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## Elevating Developers' Accountability Awareness in AI Systems Development

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# Elevating Developers' Accountability Awareness in AI Systems Development

## The Role of Process and Outcome Accountability Arguments

Jan-Hendrik Schmidt · Sebastian Clemens Bartsch · Martin Adam · Alexander Benlian

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**Abstract** The increasing proliferation of artificial intelligence (AI) systems presents new challenges for the future of information systems (IS) development, especially in terms of holding stakeholders accountable for the development and impacts of AI systems. However, current governance tools and methods in IS development, such as AI principles or audits, are often criticized for their ineffectiveness in influencing AI developers' attitudes and perceptions. Drawing on construal level theory and Toulmin's model of argumentation, this paper employed a sequential mixed method approach to integrate insights from a randomized online experiment (Study 1) and qualitative interviews (Study 2). This combined approach helped us investigate how different types of accountability arguments affect AI developers' accountability perceptions. In the online experiment, process accountability arguments were found to be more effective than outcome accountability arguments in enhancing AI developers' perceived accountability. However, when supported by

evidence, both types of accountability arguments prove to be similarly effective. The qualitative study corroborates and complements the quantitative study's conclusions, revealing that process and outcome accountability emerge as distinct theoretical constructs in AI systems development. The interviews also highlight critical organizational and individual boundary conditions that shape how AI developers perceive their accountability. Together, the results contribute to IS research on algorithmic accountability and IS development by revealing the distinct nature of process and outcome accountability while demonstrating the effectiveness of tailored arguments as governance tools and methods in AI systems development.

**Keywords** Artificial intelligence · AI systems development · Accountability · Construal level theory · Toulmin's model of argumentation · Mixed methods

## 1 Introduction

Advancements in big data and machine learning technologies have significantly enhanced the development of artificial intelligence (AI) systems, offering remarkable improvements in efficiency and novel information processing abilities (Asatiani et al. 2021). As these systems evolve from simple rule-based algorithms to more autonomous and inscrutable AI systems capable of perceiving their environments and deriving predictions, recommendations, and decisions (Berente et al. 2021; Wu-Gehbauer and Rosenkranz 2024), the risk of unintended consequences increases. This evolution introduces complex challenges in the management of information systems development (ISD) activities (Dey and Lee 2021) and underscores the importance of socio-technical approaches

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(Hennel and Rosenkranz 2021; Sawyer et al. 2010) focusing on the ethical and safe design of AI systems and AI developers' accountability (Dey and Lee 2021; Horner and Laumer 2023; Rosenkranz et al. 2023). AI developers play a critical role in AI systems development, as their decisions significantly influence how AI systems infer from data and interact with users (Wu-Gehbauer and Rosenkranz 2024). They are thus tasked with assuming algorithmic accountability (Martin 2019), which involves justifying and explaining the design, use, and outcomes of AI systems and taking responsibility for any negative impacts these systems cause (Bovens 2007; Wieringa 2020).

Given the reliance of ISD activities on the reflective sense-making processes of the individuals involved (Vial and Rivard 2022), understanding AI developers' subjective perceptions of their accountability is crucial (Frink and Klimoski 1998). Accountability perceptions significantly influence individual behavior (Lewin 1936), leading to more informed, prudent, and defensible decisions (Lowry et al. 2012; Vance et al. 2015). Therefore, effectively communicating accountability expectations to AI developers is essential for fostering ethical and responsible decision-making in the design, implementation, and governance of AI systems.

In information systems (IS) research, various arguments have been put forward for why AI developers should be held accountable for their AI systems. These range from technical justifications, such as AI developers' ability to enable reverse engineering of AI-produced insights (e.g., Benbya et al. 2021), to ethical considerations about how their development decisions embed responsibility attributions into AI systems (e.g., Martin 2019). In this context, arguments for AI developers' accountability – drawing on distinctions established in social and organizational psychology – vary in their focus: some emphasize *accountability for development processes*, such as methodology choice and training data selection, while others stress *accountability for AI systems' outcomes*, including unintended consequences and ethical issues that may arise post-deployment (Hochwarter et al. 2007; Lerner and Tetlock 1999; Siegel-Jacobs and Yates 1996). This variation reflects the complex nature of AI systems development, where often significant time gaps exist between development decisions and their manifestations in AI systems' outcomes (van den Broek et al. 2021). Despite this variation in argument focus, there has been minimal research conducted to date into how different types of accountability arguments affect AI developers' perceptions and awareness of their accountability.

Understanding how process versus outcome accountability arguments influence AI developers is particularly crucial given the evolving nature of AI systems (Berente

et al. 2021). While process arguments address immediate development decisions and actions, outcome arguments deal with future impacts that may only become apparent during AI system operation. Recognizing which types of arguments most effectively communicate accountability to AI developers is vital for the effective governance of AI systems development, ensuring comprehensive consideration of immediate development practices and longer-term operational impacts. This understanding becomes especially important as AI systems grow more autonomous and complex (Saffarizadeh et al. 2024), potentially leading to outcomes that were not foreseeable during development.

ISD research has long established that effective communication and appropriate tools are crucial for successful development outcomes and shared understanding among ISD stakeholders (Conboy 2009; Corvera Charaf et al. 2013; Rosenkranz et al. 2013). This is particularly relevant for AI systems development, where complex technical decisions must align with business objectives and ethical considerations (Meckenstock et al. 2022; Ravn et al. 2022). However, current governance tools and methods for promoting accountability in AI systems development, such as AI principles or audits (e.g., Floridi 2019; Raji et al. 2020), often fall short due to their abstract nature and reliance on subjective judgments, which hinder effective communication (Berente et al. 2024; Mittelstadt 2019). While ISD teams typically benefit from methods and tools that promote transparency and collaboration (Shidende et al. 2016; Ter Hofstede and Verhoef 1997), these approaches have not yet been effectively adapted for communicating accountability in AI systems development. Nevertheless, experimental evidence suggests incorporating user interface (UI) design elements that visualize accountability mechanisms effectively raise users' accountability perceptions (e.g., Adam 2022; Vance et al. 2015). This presents an opportunity to utilize UI design elements within integrated development environments (IDEs) to foster accountability awareness within AI systems development.

Against this backdrop, our paper sets out to explore AI developers' responses to varied accountability arguments visualized in IDEs, structured in accordance with Toulmin's model of argumentation (1958) and integrating construal level theory (CLT) (Trope and Liberman 2010). Within Toulmin's model, a claim represents an assertion to be established as truth – such as AI developers' process or outcome accountability, thereby addressing different mental construals according to CLT (Liberman and Trope 2008; Trope and Liberman 2010). Further, we examine whether the presence of supporting data alongside these accountability claims enhances their effectiveness, as suggested by Toulmin's model. Consequently, this paper poses two research questions: *How do process versus outcome accountability arguments, when presented as*

*claims only, affect AI developers' perceived accountability? And how is this effect influenced by the absence versus presence of support alongside the claims (i.e., claim-supporting data)?*

To answer our research questions, we employed a sequential mixed method approach, gathering both quantitative and qualitative data to analyze and comprehend how different accountability arguments influence AI developers engaged in AI systems development. In the first study, we conducted a 2 (accountability claims: process vs. outcome)  $\times$  2 (claim-supporting data: present vs. absent) online experiment in a between-subject design with 164 AI developers to analyze the impact of process and outcome accountability arguments visualized as UI design elements on AI developers' perceived accountability. The results indicate that incorporating corresponding UI design elements into IDEs enhances AI developers' accountability perceptions. Notably, arguments focusing on accountability for development processes exert a greater impact on AI developers' accountability perceptions compared to those emphasizing accountability for AI system outcomes. Nevertheless, with present claim-supporting data, both types of arguments prove similarly effective in strengthening AI developers' accountability perceptions. Accordingly, AI developers more effectively perceive their accountability when they receive clear arguments about their obligations in conjunction with supporting evidence.

Building on these findings and responding to calls for a deeper understanding of communication approaches in ISD (e.g., Hennel and Rosenkranz 2021; Kautz et al. 2007), we conducted a second study to validate and expand our insights (Venkatesh et al. 2013, 2016). 15 interviews with AI developers and professionals working in related roles within AI systems development teams confirmed more pronounced accountability perceptions for development processes than for outcomes of AI systems. This emphasis largely stems from AI developers' perceived higher influence over development processes. Furthermore, our study highlights the importance of considering organizational and individual boundary conditions, which significantly shape how AI developers respond to different types of accountability arguments, suggesting a complex interplay between personal agency and institutional frameworks in AI systems development.

Our research contributes to IS research on algorithmic accountability (e.g., Horneber and Laumer 2023; Wieringa 2020) and advances our understanding of AI systems development, a key aspect of managing future ISD activities (Rosenkranz et al. 2023). First, we extend existing IS research on accountability perceptions (e.g., Adam 2022; Vance et al. 2013, 2015) by revealing how process and outcome accountability emerge from the experiences of AI developers as distinct theoretical constructs in AI systems

development while demonstrating how different argument types influence developers' accountability perceptions. Second, we show how AI developers respond differently to process versus outcome accountability arguments, enhancing our understanding of how accountability should be communicated at various phases of AI systems development. Third, we advance ISD research by showing how established development tools can be adapted to address emerging governance challenges in AI systems development (Rosenkranz et al. 2023; Urbach et al. 2019). From a practical standpoint, our research provides organizations with concrete guidance for integrating accountability arguments into their development environments, offering a pragmatic approach to enhancing accountability awareness throughout the AI systems development process.

## 2 Theoretical Background and Related Literature

### 2.1 AI Developers' Accountability in AI Systems Development

The rising influence of increasingly adaptive, autonomous, and inscrutable AI systems on critical decision-making processes (Berente et al. 2021) raises pressing questions about algorithmic accountability (Horneber and Laumer 2023; Wieringa 2020), especially as AI systems become more capable of interacting with and responding to their environments (Russell and Norvig 2021; Wu-Gehbauer and Rosenkranz 2024). Algorithmic accountability, which builds on broader accountability concepts in political and academic discourse (e.g., Bovens 2007, 2010; Lindberg 2013), demands that stakeholders engaged in AI systems are able to explain and justify the design, usage, and outcomes of AI systems, and bear consequences for any negative impacts arising from such systems (Horneber and Laumer 2023; Wieringa 2020).

Previous IS research has raised various arguments for why AI developers should be held accountable in AI systems development. The focus on AI developers is often justified by their critical influence over how AI systems process and act upon data, shaped significantly by AI developers' technical skill and knowledge (Seidel et al. 2019; Sturm et al. 2021; Vaast and Pinsonneault 2021). Accountability arguments vary in their focus: some emphasize accountability for development processes, such as design and methodology choices to foster transparent and auditable systems (e.g., Horneber and Laumer 2023; Martin 2019, 2022), while others stress accountability for outcomes by pointing to AI developers' ability to critically question or even reverse engineer these outcomes (e.g., Benbya et al. 2021). However, despite this variety of arguments, IS research has yet to investigate how these different types of accountability arguments affect AI

developers' perceptions and awareness of their accountability.

