

Collaborative Governance for Accountable AI Systems in Tribal Emergency Management.

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Publishing history: Submitted*: 06 February 2026, Revised*: e.g. 01 June 2021, Accepted*: e.g. 02 June 2021, Published*: e.g. 10 June 2021
(Revised date: In the case of multiple rounds of reviews, we need both revised dates).

Abstract. The study explores how collaborative governance—operationalized through co-design processes—influences tribal stakeholders’ perceptions of accountability in Artificial Intelligence (AI) systems in U.S. tribal emergency management. Previous scholarship highlights the normative importance of transparency, participation, and accountability in governance; however, empirical evidence remains limited—especially in cross-jurisdictional contexts involving federal and tribal governments. To address this gap, this study develops a conceptual model based on collaborative governance and public value theory to analyze how governance design features shape perceived accountability in AI system co-design processes. Using three survey data sets collected from 146 participants representing 63 federally recognized tribal nations across the U.S. events in 2024, we use a fractional logit model to examine the effects of data and system controls, transparency, AI benefits, AI concerns, and trust in the government (federal and state levels) on accountability perceptions. The findings show that transparency is the strongest and most significant predictor of accountability, indicating that stakeholders are more likely to attribute responsibility when AI systems are understandable in terms of design, data use, and decision-making process. Perceived AI benefits are positively associated with accountability, indicating that practical utility improves stakeholders’ engagement and willingness to assign responsibility. In contrast, data and system controls, AI concerns, and trust in governments do not show statistically significant effects. These findings contribute theoretically by showing that accountability is shaped more by transparency and perceived AI benefits than by formal control or institutional trust. In practice, these findings also suggest that policymakers should prioritize transparent, user-centered AI design to enhance accountability in cross-jurisdictional and Indigenous contexts.

Keywords. Artificial Intelligence Governance, Collaborative Governance, Accountability, Transparency, Tribal Emergency Management

DOI: number to be added after acceptance

1. Introduction

Artificial intelligence (AI) is increasingly integrated into public administration, transforming policymaking, service delivery, and the management of societal risks (Choi et al., 2025). Although AI offers efficiency, better predictions, and increased participation (Bullock et al., 2024; Chun & Noveck, 2025; Wirtz et al., 2022), it also raises governance issues like transparency, accountability, bias, and data sovereignty (Busuioc, 2021; Eubanks, 2018; Janssen & Kuk, 2016; Zuiderwijk et al., 2021). These concerns are significant in cross-jurisdictional contexts with the fragmented authority and asymmetries. Collaborative governance is a framework for managing complexity that highlights the deliberative engagement, shared decision-making, and collective problem-solving among public, private, and civic stakeholders (Ansell & Gash, 2008; Emerson et al., 2012; Frederickson et al., 2018). Yet, despite growing normative calls for participatory and accountable AI governance (Ahn & Chen, 2022; Moon, 2023; Price et al., 2023), empirical studies remain limited in their examination of how collaborative governance shapes perceptions of accountability in AI system development—especially in federal-tribal governance contexts. Moreover, co-design processes enable stakeholders to collaboratively define their roles, responsibilities, and expectations, thereby shaping perceptions of accountability.

These gaps are particularly significant in U.S. tribal emergency management, where the use of AI systems raises concerns about sovereignty, trust, and historical marginalization (Quick, 2021; Tsosie, 2003). Tribal nations handle complex intergovernmental relations, balancing federal cooperation and Indigenous self-determination, including authority over data and technology (Hummel et al., 2021; Lovett et al., 2019). Emergency management requires its coordination among federal, state, and tribal governments, but AI systems can complicate authority, data control, system control, and responsibility. Particularly, key concerns for Indigenous communities include who decides on AI operations, whose values are embedded in these systems, and who is accountable if these systems fail. Although Indigenous-led co-design processes has been shown to enhance legitimacy and system effectiveness in emergency management (Tsai et al., 2023), little is known about how cross-jurisdictional AI collaboration shapes perceptions of accountability in AI co-design, particularly in U.S. tribal emergency management. As a result, this study examines how collaborative governance—particularly through co-design processes—influences stakeholders' perceptions of accountability in AI systems for U.S. tribal emergency management. The findings can provide evidence of public values in cross-sovereign AI governance.

This paper is structured as follows. In Section 2, we establish a theoretical framework grounded in collaborative governance and public value creation for AI governance. We clarify key concepts like data control, system control, transparency, AI benefits, AI concerns, trust in the federal government, and trust in the state government. Section 3 outlines the conceptual model and hypotheses linking governance design features to perceived accountability in AI co-design for U.S. tribal emergency management. In Section 4, we address data, measurements, and methods, including survey design, variable operationalization, and fractional logit regression models. In Section 5, we show empirical results and examine the primary factors affecting perceived accountability in AI co-design processes. In Sections 6 and 7, this study concludes the implications of our key findings for collaborative AI governance across different jurisdictions, focusing on U.S. tribal emergency management, and outlines directions for future research.

2. Theoretical Framework

2.1 Collaborative Governance in Artificial Intelligence

Governance is defined as the regimes, laws, rules, judicial decisions, and administrative practices that influence the delivery of publicly supported goals and services (Lynn et al., 2001). In public administration (PA), governance has evolved as an analytical framework for examining the field and its context, including intergovernmental relations, third-party policy implementation, and non-state actors (Frederickson, 2005). It highlights a shift from traditional, hierarchical government models to decentralized, network-based coordination, in which public, private, and non-profit actors collaboratively develop policies and deliver services (Frederickson et al., 2018).

