Pujol, O. (2020). Risk mitigation in algorithmic accountability: The role of machine learning copies. *PLoS One, 15*(11), e0241286. https://doi.org/10.1371/journal.pone.0241286

[5] Metcalf, J., Moss, E., Watkins, E. A., Singh, R., & Elish, M. C. (2021). Algorithmic impact assessments and accountability: The co-construction of impacts. In *FAccT 2021: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 735-746). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445935

[6] Shneiderman, B. (2020). Bridging the gap between ethics and practice: Guidelines for reliable, safe, and trustworthy human-centered AI systems. *ACM Transactions on Interactive Intelligent Systems, 10*(40), 1-31. https://doi.org/10.1145/3419764

[7] Raji, I. D., Smart, A., White, R. N., Mitchell, M., Gebru, T., Hutchinson, B., Smith-Loud, J., Theron, D., & Barnes, P. (2020). Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing. In *FAT* 2020: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 33-44). https://arxiv.org/pdf/2001.00973.pdf

[8] Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence, 1*(11), 501-507. https://doi.org/10.1038/s42256-019-0114-4

[9] Hutchinson, B., Smart, A., Hanna, A., Denton, E., Greer, C., Kjartansson, O., Barnes, P., & Mitchell, M. (2021). Towards accountability for machine learning datasets: Practices from software engineering and infrastructure. In *FAccT 2021: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 560-575). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445918

[10] Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raaji, I. D., & Gebru, T.(2019). Model cards for model reporting. In *FAT* 2019: Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 220-229). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287596

[11] Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. *Journal of Business Ethics, 167*(2), 209-234. https://doi.org/10.1007/s10551-019-04407-1

[12] Wan, W. X., & Lindenthal, T. (2021). Towards accountability in machine learning applications: A system-testing approach. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3758451

[13] Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior, 98*, -277-284. https://doi.org/10.1016/j.chb.2019.04.019

[14] Chazette, L., Brunotte, W., & Speith, T. (2021). Exploring explainability: A definition, a model, and a knowledge catalogue. In *2021 IEEE 29th International Requirements Engineering Conference (RE)* (pp. 197-208). IEEE. https://doi.org/10.1109/RE51729.2021.00025

[15] Umar Bashir, M., Sharma, S., Kar, A. K., & Manmohan Prasad, G. (2020). Critical success factors for integrating artificial intelligence and robotics. *Digital Policy, Regulation and Governance, 22*(4), 307-331. https://doi.org/10.1108/DPRG-03-2020-0032

[16] Hopkins, A., & Booth, S. (2021). Machine learning practices outside big tech: How resource constraints challenge responsible development. In *AIES 2021: Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 134-145). Association for Computing Machinery. https://doi.org/10.1145/3461702

[17] Helberger, N., Araujo, T., & de Vreese, C. H. (2020). Who is the fairest of them all? public attitudes and expectations regarding automated decision-making. *Computer Law & Security Review, 39*, 1-16. https://doi.org/10.1016/j.clsr.2020.105456

[18] Rossi, A., & Lenzini, G. (2020). Transparency by design in data-informed research: A collection of information design patterns. *Computer Law & Security Review, 37*, 1-22. https://doi.org/10.1016/j.clsr.2020.105402

[19] Gebru, T., Morgenstern, J., Vecchione, B., Wortman Vaughan, J., Wallach, H., Daumé III, H., & Crawford, K. (2021). *Datasheets for datasets*. Cornell University. https://arxiv.org/abs/1803.09010

[20] Rodrigues, R. (2020). Legal and human rights issues of AI: Gaps, challenges and vulnerabilities. *Journal of Responsible Technology, 4*, 100005. https://doi.org/10.1016/j.jrt.2020.100005

[21] Janssen, M., Brous, P., Estevez, E., Barbosa, L. S., & Janowski, T. (2020). Data governance: Organizing data for trustworthy artificial intelligence. *Government Information Quarterly, 37*(3), 101493. https://doi.org/10.1016/j.giq.2020.101493

[22] Wagner, B., Rozgonyi, K., Sekwenz, M.-T., Cobbe, J., & Singh, J. (2020). Regulating transparency? Facebook, Twitter and the German Network Enforcement Act. In *FAT* 2020: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 261-271). Association for Computing Machinery. https://dl.acm.org/doi/abs/10.1145/3351095.3372856

[23] Joerin, A., Rauws, M., Fulmer, R., & Black, V. (2020). Ethical artificial intelligence for digital health organizations. *Cureus, 12*(3), e7202. https://doi.org/10.7759/cureus.7202

[24] Loi, M., Heitz, C., & Christen, M. (2014). A comparative assessment and synthesis of twenty ethics codes on AI and big data. In *2020 7th Swiss Conference on Data Science (SDS)* (pp. 41-460). IEEE. https://doi.org/10.1109/SDS49233.2020.00015

[25] Cohen, I. G., Amarasingham, R., Shah, A., Xie, B., & Lo, B. (2014). The legal and ethical concerns that arise from using complex predictive analytics in health care. *Health Affairs, 33*(7), 1139-1147. https://doi.org/10.1377/hlthaff.2014.0048

[26] Eslami, M., Vaccaro, K., Lee, M. K., On, A. E. B., Gilbert, E., & Karahalios, K. (2019). User attitudes towards algorithmic opacity and transparency in online reviewing platforms. in *CHI 2019: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (pp. 1-14). Association for Computing Machinery. https://doi.org/10.1145/3290605.3300724

[27] Langer, M., & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. *Computers in Human Behavior, 123*, 106878. https://doi.org/10.1016/j.chb.2021.106878

[28] Bhatt, U., Xiang, A., Sharma, S., Weller, A., Taly, A., Jia, Y., Ghosh, J., Puri, R., Moura, J. M. F., & Eckersley, P. (2020). Explainable machine learning in deployment. In *FAT* 2020: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 648-657). Association for Computing Machinery. https://doi.org/10.1145/3351095.3375624

[29] Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big?" In *FAccT 2021: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610-623). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445922

[30] Gandy, O. H., Jr (2010). Engaging rational discrimination: Exploring reasons for placing regulatory constraints on decision support systems. *Ethics and Information Technology, 12*(1), 29-42. https://doi.org/10.1007/s10676-009-9198-6

[31] Turner, R. J., & Zolin, R. (2012). Forecasting success on large projects: Developing reliable scales to predict multiple perspectives by multiple stakeholders over multiple time frames. *Project Management Journal, 43*(5), 87-99. https://doi.org/10.1002/pmj.21289