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Stakeholder roles in artificial intelligence projects

Gloria J. Miller

Maxmetrics, Heidelberg, Germany

A R T I C L E I N F O

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A B S T R A C T

Algorithmic decision-making implemented through artificial intelligence (AI) projects is augmenting or replacing human decision-making across numerous industries. Although AI systems may impact individuals and society in life-and-death situations, project organizations or plans may ignore the concerns of the passive stakeholders. This research describes the components, lifecycle, and characteristics of AI projects. It employs stakeholder theory and a systematic literature review with thematic analysis to identify and classify individuals, groups, and organizations into six stakeholder project roles. It configures the stakeholder salience model with a harm attribute to identify passive stakeholders—individuals affected by AI systems but powerless to affect the project—and their nexus to the project. The study contributes a novel method for identifying passive stakeholders and highlights the need to engage developers, operators, and representatives of passive stakeholders to achieve moral, ethical, and sustainable development.

1. Introduction

Artificial intelligence (AI) adoption is growing rapidly, and AI is expected to revolutionize and transform production processes, thereby influencing the behavior of economic actors (OECD, 2019). Scholars have argued that system developers are moral agents responsible for the impacts of their systems on individuals and society (Cohen et al., 2014; Manders-Huits, 2006; Martin, 2019; Miller, 2022; Wieringa, 2020). A "moral issue is present where a person's actions, when freely performed, may harm or benefit others … A moral agent is a person who makes a moral decision, even though they may not recognize that moral issues are at stake" (Jones, 1991, p. 367). However, no clear definition of system developers exists, as this group includes a wide range of roles and professions, such as designers, technicians, finance providers, instructors, and operators (Manders-Huits, 2006). Moreover, it is difficult to identify the people and organizations affected by AI system development and usage (Wieringa, 2020). These issues become even more salient when AI systems are developed in projects, which are temporary organizations whose team members may not be available once the project terminates.

Some AI systems run automatically and do not allow human intervention, making them unique from other information systems (Kriebitz and Lütge, 2020). These systems can impact human, civil, and workers' rights; they have characteristics close to pharmaceutical and healthcare industries for their human impact and infrastructure projects for their environmental impacts. Consequently, the United States and the European Union have introduced or updated AI policies and regulations in the months preceding this study (116th Congress (2019–2020), 2020; European Commission, 2021). Nevertheless, many of the impacts of AI systems have no formulation in existing technology frameworks (Fazelpour and Lipton, 2020).

The extant literature on AI investigates how AI will change the project management profession (Hossain and Wu, 2009; Missonier and Loufrani-Fedida, 2014; Nemati et al., 2002; Ong and Uddin, 2020; Snider et al., 2019; Toomey, 2012; Willems and Vanhoucke, 2015). Against this backdrop, scholars have reported that "AI would likely have the least effect on project stakeholder management in the next 10 years" (Fridgeirsson et al., 2021, p. 7). However, this perspective ignores the impact of AI projects on society and the environment. Moreover, the emerging body of literature on AI in the computer science, data science, business ethics, and law domains (OECD, 2019; Wieringa, 2020) has yet to consider the project management perspective.

A stakeholder is defined as "any group or individual who is affected by or can affect the achievement of an organization's objectives" (Freeman and McVea, 2001, p. 2). This view of stakeholders is similar to that used by the project management standards; that is, the stakeholders should be associated with meeting the project objectives (PMI, 2021). This instrumental view of stakeholders does not prioritize individuals and organizations who may be impacted by AI projects but do not contribute anything to or influence the project (Derakhshan et al., 2019; Eskerod and Huemann, 2013). Researchers have criticized this view as lacking an ethical approach to stakeholders not deemed important to the

E-mail address: g.j.m@ieee.org.

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project (Eskerod and Huemann, 2013).

Derry (2012) suggested we challenge the role of the firm, or in this case, the project, at the center of the stakeholder model. Specifically, the concerns of all stakeholders—community, environment, and business—should be balanced. Consequently, to address the moral and ethical concerns arising with AI systems, the stakeholder perspective should identify all stakeholders, especially the passive ones. Passive stakeholders may be affected by the project but do not actively contribute to the project outcome; they are usually engaged in projects through a form of representation. In contrast, active stakeholders influence or contribute to the outcome of the project (Vos Janita and Achterkamp Marjolein, 2006).

A robust body of project management literature exists on stakeholders from different project types: private–public partnerships, sustainability projects, mega–projects, and information technology projects (De Schepper et al., 2014; Di Maddaloni and Davis, 2018; Nguyen et al., 2019; Wegrzyn and Wojewnik-Filipkowska, 2022). The existing research supports identifying some passive stakeholders, such as discretionary or marginalized stakeholders. However, the project context has implications on identifying the stakeholders (Vos Janita and Achterkamp Marjolein, 2006) and project management (Shenhar and Dvir, 2007).

This research uses a systematic literature review and thematic analysis to identify and classify stakeholder roles in project situations where the decisions and actions taken in the project may harm (or benefit) individuals, society, and the environment for years after project completion. Specifically, the research answers the following questions: *What are the roles involved in the decision-making and acting in AI projects? Who are the stakeholders affected by AI projects and systems?* The study uses role theory to synthesize descriptions found in the literature into AI roles and functions (Biddle, 1979). It applies the descriptive stakeholder theory to the relationship between stakeholders and a phenomenon, the project (Reed et al., 2009). It specifically identifies the passive stakeholders that an AI project may harm.

This research makes five contributions. First, it describes the components and characteristics of an AI project. This information provides a context for understanding how different aspects of an AI project relate to the stakeholders. Second, it identifies the roles within a prototypical AI project based on a literature survey of the individuals and organizations identified in the AI community.

Third, by extending the stakeholder salience model with a harm attribute, the study provides a view of all stakeholders that may have a legitimate right to management attention without regard to their ability to contribute to the project or its output (Derry, 2012). This expands the list of external and passive stakeholders found in other project management stakeholder models (Davis, 2014; Turner and Zolin, 2012).

Fourth, it confirms the role of the project team as the principal judges of the outcomes and impacts of the AI systems they develop. The project team members are moral agents; they make in-project decisions where moral issues are at stake (Jones, 1991). The AI systems they build have agency as they enable, inform, guide, and steer human judgment in decision-making (Moser et al., 2022), and in some cases, the systems may not allow human intervention.

Finally, the study assigns the AI lifecycle stages to the urgency attribute of the stakeholder salience model. Thus, it places the stakeholders on a time continuum that indicates when they are likely to judge or influence the project or system. This builds on the view from Turner and Zolin (2012) that a project should anticipate and develop leading indicators to account for impacts that can occur years after project closure.

These contributions address the limited coverage of the AI context in the project management literature. As recommended by Derakhshan et al. (2019), this research explores the non-monetary aspects of the relationship between projects and society. It also adds to the conceptual work by Eskerod and Huemann (2013) on balancing the management-of-stakeholder and the management-for-stakeholder approaches. Moreover, project managers and sponsors can use the results at an early stage of planning to account for, include, and engage the stakeholders. Further, it answers the call to action that AI should be investigated before it leads to fundamental and irreversible changes. As Moser et al. (2022) argued “we need to reconsider how we develop, understand, and apply algorithms in our daily lives and businesses” (p. 150).

The paper provides a literature review, a description of the methodology used, an analysis of the findings, a discussion of the research question, and conclusions.

2. Literature review

2.1. Artificial intelligence systems

AI systems are developed using various data science technologies, methods, and techniques from the fields of computing, communication, management, and sociology (Michalczyk et al., 2021; Ong and Uddin, 2020). They are machine-based systems that learn from data and use models to make predictions or recommendations or influence decision-making and are implemented as algorithms (OECD, 2019). As Sherer (2017) stated “an algorithm is a defined, repeatable process and outcome based on data, processes, and assumptions” (p. 7).

Algorithms are developed using various computer science methods, for example, natural language processing, machine learning, deep learning, and artificial neural networks (Aggarwal & Kumar, 2018; Iqbal et al., 2017). Natural language processing refers to manipulating human language. Machine learning uses different supervised and unsupervised methods to discover and model the patterns and relationships in data, allowing the algorithm to make predictions. Deep learning uses machine-learning approaches to automatically learn and extract features from complex unverified data without human involvement. Artificial neural networks are models trained on data to make predictions.

The degree of human intervention in decision-making varies according to the type, purpose, and method of integrating the algorithms into other systems or processes. For example, robots or other artificial agents perform a complex series of actions without the need for human control or guidance (OECD, 2019). Thus, the decision-making autonomy of these artificial agents has provoked a review of civil liability, criminal liability, data protection, and security issues and raised ethical questions about how moral decisions are made when humans are not involved (Miller, 2022; Ryan and Stahl, 2021; Wieringa, 2020).

For the current study, AI systems include data-driven computer systems that incorporate algorithms that learn from data and algorithmic decision-making that uses computerized systems for autonomous or human decision-making and problem-solving.