To translate accountability arguments into practice, various governance tools and methods have been proposed, such as AI principles (e.g., Floridi 2019), frameworks (e.g., Tóth et al. 2022), certification systems (e.g., Matus and Veale 2022), and audit systems (e.g., Raji et al. 2020). However, these approaches often remain abstract and vague, requiring subjective judgments and lacking standardization (e.g., Berente et al. 2024; Schulte-Derne and Gnewuch 2024). Accordingly, the challenge lies not just in establishing process or outcome accountability arguments, but in effectively communicating them to AI developers in ways that influence their awareness and behavior.

An important approach to establishing such understanding in ISD activities involves utilizing various ISD tools and methods designed to enhance communication and collaboration among stakeholders (Bittner and Leimeister 2014; Gallivan and Keil 2003; Rosenkranz et al. 2013, 2014). Such tools and methods help shape stakeholder perceptions of the ostensive aspects of ISD activities, clarifying how ISD objectives should be carried out in principle and aligning them with actual implementation (Vial and Rivard 2022). These tools and methods encompass a broad range of strategies, including organizational metaphors that provide rich conceptualizations for understanding the social context of ISD activities (Oates and Fitzgerald 2007), procedural prompts to assist stakeholders in ISD activities such as requirements elicitation (Pitts and Browne 2007) or enhanced meeting practices supported by tools (Stray and Moe 2020; Stray et al. 2024). Thus, ISD tools and methods collectively contribute to more coherent, efficient, and successful ISD processes.

In contexts like preventing access policy violations, empirical evidence demonstrates that UI design elements visualizing accountability mechanisms effectively enhance IS users' accountability perceptions (Vance et al. 2015). Similarly, UI elements could serve as powerful governance tools to communicate both process and outcome accountability arguments clearly and comprehensively to AI developers. By rendering abstract concepts more tangible and immediate through appropriate visualization, UI elements could help bridge the psychological distance created by the temporal gap between the development processes and the outcomes of AI systems, enabling AI developers to better understand and embrace their accountability.

## 2.2 Construal Level Theory and AI Developers' Accountability Perceptions

The design of UI elements, both visual and argumentative, should consider how AI developers mentally process and respond to different types of accountability arguments. This

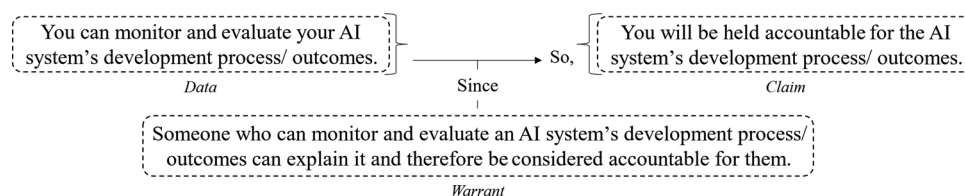
diversity stems from how individuals form mental representations of goals and related messages, which vary in concreteness depending on their psychological distance from the event or object in question (Trope and Liberman 2010). Within CLT, psychological distance is characterized as the subjective perception of how close or far something appears, with variations such as temporal (time-related) and hypothetical (likelihood-related) distances (Trope and Liberman 2003, 2010). In the context of AI systems development, CLT can be drawn upon to understand how AI developers process different types of accountability arguments. Accountability arguments focusing on development processes, such as methodology choices or training data selection (e.g., Zhang et al. 2020), address immediate actions and decisions that feel closer in time and more certain to occur. In contrast, accountability arguments about potential future outcomes of AI systems, such as unintended discrimination or model drift (e.g., Benbya et al. 2021), involve greater temporal and hypothetical distance. This variation in psychological distance suggests that process and outcome accountability arguments may elicit different levels of mental construal among AI developers.

Previous IS research has investigated the effects of temporal distances on IS users' decision or choice behavior by altering their levels of abstraction and, thus, their construal levels. For example, information associated with low (vs. high) temporal distance (e.g., by being highly topical or representing real-time data) has been shown to elicit higher IS reuse intentions and lead to more vivid perceptions, positively affecting IS users' choice behavior (Adam et al. 2020; Wendt et al. 2022). Accordingly, it can be assumed that UI design elements visualizing process accountability arguments, representing less temporal distance, elicit a more concrete mental construal compared to UI design elements visualizing outcome accountability arguments. However, as accountability arguments for AI systems often remain vague or implicit (Berente et al. 2024; Schulte-Derne and Gnewuch 2024), the question arises as to how accountability arguments should be composed so that they are suitable for conveying to AI developers their accountability for the development processes or outcomes of AI systems.

## 2.3 Toulmin's Model of Argumentation

Toulmin (1958) established a model of argumentation according to which arguments of daily communication mainly consist of the three central components *claim*, *data*, and *warrant*, that are needed to compose a "skeleton of a pattern for analyzing arguments" (Toulmin 2003, p. 92). While a claim describes an assertion or conclusion presented for general acceptance (Ye and Johnson 1995), data represent the evidence used to support the claim



**Fig. 1** Structure of communication arguments

(VerLinden 1998). Warrants are propositions linking data and claims, often taking on an incidental and explanatory function (Toulmin 1958). They aim to explicitly establish the legitimacy of the step from data to claim against the background of larger contexts whose legitimacy is presupposed (Toulmin 2003). Figure 1 shows an example argument in the context of algorithmic accountability with the relationships between these three components. Since warrants are often only implicitly referred to without being explicitly expressed like claim-supporting data (Toulmin 2003), we focus on claim and claim-supporting data in our research. Accordingly, our accountability arguments consist of only a claim alone or a combination of a claim and claim-supporting data.

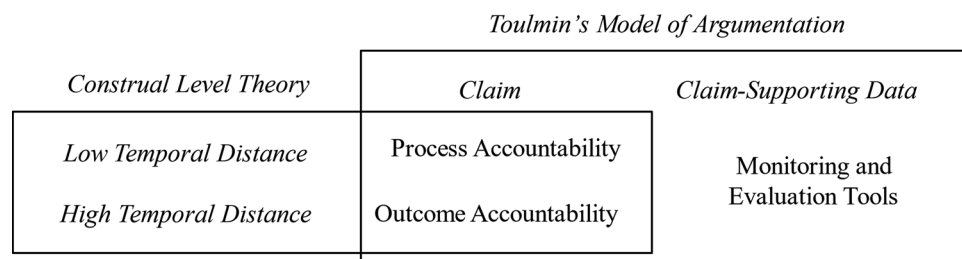
Previous IS research indicates that arguments have a more substantial effect when they consist of a claim and claim-supporting data. More specifically, the combination of claim and claim-supporting data has been shown to increase customers' trust in online stores, which has not been achieved with claims alone (e.g., Kim and Benbasat 2006). Furthermore, the persuasiveness of arguments has also been shown to vary depending on the contextual setting, such as when addressing different motivational orientations (e.g., Schneider et al. 2017). In the context of AI systems, there is a prevalent claim that AI developers should assume algorithmic accountability (e.g., Benbya et al. 2021; Martin 2019). However, as AI systems become more autonomous and inscrutable (Berente et al. 2021; Saffarizadeh et al. 2024), the feasibility of holding AI developers accountable is increasingly challenged. AI systems' opaque and automated nature thwarts understanding their inner workings, thus impeding algorithmic accountability for AI developers.

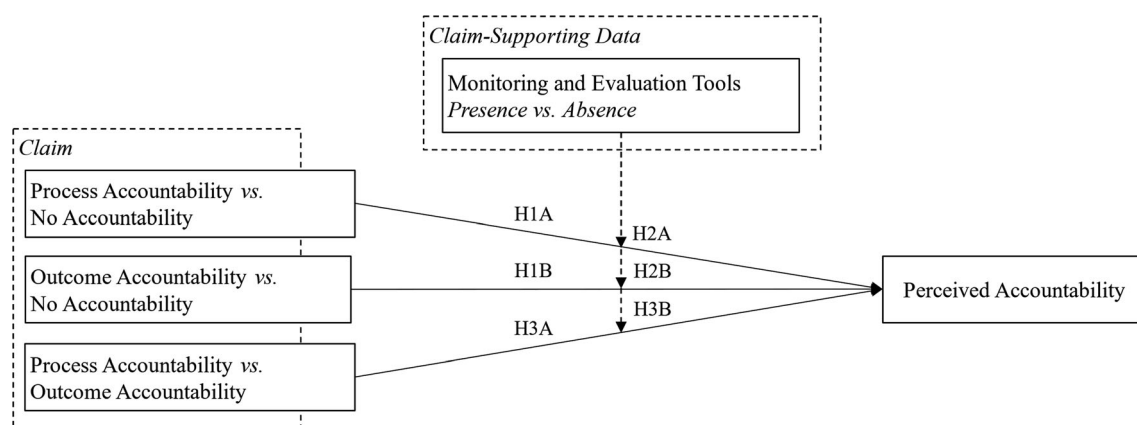
To convincingly argue for AI developers' accountability for AI systems development processes and outcomes, AI developers must have the means to monitor and evaluate their work. For example, IDEs equipped with tools for

monitoring and evaluating development processes and outcomes of AI systems could provide the necessary data to support claims of AI developers' respective accountability. Such capabilities are essential for AI developers to effectively oversee and justify their development processes and the outcomes of their AI systems, lending credibility to claims of their respective accountability. Accordingly, integrating psychological distances with the structure of arguments (comprising claims and claim-supporting data) provides a lens through which we understand whether and how AI developers can be persuaded of their process or outcome accountability for AI systems. Figure 2 shows the conceptual framework underlying the development of our hypotheses and the design of the accountability arguments we used in our experimental study.

### 3 Research Model and Hypotheses Development

Our research model evaluates the effects of process and outcome accountability arguments on AI developers' perceived accountability, both in absolute and relative terms. Initially, we assess the effectiveness of process and outcome accountability claims on AI developers' perceived accountability (H1A/ H1B). This is followed by an analysis of how the presence or absence of claim-supporting data moderates the effects of these claims (H2A/ H2B). We then proceed to contrast the relative effectiveness of process versus outcome accountability claims (H3A). Further, we examine the relative effects of the presence or absence of claim-supporting data on the differential impact of these claims on AI developers' perceived accountability (H3B). This approach allows for a comprehensive understanding of the role of accountability claims and their supporting data in shaping AI developers' perceived accountability, as systematically illustrated in Fig. 3 of our research model.

**Fig. 2** Conceptual framework of accountability arguments



**Fig. 3** Research model

When individuals encounter the presence of accountability claims, they should feel compelled to explain and justify their respective behavior and decisions to an audience, thereby intensifying their accountability perceptions. Such heightened awareness increases the likelihood that individuals will systematically and deeply consider their behavior, a phenomenon referred to as systematic processing (Crano and Prislin 2006). Conversely, in the absence of accountability claims, individuals' accountability perceptions and the ensuing depth of processing may diminish. Systematic processing, perhaps fostered by the presence of accountability claims, encourages individuals to consider the factual consequences of their actions more thoroughly, leading to a heightened perception of accountability for their actions (Vance et al. 2015).