Collaborative governance refers to a process in which public, private, and civil society stakeholders work together through a formal, consensus-driven process of collective decision-making on complex societal problems to achieve shared goals beyond the capacity of any single stakeholder (Ansell & Gash, 2008; Emerson et al., 2012). A diverse perspective can improve deliberation, support policy negotiations, and promote consensus, thereby strengthening democratic values in decision-making, particularly for complex societal problems (Wang, 2023). The government engages with non-state actors to share resources, negotiate, and jointly develop their rules to improve governance and public service delivery (Røiseland, 2011; Thomson et al., 2009).

In recent years, societal problems have become increasingly complicated and multifaceted, often characterized by fragmented political and administrative authority across multiple levels and actors (Geyer & Rihani, 2012). Neither the public sector nor the private sector effectively addresses the growing complexity of societal problems, making collaborative governance increasingly vital for coordinating multiple actors and resources (Wang & Ran, 2023). In AI contexts, for example, these challenges may be worsened by governance problems such as limited transparency,

accountability gaps, and fragmented authority among multiple stakeholders (Ahn & Chen, 2022; Wirtz et al., 2022; Zuiderwijk et al., 2021). Therefore, collaborative governance can play a vital role by facilitating coordination among multiple actors engaged in co-designing AI systems. Much recent literature about AI governance (Ahn & Chen, 2022; Chen et al., 2023; Moon, 2023) has primarily focused on normative rules or process-based recommendations but has provided limited insights into how cross-jurisdictional context (between federal and tribal governments) AI governance influences perceived accountability in the AI system co-design processes. To fill this gap, we examine how collaborative governance shapes accountability in AI system co-design processes across multiple jurisdictions, especially in U.S. tribal emergency management.

2.2 Public Value Creation in Accountable AI Systems for Indigenous Communities

Accountability

Accountability is defined as a social relationship in which an actor is required to describe and justify their conduct to a forum (Bovens, 2007; Lindberg, 2013; Mulgan, 2000). The actor is the entity that performs actions and is subject to evaluation, while the forum is the entity that demands explanations and evaluates the context. Accountability is often examined in the principal-agent relationships, in which shareholders delegate authority to managers (Broadbent et al., 1996; Gray & Jenkins, 1993; Sinclair, 1995). However, accountability has expanded in recent decades to broader institutional and social interactions, particularly in addressing complex societal issues. It is no longer limited to principal-agent relationships; actors may be accountable to multiple stakeholders inside and outside their organizations (Almquist et al., 2013). Additionally, accountability depends on context and varies with the organizational settings and the nature of the activities or outcomes under evaluation (Roberts & Scapens, 1985; Romzek & Dubnick, 2018). Building on this view, accountability can be conceptualized as a multi-directional relationship that extends beyond traditional principal-agent structures toward networked and cross-jurisdictional forms of governance (Lampson, 2004; Grant & Keohane, 2005; Koliba et al., 2011).

In AI, accountability can be extended to ensure that software systems meet established standards, align with public values, and can ultimately be attributed to identifiable individuals or organizations (Feigenbaum et al., 2011). This becomes more complicated because of the sociotechnical features of AI systems, in which multiple human and non-human actors are involved, and responsibilities are distributed across various stages of design, development, and deployment (Novelli et al., 2024). Moreover, in these contexts, decision-making is opaque, and responsibilities are dispersed, making it difficult to identify who is responsible for AI system outcomes (Bracci, 2023; Busuioc, 2021). Theoretically, accountability is assigned to identifiable actors; in practice, it can become obscured, particularly in public-sector contexts involving multiple stakeholders (Chen & Ahn, 2022; Brummel, 2025). This challenge is especially important in federal-tribal governance contexts, where responsibilities are distributed across sovereign entities and multiple jurisdictions. In these cross-jurisdictional contexts, clearly identifying the responsible actors is important for effective governance and coordination, and co-design processes can play a vital role in enhancing this clarity. Building on this perspective, we conceptualize accountability as the perceived clarity of responsibility attribution in AI systems—the extent to which stakeholders can identify who should be accountable for AI system outcomes, particularly in U.S. tribal emergency management, and as shaped by co-design processes.

Data Control and System Control

Sovereignty is defined as independence from external authority with full control over populations within defined borders (Strayer, 2011). In the digital era, this idea extends to the governance of data and information technology, giving rise to the concept of data sovereignty—the right of a nation to govern the collection, ownership, and use of its own data (Kukutai & Taylor, 2016). Data control and system control are the operationalized expressions of this sovereign authority: data control is authority over the inputs of a technological system—what data are collected, curated, and shared (DAMA International, 2009; Plotkin, 2020)—while system control is authority over the system’s internal logic and outputs, including how decisions are generated and operationalized (Busuioc, 2021; Hummel et al., 2021). In AI systems, data and system controls are particularly important. Because such systems are inherently data-driven, the values embedded in their design reflect the priorities of those who govern their inputs and outputs (Janssen & Kuk, 2016). In Indigenous contexts, these controls are also closely associated with the principles of self-determination and tribal sovereignty (Hummel et al., 2021; Tsosie, 2003). Historically, Indigenous communities have had limited control over data and technological systems, raising concerns about misrepresentation, exclusion, and external dominance in decision-making processes (Lovett et al., 2019). Reflecting these historical contexts, the CARE principles (Collective Benefit, Authority to Control, Responsibility, and Ethics), established by the Indigenous scholars and organizations, underscore Indigenous authority over data and technological systems (Carroll et al., 2021). Without such authority, AI systems may replicate existing colonial patterns and marginalize Indigenous communities from decisions that directly affect them (Perera et al., 2025; Tsai et al., 2024). In this context, control over data and systems enhances accountability by clarifying who holds authority over AI system inputs and outputs. When such control is clearly defined, stakeholders are better able to identify who should be accountable for the outcomes of AI systems. Accordingly, we hypothesize that data control and system control are positively associated with perceived accountability in AI system co-design processes.