2.2. Artificial intelligence project lifecycle

Projects are temporary endeavors constrained by time and budgets, limiting the available resources. AI has been applied to many project management processes, such as estimation (Nemati et al., 2002), stakeholder engagement (Missonier and Loufrani-Fedida, 2014), performance management (Hossain and Wu, 2009; Snider et al., 2019; Toomey, 2012), and monitoring and controlling (Willems and Vanhoucke, 2015). Some researchers have argued that project performance should be evaluated by analyzing data artifacts produced from everyday project activities rather than by relying on managerial understanding (Hossain and Wu, 2009). Other researchers have been more cautious, recognizing that human leadership skills are necessary for developing and managing teams and stakeholder management (Fridgeirsson et al., 2021). While the extant literature debates the effect of AI on project management, a similarly robust discussion of the effects of AI projects on stakeholders is lacking.

Big data, predictive analytics, and facial recognition are some project types that apply data science in developing AI systems. “The AI system lifecycle phases are i) planning and design, data collection and processing, and model building and interpretation; ii) verification and validation; iii) deployment; and iv) operation and monitoring" (OECD, 2019). Operations and monitoring and the impact or consequence of usage may accrue months or years after the initial development project (Turner and Zolin, 2012). The individual roles and stakeholders involved in or impacted by projects vary depending on the lifecycle phase (Vos Janita and Achterkamp Marjolein, 2006).

2.2.1. Development

In the first stage of the AI system development process after planning and designing the system, data collection and processing are completed (Dumrak and Zarghami, 2020; OECD, 2019). The source data are from original systems, such as enterprise resource planning systems, websites, or social media sites. During the data collection and storage process, source data are collected and manipulated to make them fit for purpose. This manipulation may include human intervention for augmenting the data with labels, tags, identifiers, or metadata (Moser et al., 2022). It may also include anonymizing personal data. The volumes of the data may be vast, including millions of transactions and massive databases. Robust technology and processes are required to collect, process, and store the data (Bender et al., 2021; Miller, 2019b).

A subset of the data is then used to design and develop AI models and algorithms. These data enable the models to learn and are usually referred to as training data (Bender et al., 2021; Martin, 2019). Model and algorithm building and their interpretation emerge from the development of algorithms for explanation and prediction based on data science methods and techniques already described (Martin, 2019). The algorithms are verified and validated against relevant measures such as bias and false positives (OECD, 2019). Accordingly, high-performance computing systems and architecture are required to support computational needs and data loads (Bender et al., 2021; Miller, 2019b).

Finally, a user interface is developed for inputting parameters to trigger the algorithm or make autonomous decisions and present the results. The interface may be a dialogue entry form, an automated system, an application programming interface, a chatbot, social media or e-commerce site, or an appliance such as a smartphone or smart device (OECD, 2019; Simon, 2019; Vesa and Tienari, 2020). The algorithms may support or implement fully autonomous decisions. The system configuration, including the architecture and deployment, determines how the algorithms function.

2.2.2. Usage

End users input several parameters to the user interface to trigger the algorithm. The model, algorithm, and user interface produce the output with or without the user's knowledge of the algorithm's existence (Martin, 2019; Vesa and Tienari, 2020). Operations and monitoring are the continual surveying of the system's performance, environment, and staff for problem identification and learning. Model values or choices become obsolete over time, so monitoring and renewal processes are relevant in ongoing operations. A renewal process refreshes obsolete model values or choices (OECD, 2019; Wieringa, 2020).

2.2.3. Consequence

Decisions are the model or algorithm output that impacts specific people, organizations, or groups. Ethical principles for fairness, trustworthiness, transparency, explainability, accountability, and sustainability are important factors in judging various consequences (Jobin et al., 2019; Ryan and Stahl, 2021). Fig. 1 provides an overview of the project components and their interrelationship.

2.3. Artificial intelligence projects compared to other project types

AI projects differ from other information system projects in their ability to impact human rights, civil rights, and workers' rights; they have characteristics close to pharmaceutical and healthcare for their human impact and infrastructure projects for their environmental impacts. Furthermore, they can have global consequences when integrated into digital platforms, such as Facebook, Twitter, or Amazon, or appliances such as smartphones, wearable devices, or chatbots (Ryan and Stahl, 2021; Vesa and Tienari, 2020; Webb et al., 2018). Drawing on the comparative information from other studies (Miller, 2019a; Shenhar and Dvir, 2007), Table 1 provides a comparative overview of AI project types and other project types.

First, AI systems are capable of supporting critical and life-saving decisions, such as diagnosing Parkinson's disease (Yadav et al., 2012), breast cancer (Abdelaal et al., 2010), or COVID-19 (Hamon et al., 2021). Conversely, AI are "systems capable of inflicting (minor to serious or even lethal) harms as well, be it intentional/unintentional" (Wieringa, 2020, p. 1). Documented examples of failures include AI discriminating against hiring women (Dastin, 2018); a Boeing algorithm adjusting flight angles causing multiple plane crashes (Gröndahl et al., 2019; Hawkins, 2019); a Volkswagen system adjusting car emissions to show better performance (Hotten, 2015); and erroneous facial recognition leading to the arrest and detainment of the wrong person (Hill, 2020).

Thus, AI systems can impact human rights based on the design and nature of the system, its implementation, use, or both (Boyer and Veigl, 2015; Miao, 2018; OECD, 2019). Human rights refer to "all the rights and obligations that people should enjoy to survive and develop, and to live in harmony with others and society under a certain social and historical condition and under a relatively stable social and natural environment" (Miao, 2018, p. 922).

The system's designers and developers make important decisions, and their personal biases, blind spots, and design choices can influence the consequences of using the systems (Kasinidou et al., 2021; Manders-Huits, 2006; Martin, 2019). For example, computing methods such as artificial neural networks produce models with hidden features, and the designers may not know or understand which parameters influence the model. The data used for training the models may be biased, incomplete, or influenced by past practices (Chasalow and Levy, 2021; Sambasivan et al., 2021). Entire communities of people may be missed or misrepresented in data due to social infrastructure, systematic

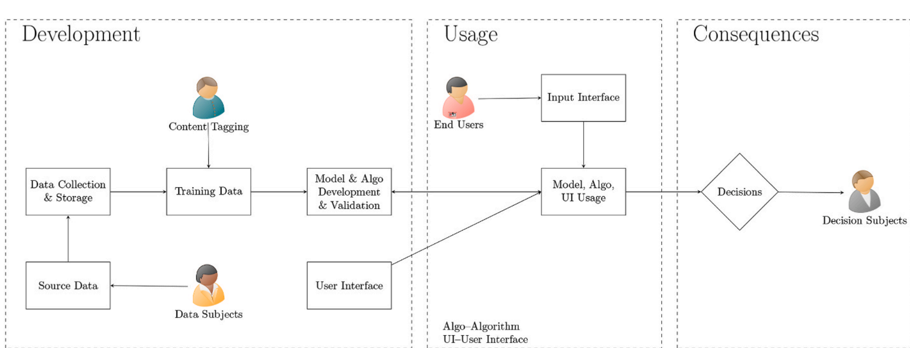

Fig. 1. AI development and usage project components. Author's own elaboration.

Table 1
Comparison of AI systems and other project types.

Characteristic	Pharma/healthcare	Infrastructure	Information Systems	AI Systems
Product examples	Drugs, medical devices	Construction, buildings, roads, etc.	Business applications, Enterprise resource planning, etc.	Monetize data, autonomous decisions
Benefit focus	Public health, longevity	Functional, architectural	Business performance	Business performance
Regulations, standards, approvals	Regulations and government approvals	Construction and municipal regulations and approvals	Industry guidelines, data protection regulations	Data protection regulations, ethical policies, risk assessment
Key developers	*Licensed, fiduciaries duties	*Licensed architects	Software developers	Data scientists, data engineers
Client acceptance	Client, government	Client, contractor	Client	Developer, client
End users	Consumers	Client, customers, local communities	Client decision-makers, staff, suppliers	Case-specific: client decision-makers, staff, consumers, public
Stakeholder impacts	Human life and side effects for consumers	Customers, workers, local community	Workers' rights	Human, civil, workers' rights, local community
Environment impact	Residue in water, soil	Energy usage, water pollution, landfill waste, carbon emissions		Energy usage, carbon emissions
Geographical impact	Can be global	Local communities	Scope-specific	Scope-specific: can be global

Note: * Government sanctioned.

disparities, technology policies, or the costs of data collection (Sambasivan et al., 2021).

The developers can provide systems for which the end users cannot explain or interpret the results. Consequently, AI systems may be black boxes. The designers may not understand some model decisions, the end users may not be able to explain or interpret the results, or both (Cohen et al., 2014; Sambasivan et al., 2021). This lack of transparency and explainability can be due to the method used or other reasons, such as the user interface design. Nevertheless, the developed systems are artificial agents (Miller, 2022; Singh et al., 2019). As such, "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).