Accordingly, AI developers exposed to claims expressing their accountability for the processes or outcomes of AI systems development should likely perceive a heightened sense of accountability. This assumption aligns with CLT, which posits that the presence of accountability claims may induce a mental construal in AI developers, albeit perhaps abstract, affecting their accountability perceptions (Trobe and Liberman 2010). In the context of AI systems development, the presence of process or outcome accountability claims could lead to a more immediate and concrete accountability perception. For instance, when AI developers receive explicit reminders or notifications about the importance of responsible coding practices or the immediate consequences of biases in their training data, they should become more acutely aware of their accountability in AI systems development processes. This concrete mental construal of their accountability is closely linked to the visible and immediate results of their actions within development processes. Conversely, when outcome accountability claims are explicitly present, AI developers are prompted to consider their developed AI systems' long-term impacts and broader implications. For example,

suppose AI developers are regularly reminded of how their AI system outcomes might affect societal norms or the interests of individuals. In that case, they should be more likely to factor in these abstract, future-oriented consequences in their development decisions and actions. Thus, the presence of outcome accountability claims should encourage a broader perspective, extending AI developers' accountability perceptions beyond immediate technical challenges to include the potential long-term effects of their work. Accordingly, the presence of accountability claims, whether relating to development processes or future outcomes of AI systems, should play a critical role in shaping AI developers' mental construal and directly influence their accountability perception in AI systems development. We thus formulate our first set of hypotheses:

**H1A** The presence (vs. absence) of process accountability claims creates higher perceived accountability among AI developers.

**H1B** The presence (vs. absence) of outcome accountability claims creates higher perceived accountability among AI developers.

According to Toulmin's model of argumentation (1958), an argument persuades individuals more when its claim is supported by data (i.e., evidence of the claim), as claim-supporting data provides an empirical or logical grounding, thereby enhancing the credibility and perceived validity of the respective argument. Prior IS research supports this, showing that individuals are more likely to accept an expert system's conclusions when its explanations align with Toulmin's model of argumentation (Ye and Johnson 1995). Arguments that include both claim and claim-supporting data have also proven more effective in influencing consumers' beliefs (e.g., Kim and Benbasat 2009). Therefore, we posit that claims of process and outcome accountability in the context of AI systems development will be more persuasive with accompanying claim-supporting data.

However, claim-supporting data in the context of AI systems development needs to be contextually relevant and specific to be persuasive. For process accountability claims, supporting data could include detailed documentation of AI developers' assumptions and decisions during development processes. For example, this might involve logs or records showing how ethical considerations were incorporated into decision-making processes or evidence of rigorous testing protocols to ensure the reliability of developed AI systems. Such data substantiates the claim that AI developers are accountable for their development processes. For outcome accountability claims, supporting data could encompass the review of databases and performance analyses of deployed AI systems. This could entail showcasing how different input data varieties influence an AI system's behavior or providing examples of how an AI system's performance varies in diverse real-world scenarios. Such type of evidence demonstrates the direct impact of AI developers' actions and decisions on AI systems' outcomes, emphasizing AI developers' accountability for these outcomes.

By incorporating such claim-supporting data, the relationship between accountability claims and AI developers' perceived accountability can be expected to be positively moderated, leading to our second set of hypotheses:

**H2A** *Claim-supporting data moderates the effects of process accountability claims on AI developers' perceived accountability, such that the presence of claim-supporting data amplifies the effect of process accountability claims on AI developers' perceived accountability.*

**H2B** *Claim-supporting data moderates the effects of outcome accountability claims on AI developers' perceived accountability, such that the presence of claim-supporting data amplifies the effect of outcome accountability claims on AI developers' perceived accountability.*

How do process and outcome accountability arguments differ in shaping AI developers' perceptions of their own accountability in AI systems development? CLT suggests that arguments for their process accountability affect AI developers' accountability perceptions differently than arguments for their outcome accountability, as the development processes of AI systems elicit different temporal distances than the outcomes of AI systems. Process accountability focuses on development activities that are currently in progress, thereby referencing the present. Consequently, being held accountable for development processes induces a relatively closer temporal distance and, thus, a more concrete and low-level mental construal (Trope and Liberman 2003). Conversely, accountability for AI systems' outcomes leads to more abstract and high-level mental construals, as AI systems' outcomes occur, if at all,

only later (Trope and Liberman 2003). Following CLT, concrete and low-level mental construals are more persuasive than abstract and high-level mental construals, as their reference points are more salient in individuals' minds. As a result, individuals are more likely to rely on concrete details to form their judgments and beliefs. In contrast, more abstract and higher-level mental construal reference points are less salient and more likely to be forgotten or pushed out of memory (Trope and Liberman 2010).

We first consider situations where process and outcome accountability claims appear without claim-supporting data. In these situations, CLT suggests that process accountability claims, focusing on AI developers' immediate development activities, would be more persuasive to AI developers than outcome accountability claims, which pertain to the future behavior of AI systems. Process accountability's immediate and concrete nature should induce a lower temporal distance and, thus, a more concrete mental construal, making it more influential in shaping AI developers' accountability perceptions. In contrast, outcome accountability, being more abstract and temporally distant, should be less salient and, thus, less persuasive in day-to-day development tasks. Hence, we posit that in the absence of claim-supporting data, AI developers are more likely to perceive higher accountability with process accountability claims compared to outcome accountability claims. Therefore, we posit the following hypothesis:

**H3A** Process accountability claims (vs. outcome accountability claims) create higher perceived accountability among AI developers.

Second, in situations where claim-supporting data back up process and outcome accountability claims, the matching evidence aligns with the claims, inducing a construal fit as outlined by CLT (Hansen and Wänke 2010). This fit enhances processing fluency, reinforcing the perceived validity of the respective claims (Hansen and Wänke 2010) and, consequently, should strengthen AI developers' perceived accountability. Thus, when both process and outcome accountability claims are accompanied by supporting data, they are likely more persuasive than claims presented alone. However, for process accountability, where claims alone should already elicit a concrete, low-level construal of AI developers' accountability, providing supporting data might not significantly intensify this effect. As AI developers' mental construal of their process accountability should be inherently concrete, claim-supporting data may only marginally enhance their accountability perception. In contrast, incorporating supporting data could substantially amplify the effect for outcome accountability. Suppose this data provides concrete evidence for AI developers'



accountability for AI systems' outcomes, such as showcasing their ability to monitor and evaluate those systems. In that case, it helps solidify an otherwise abstract concept. This should elicit a more concrete mental construal among AI developers, effectively bridging the gap between abstract outcomes of AI systems and tangible actions within AI systems development. Thus, adding supporting data to outcome accountability claims should markedly increase AI developers' perceived accountability.

Based on these considerations, we posit that for outcome accountability, including supporting data to claims significantly elevates AI developers' perceived accountability, more so than for process accountability claims. This effect should stem from the transition of respective mental construal from abstract to concrete, facilitated by the present claim-supporting data, functioning as supporting evidence. Accordingly, we derive our final hypothesis:

**H3B** The presence of claim-supporting data moderates the impact of accountability claims on AI developers' perceived accountability. Specifically, claim-supporting data amplifies the effect of outcome accountability claims on AI developers' perceived accountability more than it does for process accountability claims.

## 4 Research Design

Given the paucity of empirical research on algorithmic accountability, we adopted a mixed method approach with two interdependent studies to investigate our research model. The first study involved a controlled online experiment with AI developers based in the United States (US), focusing on testing our hypotheses related to accountability perceptions. Guided by a strong theoretical foundation in CLT (Trope and Liberman 2010) and Toulmin's model of argumentation (1958), this study provided a solid base for exploring the relationship between accountability arguments and AI developers' perceived accountability and the moderating effect of claim-supporting data within the emerging domain of algorithmic accountability (Venkatesh et al. 2013). However, for a richer understanding of developers' accountability perceptions as a new phenomenon in AI systems development, we deemed it crucial to triangulate these findings (Levine et al. 2023). Thus, we conducted a follow-up qualitative study through semi-structured interviews with AI developers and related professionals in AI systems development working in Germany. Our research design sought to achieve two primary objectives of mixed method research: corroboration and complementarity (Mingers 2001; Venkatesh et al. 2013). The corroboration objective was met by triangulating the theoretical insights from the quantitative study with

practical, real-world perspectives, enhancing our comprehension's depth and breadth (Benlian et al. 2020; Hinz et al. 2015). Furthermore, the qualitative study enabled us to explore AI developers' contextualized experiences with accountability and uncover important boundary conditions that shape their perceptions (Srivastava and Chandra 2018). Collectively, our comprehensive approach allowed us to test our research model and develop a deeper theoretical understanding of how accountability manifests in AI systems development contexts.

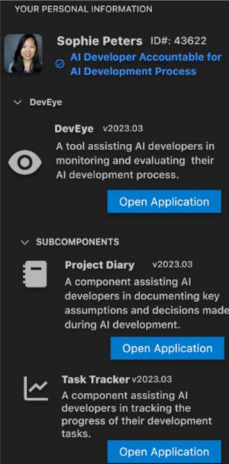
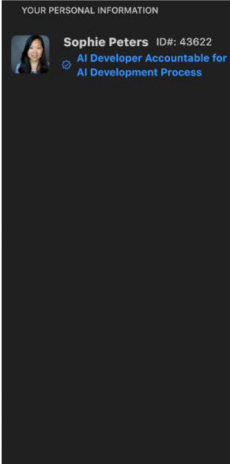
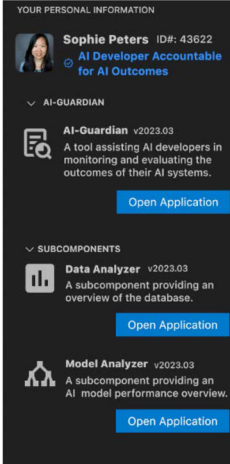
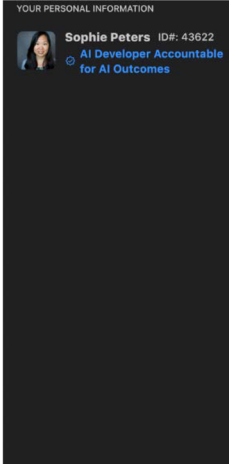
## 5 Quantitative Online Experiment Study

### 5.1 Experimental Design

To investigate and compare the effects of process and outcome accountability arguments on AI developers' accountability perceptions, our first study utilized scenario-based vignettes in an online experiment, adhering to recognized guidelines for experimental design (e.g., Aguinis and Bradley 2014). Participants were introduced to IDEs that contained UI design elements that we used to visualize arguments of AI developers' process or outcome accountability with monitoring and evaluation tools either present or absent. By manipulating the inclusion of monitoring and evaluation tools that served as claim-supporting data, we crafted distinct process and outcome accountability arguments. Consequently, the effects of those arguments were also to be examined depending on whether claim-supporting data is present versus absent in the UI design elements. More specifically, we employed a 2 (claim: process accountability versus outcome accountability)  $\times$  2 (claim-supporting data: present vs. absent) between-subjects design with an additional hanging control group. This study design allowed us to perform both relative and absolute treatment comparisons (Shadish et al. 2002). Furthermore, this study design enabled us to investigate the individual effects of the argument components in isolation, namely claim (process versus outcome accountability) and claim-supporting data (absent versus present), on AI developers' perceived accountability. The hanging control group represents the perceived accountability of AI developers who were not shown any accountability arguments visualized as UI design elements. Furthermore, as Toulmin's model of argumentation (1958) suggests that arguments that consist only of claim-supporting data without a claim are unlikely to produce the intended effect, we excluded this group. Table 1 shows the resulting five experimental conditions.