Transparency

Transparency is the openness and accessibility of information, processes, and decisions that enable external actors to observe, understand, and evaluate them, and as a multifaceted concept, it reduces information asymmetries and promotes accountability (Ball, 2009; Larsson & Heintz, 2020). In governance contexts, transparency can play a key role in enhancing legitimacy, facilitating oversight, and supporting accountability by increasing the visibility of the institutional processes (Grimmelikhuijsen & Meijer, 2014; Hood & Heald, 2006). In AI contexts, transparency can extend beyond simple disclosure to include visibility into data sources, algorithms, and decision-making processes embedded within complex sociotechnical systems (Larsson & Heintz, 2020). It is important since AI systems often function as “black boxes,” making it hard for stakeholders to interpret how decisions are made and to identify who is responsible for those outcomes (Burrell, 2016; Busuioc, 2021). Consequently, transparency can play a core role in enhancing accountability and making decision-making processes more interpretable to stakeholders (Janssen & Kuk, 2016; Janssen et al., 2020). When AI systems are more transparent, stakeholders can better understand how outcomes are generated and identify who is accountable for outcomes. Furthermore, transparency is important for collaboration with Indigenous communities, particularly considering the historical experiences of marginalization, exclusion, and a lack of representation in decision-making processes (Anderson et al., 2024; Tsai et al., 2023; Peters et al., 2018; Wang, Chen, Huang et al., 2024). These contexts have led to lower trust in external institutions, making transparency vital for building trust, reflecting community perspectives, and improving accountability in AI system co-design processes. Accordingly, we hypothesize that transparency is positively associated with accountability in AI system co-design processes.

AI Benefits and AI Concerns

In public administration, AI presents benefits and concerns (Eom & Kim, 2024). For example, AI facilitates tasks by automating routine activities such as drafting, reviewing, data analysis, filing, scheduling, and data entry (Choi et al., 2025; Young et al., 2019). Its advantages enable individuals, particularly civil servants, to focus on higher-value activities because they spend up to 30% of their time on paperwork and administrative duties (Gmyrek et al., 2023; Viechnicki & Eggers, 2017). Given its benefits, its application extends to various policy fields, including smart cities, policies, courts, education, health, and program evaluation (Chun & Noveck, 2025). In the United States, AI use cases at 11 federal agencies nearly doubled from 571 in 2023 to 1,110 in 2024, while generative AI use cases increased ninefold from 32 to 282 (U.S. Government Accountability Office, 2025). In this context, its advantages can enhance governance by improving citizen-government interactions, increasing access to public services, and enabling more participatory decision-making (Bullock et al., 2024; Dunleavy & Margetts, 2025; Yun et al., 2024; Zuiderwijk et al., 2021). These applications can support key public values—transparency, accountability, efficiency, and democratic governance—ultimately strengthening governance capacity, particularly in emergency management. Building on these advantages, AI is expected to enhance accountability by improving transparency and clarifying responsibility attribution among stakeholders, particularly in federal-tribal governance, where responsibilities are shared across sovereign entities.

In contrast, the use of AI in public administration also raises significant challenges. It underscores ethical and legal issues, including the potential to generate inaccurate, biased, or irrelevant results, which may hinder reliability and effectiveness (Bloch-Wehba, 2021; Bender et al., 2021). For instance, AI systems could inherit biases from training data, leading to unfair and inaccurate outcomes, and produce false or nonsensical outputs (i.e., hallucination) when generating predictions based on incomplete or misleading patterns in the data. Additionally, the use of AI in public administration raises concerns about data security, as AI models can collect and analyze large amounts of personal data. Unauthorized data may lead to breaches, identity theft, or misuse, further highlighting the risks related to AI systems (Khanzode & Sarode, 2020). In this context, these disadvantages could undermine governance by reducing the reliability of decision-making, increasing uncertainty, and eroding key public values (e.g., transparency, trust, accountability, and fairness) that AI systems are primarily anticipated to support (Busuioc, 2021; Cath et al., 2018; Eubanks, 2018; Janssen & Kuk, 2016), particularly in U.S. tribal emergency management. Indigenous communities may be vulnerable to these challenges due to historical biases and colonial patterns that can be reproduced in data, thereby exacerbating existing inequalities and marginalization (Perera et al., 2025; Tsai et al., 2024). These issues about data sovereignty, cultural misrepresentation, and limited participation in AI design may further complicate responsibility attribution and weaken accountability within federal-tribal governance. In particular, the challenges may obscure responsibility attribution and make it more difficult to identify who is accountable for the outcomes of AI systems. Accordingly, we hypothesize that AI benefits are positively associated with perceived accountability in AI system co-design processes, whereas AI concerns are negatively associated with it.