Next, AI projects rely on self-regulation. In contrast, pharmaceutical, healthcare, and infrastructure projects face strong regulations and political constraints and require government approvals (Mittelstadt, 2019; Shenhar and Dvir, 2007; Wieringa, 2020). Professionals, especially in medicine, are "governed by legal and professional frameworks which uphold professional standards and provide patients with redress for negligent behavior, including malpractice law, licensing and certification schemes, ethics committees, and professional medical boards" (Mittelstadt, 2019, p. 8). Similar governance structures and fiduciary requirements do not exist for private-sector AI developers (Mittelstadt, 2019).

Governments are considering new and revised regulatory protections for AI systems (European Commission, 2021; 116th Congress (2019–2020), 2020). However, existing laws and regulations rely on organizations to comply with data protection regulations or other laws such as the Americans with Disabilities Act (Büchi et al., 2020). The proposed EU Artificial Intelligence Act will require a risk assessment for high-risk AI systems before deployment. Nevertheless, weak technology policies, inadequate enforcement, and lack of laws and regulations create situations in which citizens endure extensive personal data collection, intrusive models, privacy violations, and constant surveillance with no ability to influence or contest their treatment (Chasalow and Levy, 2021; Sambasivan et al., 2021).

Finally, AI projects that train large data models have high energy consumption and produce carbon emissions that may affect the environment; the scale of carbon emissions for training some models is on the scale of a trans-American flight (Bender et al., 2021; Ryan and Stahl, 2021; Strubell et al., 2019). Moreover, the community that pays the environmental price may not be the community that benefits from the AI system.

2.4. Stakeholder theory

Stakeholder theory was first applied to strategic management as a way to strategically group relationships; a stakeholder was defined as "any group or individual who is affected by or can affect the achievement of an organization's objectives" (Freeman and McVea, 2001, p. 2). However, different views and theories of who or what stakeholders are have developed since. Donaldson and Preston (1995) identified three types of stakeholder analysis theories: descriptive, instrumental, and normative. The descriptive stakeholder theory describes a relationship between stakeholders and a phenomenon. The instrumental stakeholder theory is oriented around how managers meet specific objectives for their firms. The normative stakeholder theory takes an ethical perspective on whom the manager should be responsible for and how the firm should be governed (Donaldson and Preston, 1995; Reed et al., 2009).

Similarly, Eskerod & Huemann (2013) identified two approaches to stakeholder theory: the management-of-stakeholders approach and the management-for-stakeholders approach. The management-of-stake holders approach views stakeholders as resources whose potential to harm or help guides the degree of attention they get from the firm; this follows the instrumental stakeholder view. With the management-for-stakeholders approach, all stakeholders have a legitimate right to management attention without regard to their ability to contribute. This implies a normative view. The authors argue that sustainable development is necessary for the future and that project stakeholder management must integrate both approaches.

Project management standards such as the Project Management Body of Knowledge (PMBOK) (PMI, 2021) take the instrumental view that the stakeholders should be associated with meeting the project objectives. They argue that stakeholders should be identified regarding their ability to help or harm the project (PMI, 2021; Eskerod and Huemann, 2013). Conversely, project management literature on sustainability, mega–projects, and public–private partnerships have taken a normative view of stakeholders, emphasizing various passive stakeholder groups such as external, disenfranchised, discretionary, and marginalized stakeholders (Derry, 2012; De Schepper et al., 2014; Nguyen et al., 2019). Passive stakeholders are those affected by the project's outcome without being able to influence the outcome (Achterkamp and Vos, 2008). In all these cases, stakeholder categorization revolves around the stated objectives and the definition of project success given to the project manager and is considered from the firm's or the project manager's perspective.

2.5. Stakeholder identification

Mitchell et al. (1997) classified the salience of stakeholders based on power, legitimacy, and urgency attributes, and stated that all stakeholders possess at least one of these attributes. The stakeholder salience model is a descriptive model that gives managers a way to justify who the stakeholders are and prioritize who deserves attention. Researchers have criticized the model for not addressing dynamic project needs or moral issues, as it does not reflect the change in people's attitudes, network positions, and roles that occur during a project lifecycle (Di Maddaloni and Davis, 2018; Eskerod and Huemann, 2013). Moreover, the model is inconsistent with a sustainable world of well-being and justice. Specifically, the definition of legitimacy reinforces corporate power and marginalizes the rights and interests of certain populations (Derry, 2012).

Derry (2012) suggested challenging the role of the firm, or in this case the project, at the center of the stakeholder model, and asking, "who or what should be at the hub of the stakeholder model?" (Derry, 2012, p. 263). Specifically, the author stated

> "If we shift the stakeholder model to center around our commons, defined broadly as our community and environment, then we are pushed into thinking 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 reasoning comports with arguments that managers should serve the legal and moral interests of legitimate stakeholders (Mitchell et al., 1997).

Di Maddaloni and Davis (2018) investigated local community stakeholders in a major infrastructure and construction project. The authors determined that the conceptualization of communities depends on the nature and type of the project; geographical proximity, people's demographics, backgrounds, and cultures; and common behavioral attitudes and actions of the local community. The study identified six types of local communities based on proximity (geography), opinions (interests), and perceived impacts. The authors offered a model for classifying this new group of stakeholders as a means to identify and engage them for the benefit of the project.

Nguyen et al. (2019) evaluated the impact of internal and external stakeholders on different projects. Internal groups normally have direct or indirect contractual relationships with the client. External groups do not usually have an enforceable claim; instead, they rely on representation, such as regulators, to act on their behalf. External stakeholders can greatly affect the project using indirect influencing techniques even if they are not engaged in the project.

Wegrzyn and Wojewnik-Filipkowska (2022) identified and classified the stakeholders of public–private partnership projects based on stakeholder preferences and project engagement. The authors defined stakeholder preferences based on the sustainable dimensions: economic, social, and environmental; the economic requirements were the financial benefits, while the social and environmental were nonfinancial. They classified the stakeholders based on their preferred benefits (financial vs. nonfinancial) and their project engagement (direct vs. indirect). The authors argued that engagement incorporates the power and urgency attributes from the stakeholder salience model. The benefits dimension considers the short- and long-term evaluation of the project's sustainability.

2.6. Stakeholder roles

Roles concern the behavior of individuals in a context and guide and direct an individual's behavior in a particular setting (Biddle, 1979; Zwikael and Meredith, 2018). Davis (2014) and Turner and Zolin (2012) have proposed role-based project stakeholder models; however, they are limited in recognizing passive roles. The Vos Janita and Achterkamp Marjolein (2006) stakeholder role-based model defines four stakeholder roles (clients, decision-makers, designers, and passive stakeholders) using concepts from critical system heuristics. The active stakeholders, who can affect the project, are involved because they contribute resources or influence the outcomes; they include clients (whose purposes are served), decision-makers (who have the power to decide), and designers (who contribute expertise). The project's passive stakeholders may be affected and are usually engaged through a form of representation (Vos Janita and Achterkamp Marjolein, 2006). The authors note the challenges with identifying passive stakeholders and involving individuals and organizations that can represent them in projects.

3. Methodology

The research aimed to clarify what roles are involved in the decision-making and acting in AI projects and identify the stakeholders affected by AI projects and AI system usage. First, data were collected using a systematic literature review, then a thematic analysis for stakeholder and role identification was performed. This section describes the data collection and analysis process and the coding framework.

3.1. Systematic literature review

A systematic literature review was used to collect data on the AI stakeholders and their roles. "A systematic review is a review of a clearly formulated question that uses systematic and explicit methods to identify, select, and critically appraise relevant research, and to collect and analyze data from the studies that are included in the review" (Moher et al., 2010, p. 336). The objective of the systematic review is to synthesize existing knowledge in a structured and rigorous manner.

3.1.1. Procedure

The procedure included 1) identification of bibliographic databases from which to collect the literature, 2) definition of the search process including the keywords and the search string, 3) definition of inclusion and exclusion criteria, 4) removing duplicates and screening the articles, 5) extracting data based on a full-text review of the articles, and 6) synthesizing the data using a coherent coding method. Details are described in the following sections. Fig. 2 depicts the flow of information through the systematic review. The process was conducted by a single researcher.

3.1.2. Bibliographic databases

The literature search queried the ProQuest, Emerald, ScienceDirect, and IEEE Xplore bibliographic databases for peer-reviewed articles. Besides, the bibliographic data from the main project management journals (Drouin et al., 2013) (i.e., Project Management Journal, International Journal of Project Management, IEEE Transactions on Engineering Management, and International Journal of Managing Projects in Business) from 2000 to 2021 from the Emerald, ScienceDirect, IEEE Xplore, and Sage databases were included in the keyword search. The databases were selected to cover a wide selection of peer-reviewed journals, the main project management journals, and computer science conference papers. Computer science research is mainly presented at conferences (Wang, 2018).