To test the hypotheses, we devised a scenario focused on the development of an AI system for evaluating bank customers' creditworthiness. Thus, the scenario aligns with a category legally recognized as high-risk in the wake of

**Table 1** Five experimental conditions ( $2 \times 2$  between-subject design plus hanging control group)

Claim: Process Accountability		Claim: Outcome Accountability		Hanging Control Group
Data: Present	Data: Absent	Data: Present	Data: Absent	
				

**Hanging Control Group**

*No UI design elements were shown*

recent legislation (European Union 2024). Additionally, the development of such AI systems is not only legally pertinent but also mirrors ongoing, realistic projects in the industry (e.g., Strich et al. 2021). In the scenario, participants were asked to assume the role of a core AI developer at a software organization responsible for developing an AI system for credit scoring. Based on the random allocation to their experimental condition, participants were instructed to focus on the accountability for either the development processes or the outcomes of the AI system. Additionally, participants were informed about a customized IDE provided by their employer, which they had to use in their tasks accordingly.

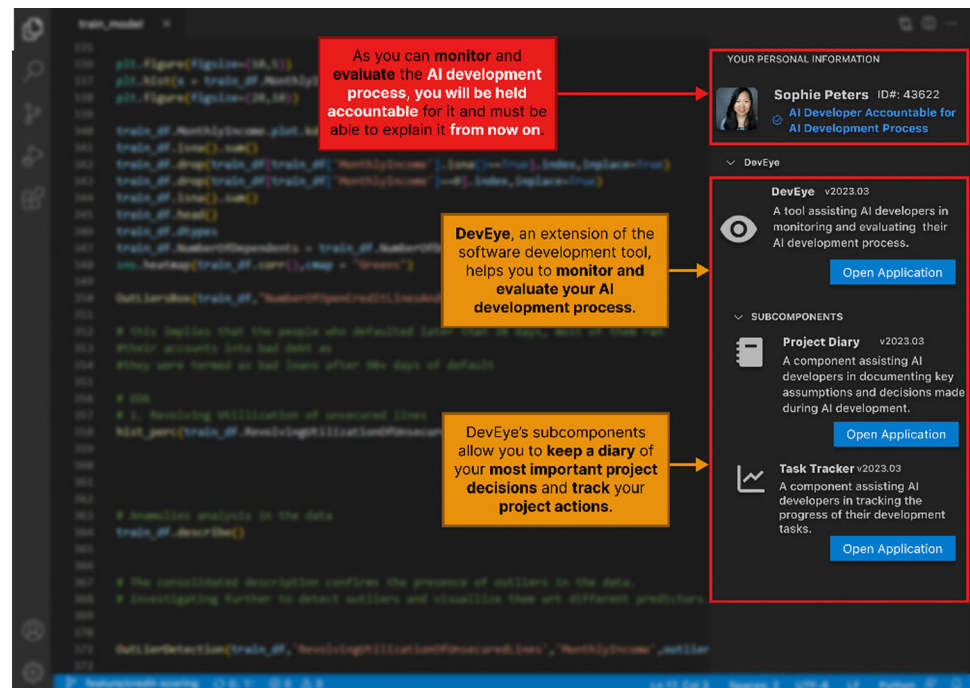
We developed the UI design elements for our customized IDE following previous IS studies on accountability perceptions (i.e., Adam 2022; Vance et al. 2015). More specifically, we adapted two accountability mechanisms utilized within these studies to develop the UI design elements, namely, expectation of evaluation and awareness of monitoring (Lerner and Tetlock 1999). Expectation of evaluation represented the claim, as participants were communicated to be held accountable for either the AI systems' development process or its outcomes. Awareness of monitoring represented the claim-supporting data, as participants were shown the possibility of using governance tools to explicitly monitor and evaluate either the development processes or the outcomes of the AI system to be developed. Our study used these accountability mechanisms as manipulated treatment factors. All UI design elements were consistent across participants and varied only in their accompanying icons and positioning in the

customized IDE. Following previous IS research (i.e., Adam 2022; Vance et al. 2015), we added labels to the customized IDE to increase recognition of the UI design elements in the experimental conditions. Each participant was randomly assigned to one experimental condition and rated their perceived accountability after seeing the customized IDE. Figure 4 shows an example of an IDE that contains a UI design element that visualizes a process accountability argument and includes both claim and claim-supporting data.

## 5.2 Measurement of Variables

We followed previous IS studies on accountability perceptions (i.e., Adam 2022; Vance et al. 2015) by adapting and using an existing scale to measure AI developers' perceived accountability (i.e., Hochwarter et al. 2005) to elicit AI developers' perception of their accountability. We carefully selected items representing a breadth in the perception of one's accountability, including the presence of a forum to which one may perceive being accountable and the need to justify and explain to that forum. The adaptations of the items we used were: "I would feel very accountable for my actions on the presented AI systems development project that I am working on.", "If the presented AI systems development project would not go as planned, I would expect to hear about it from my superiors.", and "I would often have to explain my actions in the presented AI systems development project." The items were measured on a 7-point Likert-type scale, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). In addition,

**Fig. 4** Sample IDE with UI design elements



items were included to assess the realism of the scenario (Lapierre 2007) and demographic data (i.e., gender, age, and AI systems development experience in years). Further, we followed comparable IS research on user's perceived accountability (i.e., Adam 2022; Vance et al. 2015) and included organizational trust (Robinson 1996) and impulsivity (Pogarsky 2004) as control variables. Organizational trust was measured because it could lead to more positive perceptions of UI design elements caused by a positivity bias toward the organization, thus influencing how participants perceive and react to those UI design elements. Higher organizational trust may lead to a more favorable perception of mandated actions, while lower organizational trust may increase scrutiny towards the same. Similarly, we assessed impulsivity as it could affect the immediacy and intensity of AI developers' responses to accountability arguments visualized in UI design elements, providing a broader understanding of behavioral responses in diverse personality contexts.

### 5.3 Data Analysis and Results

We conducted three explanatory interviews to ensure functionality and understanding of the scenario and our manipulated UI design elements for IDEs (Hauser et al. 2018; Oppenheimer et al. 2009). The interviews, each about 45 min long, were conducted with participants who had professional experience managing or developing AI systems and were primarily aimed at ensuring that the designed UI design elements for IDEs, including their

manipulations, were perceived as having practical relevance and that the scenario presented was evaluated as realistic. Based on the results of these interviews, we optimized our developed UI design elements for IDEs.

We collected the final dataset via the crowdsourcing platform Prolific, which is known for its high reliability and high-quality data (e.g., Palan and Schitter 2018). Following previous IS research, we focused on individuals whose primary job function involved developing AI systems through coding, modeling, and deployment (Seguel and Vaast 2021). Participants were required to have professional experience in developing various AI functions, such as natural language processing, deep learning, machine vision, and robotics (Collins et al. 2021). To verify the suitability of the candidates, these requirements were double-checked through detailed screening of their current job titles. Additionally, participants had to be US-citizens to ensure a good understanding of the English language. The participants received monetary compensation for participating in the study.

Our data collection resulted in 200 participants, of which, to ensure high data quality, we excluded 36 participants: 25 due to failing nonsensical items such as "I swim across the Atlantic Ocean to get to work every day" (Paolacci et al. 2010) used as attention checks, and 11 based on the relative speed index (RSI) criterion. The RSI criterion relates the time required to complete the study for a single participant to the time required to complete the study for all participants, with data from participants who complete the experiment at least twice as fast as the typical

**Table 2** Descriptive statistics

Construct	Mean	SD	Min	Max	N
AI systems development experience	3.116	2.374	0.000	14.000	164
Organizational trust	5.837	1.086	1.000	7.000	164
Impulsivity	2.693	1.424	1.000	7.000	164
Perceived accountability	5.793	1.142	1.000	7.000	164
Control group	4.914	1.139	1.000	7.000	35
Outcome accountability without data	5.609	1.039	3.000	7.000	29
Outcome accountability with data	6.115	0.746	4.000	7.000	32
Process accountability without data	6.141	0.687	4.333	7.000	35
Process accountability with data	6.200	0.696	4.333	7.000	33

**Table 3** Internal consistency and convergent validity

	Range of Loadings	Mean	SD	$\alpha$	PA	OT	I
PA	0.847 – 0.867	5.793	1.142	0.851	<b>0.809</b>		
OT	0.865 – 0.909	5.837	1.181	0.909	0.190	<b>0.885</b>	
I	0.830 – 0.924	2.693	1.640	0.860	0.050	-0.045	<b>0.863</b>

$p < 0.05$ ;  $\alpha$  = Cronbach's alpha; SD = Standard deviation; square root of AVE in bolded cells

PA = Perceived Accountability; OT = Organizational Trust; I = Impulsivity

participant not considered high quality (Leiner 2019). Accordingly, our final dataset includes 164 participants, resulting in a valid response rate of 82.0%. The participants primarily held positions as AI engineers and (full-stack) developers, directly involved in AI systems development. The average age of the respondents was 36.4 years (standard deviation of 10.8 years), of which 75.0% identified as male and 24.4% as female, 84.8% had a Bachelor's degree or higher, and on average, the study participants had 3.2 years of experience developing AI systems (standard deviation of 2.4 years).

A summary of the descriptive statistics is provided in Table 2. Using multiple one-way ANOVAs, we verified that the assignment of participants to the different experimental conditions was random. For the items gender ( $F = 0.598$ ,  $df = 4$ ,  $p > 0.05$ ), age ( $F = 2.166$ ,  $df = 4$ ,  $p > 0.05$ ), AI systems development experience ( $F = 1.041$ ,  $df = 4$ ,  $p > 0.05$ ), organizational trust ( $F = 0.72$ ,  $df = 4$ ,  $p > 0.05$ ), and impulsivity ( $F = 0.236$ ,  $df = 4$ ,  $p > 0.05$ ), no significant differences were found between the experimental groups. Thus, we can conclude that these individual characteristics were randomly distributed among the experimental conditions.

We performed a principal component analysis with varimax rotation to measure the items' discriminant and convergent validity. Based on Kaiser's criterion, all components with Eigenvalues greater than 1.00 were extracted, with the resulting three components corresponding to the expected number of theoretical components (Hair et al.