Trust in Government

Although trust is a contested concept without a single and clear definition, it is commonly perceived as a relational construct involving a willingness to be vulnerable to the actions of others who might cause harm or betrayal (Levi & Stoker, 2000). It is directed toward specific individuals or institutions. Specifically, trust in government refers to citizens' confidence that governments act in the public interest, as reflected in their willingness to grant authority

and comply with government decisions (Cooper et al., 2008; Hetherington, 2005; Levi & Stoker, 2000; Miller, 1974). In governance contexts, trust can play a core role in shaping how individuals evaluate public institutions, interpret policy processes, and accept institutional decisions (Carter & Bélanger, 2005; Grimmelikhuijsen & Knies, 2017). In the context of AI systems, trust can significantly influence how individuals interpret the decision-making process and attribute responsibility for results. When stakeholders trust the government, they are more likely to perceive AI systems as legitimate and to accept responsibility within these systems. In multi-level governance contexts, such as federal-tribal emergency management, where authority and responsibility may be distributed among federal, state, and tribal governments, trust cannot be uniform and varies across levels of government. Specifically, trust in government (at the federal and state levels) may shape stakeholders' perceptions of accountability differently, as responsibilities for AI system design and implementation are shared across jurisdictions. Higher levels of trust in these institutions may enhance the perceived accountability, while lower levels of trust may increase uncertainty about who should be held accountable for the AI system's outcome. As a result, trust in governments (at the federal and state levels) is positively associated with perceived accountability in AI system co-design processes.

3. Conceptual Model & Hypothesis

This study explores how to design collaborative governance to enhance accountability in the AI system co-design processes in U.S. tribal emergency management. We examine the factors that shape perceptions of accountability in the collaborative co-design of AI systems by tribal nations and their communities. Figure 1 shows a conceptual model in which factors—data control, system control, AI benefits, AI concerns, trust in the federal government, and trust in the state government—examine the accountability in AI system co-design processes. Additionally, Control variables are demographic features—tribal position, gender, age, and education—and AI familiarity to account for individual differences among survey respondents.

H1a assumes that data control is positively associated with accountability in AI system co-design processes, while H1b suggests that system control is positively associated with accountability in AI system co-design processes. H2 assumes that transparency is positively associated with accountability in such processes. Additionally, H3 suggests that AI benefits are positively associated with accountability, whereas H4 assumes that AI concerns are negatively associated with accountability in such processes. H5a and H5b suggest that trust in government (at both the federal and state levels) is positively associated with accountability in such processes.

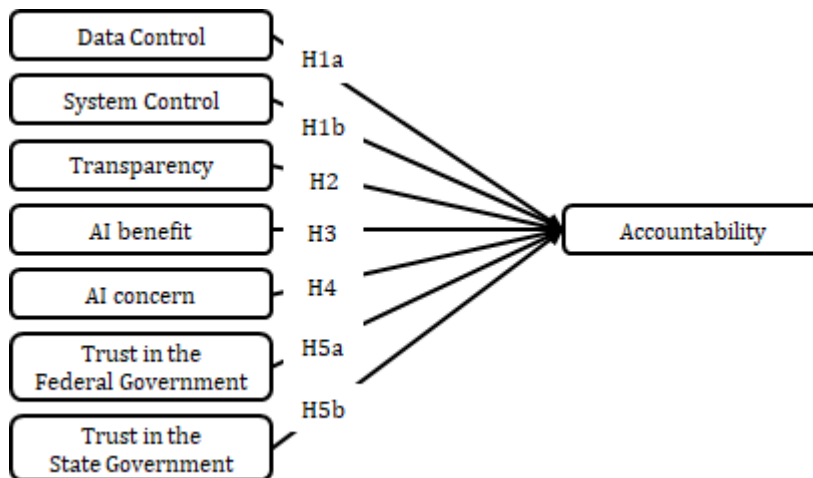


Fig. 1 – Conceptual Model

H1a. Data control is positively associated with accountability in AI system co-design processes

H1b. System control is positively associated with accountability in AI system co-design processes

H2. Transparency is positively associated with accountability in AI system co-design processes

H3. AI benefits are positively associated with accountability in AI system co-design processes.

H4. AI concerns are negatively associated with accountability in AI system co-design processes

H5a. Trust in the Federal government is positively associated with accountability in AI system co-design processes

H5b. Trust in the State government is positively associated with accountability in AI system co-design processes

4. Methodology

4.1 Data

This study employed survey data from three sources across the U.S.: a Midwest Pow Wow conference in April 2024, an Emergency Management summit for American Indians in the Midwest in June 2024, and the National Congress of American Indians in June 2024. Three surveys were conducted separately, but they aimed to explore tribal stakeholders’ perceptions of a co-designed AI system in U.S. tribal emergency management. Participants in the surveys included a wide range of tribal roles—elected tribal leaders, tribal elders, and tribal community members. Three surveys primarily focused on topics—accountability, data control, AI system control, AI benefits, AI concerns, and trust in the federal and state governments. Although the content was consistent, response formats differed: 3- and 7-point Likert scales. Consequently, these responses were standardized using min-max normalization, and the datasets were then merged into a single integrated dataset.

There are 574 federally recognized tribal nations in the U.S. (Schwartz, 2023), and we include participants from 63 tribal nations, which represent about 11% of all federally recognized tribes in the U.S. The datasets comprise 146 responses—84 from the National Congress of American Indians (NCAI) conference, 44 from the Midwest Pow Wow conference, and 18 from the Regional Emergency Management conference. Participants represented various tribal communities, primarily the Omaha (22), the Eastern Band of Cherokee (15), and the Oglala Sioux (8). Participants improve the data representativeness and provide insights into different inter-tribal perspectives on AI systems in U.S. tribal emergency management. Table 1 shows participants’ demographic characteristics—tribal position, gender, age, and education. Among the 146 participants, most were members of the tribal communities (72.6%), followed by tribal elected leaders (15.75%) and tribal elders (11.64%). Most participants were female (59.59%). The largest age group was 30-39 years old (21.92%), with respondents distributed across a wide range. Half of the participants held a college degree (undergraduate level) (47.26%), and more than 70% had completed some form of higher education—master’s degree, doctoral (Ph.D. or J.D.), or professional degrees.