There were multiple iterations of the search. The first search identified the "ACM Conference on Fairness, Accountability, and Transparency (ACM FAccT)" as an important source for cross-disciplinary research. Thus, additional bibliographic searches were undertaken in March, July, and December 2021, including those from previous bibliographic databases and the ACM Digital Library.

3.1.3. Search string

The first search was performed in October 2020, when "algorithm" and "stakeholder" were selected as the focal keywords for the study. The keyword "algorithm" was chosen instead of AI since algorithmic usage is an expected outcome of AI projects. In contrast, there are a diversity of terms that could represent an AI project: algorithm, AI, machine learning, etc. This search revealed key themes and terms in algorithmic projects. Keywords such as ethics, fairness, accountability, transparency, and explainability were frequently referenced in the articles.

The keyword "stakeholder" in combination with "algorithm" identified 10 articles published since 2010 from five publications and five

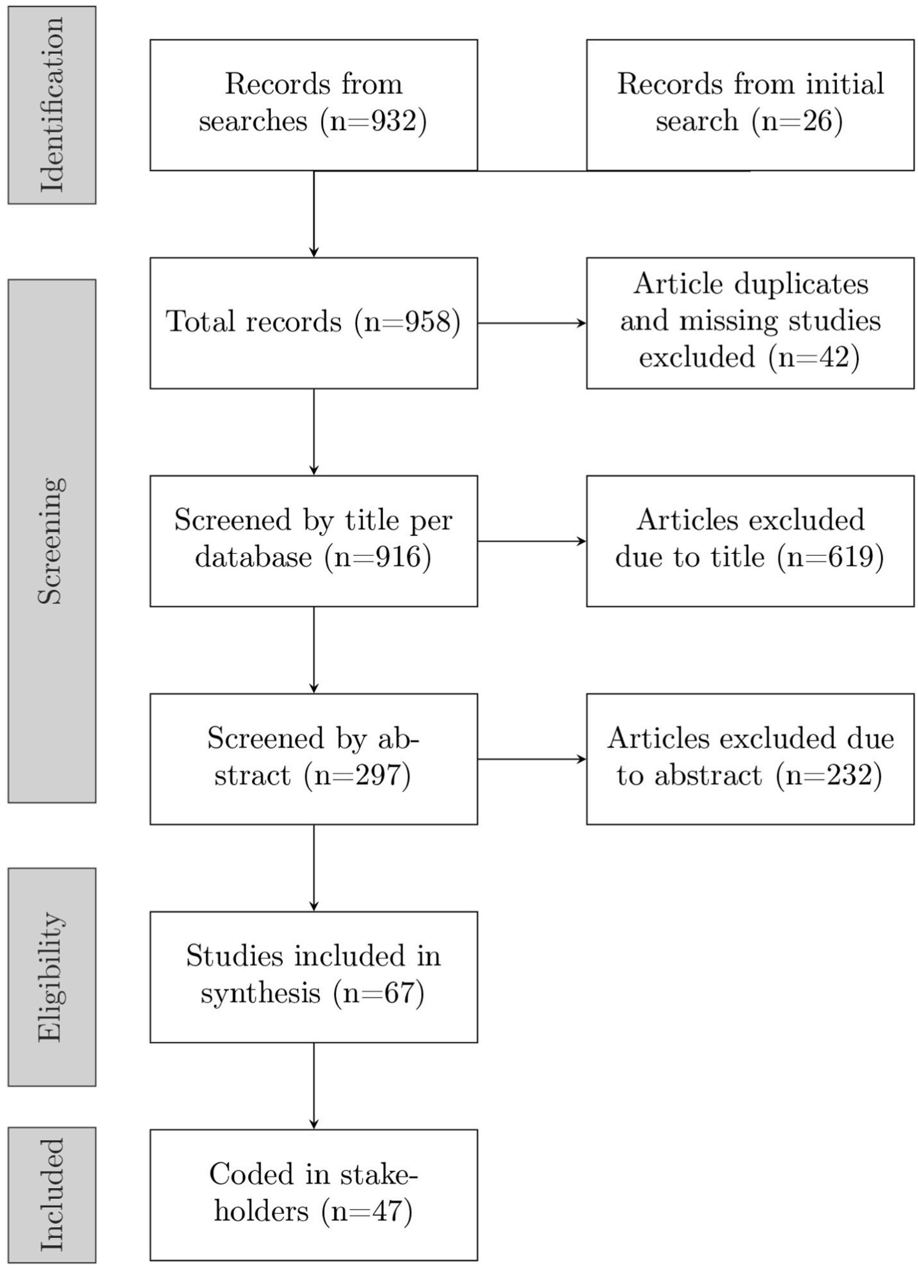

Fig. 2. PRISMA process flow.

conferences. The number of articles was limited by the "stakeholder" keyword. Thus all 26 articles that included the keyword "algorithm" were included in the first analysis. Subsequent searches were performed, emphasizing "accountability" instead of "stakeholder." Accountability focuses on the relationship between project actors and those to whom the actors should be accountable (Wieringa, 2020).

The final version of the search string emphasized the frequent keywords associated with AI projects. Variations of the search string were used because not all databases allowed wild cards, and adjustments were made in the syntax for each search engine. The final version of the search string with wildcards is as follows:

All = accountabl* AND

Title = ("machine learning" OR "artificial intelligence" OR AI OR "big data" OR algorithm*) AND

Title = (fair* OR ethic* OR moral* OR success OR transparency OR explainabl*)

3.1.4. Inclusion and exclusion criteria

Peer-reviewed journal articles or conference papers and English language were retained; book reviews were excluded. There were no additional filters for dates. Duplicate entries and entries with no documents were removed. Thereafter, literature was excluded or retained in an iterative process based on a review of the title, a review of the abstract, and a close reading of the full article text.

First, the titles of the articles were reviewed, and articles about the people or organizations involved in the development, use, or outcomes of AI systems were retained. Articles incorrectly identified, such as magazine articles or panel descriptions, were excluded. Next, the abstracts were reviewed to determine if the article could yield information on the stakeholders or project participants. Finally, the full text of the included articles was reviewed and coded to answer the research questions. The articles identified during the initial search were retained throughout the analysis process. In total, the full text of 67 articles was included for analysis. Most of the reviewed articles (82%) were published after 2019, and many (39%) were conference papers. Less than 5% of the reviewed articles were published before 2016. Table 2 shows the article distribution by database. Fig. 2 shows the preferred reporting items for systematic reviews and meta-analyses (PRISMA) process flow.

3.2. Thematic analysis

3.2.1. Coding process

The data were analyzed using thematic analysis and coding in Nvivo 12 (Windows) software in five steps. Fig. 3 provides an overview of the coding process.

First, the analysis involved reviewing the 67 articles found during the literature review to identify individuals, collectives, groups, or organizations. These parties were considered part of the AI community. The identified parties are interested in the AI topic but may or may not be stakeholders in a specific AI project.

Second, the parties were grouped into common roles based on the functions they should accomplish or using role attributes of generality (Biddle, 1979). Clear and consistent roles and terms across the literature were retained. Conflicting or inconsistent terms were defined using a meta-analysis. If necessary, the roles were differentiated based on the dimensions of generality: contextualization and personalization (Biddle, 1979). Contextualization is the setting, activity, or other criteria; personalization is the degree to which the role is limited to a single individual.

Third, according to the coding framework, we assessed the roles to determine if they were stakeholders based on the stakeholder attributes of power, legitimacy, urgency, and harmful impacts. Each AI community member was evaluated and grouped using their relationship to the project or the project output and these attributes. Fourth, the stakeholders were assigned project roles and stakeholders according to the coding framework. This approach is consistent with the strategy used by Vos Janita and Achterkamp Marjolein (2006) for analyzing roles by project stage. Finally, there was a cross role analysis to identify the development stakeholders.

3.2.2. Coding framework

3.2.2.1. Stakeholder identification. Building on the salience model from Mitchell et al. (1997), four attributes were defined for identifying stakeholders and non-stakeholders: power, legitimacy, urgency, and harm. This method provides an ethical dimension to the basic stakeholder salience model, addressing the limitation identified by Derry (2012) that moral issues must be considered. Furthermore, the analysis incorporates economic, social, and environmental sustainability considerations. These attributes make the passive stakeholders explicit. Stakeholders have at least one of the attributes, while non-stakeholders have none.

Table 2
Publications by database.

Database	Search Results	Dup/ Excl	Screened By Title	Screened By Abs	Full Text
ACM	300	5	295	119	27
Emerald	25	5	20	6	2
IEEE Xplore	143	3	140	32	3
ProQuest	299	13	286	96	19
Science Direct	165	4	161	28	9
Initial search	26	12	14	16	7
	958	42	916	297	67

Abbreviations: Dup-Duplicates, Excl-Exclusions, Abs-Abstract.