2009). All items loaded above the threshold of 0.75 and thus can be attested strong convergence validity (Hair et al. 2009). High discriminant validity can also be attested as no item cross-loaded higher than 0.30 to a component to which it did not belong. By calculating Cronbach's  $\alpha$ , we tested the internal reliability of the items. Since all constructs exceeded the threshold of 0.80, we can assume high reliability (Streiner 2003). Table 3 shows the discriminant and convergent validity measures.

We also performed Harman's single-factor test with principal axis factoring and restricting factors to analyze whether the results were affected by common method bias (CMB). As the results showed that a single factor accounted only for 12.7% and thus well below the critical value of 50.0%, it is unlikely that CMB occurred in the study or affected the results (Podsakoff et al. 2003). Finally, we evaluated the external validity of the results based on participants' assessments of the scenario's fidelity to reality, which was also collected on a 7-point Likert-type scale, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Since the participants indicated high values and accordingly considered the scenario to be realistic ( $\bar{x} = 5.649$ ,  $\sigma = 1.131$ ), external validity can be assumed.

Planned contrast analyses were conducted across all five groups, including the hanging control group, to examine the effects of process versus outcome accountability arguments visualized as UI design elements for IDEs on AI developers' perceived accountability (Benlian 2015). We performed hierarchical regressions to directly compare the



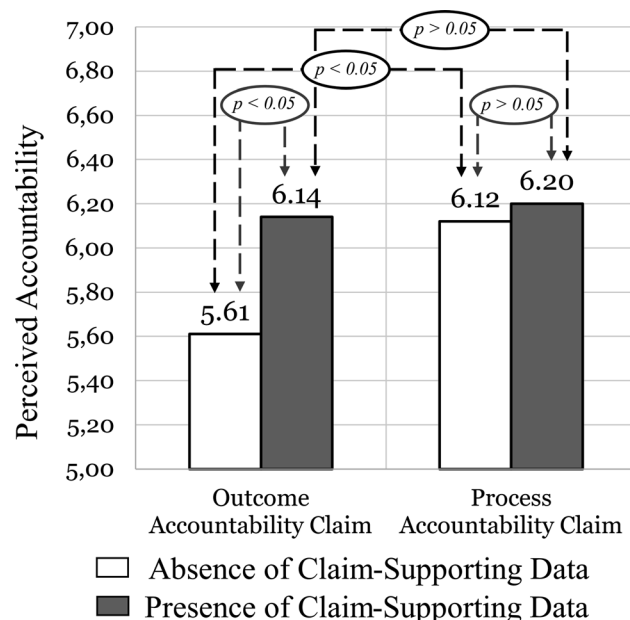
**Table 4** Results of the planned contrast analysis

Condition	Mean (SD)	Mean Differences (Value of Contrast)			
		2	3	4	5
Control Group	4.914 (1.139)	– 1.227***	– 1.286***	– 0.695**	– 1.201***
Process accountability <i>Claim Only</i>	6.141 (0.687)		– 0.059	0.532*	0.027
Process accountability <i>Claim and Claim-Supporting Data</i>	6.200 (0.696)			0.591**	0.085
Outcome accountability <i>Claim Only</i>	5.609 (1.039)				– 0.505*
Outcome accountability <i>Claim and Claim-Supporting Data</i>	6.115 (0.746)				

Significance: \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$

effects of UI design elements visualizing arguments of process versus outcome accountability on AI developers' perceived accountability in both the presence and absence of claim-supporting data. We excluded the hanging control group from the hierarchical regressions as our objective was to compare the effects of UI design elements visualizing arguments of process versus outcome accountability against each other.

As can be seen in the results of the planned contrast analyses in Table 4, UI design elements that visualize arguments of process accountability with only a claim significantly increase AI developers' perceived accountability compared to the hanging control group ( $\bar{x} = 6.141$  vs.  $\bar{x} = 4.914$ ,  $p < 0.001$ ), thereby supporting H1A.

**Fig. 5** Comparison of process versus outcome accountability UI design elements in IDEs

Similarly, H1B is supported as UI design elements that visualize outcome accountability arguments with only a claim also significantly increase AI developers' perceived accountability compared to the hanging control group ( $\bar{x} = 5.609$  vs.  $\bar{x} = 4.914$ ,  $p < 0.01$ ). Similar results emerge when AI developers face UI design elements that include claim-supporting data in addition to claims. AI developers presented with UI design elements that visualize arguments for process accountability and contain a claim and claim-supporting data exhibit higher perceived accountability compared to AI developers presented with corresponding UI design elements that contain only a respective claim ( $\bar{x} = 6.200$  vs.  $\bar{x} = 6.141$ ,  $p > 0.05$ ). Yet, H2A is not supported as the difference is insignificant. However, we find support for H2B, as AI developers' perceived accountability increases when they are presented with UI design elements that visualize outcome accountability arguments and include both claim and claim-supporting data, compared to corresponding UI design elements that include only a respective claim ( $\bar{x} = 6.115$  vs.  $\bar{x} = 5.609$ ,  $p < 0.05$ ). We can, therefore, conclude that being presented with arguments containing claims of both process and outcome accountability increases AI developers' perceived accountability. While adding claim-supporting data to arguments of outcome accountability further significantly increases AI developers' perceived accountability, this effect does not occur when adding claim-supporting data to arguments of process accountability.

In the previous step, we examined the effects of visualized arguments of process and outcome accountability, each consisting of either only a claim or also additional claim-supporting data, on AI developers' perceived accountability compared to a hanging control group. Figure 5 compares the effects of UI design elements for IDEs visualizing process and outcome accountability arguments without the hanging control group. Most strikingly, UI



**Table 5** Hierarchical regression results

	Model I		Model II	
	Coefficient	Std. Error	Coefficient	Std. Error
Intercept	4.041	0.576	3.856	0.576
<i>Manipulation</i>				
Claim <sup>a</sup>	0.286*	0.134	0.544**	0.192
Data <sup>b</sup>	0.193	0.139	0.461*	0.193
Claim x Data	–	–	–0.528*	0.266
<i>Controls</i>				
Age	0.001	0.007	0.000	0.007
Gender	0.068	0.153	0.092	0.151
AI systems development experience	0.032	0.030	0.031	0.029
Organizational trust	0.265	0.067	0.274***	0.066
Impulsivity	-0.019	0.048	-0.023	0.266
<i>R<sup>2</sup></i>	0.197		0.223	
<i>Adjusted R<sup>2</sup></i>	0.151		0.171	
<i>Residual Std. Error</i>	0.755 (df = 121)		0.746 (df = 120)	
<i>F-statistic</i>	4.249*** (df = 7; 121)		4.301*** (df = 8; 120)	

\* $p < 0.05$ ; \*\* $p < 0.01$ ;\*\*\* $p < 0.001$ ;  $n = 129$ 

a Claim was dummy coded with 0 = Outcome Accountability and 1 = Process Accountability

b Data was dummy coded with 0 = Absence of Data and 1 = Presence of Data

design elements that visualize process accountability arguments with and without claim-supporting data elicit high perceptions of accountability among AI developers. Also, including claim-supporting data in UI design elements increases AI developers' perceived accountability in the case of both visualized arguments for process and outcome accountability. However, the effect of claim-supporting data in the case of outcome accountability arguments is stronger and only significant in this case. It raises AI developers' perceived accountability almost to the level it holds in the case of process accountability arguments. Therefore, while a claim of process accountability alone is sufficient to increase AI developers' perceived accountability strongly, adding claim-supporting data is advisable regarding arguments concerning AI developers' accountability for AI systems' outcomes.

To examine H3A and H3B, we performed a hierarchical regression on the data from the experimental conditions of process and outcome accountability, the results of which can be seen in Table 5. We first included the two main effects, claim and claim-supporting data (Model I), before adding the interaction effect (Model II). Both models are highly significant ( $p < 0.001$ ). Model I reveals a statistical effect of claim on AI developers' perceived accountability in the case of process accountability versus outcome accountability, both without claim-supporting data ( $\beta = 0.286$ ,  $p < 0.05$ ), thus supporting H3A. Accordingly, in the absence of claim-supporting data, UI design elements for IDEs that visualize arguments of process accountability increase AI developers' perceived accountability more strongly than UI design elements for IDEs that visualize arguments of outcome

accountability. Model II shows that when an interaction effect is included, UI design elements for IDEs that visualize process accountability arguments and consist only of a claim still lead to stronger perceived accountability by AI developers than UI design elements for IDEs that visualize outcome accountability arguments and consist only of a claim ( $\beta = 0.544$ ,  $p < 0.01$ ). However, this tendency changes when data is present to support the corresponding claim. As can be seen from the negative interaction effect ( $\beta = -0.528$ ,  $p < 0.05$ ), the effects of claim and claim-supporting data are dependent on the presence of each other in the case of outcome accountability. In this, we find support for H3B. Outcome accountability arguments thus benefit particularly strongly from the presence of claim-supporting data. Organizational trust as the only significant control variable suggests that AI developers with high trust in their organization are also receptive to its arguments regarding their accountability ( $\beta = 0.274$ ,  $p < 0.001$ ). Additionally, the significant effect of the presence of claim-supporting data suggests that the presence of monitoring and evaluation tools has the potential to increase AI developers' perceived accountability, regardless of the specific arguments of process or outcome accountability ( $\beta = 0.461$ ,  $p < 0.05$ ).

## 6 Qualitative Interview Study

### 6.1 Purpose and Data Collection

Our second study utilized semi-structured interviews to corroborate and complement the findings of our

quantitative study. While our first study provided valuable insights through its empirical investigation of our hypotheses, our second study aimed to build upon these findings by adding depth and dimension. More precisely, our interviews were structured to explore the intricacies and nuances behind our quantitative results, particularly focusing on the underlying reasons and motivations that drive AI developers' accountability perceptions, which, though implicit in the quantitative data, required a more nuanced exploration. Besides corroboration, the analysis of the qualitative data allowed us to complement our quantitative findings by identifying organizational and individual boundary conditions that affect AI developers' accountability perceptions. Thus, by engaging directly with AI developers through qualitative interviews, our second study sought to illuminate the broader narrative around process and outcome accountability in AI systems development. Together, our two studies created a more comprehensive picture by merging quantitative robustness with qualitative richness (Venkatesh et al. 2013, 2016).

Building on our quantitative study of core AI developers, we broadened our qualitative investigation to also include related roles within AI systems development teams. This expansion was motivated by our understanding that accountability in AI systems development projects extends beyond core development tasks to affect various team members involved in the AI systems development lifecycle. Modern AI systems development is inherently collaborative, with different team members contributing their expertise to various aspects of the development process.

While some team members focus on core development tasks, others contribute to aspects like data preparation, testing, or project management – all of which carry their own accountability implications. Therefore, to gain a more comprehensive understanding of how accountability manifests in practice and validate our quantitative findings in a broader context, we purposefully expanded our interview sample to include not only core AI developers, such as AI engineers, but also participants from related roles within AI systems development teams.