Tab. 1 - Demographic Characteristics of the Participants

Demographics	Category	Subjects (N = 146)	
		Frequency	Percentage
Tribal Position	Elected Tribal Leaders	23	15.75
	Tribal Elders	17	11.64
	Tribal Members	106	72.60
Gender	Male	59	40.41
	Female	87	59.59
Age	15 – 19	7	4.79
	20 – 29	14	9.59
	30 – 39	32	21.92
	40 – 49	29	19.86
	50 – 59	26	17.81
	60 – 69	29	19.86
	70 – 79	9	6.16
Education	Less than High School	0	0
	Junior High School	3	2.05
	Senior High School	39	26.71
	College (Undergraduate Level)	69	47.26
	Graduate or Professional Degree	35	23.97

4.2 Measurements

The dependent variable was measured using an item [G16_1]: “I believe that the system co-design can let me know who should be accountable for the AI chatbot for tribal emergency management.” Responses were measured on an ordinal scale, with higher values indicating a stronger perception of accountability in the AI system co-design process. This suggests that participants’ perceptions of accountability are outcomes of the cross-jurisdictional AI co-design process in U.S. tribal emergency management.

Collaborative Governance for Accountable AI Systems in Tribal Emergency Management.

The independent variables were operationalized as latent constructs, following the conceptual model in Figure 1. First, data control was measured using an item [G1_1]: “When the tribal nation and the U.S. government collaborate on emergency management systems, I believe my tribal government should decide on what information is used.” AI system control was also measured with an item [G1_2]: “When the tribal nation and the U.S. government collaborate on the emergency management systems, I believe my tribal government should decide the content of the chatbot responses.” (Ambros & Buzinde, 2021; Avila Pinto, 2018). Both Items were measured on ordinal scales, with higher values indicating stronger preferences for tribal sovereignty in AI co-design processes. Second, transparency was assessed using four items that represent its key dimensions. “Who designed the chatbot?” [G11_1]; “How does the chatbot generate responses to users’ questions?” [G11_2]; “What data does the chatbot use?” [G11_3]; and “Will their tribal nations approve this AI chatbot?” (Grimmelikhuijsen, 2023). All items were measured on ordinal scales, with higher values indicating stronger expectations for transparency in the AI system. Factor analysis showed a single-factor structure, with the first factor’s eigenvalue at 2.52 and items loading strongly (0.68 to 0.89). The composite transparency index was created by averaging the items. Third, AI benefits were measured using five items: “The chatbot can help me understand how to prepare for the upcoming natural disasters.” [G5_1]; “The chatbot can help me understand how to apply for financial assistance.” [G5_2]; “The chatbot can help me understand how to recover from natural disasters.” [G5_3]; “The chatbot can help me gain access to emergency managers.” [G5_4]; and “The chatbot can help me gain access to tribal leaders.” [G5_5] (Scutella et al., 2024; Wang, Chen, Huang et al., 2024). All items were measured on ordinal scales with higher values indicating greater perceived benefits of the AI system. Factor analysis supported the construct’s one-dimensionality, with the first factor exceeding the Kaiser criterion (eigenvalue = 2.98) and factor loadings ranging from 0.61 to 0.87. This composite index was calculated as the mean of the items. Fourth, AI concerns were measured using four items: “The chatbot is difficult to use.” [G6_1]; “The chatbot may result in the loss of personal information.” [G6_2]; “The chatbot exposes my problems to too many people.” [G6_3]; and “The chatbot may involve interaction with people outside my tribe.” [G6_4] (Wang, Chen, Chien et al., 2024). All items were measured on ordinal scales, with higher values indicating greater perceived concerns about the AI system. Exploratory factor analysis indicated a single-factor structure, with the first factor exceeding the eigenvalue threshold of 1 (1.58) and acceptable loadings ranging from 0.56 to 0.69. The composite AI concern index was constructed by averaging the items. Fifth, trust in the federal government was measured using an item [G3_1]: “I trust the federal government to act in my tribe’s best interests,” while trust in the state government was measured with a single item [G3_2]: “I trust the state government to act in my tribe’s best interests.” Two items were measured on ordinal scales, with higher values indicating greater levels of trust.

Control variables were as follows. Tribal positions [D4] were categorized as community members (1), tribal elders (2), or elected leaders (3). Gender [D7] was recoded as male = 1 and female = 0. Age was recoded as a categorical variable representing respondents’ age groups, ranging from 1 to 7, with higher values indicating older age groups. Education [D9] was recoded to reflect the highest level of educational attainment, ranging from 1 (Less than High School) to 5 (Graduate or Professional degrees), with higher numbers indicating higher educational levels. Lastly, AI familiarity was measured with an item [D10]: “What is your familiarity with AI-powered chatbots?” Responses were measured on an ordinal scale, with higher values indicating greater familiarity.