The benefit was considered and dismissed as an attribute; the attribute provided no distinguishing element. We determined that the project could be of potential benefit to most, if not all, stakeholders. For example, passive stakeholders could benefit from conveniences, availability of services, unbiased decision-making, and better performance. The attributes were assessed as follows:

- *Power* is the extent to which the stakeholder can impose their will on the project implementation or output usage. Here we use the power dynamics as defined by Nguyen et al. (2019). This includes the power to punish for non-compliance, which is dependent on fear of negative results from failing to comply (coercive); power to give a positive reward for complying (reward); formal authority to control or use organizational resources based on structural position in the organization (legitimate); power from the possession of some special knowledge, skill, or expertise (expert); and power of being a role model (referent).
- *Legitimacy* is evaluated when the stakeholder enjoys a socially constructed standing shared by the parties. We evaluate the nature of the contractual relationships between the parties to determine if an individual, organizational, or societal agreement exists with the developing or the operating organization: terms of services (terms), project statement of work (SOW), employment contract (employ), organizational agreements and rules (rules), regulations or laws (laws), or organizational positions (hierarchy).
- *Urgency* is assessed when the stakeholder claim or relationship calls for immediate attention either as a time-sensitive or critical relationship or claim. Here we fall back on Jones' (1991) definition of temporal immediacy and proximity. Temporal immediacy implies the time between the present and the act's consequences. Proximity is the closeness of the moral agent to the victims. We use the project stages to represent proximity and temporal urgency: development stage (D), usage stage (U), and consequences stage (C).
- *Harm* evaluates if the stakeholder would be harmed by the implementation or use of the system. Here we can build from ethical issues identified by Someh et al. (2019) for big data analytics for individuals, organizations, and society and classify harms, damages, or losses as follows: harms: bodily harm, loss of life, limitation of rights (freedom of movement), surveillance, psychological; loss: violations of human or civil rights such as loss of privacy, security, freedom, financial, job; damage: trust, reputation, environment.

3.2.2.2. Stakeholder grouping. The roles were grouped by AI lifecycle stage, the project organization model from Zwikael and Meredith (2018), and AI roles from Michalczyk et al. (2021). The model by Zwikael and Meredith (2018) was selected as it includes the most prevalent project roles across literature, provides clear definitions for the roles, and considers their organizational relationships.

- The *funding entity* is part of the parent organization that invests in and expects to benefit from the development and use of the AI system.
- The *performing entity* is the temporary organization that develops the AI system and may be called upon to refine the AI system at different time intervals.

AI team specializations were drawn from the job roles as defined by Michalczyk et al. (2021). They include business users, data analysts, data scientists, data engineers, software architects, and software developers. The model was chosen for four reasons. First, it covers the knowledge, skills, and abilities of the subject domain of the current study. Second, it is based upon a substantial number of job advertisements in the domain (25,104) investigated during the corresponding period of this study. Third, job roles are functional and task-oriented: functions provide observable consequences of activity and tasks refer

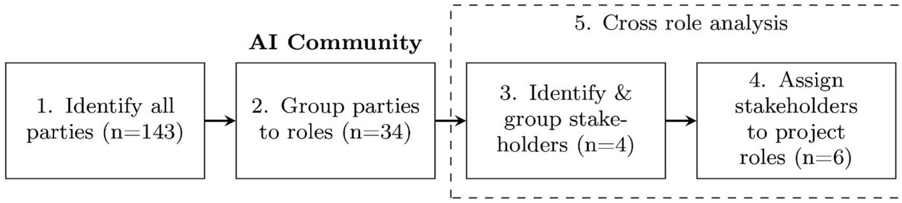

Fig. 3. Coding process. Author's own elaboration.

to shared intention (Biddle, 1979). Fourth, the descriptive information in Michalczyk et al. (2021) was sufficient to match the roles mentioned in the reviewed literature with the descriptive details provided in the study.

3.2.2.3. Stakeholder project roles. The stakeholder project roles were identified based on the reference model proposed by Vos Janita and Achterkamp Marjolein (2006). This model was chosen as it is a general model and has been verified against cases in innovation projects. The roles of the model include clients, decision-makers, designers, passive stakeholders, and stakeholder representatives. Reference was added for referent stakeholders, and not applicable was added for non-stakeholders.

3.3. Validity and reliability

The checklist and phase flow from the PRISMA statement were used to guide the data collection and report the results (Moher et al., 2010). This approach to defining elements is an acceptable method for placing boundaries around the meaning of a term (Moher et al., 2010). Relevant theoretical models for role definition and stakeholder salience, taken from the project management domain, were evaluated and used to define the coding framework. This approach was chosen to be consistent with the descriptive stakeholder theory and to closely link the dynamic activities and tasks of the people involved. Next, the results were cross-validated with literature reviews on other project stakeholders to ensure completeness (Achterkamp and Vos, 2008; Davis, 2014; Turner and Zolin, 2012).

4. Research findings

In summary, 34 AI community members were identified and assigned to one of four stakeholder groups and six stakeholder project roles. Fig. 4 shows the interrelationship between the AI community members.

The stakeholder groups are non-stakeholders, development, usage, and external. The development and usage stakeholders have a formal relationship with the project in the development or usage stages of the AI lifecycle; whether they are internal to the parent firm of the project is determined by the project's governance structure and is context- and project-specific. The external stakeholders are not part of the project but may affect or be affected by the project. The non-stakeholders are part of the AI community but are not associated with or affected by the project.

Tables 3 and 4 summarize the development and usage stage stakeholders, respectively. Table 5 summarizes the external stakeholders; non-stakeholders—academics and industry partners—are not included in any tables. In the tables, level refers to an organizational level as shown in Fig. 4; the subgroup is a categorization of the external stakeholders.

The six stakeholder project roles provide context and guidance on how the stakeholders are involved in the project. Table 6 presents the

Table 3
Stakeholder group—Development stage.

Level	Project role	Power	Legitimacy	Harm
Organization	Developing organization	legitimate	hierarchy	loss + damage
	Executive management	legitimate	hierarchy	damage
	Functional departments	referent	hierarchy	–
	Legal and ethical	referent	hierarchy	–
Funding entity	Project funder	legitimate	hierarchy	loss
	Project owner	legitimate	hierarchy	damage
	Data controller	referent	hierarchy	–
Performing entity	Project managers	legitimate	SOW	damage
	Project team	expert	SOW	harms

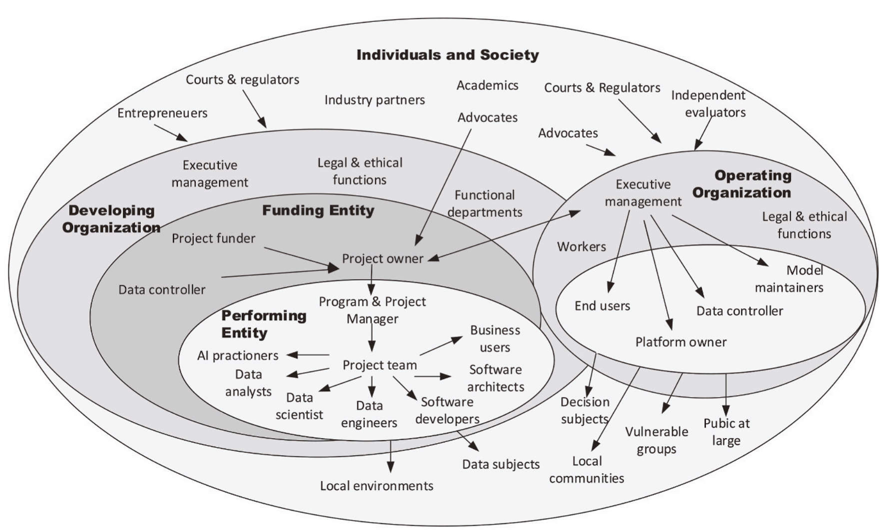

Fig. 4. The interrelationship between AI community members. Author's own elaboration.

Table 4
Stakeholder group—Usage stage.

Level	Project role	Power	Legitimacy	Harm
Organization	Operating organization	legitimate	license	loss
Operations	Data custodian	referent	hierarchy	–
	End users	expert	employ	harms
	Platform owners	legitimate	license	–
	Model maintainers	expert	license	–

stakeholder project roles. The definition of the stakeholder project roles closely follows those proposed by Vos Janita and Achterkamp Marjolein (2006). The project serves the client's purpose, the decision-maker has the power to decide, the designer has the expertise, and the reference role serves specific functions in the project; these roles represent actively involved stakeholders that are members of the development and usage groups. Passive stakeholders may be affected by the project but lack any power to influence the project. They may have representation in the project through the representative roles. The passive stakeholders and representative roles are members of the external stakeholder group. Descriptions of each stakeholder group and their roles are given in this section.