We followed a purposeful sampling strategy (Palinkas et al. 2015; Patton 1990) and interviewed a total of 15 participants (coded as AID1-AID15), all of whom participated in AI systems development projects and were working in Germany at the time of the interviews. We contacted the participants via our personal network, the professional online network LinkedIn, and invited our personal network to forward the request to suitable interviewees. After the 15th interview, we observed that the newly collected data did not provide any substantial new insights for our research project and that we had, therefore, reached saturation (Keutel et al. 2014). All interviews, which lasted 32.4 min on average (standard deviation of 3.5 min), were conducted via video conference tools in English or German, recorded, and subsequently transcribed. Our interviewees were between 27 and 57 years old (average of 34 years, standard deviation of 8.1 years), had an average of 8.0 years of professional AI systems development experience (standard deviation of 9.5 years), and worked on average in a team of 21 people (standard

**Table 6** Descriptive statistics of interviewees

AID #	Age	Industry group	Job title	Team size	AI systems development experience (in Years)
1	34	Automobiles & Auto Parts	Data Scientist	12	5
2	27	Professional & Commercial Services	Full Stack Developer	10	3
3	33	Banking Services	Vice President AI for Data Analytics	12	7
4	34	Software & IT Services	Research AI Scientist	50	6
5	39	Transport Infrastructure	Senior AI Engineer	40	7
6	33	Banking Services	Data Scientist	10	5
7	57	Automobiles & Auto Parts	Head of AI Research	50	39
8	26	Telecommunications Services	Data Scientist	3	3
9	44	Transport Infrastructure	Head of Algorithms for Operations	42	20
10	27	Automobiles & Auto Parts	AI Engineer	10	2
11	52	Textiles & Apparel	AI Engineer	6	8
12	28	Industrial Technology	AI DevOps Engineer	15	1
13	30	Software & IT Services	AI Engineer	50	1
14	30	Real Estate	AI Engineer	4	6
15	28	Software & IT Services	Data Scientist	8	3

deviation of 18.1 people). Table 6 summarizes the sociodemographics of the interviewed participants, showing both core AI developers and related roles within AI systems development teams.

The semi-structured interviews adhered to established guidelines for qualitative interviews as outlined by Myers and Newman (2007). In designing the interview guide, our primary focus was on understanding the effects of accountability arguments on accountability perceptions in AI systems development teams. Alongside this primary focus, the interviews also explored how our interviewees differentiate between process and outcome accountability, reflecting the distinctions made in the quantitative study. Another key aspect was identifying boundary conditions that might moderate the effects of accountability arguments on corresponding perceptions. The initial version of our interview guide, which we modified over time to include more specific follow-up questions, is included in the Appendix (available online via <http://link.springer.com>).

## 6.2 Data Analysis

Employing an interpretative analysis strategy, we used CLT (Trope and Liberman 2010) and Toulmin's model of argumentation (1958) as theoretical lenses to guide our interpretation of the results (Sarker et al. 2018). This approach allowed us to explore the nuances of our interviewees' accountability perceptions while remaining open to emerging patterns and themes. The data analysis was structured into a three-step process, aligning with well-established qualitative data analysis methods (Miles and Huberman 1994). The initial phase focused on analyzing the data from each interview, while the latter two extended to individual and comparative analysis of the interview data.

In the first phase, we focused on developing individual profiles for each interviewee based on their responses. This involved a detailed analysis of their accountability perceptions, supplemented by contextual factors such as their industry sector and the size of their organization. The aim was to gain a deeper understanding of each individual's viewpoint, which served as a foundation for the subsequent phases. These individual analyses were conducted progressively, with each interview offering new insights. After the final interview, we revisited and refined these analyses, ensuring the interpretations were consistent and comprehensive, reflecting our interviewees' diverse perspectives and experiences in relation to their accountability perceptions.

The second phase involved inductively analyzing the interview data, allowing themes and patterns to emerge while using our theoretical lenses as sensitizing concepts. Through iterative coding and analysis, we identified

recurring themes and patterns in how AI developers discussed and understood their accountability. While CLT (Trope and Liberman 2010) and Toulmin's model of argumentation (1958) provided valuable perspectives for interpreting these patterns, we remained open to unexpected findings and novel insights that emerged from the data. This inductive approach led to the final categories shown in Table 7, which reflect both theoretically-informed and empirically-grounded understanding of accountability perceptions within AI systems development teams. The coding process involved multiple members of the author team who independently coded the interview data. After initial individual coding, we held regular meetings to compare our interpretations and discuss any differences until reaching a consensus on the final coding scheme. This collaborative approach helped ensure the robustness of our qualitative analysis while allowing us to benefit from multiple perspectives in interpreting the data.

The third phase concentrated on understanding the effects of different accountability arguments on our interviewees' mental construals and examining the interplay between these arguments, their mental construals, and the emerging moderating boundary conditions. This phase was pivotal in exploring how our interviewees reconciled conflicts between the accountability arguments they encountered and their perceptions. Particular emphasis was placed on the differential effects of process and outcome accountability arguments and the rationales used to justify perceptions in these areas.

This structured approach allowed us to distinguish between the collection of broad perceptions in the first phase, the focused analysis of process and outcome accountability arguments and their impact in the second phase, and the deeper exploration of mental construals and reconciling discrepancies in the third phase, thereby providing a comprehensive understanding of accountability perceptions in AI systems development teams.

## 6.3 Findings

In our qualitative analysis, we employed the bridging approach (Lewis and Grimes 1999), an approach particularly suited for sequential mixed methods research. This approach involves using qualitative findings to substantiate and enhance quantitative results, thereby creating a consensus between the two (Srivastava and Chandra 2018; Venkatesh et al. 2013). The results of our qualitative data bolster our quantitative findings, which support all but one hypothesis, and provide a theoretical understanding of how different accountability arguments shape accountability perceptions in AI systems development by revealing underlying accountability concepts. To align and integrate the findings from both studies, we position the insights

**Table 7** Data structure

First-order codes*	Second-order categories	Themes
Reporting on Justification to be Provided or Explanations Expected	Accountability Claims	Accountability Arguments
Mentoring (Regulatory) Compliance		
Stating Own Responsibility for AI Systems (Development Processes or Outcomes)		
Emphasizing the Importance of Accountability within AI Systems Development		
Providing Examples of Past Actions (e.g., Audits, Reviews, Evaluations)	Accountability Claim-Supporting Data	
Referring to Metrics or Data (e.g., Accuracy, Performance, Reliability)		
Citing Standards or Guidelines (e.g., Protocols, Regulations)		
Referring to Own Competencies (e.g., Education, Professional Role)		
Conjecture About Future Implications of AI Systems Development Decisions or Outcomes	High Psychological Distance to Own Accountability	Mental Construal of Accountability
Discussing (Hypothetical) Scenarios of Using Developed AI Systems		
Talking About Potential Future Regulations		
Talking About Immediate Effects of AI Systems Development Decisions	Low Psychological Distance to Own Accountability	
Expressing Awareness of Potential Accountability Consequences		
Emphasizing Short-Term Impacts of AI Systems Development Decisions		
Ignoring or Unawareness of Accountability Issues in AI Systems Development	Unawareness of Accountability	
Downplaying the Importance of Accountability		
Focusing Solely on Technical Aspects Without Ethical Considerations		
Discussing AI Systems Development Practices	Process Accountability	Accountability Distinction
Emphasizing AI Systems Development Methodology		
Explaining the Decision-Making Processes in AI Systems Development		
Focusing On Outcomes and Impact of Developed AI Systems	Outcome Accountability	
Talking About AI System Performance Metrics		
Discussion of the Context of Use of AI Systems and User Satisfaction with AI Outcomes		
Discussing Personal Ethical Beliefs	Individual Boundary Conditions	Boundary Conditions
Describing Individual Development Experiences		
Reporting on Personal Challenges Faced During AI Systems Development		
Citing Personal Motivation for AI Systems Development		
Citing Organizational/Industry Standards or Regulations	Organizational Boundary Conditions	
Discussing the Organization's (Ethical) Culture		
Reporting on Team Dynamics and Peer Influence		

\*Listed first-order codes are examples. Other first-order codes, which are not listed here for space reasons, are similar in character to those listed

gained from the qualitative study within the context of the quantitative study's findings. This approach enables us to clearly define and articulate the integrated findings drawn from the combined study results.

### 6.3.1 Accountability Perceptions in AI Systems Development

We first examined our interviewees' mental construal of their accountability in AI systems development,

uncovering a spectrum from very abstract to concrete mental construals and the attribution of accountability to different stakeholders involved. Some interviewees expressed abstract and vague accountability perceptions, exemplifying a more abstract level of mental construal. For instance, one interviewee articulated this vagueness by using sweeping generalizations about accountability requirements and distant metaphorical comparisons:

“Especially in Europe, the mindset always predominates that AI is evil and you must give exact accountability and check that exactly. That’s always immediately this mindset somehow, as if it was like something like, what do I know, a chemical weapon or something.” (AID1).

In contrast, other interviewees provided detailed and concrete perspectives indicative of lower-level mental construals. One interviewee highlighted legal and operational aspects of accountability, showing a more tangible understanding:

“There are obvious legal restrictions and accountability issues. We have to make sure that personal data, if we use it, is properly tracked [and that] we’re able to know what personal data went into the development of what models. If we don’t use personal data, we still need to be able to have accountability and, in some ways, reproducibility. In this particular case, they kind of go hand in hand in terms of which models are trained with which data, and then for inference, once the model is running in production, to figure out what data is going into the model.” (AID11).

Regardless of how concrete the individual mental construals of accountability were, different stakeholders were seen as having varying degrees of accountability in AI systems development. The level of stakeholder involvement was critical, reflecting four accountability relations identified by prior research (Bovens 2007; Wieringa 2020): individual, hierarchical, collective, and corporate accountability. Our interviewees emphasized individual accountability for core AI developers and hierarchical accountability, where team leads or organizational leaders are considered accountable. This understanding is influenced by their respective roles in the organization, as two interviewees illustrated succinctly:

“Well, it [algorithmic accountability] is a broad topic, right? And it depends a little bit on who you are in the whole value chain, if you want to use that word.” (AID7).

“From a legal standpoint, the people who are accountable are usually the team leads or the leads of

the team leads. Then it’s the individual developers who need to take on the responsibility to actually feel accountable.” (AID11).

The interviews also particularly highlighted the importance of effective communication in shaping accountability perceptions in AI systems development, validating our approach of choosing distinct visualized accountability arguments in the quantitative study. Most of our interviewees stressed the need for specificity and clarity in conveying accountability, as illustrated by the following statement:

“What comes to mind spontaneously is that you can basically say that the best way to talk to developers is to be very specific. (...) There is often a communication gap between the person who is communicating it and the person who is sitting there at the end who is supposed to do something with it and doesn’t really know what they’re being asked to do.” (AD5).