Tab. 2 - Measurements and Operationalization

Type	Variable	Items	Scale	Questions
Dependent	Accountability	G16_1	Ordinal	I believe that the system co-design can let me know who should be accountable for the AI chatbot for tribal emergency management
Independent	Data Control	G1_1	Ordinal	When the tribal nation and the U.S. government collaborate on emergency management systems, I believe my tribal government should decide on what information is used
	System Control	G1_2	Ordinal	When the tribal nation and the U.S. government collaborate on emergency management systems, I believe my tribal government should decide the content of chatbot responses
	Transparency	G11_1	Ordinal	Who designed the chatbot?
		G11_2	Ordinal	How does the chatbot generate responses to users’ questions?
		G11_3	Ordinal	What data does the chatbot use?
		G11_4	Ordinal	Will their tribal government approve this AI chatbot?

	AI Benefit	G5_1	Ordinal	The chatbot can help me understand how to prepare for the upcoming natural disasters
		G5_2	Ordinal	The chatbot can help me understand how to apply for financial assistance
		G5_3	Ordinal	The chatbot can help me understand how to recover from natural disasters
		G5_4	Ordinal	The chatbot can help me gain access to emergency managers
		G5_5	Ordinal	The chatbot can help me gain access to tribal leaders
	AI Concern	G6_1	Ordinal	The chatbot is difficult to use
		G6_2	Ordinal	The chatbot may result in the loss of personal information
		G6_3	Ordinal	The chatbot exposes my problems to too many people
		G6_4	Ordinal	The chatbot may involve interaction with people outside my tribe
	Trust in the Federal Government	G3_1	Ordinal	I trust the federal government to act in my tribe's best interests
Control	Trust in the State Government	G3_2	Ordinal	I trust the state government to act in my tribe's best interests
	Tribal Position	D4	Categorical	What is your role within your tribe?
	Gender	D7	Binary	What is your gender?
	Age	D8	Categorical	What is your age group?
	Education	D9	Categorical	What is the highest degree or level of school you have completed?
	AI Familiarity	D10	Ordinal	What is your familiarity with AI-powered chatbots?

4.3 Methods

We used a fractional logit model (Papke & Wooldridge, 1996) to examine factors shaping perceived accountability in an AI system co-design process in the U.S. tribal emergency management. The dependent variable was initially measured using an ordinal Likert-type scale and later rescaled to the [0, 1] interval using min-max normalization. This transformation allows the dependent variable to be treated as a bounded continuous outcome, making the fractional logit model suitable. Based on the conceptual model, this study examines the extent to which data control, AI system control, transparency, AI benefits, AI concerns, and government trust (at both federal and state levels) influence perceived accountability in AI system co-design processes. All independent variables were measured using Likert-type scales and rescaled to the [0, 1] interval using min-max normalization to ensure comparability across variables and datasets. We controlled individual-level characteristics, including tribal positions, gender, age, education, and AI familiarity. Because the data were collected across three distinct events—the Midwest Pow Wow Conference, the Emergency Management Summit, and the National Congress of American Indians Conference—we included a categorical control variable indicating the survey source to account for potential contextual differences. This serves as a robustness check to ensure that the results are not driven by the data collection context. The model was estimated using heteroskedasticity-robust standard errors.

5. Results

Table 3 shows the results of the fractional logit model examining factors associated with perceived accountability. The model is statistically significant (Wald $\chi^2 = 102.46$, $p < .001$), with a pseudo R^2 of 0.1603, indicating moderate explanatory power, which is acceptable for fractional logit models. The results show that transparency is strongly and statistically significantly associated with perceived accountability in AI system co-design processes ($p = 0.000$), suggesting that greater transparency is associated with higher levels of accountability among tribal stakeholders and represents the most influential predictor in the model. Additionally, AI benefits are positively and statistically significantly associated with accountability in such processes ($p = 0.033$), indicating that individuals who perceive greater AI benefits tend to report higher levels of accountability. In contrast, data and system controls, AI concerns, and government trust (at both federal and state levels) do not show statistically significant effects, suggesting that these factors are not directly associated with perceived accountability in this context. Among the control variables, age is negatively associated with accountability, whereas education level is positively and statistically significantly associated. Lastly, the survey source variable is not statistically significant, indicating that the results are not driven by variations in data collection contexts.

Tab. 3 – Fractional Logit Regression Results

	<i>Variable</i>	<i>Coefficient</i>	<i>Robust Standard Error</i>	<i>P-Value</i>	<i>Hypothesis Testing</i>
<i>H1a</i>	Data Control	-0.340	0.579	0.557	Not Supported
<i>H1b</i>	System Control	0.560	0.604	0.354	Not Supported
<i>H2</i>	Transparency	2.437***	0.488	0.000	Supported
<i>H3</i>	AI Benefit	1.144**	0.536	0.033	Supported
<i>H4</i>	AI Concern	-0.571	0.429	0.183	Not Supported
<i>H5a</i>	Trust in the Federal Government	-0.205	0.384	0.593	Not Supported
<i>H5b</i>	Trust in the State Government	0.022	0.383	0.954	Not Supported

* $p < .1$. ** $p < .05$. *** $p < .01$.

6. Discussions

6.1 Theoretical and Practical Implications

This study has theoretical and practical implications for collaborative AI governance across jurisdictions and in Indigenous contexts. First, transparency is strongly and positively associated with accountability in AI system co-design processes, thereby supporting H2. Although previous scholarship links transparency to accountability in AI systems (Busuioc, 2021), empirical evidence on cross-sovereign governance remains limited. Our findings suggest that tribal stakeholders are more likely to attribute responsibility in AI system co-design processes when they can clearly understand who designed the system, how it generates outputs, and which data it uses. This indicates that accountability depends not only on formal institutions but also on the visibility and interpretability of governance processes. Moreover, this finding extends Bovens' (2007) actor-forum framework to complex, multi-jurisdictional AI governance by showing that transparency serves not merely as a procedural virtue but as a critical mechanism through which accountability is constructed across sovereign boundaries. In practice, transparency's strong effect suggests that policymakers should prioritize designing transparent and explainable AI systems. It includes clearly communicating responsibility for system design, how decisions are generated, and what data are used. Especially, such transparency can be important for reducing ambiguity between federal and tribal authorities, as tribal nations have experienced deep mistrust toward federal authorities and a history of marginalization.