4.1. Development stage

4.1.1. Organization

The developing organization sponsors the project and establishes the project scope. The organization benefits from the AI system and may face damages or losses, including financial, reputation, or legal, through the execution of the project. The developing organization is a decision-making stakeholder.

The executive management includes senior and top management support for the project manager (Miller, 2019b; Zwikael and Meredith, 2018). The legal and ethical functions include supervisors, boards, or internal support roles (e.g., whistle-blower, ombudsman) that provide needful guidance, policies, and support for ethical practices and issues (Ryan and Stahl, 2021; Wieringa, 2020). The project within the development organization is divided into the funding and the performing entity.

4.1.2. Funding entity

A funding entity pays for and governs the project; the project funder and owner were identified to play key roles (Zwikael and Meredith, 2018). Within the organization, the project funder is the executive management who commits the resources (labor or money, for example) to the project (Cohen et al., 2014; Kauffman et al., 2015; Turner and Zolin, 2012; Zwikael and Meredith, 2018). Multiple funders may become involved between the development and usage stages, and funders do not play an active role in the project (Zwikael and Meredith, 2018).

A project owner provides strategic direction to the project, defining the project scope, arranging the performing entity, and chairing the steering committee (Zwikael and Meredith, 2018). Thus, the project owner issues the statement of work (SOW), the scope definition document, or the problem statement that defines the aims and rationale for the system (Cobbe et al., 2021). The scope definition is one factor that determines the AI system's relationship to society, that is, how the project or system benefits or harms society (Miller, 2022; Cobbe et al., 2021). The project owner is a decision-making stakeholder.

The data controller is responsible for data governance and its use in system development. Several regulatory and legal requirements exist for working with data and algorithmic decision-making, and violations or non-compliance can result in substantial penalties. For example, the administrative fines for infringements of some General Data Protection Regulation (GDPR) rules can be up to 4% of an organization's total worldwide annual revenue of the preceding financial year (European Commission, 2016).

4.1.3. Performing entity

The project manager is accountable for the project's outputs per an agreed SOW provided by the project owner (Turner and Zolin, 2012; Zwikael and Meredith, 2018). Moreover, the project manager ensures adherence to ethical, privacy, and security norms and expectations and the engagement of the relevant stakeholders (Miller, 2019a). The project team composition is context specific and decided by the project scope and agreed SOW. The project team includes the individuals engaged in development activities through employment or contracts with the development organization. Furthermore, the people responsible for labeling, annotating, tagging, or curating training datasets or moderating content may be temporary, contract, or gig workers engaged through

Table 6
Stakeholder project roles in AI projects.

Stakeholder project role	Project role
Client	Operating organization, model maintainers, platform owners
Reference	Data controller and data custodian, functional departments, legal and ethical functions
Decision maker	Developing organization, executive management, project funder project and program managers, project owner, project team, operating organization, *end users
Designer	Project owner, project team (business users, data analyst, data scientist, data engineer, software architects, software developers, AI practitioners)
Passive	Data subjects, decision subjects, *end users, entrepreneurs, local communities, local environments, public at large, vulnerable groups, workers
Representatives	Advocates, courts and regulators, independent evaluators, labor unions

Note: * Extremely context dependent.

Table 5
Stakeholder group—External stakeholders.

Sub-group	Project role	Power	Legitimacy	Harm	Urgency
Individual	Data subjects	–	terms	loss	D
	Decision subjects	–	terms	harms	C
	Workers	–	employ	loss	U–C
Society	Local environments	–	–	damage	D
	Vulnerable groups	–	–	harms	C
	Public at large	–	–	harms	C
	Local communities	–		harms	C
Representative	Courts and regulators	legitimate	laws	–	D-U-C
	Labor unions	legitimate	rules	–	D-U-C
	Advocates	coercive	–	–	D-U-C
	Entrepreneurs	reward	–	–	D-U
	Independent evaluators	coercive	–	–	D-U-C

Abbreviations: D = Development, U = Usage, C = Consequence.

platforms such as Mechanical Turk (Moser et al., 2022).

If the project team is responsible for data manipulation of sensitive topics (e.g., pornography, hate speech, violence), it may face psychological harm in developing the systems (Munoko et al., 2020). In addition, they may face other harm when they conflict with the project direction on moral grounds (Kerr et al., 2020; Ryan and Stahl, 2021). Nevertheless, the project team members are decision-makers and designers who directly influence the project output. The team may include the following specializations: business users, data analysts, data scientists or AI practitioners, data engineers, software architects, and software developers Michalczyk et al. (2021); the number of articles from the literature review referencing the role is included in the parenthesis.

The *business users* (2) are responsible for specific content development, editing, or coaching the team or users. *Data analysts* (6) include domain experts, industry experts, analysts, and consultants who understand processes and government policy; they have expertise in the context needed to interpret raw data, ask relevant questions, generate relevant hypotheses and interpret the results. *Data scientist* (18) is an interdisciplinary role that aims to transform data into knowledge by finding patterns and trends in the data. However, the role of an *AI practitioner* (3) (e.g., computer vision engineer) may be relevant, depending on the technology and context of the project.

A *data engineer* (7) is responsible for data preparation and quality, including extracting, cleaning, enriching, and transforming the data. This role may be directly or indirectly responsible for annotating or labeling data within a dataset. Data engineers may include curators, data collectors, data custodians, data experts, and data stewards. The *software architect* (6) is responsible for technical infrastructure and may include architects, the IT team, the process manager, and security specialists. *Software development* (17) includes computer scientists who use software tools and technologies, programming language, and technical infrastructure to implement and optimize the processing of large data sets or developing user interfaces. Software development may include report visualization developers, designers, and other developers.

4.2. Usage stage

4.2.1. Organization

An operating organization is the purchaser or consumer and may have some expectations and notions of success different from the end users (Cohen et al., 2014; Miller, 2019b). The organization may face financial, reputation, and legal harm from using the AI system. Their relationship to the development may be organizational or through license or service agreements. In any case, they are client stakeholders.

4.2.2. Operations

The technology platform is the technical infrastructure and architecture upon which the AI system resides. It can be owned and hosted by the platform owner, which means that it could be owned and hosted in-house or in the cloud by the operating organization, or it could be hosted on online platforms managed by third-party providers such as cloud service providers, social media sites, or search engines (Webb et al., 2018).

The data custodian must manage, assure, secure, and preserve the data (Bertino et al., 2019). Preserving data privacy and complying with privacy laws during the execution of the business process is one of the main challenges when using cloud services; this is even more complicated when multiple companies are involved in the business process (Schwarzbach et al., 2016).

End users include individuals engaged in system usage through employment or service contracts with the operating organization or as consumers. They may have direct system access or receive the system outputs through an intermediary user. Like the project team, direct system users may face psychological harm in using systems that address sensitive topics (Munoko et al., 2020). Besides, they may be harmed if the system is inaccessible to people with a disability. They have a direct influence on system usage through their availability and expertise. This group is a stakeholder; the project organization determines if they are passive stakeholders represented by another party.

The end users are the operators of the developed AI system. The decision maker is the end user who is faced with a decision, must take action, and will be responsible for the outcome, but may or may not interact directly with the system. Intermediary users may help the decision maker interact with the system or make suggestions (Miller, 2019a; Turner and Zolin, 2012; Zwikael and Meredith, 2018). The distinction between types of users seems important for AI, given the numerous outsourcing service models and liability concerns. That is, the person who interacts with the system may not belong to the same organization as the person accountable for the decisions (Miller, 2019a). Depending on the design of the system, organizational policies, and the end-users autonomy, end users may or may not be decision-making stakeholders. Furthermore, for enterprise systems, the end users do not always have the same goal and requirements for the system as their organizations.

Model values or choices can become obsolete. They must be reviewed and assessed for fitness and refreshed over time. This action is performed by model maintainers (Veale et al., 2018; Wieringa, 2020).

4.3. External stakeholders

4.3.1. Individual subjects

Individual subjects include the people who may have an agreement with the development organization or the operating organization, such as terms of services or service or employment contracts. They include data subjects, decision subjects, and workers. They are passive stakeholders.

During the development, data subjects may be affected by the loss of privacy of their personal data (Bertino et al., 2019). During usage, decision subjects are the recipients who face the consequences of usage that may be as severe as loss of life or freedom (Bertino et al., 2019; Wieringa, 2020).

The workers may face new job structures and patterns, eliminate specific jobs, or change their way of working (Rodrigues, 2020; Ryan and Stahl, 2021). For example, workers may have their jobs controlled by algorithms, replacing human managers and changing the relationship between the worker and work (Cameron and Rahman, 2022; Moser et al., 2022). Conversely new jobs are created for labeling, annotating, tagging, or curating training datasets or moderating content (Moser et al., 2022).

4.3.2. Society

Society includes individuals and the public who may be harmed by the development or use of the system. They do not have any agreement with the development or operating organizations. This group includes local communities, environments, vulnerable groups, such as people with disabilities, minority groups, minors, and the public. They are passive stakeholders (Rodrigues, 2020).