Moreover, other interviewees pointed to their strong desire for clearly defined metrics and frameworks when being held accountable in AI systems development, explicitly articulating how claim-supporting data transforms abstract accountability demands into actionable guidance. The following quote illustrates how concrete evidence and frameworks are perceived as essential for making accountability claims meaningful and actionable:

“If you say, ‘Okay, as a developer of these models, you are also accountable,’ then it would be infinitely important to me as a developer that these cases are clearly defined, that they are clearly laid out somewhere with corresponding metrics, what you have to achieve, and so on, that there is a clear internal regulatory framework for how you have to work through this.” (AD15).

These insights corroborate our quantitative findings that accountability arguments benefit from present claim-supporting data to be effectively translated into concrete mental construals. Furthermore, our qualitative responses confirm the moderating role of present claim-supporting data for the relationships between accountability arguments and perceived accountability in AI systems development.

### 6.3.2 *Comparing Accountability Perceptions in AI Systems Development*

In exploring the differentiation between individual accountability perceptions, our qualitative findings revealed a distinction between process and outcome accountability that emerged from the interviewees’ own accounts. While our quantitative study measured core AI



developers' overall perceived accountability, our interview data suggests this unified measure may not fully capture the nuanced way professionals in AI systems development teams think about and perceive their accountability. The interviewees recognized different dimensions of algorithmic accountability, although there was a clear tendency to feel more accountable for their development processes than the outcomes of their developed AI systems. This distinction and its implications were described by two interviewees as follows:

“What I feel more accountable for, of course, is the development process. So, if something goes wrong with the outcome, it's usually because something went wrong with the development process.” (AID6).  
 “At the end of the day, there's a big process, and that process produces an artifact. The artifact is the weights for a model. Errors that occur in that model are almost always due to problems with the process.” (AID4).

When examining differentiated perceptions of process versus outcome accountability, it became noticeable that outcome accountability perceptions are often influenced by external factors such as other stakeholders' communicated expectations and the broader implications of AI systems in general. In most cases, these expectations relate to AI systems' outcomes and leave individuals alone with what requirements they entail for their work, as the following two interviewees emphasized:

“In my opinion, the stakeholders don't really tell you much about what data you should or shouldn't use, but the output performance is what is relevant.” (AID8).  
 “My experience is that developers who come from an IT background, who may have only worked in software engineering, and who are pretty far away from the actual product, have a hard time understanding it. They are basically just focused on how they are developing and whether everything fits. (...) They measure themselves against that and say: ‘Yes, I did what was required.’ But then there might be other people who say: ‘Yes, okay, but I'd rather look at the outcome.’” (AID6).

Consequently, the abstract mental construal of their outcome accountability often caused a defensive attitude among our interviewees. They frequently expressed reluctance to assume accountability for outcomes, citing their limited influence over project decisions and broader company policies. This perspective aligns with a desire for more concrete mental construal, where accountability can be perceived as being tied to specific, controllable aspects of their role. Two interviewees emphasized their existing

influence on the development processes within AI systems development projects and their perceived lack of influence on general project characteristics as follows:

“The point is that I have no influence on the initial projects (...) but the whole process from that decision to the final model, the implementation, and of course the whole issue of maintenance and so on, even if it's for another department, is my accountability.” (AID3).

“In my case, I just do my small functions. I try to develop them somehow, but I see my influence if somehow the business case changes and we suddenly want to manufacture weapons, for example, then the only thing I can do is to decide if I still want to work for such a company or not, but I can't decide whether my AI functions will now go into a drone. That's completely above my pay grade.” (AID10).

However, the complexity of AI systems adds another abstract layer to outcome accountability perceptions, as technical facets of AI systems, like autonomy or inscrutability, complicate these perceptions (Berente et al. 2021; Saffarizadeh et al. 2024). Two interviewees succinctly and pictorially acknowledged these challenges, illustrating an abstract mental construal that recognizes inherent uncertainties and broader implications:

“In the end, no one can take accountability for this [outcomes]. These are statistical models. This means that any outcome is possible, even undesirable outcomes.” (AID4).

“I would say that the developers of AI systems can be held accountable for this [the outcomes of AI systems] if they have tested negligently. But you can't test everything. And anything beyond that, without being able to define exactly what that would be, is just chance or other people are accountable for that.” (AD15).

Taken together, our findings indicate a significant contrast in how accountability for AI systems' development processes versus outcomes is perceived in AI systems development and suggest that process and outcome accountability should also be conceptually distinguished in AI systems development. The qualitative data reveals that higher perceived accountability for processes than outcomes stems from fundamental differences in how these responsibilities are understood, experienced, and enacted by individuals engaged in AI systems development. This suggests that treating algorithmic accountability as a unified construct may obscure important variations in how AI developers and related roles relate to different aspects of their work. Our findings thus provide empirical support for a theoretical distinction between process and outcome

accountability in AI systems development while also explaining why process-focused accountability mechanisms might be more effective in practice.

### 6.3.3 Boundary Conditions Shaping Accountability Perceptions in AI Systems Development

Building on prior research, the adoption of a mixed methods approach is advocated not only for validating the robustness of the findings obtained from a first study through confirmation and corroboration but also for gaining deeper, more comprehensive insights (complementarity) than what is achievable through a singular methodological approach (Srivastava and Chandra 2018; Venkatesh et al. 2013). In line with this guidance, our qualitative study was designed to confirm and enrich the findings of our quantitative study. In addition to the bridging approach, we also followed the bracketing approach in our qualitative analysis (Lewis and Grimes 1999). Bracketing involves acknowledging and incorporating a diverse range of views, including those that may oppose or differ from initial findings, to unravel and clarify any mysteries and unexpected findings (Srivastava and Chandra 2018; Venkatesh et al. 2013). Accordingly, combining the bridging and bracketing approach allowed us to derive integrated insights by weaving our quantitative and qualitative results together. In particular, we applied bracketing to acquire supplementary insights to pinpoint boundary conditions for the theoretical model tested quantitatively. Within the context of our interviewees' perceptions of process and outcome accountability, four distinct boundary conditions surfaced:

**Boundary Condition #1: Organizational Characteristics:** A pivotal boundary condition identified is the role of the characteristics of the employing organization, including its size, industry context, and stage of business model development. The specialized focus of accountability obligations in larger organizations contrasts with the willingness of individuals working in smaller organizations to embrace broader accountability. An interviewee from a smaller organization encapsulated this as follows:

“We as a company are simply small. If you have a job here, you have to do a lot of things, and with the competition, it's more like you're doing exactly one step in a huge chain, and you're not allowed to do anything before or after, and it's all very clearly defined. With us, it's more like you have to do a lot. And that's the nice thing, but it's also exhausting.” (AD1).

Additionally, the stage of the respective organization's business model development, especially in startups, was revealed to be crucial in influencing the effects of

accountability arguments on accountability perceptions. For example, in startups that are still exploring their business case, interviewees faced unique challenges in defining their outcome accountability, as the exact context of their AI systems' later use remained fluid.

**Boundary Condition #2: Computational Advancements:** According to Berente et al. (2021, p. 1433), AI systems can be understood “as a continually evolving frontier of emerging computing capabilities.” This understanding highlights how the degree of computational advancements underlying a given AI system significantly influences accountability perceptions. For instance, the inscrutability and autonomy of large language models (LLMs) introduce unique accountability challenges, particularly concerning their potential outcomes and ethical implications. The following two insights illustrate this:

“I think classic computer vision models are very, very data dependent. If you have a very curated set that you train on, you tend to get pretty predictable results. That's not necessarily the case with LLMs [...]. Given their creativity, you can throw [something] in, and the likelihood of something different coming out is higher and tends to be more independent of the data.” (AID15).

“I think you have to distinguish between the types of models you're talking about. For example, if you're talking about image classification, then you don't have to worry about things like toxic outcomes because the classification is simply correct or not.” (AID4).

**Boundary Condition #3: Organizational Ethical Culture and Value Alignment:** The ethical culture within an organization emerged as another critical determinant of accountability perceptions. In organizations with strong ethical values, interviewees exhibit an enhanced awareness of accountability. Illustrating this, an interviewee mentioned:

“I fundamentally believe that the best possible way is the cultural approach (...). If it's part of the culture of a team or a company and everyone agrees that it's the right thing to do, then you have a good common internal compass for what you do and what you don't do.” (AID9).

**Boundary Condition #4: Individual Experience and Ethical Awareness:** Further, individual experiences and ethical awareness significantly influence accountability perceptions. Interviewees who already had extensive professional experience or had a high intrinsic motivation to deal with relevant topics tend to have more profound accountability perceptions, as pointed out by the following interviewees:

“Well, I’ve been doing software development for 15 years, and I’ve heard that before, and I can imagine what it means. But if I’ve somehow, I don’t know, only been in the job for two years, it might be hard for me to apply that to what I’m supposed to be doing now.” (AID5).

“I don’t have a particular background in that aspect. I think it’s just, well, I’m very much aware of these things. And you know, I want to be a professional who cares not only about good code or good models in the end but also about those aspects. So, me as an AI developer, like sure, I can develop one small product here and there in a company. But in the end, I think the bigger picture is that we are just keeping the technology wheel running, right? And in the end, I think that it’s important we do that in a responsible way.” (AID14).

Notably, despite the diversity in roles among our interview participants, we observed consistent patterns in how accountability was perceived and experienced across different positions. This suggests that while organizational and individual factors create important boundary conditions, the fundamental dynamics of process and outcome accountability transcend specific job roles within AI systems development teams. This consistency in findings across different roles provides additional confidence in our quantitative results, which focused on core AI developers, while suggesting that accountability mechanisms operate similarly across various positions within AI systems development teams.

#### 6.4 Integration of Quantitative and Qualitative Study Results

Our integrated analysis of our quantitative and qualitative study results offers important theoretical insights into the nature of accountability in AI systems development. While our quantitative study measured overall perceived accountability in response to different accountability arguments, our qualitative findings reveal that AI developers conceptualize accountability in AI systems development as comprising two distinct dimensions – process and outcome accountability – highlighting the need for a more nuanced theoretical framework.

Our quantitative findings showed high perceptions of accountability among core AI developers when presented with process accountability arguments (H1A). Our qualitative insights help explain this finding by revealing AI systems development professionals’ inherent connection to and understanding of process accountability due to their direct involvement in development activities. This intrinsic focus on development processes also accounts for the

limited impact of adding supporting data to process accountability claims observed in our quantitative study (H2A). In contrast, our quantitative findings showed that outcome accountability arguments, initially more abstract to core AI developers, become more convincing with the addition of supporting data (H1B and H2B). Our qualitative study helps explain this pattern by revealing individuals’ inherent uncertainty about outcome accountability, suggesting that additional evidence help concretize these otherwise abstract responsibilities. Our qualitative findings further reveal why core AI developers perceived greater accountability with process versus outcome accountability claims (H3A) and why supporting data had a stronger effect in the case of outcome accountability claims (H3B). Through our interviewees’ own accounts, we see that process accountability aligns naturally with their daily work and perceived sphere of influence, while outcome accountability often feels more distant and uncertain. This distinction emerged consistently across interviews, suggesting it reflects a fundamental aspect of how accountability is experienced and conceptualized in AI systems development.