Second, AI benefits are positively associated with accountability in such processes, supporting H3. While previous scholarship has often addressed AI benefits and accountability as distinct dimensions (Zuiderwijk et al., 2021), our findings indicate a meaningful connection between them. Specifically, stakeholders are more likely to engage with AI systems and attribute responsibility when those systems are perceived as beneficial, especially within co-design processes. This finding extends public value theories and collaborative governance by presenting that stakeholders' evaluations of AI systems are influenced not only by governance structures but also by perceived benefits. It aligns with a pragmatist view, in which governance legitimacy depends on practical utility and problem-solving capacity. Moreover, this finding extends Moore (1997) by showing that perceived usefulness not only creates public value but also shapes stakeholders' perspectives on accountability in AI governance. In practice, the positive relationship between perceived AI benefits and accountability suggests that stakeholders are more likely to view the system as accountable when they observe clear, meaningful benefits. AI systems can be designed and communicated to emphasize their practical value (e.g., improving access to emergency information, facilitating communication with authorities, and supporting disaster preparedness and recovery) in tribal emergency management.

Third, AI concerns are not negatively associated with accountability in such processes, failing to support H4. While prior literature suggests that privacy concerns and data misuse undermine governance outcomes (Busuioc, 2021; Eubanks, 2018; Janssen & Kuk, 2016), our findings do not directly support a negative relationship between AI-related concerns and accountability across jurisdictions. A possible explanation is that tribal stakeholders may not perceive AI-related concerns—such as privacy loss, data misuse, or external interference—as novel or decisive in evaluating accountability. Instead, AI concerns may be understood as part of a familiar risk environment, shaped by historical experiences of colonial data extraction, misrepresentation, and exposure to the federal system (Lovett et al., 2019; Perera et al., 2025). In this context, AI-related risks may be normalized rather than perceived as novel threats, making them less likely to significantly change perceptions of accountability. This finding suggests that the relationship between risk perception and accountability is context-dependent and may not operate uniformly across governance settings. In practice, the findings on AI-related concerns suggest that addressing risk alone may not be sufficient to shape perceptions of accountability. Instead, practitioners can prioritize attention to how risks are communicated and managed, especially in contexts where communities have historically experienced systemic

risks (e.g., U.S. Indigenous communities).

Fourth, data control and system control are not positively associated with accountability in such processes, failing to support H1a and H1b. Although data control and system control are normatively important for Indigenous self-determination and the CARE principles (Carroll et al., 2021; Hummel et al., 2021), our findings suggest that neither control directly influences stakeholders' perceived accountability. One possible explanation is that the relationship between control and accountability may be context-dependent. In federal-tribal governance, where jurisdictional authority is often ambiguous and overlapping, perceived control over data and systems alone may not be enough to clarify who is ultimately responsible for AI system outcomes. Tribal stakeholders may recognize their sovereign right to control over data and systems, but also note that accountability remains unresolved across jurisdictions—indicating control and accountability are linked in theory but distinct in practice in cross-sovereign AI governance. This interpretation aligns with the history of colonial dispossession and federal intervention (Lovett et al., 2019; Tsosie, 2003), where control over data has long been regarded as a sovereign right rather than merely a procedural aspect shaping governance. In practice, this finding suggests that policymakers should not conclude that increasing tribal control over data and systems will enhance perceived accountability. Instead, control mechanisms should be complemented by transparent processes that clearly define the roles and responsibilities across jurisdictions. Co-design processes can function as a critical institutional mechanism to bridge this gap by explicitly negotiating and documenting who is responsible for what aspects of AI system development and deployment.

Fifth, trust in the government (federal and state levels) is not positively associated with accountability in AI system co-design processes, failing to support H5a and H5b. While previous scholarship grounded in principal-agent and institutional trust theory suggests that trust in government institutions increases acceptance and compliance with their decisions (Hetherington, 2005; Levi & Stoker, 2000), our findings indicate that the trust in federal and state governments does not directly influence perceived accountability in AI system co-design processes in the U.S. tribal emergency management. One possible explanation is that tribal stakeholders' historical skepticism toward federal and state institutions may weaken the trust-accountability relationship. In federal-tribal governance, centuries of broken treaties, forced assimilation, and federal mismanagement of tribal affairs (Tsosie, 2003; Quick, 2021) might have fundamentally altered how trust operates as a governance mechanism. As a result, the relationship between government trust and accountability may operate differently, or even inversely, in contexts marked by sovereignty disputes and marginalization, highlighting the limitations of applying primary governance theories to Indigenous contexts. In practice, without a strong trust-accountability link, policymakers should not assume institutional trust guarantees accountability in AI governance with tribal nations. Instead, building accountability in the federal-tribal AI co-design requires more than restoring trust; it demands structural changes that visibly redistribute authority, ensure meaningful tribal participation in system design, and establish formal mechanisms to assign responsibility across jurisdictions.