During development, the local environment may be most affected by the carbon emissions produced when large models are trained (Bender et al., 2021). Other stakeholders may face the consequences of usage, such as constant surveillance, discrimination, or loss of privacy (Bondi et al., 2021; Rodrigues, 2020).

4.3.3. Representatives

Representatives include several groups and organizations that are not harmed by system usage or development but may represent others in the project. There are formal representatives with an official mandate, informal representatives without a relationship with the development or operating organizations, and a final group that may voluntarily or be invited to become engaged in the project.

4.3.3.1. Formal representatives. Formal representatives, including courts, laws, regulators, and labor unions, have legitimate power (Rodrigues, 2020). They have formal means to enforce their will upon the project. They are representatives of passive stakeholders.

Multiple regional, national, and state-specific laws and regulations restrict the data collection, usage, and storage of data (Büchi et al., 2020; Cohen et al., 2014; Rossi and Lenzini, 2020; Wagner et al., 2020). Regulators and courts enforce compliance with regulations, laws, acts, and ordinances. For example, in the EU, the GDPR protects the rights of citizens in the member EU states and addresses data privacy, profiling (i.e., algorithm development), use, and contestation. Data protection laws vary from state to state in the United States.

Other laws, regulations, and ordinances, such as the Americans with Disabilities Act, the Fair Credit Reporting Act, the Health Insurance Portability and Accountability Act, the Children's Online Privacy Protection Act of 1998, and the German Network Enforcement Act (Büchi et al., 2020; Wagner et al., 2020; Cohen et al., 2014), that protect specific rights of individuals must be observed in AI systems development.

4.3.3.2. Advocates. Advocates are third parties who can represent different parties with the development organization, the operating organization, or individuals and groups in the AI community. This group is not harmed by the system usage or development and may have coercive power over the project. Examples include community boards, professional organizations, standards organizations, non-governmental organizations, and policymakers. They are representatives of passive stakeholders. In this context, a community is any group of similarly situated people (e.g., people with disabilities, ethnic minorities, and youths) (Helberger et al., 2020).

4.3.3.3. Entrepreneurs. AI systems that benefit individuals and society may involve multiple entrepreneurs during the initial development or to expand the usage to a broader community. For example, federal, state, and local governments that invest in support systems for under-served hospitals (Cohen et al., 2014).

4.3.3.4. Independent evaluators. Independent evaluators include third parties such as investigative reporters in the media, journalists, internal or external auditors, safety certifiers, institutional review boards, insurers, judges, lawyers, or third-party reviewers such as the general public. Depending on the engagement model, these parties may have coercive or reward power with the development organization or the operating organization. They may be engaged in a project by invitation or at their own risk.

The evaluators may judge algorithms in an attempt to expose or prevent algorithmic harm (Wieringa, 2020). As the watchdog of democracy, the media has the power to communicate its findings to the public (Klijn & Koppenjan, 2014). Auditors have the ability to punish organizations for breaches of internal rules or violations of regulations or laws (Cohen et al., 2014; Shneiderman, 2020; Rodrigues, 2020). The lawyers and judges assess conflicts between laws, public values, and complicated AI systems (Wieringa, 2020).

4.4. Non-stakeholders

Non-stakeholders have an interest in and are active in the AI community but do not have a legitimate relationship with the development or operating organizations concerning a specific project. They are not directly harmed by the development or use of the AI system. This group includes academics and industry partners. This group is outside the project environment.

4.5. Cross role analysis

Fig. 4 provides a conceptual view of the interrelationship of stakeholder project roles in an AI development project. Without question, the system developers are the performing entity in the development organization. However, visualizing all stakeholders clarifies that ethical and sustainable system development includes additional stakeholders from the development and operating organizations and representatives for the passive stakeholders.

In Fig. 5, development project stakeholders are represented as R1. Passive stakeholders do not have a choice or negotiation power. They are unaware of what happens within AI projects or systems (Someh et al., 2019). Consequently, representatives are engaged in AI projects to balance the needs of all stakeholders, not just those that can help the project (Eskerod and Huemann, 2013). R2 in Fig. 5 represents this relationship. If possible, the passive stakeholders have a voice in selecting the representatives (Bondi et al., 2021; Vos Janita and Achterkamp Marjolein, 2006). This relationship is represented in Fig. 5 by a dotted line to show its optionality.

The operating organization is in a central role between the development stage and the consequences for users of the AI system (R5). Thus, to consider the rights of the stakeholders, AI projects include individuals from the operating organization in the development that can represent the interests of their stakeholders (R3).

Finally, the project owner for scope definition, team members for expert knowledge, and the project manager for including relevant stakeholders are important persons in the development stage. Organizational strategic goals are imposed on the project, and policies flow downward from the organization to the project through the decision-makers (Derakhshan et al., 2019). Combined the designers and decision-makers make important decisions on the design and development of the AI system, an artificial agent (R4). Consequently, they are the only stakeholders who can consider the concerns of all stakeholders (Martin, 2019).

5. Discussion

The adoption of AI systems is growing in importance. It applies to several industry sectors: transport, agriculture, finance, marketing and advertising, science, healthcare, criminal justice, security, and the public sector (OECD, 2019). The systems can provide huge benefits but also inflict serious damage. The ability of an AI system to impact human, civil, and workers' rights of individuals and the environment makes it different than other project types. Furthermore, regulations, government approvals, and professional practices have not kept pace with the developments of AI technologies.

This study used systematic literature research and thematic analysis to answer the following questions: *What are the roles involved in the decision-making and acting in AI projects? Who are the stakeholders affected by AI projects and systems?* The study analyzed stakeholders from a descriptive point of view, identifying and classifying the development, usage, and external stakeholders involved in or affected by AI projects and systems.

The cross-role analysis (Fig. 5) demonstrates that stakeholders in both the development and usage stages are moral agents. The development stage stakeholder group (Table 3) has the power and legitimacy to decide the features of the AI system and engage other stakeholders in the project. They are creating a machine that is an artificial agent that can enable, inform, guide, and influence or bypass human judgment (Moser et al., 2022; Vesa and Tienari, 2020).

The usage stage stakeholder group (Table 4) has the power and legitimacy in the deployment and usage of the AI system and its impacts on external stakeholders (Table 5). These findings are consistent with those of Martin (2019), who stated that developers and their organizations are accountable for the outcomes of their algorithmic systems. This study extends that understanding by separating operations from development and specifying organizational and individual stakeholder project roles (Table 6).

The external stakeholders (Table 5) include the individuals and

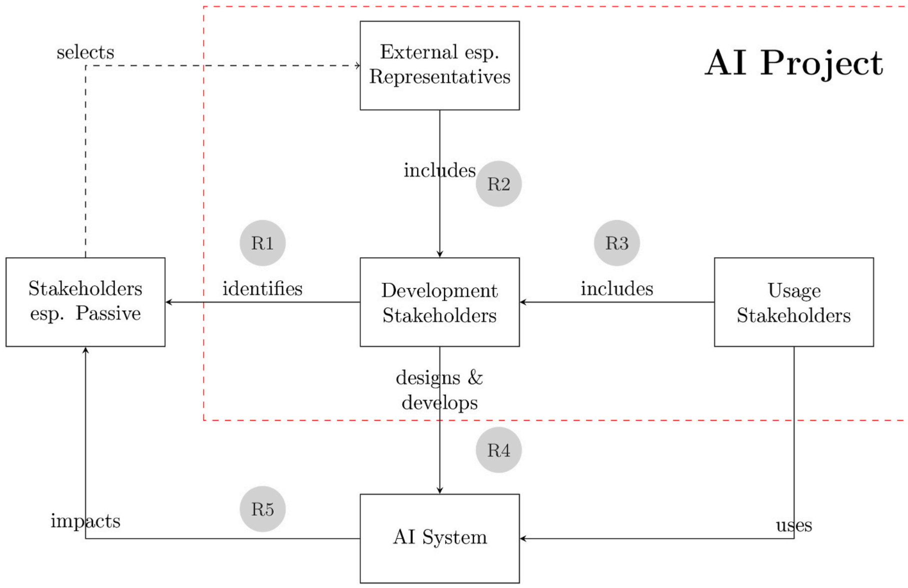

Fig. 5. Conceptual view of stakeholder engagement in development. Author's own elaboration.

societal stakeholders who may be harmed during the development or operations of AI. Developing large models have environmental consequences that can impact local environments. Individuals may face loss of privacy, security, work, or freedom. Communities may be placed under surveillance or have their freedoms otherwise limited. These passive stakeholders can be significantly impacted by the AI systems, although they have no power within the projects. Representatives, such as regulators, courts, labor unions, and other advocates, have power and can act as representation for passive stakeholders. However, they must be engaged in the projects during the development or usage stages. This study adds context on AI stakeholders. These findings reinforce project management studies that call for a broad inclusion of stakeholders for ethical and sustainable developments (Di Maddaloni and Davis, 2018; Derakhshan et al., 2019; Eskerod and Huemann, 2013; Nguyen et al., 2019; Wegrzyn and Wojewnik-Filipkowska, 2022).