6.2 Limitations and Future Research

Despite its contributions, this study has several limitations. First, it relies on cross-sectional survey data, which limits causal inference. While the findings identify significant associations among transparency, AI benefits, and accountability, they do not establish causality. For instance, individuals who perceive systems as more accountable may also be more likely to view them as transparent or as beneficial. Second, the sample size ($N = 146$) and coverage (63 tribal nations) provide insights but may constrain generalizability. Although the sample encompasses approximately 11% of federally recognized tribes, it may not fully represent the diversity of perspectives across all tribal nations, particularly those with different governance structures, technological capacities, or historical ties to federal and state governments. Third, we measure constructs—accountability, transparency, AI benefits, and AI concerns—through self-reported perception, which may be subject to response bias. Perceptions of accountability may not align with actual mechanisms or outcomes in practice. Moreover, we examine perceived accountability in hypothetical or co-designed AI chatbots, rather than in fully implemented systems in real-world settings. Therefore, the findings may not fully reflect accountability in operational contexts. Fourth, we use single-item measures for key variables—trust in government and accountability—due to data limitations. These measures capture general attitudes but may not fully reflect the multidimensional nature of these constructs in governance contexts.

To address these limitations, we should employ longitudinal or experimental designs to better establish causal relationships between governance features and accountability. For example, tracking stakeholders' perceptions throughout AI co-design shows how transparency and benefits foster accountability and whether early governance builds long-term trust and acceptance. Second, future research should expand the sample to include a broader, more representative range of tribal nations, especially those with diverse governance structures, technological capacities, geographic locations, and experiences with federal partnerships. Comparative studies across different tribal contexts and between Indigenous and non-Indigenous governance contexts would also help identify how institutional, cultural, and historical factors influence the perceptions of AI governance. Third, future research should develop and validate multi-item, multidimensional scales for the constructs of accountability, sovereignty, and trust in government. Developing validated scales that capture the multidimensional features of these concepts would improve measurement reliability and enhance the robustness of empirical findings. Fourth, we should move

beyond perception-based measures to examine accountability practices and outcomes in real-world settings. This involves examining how responsibility is assigned, communicated, and enforced in AI for U.S. tribal emergency management, and how stakeholders respond to system failures or errors. Fifth, mixed-methods approaches that integrate qualitative inquiry with survey-based measures would deepen our understanding of accountability in AI system co-design processes. For example, in-depth interviews, focus groups, and participatory action research with tribal stakeholders would capture the cultural dimensions of accountability that quantitative instruments may not fully reflect.

7. Conclusion

We examined how collaborative governance—operationalized through co-design processes—shapes stakeholders' perceptions of accountability for AI systems in U.S. tribal emergency management. It addressed a critical gap in the literature by empirically examining perceived accountability in cross-jurisdictional AI governance, particularly in federal-tribal contexts. To examine factors—data and system controls, transparency, AI benefits, AI concerns, and trust in government (federal and state levels)—that affect accountability, we used survey data (N=146) from three U.S. sources covering 63 tribal nations (11% of federally recognized tribes).

The findings are as follows: First, transparency is strongly and statistically significantly associated with perceived accountability in AI system co-design processes. It is the most influential factor in shaping perceived accountability in such processes. When stakeholders understand who designs AI systems, how decisions are generated, and what data are used, they are better able to identify responsible factors. Second, AI benefits are positively associated with perceived accountability, suggesting that stakeholders are more likely to engage with and attribute responsibility to AI systems when they view them as useful. However, data control, system controls, AI concerns, and trust in the government (federal and state levels) do not have significant direct effects on perceived accountability in AI system co-design processes. These findings challenge conventional assumptions in governance and public administration. While control over data and systems is central to sovereignty and self-determination, it doesn't necessarily lead to clearer perceptions of accountability in cross-jurisdictional AI contexts. Similarly, institutional trust does not directly boost accountability here, likely due to historical and political factors shaping federal-tribal relations.

This study contributes to the literature in three key ways. First, it advances the understanding of accountability as a socially constructed, perception-based outcome in complex, multi-actor governance. It extends governance and public value frameworks by showing that interpretability and perceived benefits are key to forming accountability. Second, it empirically provides one of the first quantitative examinations of AI governance in U.S. tribal emergency management, drawing on evidence from a diverse set of tribal stakeholders. Third, the findings practically highlight the need for transparent, user-centered AI systems, particularly in the Indigenous and cross-sovereign governance contexts.

Acknowledgement

The authors gratefully acknowledge Andrew Burk for his contributions to the research discussion and for developing the survey instrument in Qualtrics.

Funding or Grant

The authors acknowledge the support of the U.S. National Science Foundation Grant Award Number 2317086.

Data/Software Access Statement

N/A

Contributor Statement

Sukwon Choi led the development of the research question, theoretical framework, research design, and empirical analysis and drafted the manuscript. Yu-Che Chen contributed to the study design, offered overall supervision, and revised the manuscript. Yi-Fan Wang contributed to the study's conceptualization, data organization, and manuscript preparation. Chun-Hua Tsai contributed to the methodological design, performed analyses, and helped interpret the findings. Edouardo Zendejas and Sarah Krafka contributed to survey implementation, community engagement, and data collection in tribal contexts. All authors critically reviewed, revised, and approved the final manuscript.

Use of AI

While preparing this manuscript, the author(s) utilized Grammarly, an AI-powered editing tool, to enhance language clarity and readability. All suggestions from the tool were thoroughly reviewed and revised by the authors, who take

full responsibility for the accuracy, integrity, and originality of the final content.

Conflict Of Interest (COI)

There is no conflict of interest.

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