This study fills a gap in project management literature concerning practices involved in AI projects. Overall, the study makes five contributions.

5.1. Theoretical contribution

First, this research contributes context-specific information on AI projects to the project management literature. This includes descriptive information on the AI system lifecycle, project characteristics, roles, and stakeholders. Thus, this study pulls cross-disciplinary information from computer science, data science, and ethics into project management. It provides a view of managing AI projects rather than using AI in project management. Consequently, our findings contradict those of Fridgeirsson et al. (2021) that AI will not affect stakeholder management in projects over the next decade.

In AI projects, stakeholder management will need to expand to include many more parties with conflicting interests, as represented by the 12 external stakeholder roles highlighted in this study. The project team makes decisions that may impact the life and liberty of other persons and the environment. Thus, project managers have greater responsibilities for engaging and managing stakeholder interests and balancing ethical and moral issues between the team, organization, and stakeholders.

Second, the study identified the individuals and organizations from the AI community and classified them into stakeholders impacted by or who can affect the development, usage, and operations of AI systems. This adds to project management studies that describe context-specific projects (Stummer and Zuchi, 2010). The study identified a project function for labeling, annotating, tagging, or curating training datasets or moderating content; this function is not found in other types of data science projects.

The findings also expand the list of external and passive stakeholders found in other project management stakeholder models (Davis, 2014; Di Maddaloni and Davis, 2018; Turner and Zolin, 2012). It confirms and extends the stakeholder groups from Davis (2014). Specifically, the project recipient group from Davis (2014) was extended to include passive stakeholders and representative roles, and a new group was added for the reference roles. Further, this study adds specifics on the public stakeholder group identified in Turner and Zolin (2012).

Third, the study identified specific types of passive stakeholders by adding a harm attribute to the stakeholder salience model. This addresses the finding from Achterkamp and Vos (2008) that passive stakeholders are not always considered in project stakeholder models. The attribute explores the non-monetary relationship between the project and society, filling a gap identified by Derakhshan et al. (2019).

Furthermore, this extension supports the view that all stakeholders have a legitimate right to management attention without regard to their ability to contribute to the project or its output. It moves stakeholder identification in the direction of increased social and environmental accountability as suggested by Derry (2012) and the management-for-stakeholder view from Eskerod and Huemann (2013).

Fourth, the study represented time by connecting the system lifecycle to the urgency attribute of the salience model. Building on the view from Turner and Zolin (2012) of project output, outcomes, and impacts, the AI project lifecycle covers the periods from development, to immediately after development, to months and years of AI systems use. Thus, the use of this attribute has practical implications for project management, as described in the next section.

Finally, the current study addresses the question posed by Manders-Huits (2006) that asks who the AI developers are and the call from Moser et al. (2022) to rethink how we develop AI systems. It confirms that the development stakeholders are the only stakeholders who can address the concerns of all stakeholders (Martin, 2019); thus, development stakeholders play a significant role in how and to what extent AI systems impact individuals and society. Therefore, responsible development requires the engagement of developers, operators, and representatives for passive stakeholders, as shown in Fig. 5.

The accountability of the development team for project success is not a novel concept. Several scholars have identified the engagement of external stakeholders as a condition for project success (Davis, 2014; Turner and Zolin, 2012; Lehtinen and Aaltonen, 2020). In an AI project, the development team creates an artificial agent that embodies a moral code. The development process can 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). A moral buffer occurs when neither the team who developed the algorithms nor the human decision-makers who use the algorithms take responsibility for the social impact (Green and Chen, 2019). Thus, this study provides further justification for the need for the inclusion of external stakeholders in project engagements, and it reinforces the finding of studies in other contexts (Di Maddaloni and Davis, 2018; Nguyen et al., 2019; Wegrzyn and Wojewnik-Filipkowska, 2022).

5.2. Practical implications

Project owners, managers, and teams are responsible for the impacts of the systems they build. They have a moral responsibility to apply fair, ethical, and transparent processes to the data and algorithms. This is significantly challenging because future use situations will arise that the team may not anticipate (Cohen et al., 2014; Manders-Huits, 2006).

The project owner and manager can guide the project team to address the needs of all stakeholders, including passive stakeholders, by including representatives in the project, either as participants or as members of the governance committee. However, engaging external stakeholders requires planning for and introducing inter-organizational organizing solutions (Lehtinen and Aaltonen, 2020). Although governance-based solutions such as inclusion in governance committees are an option, other value-based or dynamic engagement solutions may be more appropriate for project success.

The procedure documented by Vos Janita and Achterkamp Marjolein (2006) provides a practical method for using the results of this study in project environments. The process includes the project owner, manager, and team. First, define the goal of the project. Second, conduct individual brainstorming sessions to identify stakeholders within the context of a given project. Third, conduct a group brainstorming session to identify active roles. Fourth, conduct a group brainstorming session to decide on stakeholder involvement.

The stakeholder groups and project roles described in this study provide a baseline for verifying project stakeholders and delineates roles in the third and fourth steps. The stakeholder project roles can be customized to fit the project's environment by linking to the dynamic activities and tasks of the parties involved. Furthermore, a guiding question in the third step could be *who could be harmed, suffer losses, or face damages due to conducting the project, operating the system, or relying on the results (decisions) of the system?*

The relationship and alignment of passive stakeholders to representative groups are context- and time specific. For example, labor unions could represent project team members (development stage), end users (usage stage), and workers (consequences stage). Each of these stakeholders would have different needs. Furthermore, the existence of labor unions is organization-specific.

Trustworthy, transparent, explainable, and sustainable development is a core requirement for ethical systems development (Ryan and Stahl, 2021). However, the urgency attribute in the stakeholder salience model indicates when the stakeholders are likely to judge or influence the project or system. For example, stakeholders impacted in the consequence stage will likely judge operations or service organizations instead of the development. Thus, the acceptance of the AI system by the operations will likely consider stakeholder requirements from vulnerable groups, for example. Thus, the project should anticipate and develop leading indicators to account for stakeholders that may be impacted in future periods. Furthermore, knowing when stakeholders will be impacted supports planning communication, resource assignment, risk management, and budget allocations (Miller, 2022; Turner and Zolin, 2012).

6. Conclusions

The current study used an extensive literature review to identify all parties in the AI community and classify them based on their functions and activities within an AI project context. It extended the stakeholder salience model by a harm attribute to identify passive stakeholders of AI projects and systems. The harm attribute considers harms, damages, and losses. The urgency attribute connects the stakeholders to the AI lifecycle stages. The study identified nine development stage roles, five operating stage roles, seven passive, and five representative stakeholder groups. The development stakeholders are the only group that can consider the concerns of all stakeholders.

This study has implications for organizational and project leadership. First, in AI projects, the teams make serious decisions in building artificial agents that could affect life, liberty, human, or civil rights. Next, implementations can cause environmental, financial, reputation, and political damage. Following ethical principles for fairness, accountability, transparency, and explainability in development are not enough. Potential harms should be considered for individual and societal stakeholders, and these groups should be engaged through representation.

In conclusion, AI systems can harm (or benefit) individuals, society, and the environment, so AI projects need an inclusive stakeholder approach for moral, ethical, and sustainable system development and usage.

6.1. Research limitations

This research is a conceptual model; validation with additional use cases would confirm the completeness and accuracy of the model. It does not address the financial impacts and implications of addressing the needs of passive stakeholders in AI projects, although economic cost exists for addressing or not addressing passive stakeholders' needs.

Regarding the methodological approach, an individual researcher conducted the research. Thus, biases may have been introduced in the research based on the timing, bibliographic database, and using a single researcher. Furthermore, the study uses secondary information from other studies to identify the AI community and formulate the stakeholder groups and roles. The research is based on a one-time query of the latest available literature. Additional academic participants could extend the study or validate the findings.

Overall, AI is a fast-moving topic, judging from the number of articles published since 2019. Thus, subsequent searches may produce different results as the topic evolves. Additionally, the uses and consequences of AI are multidisciplinary, and using different bibliographic databases may generate different results.

6.2. Further research

The knowledge and expertise of the stakeholder was an important factor in assigning stakeholders to project roles. Thus, further investigations using the resource-based view to understand their value contribution would be an interesting avenue of research. The overlap and relationship between the project team and the operating organization require further investigation. The applicability of the harm attribute in the stakeholder salience model to other project types is also n interesting avenue of research.

A future option may be to demonstrate the model using quantitative methods such as a survey instrument or a Delphi study with field experts. Lastly, additional qualitative research using case studies is also suggested.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.plas.2022.100068.

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