Furthermore, our qualitative study identified four boundary conditions – organizational characteristics, computational advancements, organizational ethical culture and value alignment, and individual experience and ethical awareness – that help explain when and why process and outcome accountability perceptions manifest differently. These conditions demonstrate that the distinction between process and outcome accountability is not merely theoretical but is shaped by concrete organizational and individual factors. For example, smaller organizations may blur the distinction between process and outcome accountability through broader development responsibilities, while the increasing complexity of AI systems in larger organizations may tend to amplify the gap between process and outcome accountability.

The identified commonalities between our quantitative and qualitative findings are also relevant given the different cultural and regulatory contexts: our quantitative study involved AI developers from the US, while our qualitative study included AI developers working in Germany within the European framework. Although both the European Union (EU) and the US are actively engaged in regulating AI systems, their regulatory approaches differ (Mökander et al. 2022; Vokinger and Gasser 2021): The US favors a pragmatic, decentralized strategy, assigning oversight to various federal agencies to promote innovation with minimal regulation (Vokinger and Gasser 2021). In contrast, the EU is developing a comprehensive, unified legal framework, exemplified by the EU AI Act, which takes a risk-based approach to build a trusted ecosystem (European Union 2024). While this may increase AI developers’

**Table 8** Mapped results of quantitative and qualitative studies

Hypotheses	Quantitative study	Qualitative study	Combined interpretation
<b>H1A:</b> The presence (vs. absence) of process accountability claims creates higher perceived accountability among AI developers	Supported	High perceptions due to perceived influence over development processes	Process accountability emerges as a natural, concrete construct in AI systems development aligned with AI developers' daily work experience
<b>H1B:</b> The presence (vs. absence) of outcome accountability claims creates higher perceived accountability among AI developers	Supported	Perceived lack of influence on unpredictable AI systems outcomes	Outcome accountability emerges as a more abstract construct in AI systems development, shaped by temporal and cognitive distance
<b>H2A:</b> Process accountability claims including claim-supporting data (vs. process accountability claims only) create higher perceived accountability among AI developers	Rejected	Process accountability already concrete and well-understood through direct experience	Supporting data is less crucial for process accountability due to its inherent concreteness
<b>H2B:</b> Outcome accountability claims including claim-supporting data (vs. outcome accountability claims only) create higher perceived accountability among AI developers	Supported	Supporting evidence helps bridge the abstraction gap in outcome accountability	Evidence is particularly important for outcome accountability due to its inherently abstract nature
<b>H3A:</b> Process accountability claims (vs. outcome accountability claims) create higher perceived accountability among AI developers	Supported	Clear distinction between process and outcome accountability in AI developers' accounts	Suggests theoretical distinction between process and outcome accountability as separate constructs in AI systems development
<b>H3B:</b> Outcome accountability claims (vs. process accountability claims) accompanied by claim-supporting data lead to greater increases in perceived accountability among AI developers	Supported	Concrete details needed to solidify abstract outcome accountability and address the perceived lack of influence	Demonstrates how supporting data can help bridge the theoretical gap between process and outcome accountability

workload and efforts, both regions are committed to advancing AI systems for societal benefit (Vokinger and Gasser 2021), as shown by their joint efforts on trustworthy AI and risk management (EU-US Trade and Technology Council 2022).

In summary, integrating our findings, detailed in Table 8, provides a comprehensive understanding of accountability perceptions in AI systems development against the background of the identified boundary conditions and suggests that process and outcome accountability represent distinct theoretical constructs in AI systems development, even as they interrelate in practice. This distinction emerges from core AI developers' different responses to process versus outcome accountability arguments and from direct accounts of AI systems development professionals. Our mixed method approach thus validates our experimental findings and provides a deeper theoretical understanding of how accountability manifests in AI systems development, suggesting the need for more nuanced approaches to both studying and promoting algorithmic accountability.

## 7 Discussion

AI developers' accountability is increasingly drawing attention both in academic and policy discussions, especially as existing governance tools and methods to raise AI developers' accountability awareness, like AI principles or audits, often fall flat. Our research, combining CLT and Toulmin's model of argumentation, probes the efficacy of process versus outcome accountability arguments visualized as UI design elements and integrated into IDEs to enhance AI developers' perceived accountability. Our quantitative analysis shows a 9.1% increase in perceived accountability when accountability arguments consist solely of process accountability claims. Adding data to outcome accountability arguments increases accountability perceptions by 9.5%. However, a similar increase is not observed when data is added to process accountability claims, indicating AI developers' clearer grasp of development processes. Our qualitative findings help explain these patterns while revealing that process and outcome accountability emerge as distinct theoretical constructs in AI systems development – process accountability manifesting as a concrete, experience-near phenomenon while outcome accountability appears more abstract and distinct. Overall, our research highlights the nuanced nature of



accountability in AI systems development, emphasizing the need for governance tools and methods that effectively communicate algorithmic accountability.

### 7.1 Contributions to IS Research

Our findings offer three important theoretical contributions to IS research on algorithmic accountability (Horneber and Laumer 2023; Wieringa 2020) and the future of systems development (Duda et al. 2024; Maruping and Matook 2020; Rosenkranz et al. 2023).

First, our results advance IS research on algorithmic accountability by revealing how process and outcome accountability emerge in AI systems development as distinct theoretical constructs through AI developers' experiences and perceptions. While previous approaches within IS research have treated algorithmic accountability predominantly as a unified concept, our mixed method approach shows that developers distinguish between two dimensions of algorithmic accountability, namely, process and outcome accountability, each requiring different communication approaches and support mechanisms. This distinction emerged consistently in both our quantitative study focusing on core AI developers and our qualitative study, which included related roles within AI systems development teams, suggesting these accountability dimensions reflect fundamental aspects of AI systems development work rather than role-specific perspectives. By demonstrating how accountability arguments in UI design elements for ISD tools can heighten AI developers' accountability perceptions, we also respond to recent calls for empirical research on algorithmic accountability (e.g., Horneber and Laumer 2023), especially for governance tools and methods to effectively increase accountability awareness in AI systems development (e.g., Mikalef et al. 2022). As ethical and regulatory aspects of algorithmic accountability gain prominence, our insights into using accountability arguments to enhance AI developers' accountability awareness offer a path toward more ethically responsible and socially beneficial AI systems.

Second, we advance our understanding of accountability mechanisms in AI systems development by examining how AI developers respond differently to process versus outcome accountability arguments (Horneber and Laumer 2023; Martin 2019). Our findings reveal that process and outcome accountability represent distinct theoretical constructs in AI systems development and that different communication strategies are required for effective promotion. This distinction is particularly important in the context of AI systems development, where multiple stakeholders are involved throughout the lifecycle of AI systems, and immediate development decisions must be balanced against longer-term, often

unpredictable outcomes. Viewed through the lens of CLT, we identified and empirically demonstrated the differences in AI developers' perceptions of these two kinds of algorithmic accountability, highlighting their significance for AI systems development management.

Third, we contribute to IS research on the future of systems development (Rosenkranz et al. 2023; Urbach et al. 2019), particularly in light of the increasing proliferation of AI systems in recent years (Dey and Lee 2021; Duda et al. 2024). While previous ISD research has identified successful communication between ISD stakeholders as a critical driver of overall ISD success (Bittner and Leimeister 2014; Gallivan and Keil 2003; Rosenkranz et al. 2013, 2014), existing governance tools and methods like AI principles or audits often struggle with effective communication due to their abstract nature (e.g., Berente et al. 2024; Mittelstadt 2019). Our results demonstrate that visualizing accountability arguments through UI design elements can enhance accountability perceptions while revealing that such tools must be tailored to address the distinct challenges of process versus outcome accountability. This extends Toulmin's model of argumentation (1958) beyond its conventional use in analyzing communication with IS users (Cummings and Dennis 2018; Kim and Benbasat 2006, 2009) and provides practical guidance for developing more effective governance tools and methods in AI systems development. This extension offers novel insights into the intricate dynamics between technological evolution, social dynamics, and individual responses in AI systems development.

### 7.2 Practical Contributions

Our results provide important insights for improving the allocation and awareness of accountability in AI systems development, supporting practitioners in managing future AI systems development projects. First, we assert that the distinct nature of process and outcome accountability demands differentiated approaches to communication and governance. Our findings indicate that simply assigning accountability is inadequate; rather, organizations must recognize that process and outcome accountability require different communication strategies. While process accountability aligns naturally with AI developers' daily work and can be promoted through clear articulation of expectations, outcome accountability requires additional supporting evidence and concrete examples to help AI developers bridge the conceptual gap between their immediate actions and potential future impacts. Drawing from our qualitative study, we advocate that organizations should not only notify AI developers of their respective accountability but also engage in discussions about the underlying rationale, particularly for outcome-related



responsibilities, and foster an organizational climate of ethical responsibility. This approach promotes a collaborative environment where algorithmic accountability is not merely imposed but collectively understood and embraced.

Second, our results demonstrate that visualizing accountability arguments as UI design elements in ISD tools, such as IDEs, can efficiently enhance AI developers' perceived accountability. This approach offers a practical, less resource-intensive alternative to developing AI principles or conducting audits. Moreover, UI design elements can be seamlessly integrated into various ISD tools and customized to align with specific organizational accountability needs (Conboy 2009; Lings and Lundell 2004). Importantly, such visualized accountability arguments can promote a shared understanding of ISD processes and their implementation without requiring explicit training sessions or additional workload (Vial and Rivard 2022). This is crucial for fostering a comprehensive culture of algorithmic accountability within organizations, as organizations can design ISD tools and methods but cannot dictate the actual execution of ISD processes (Feldman and Pentland 2003; Vial and Rivard 2022). By adapting ISD tools like IDEs and integrating appropriate accountability arguments, organizations can encourage AI developers to take ownership of both immediate development processes and longer-term AI system outcomes, ensuring development practices adhere to ethical and legal standards while maintaining awareness of potential future impacts. Distinguishing between process and outcome accountability further allows organizations to be aware of the full range of impacts of the AI systems they provide, including unanticipated outcomes that may arise after development.

### 7.3 Limitations and Directions for Future Research

As with any other research study, ours is not without limitations. Considering increasing legislative and regulatory requirements and private initiatives, we believe these limitations open up fruitful avenues for future research. First, within our quantitative study, we conducted an online experiment examining AI developers' overall perceived accountability in a scenario rather than distinguishing between process and outcome accountability perceptions. As our qualitative findings revealed these as distinct theoretical constructs in AI systems development, future research should develop and validate separate measures for process and outcome accountability perceptions, examining how different types of accountability arguments might affect these perceptions differently. Such research could investigate whether previous findings of increased diligence under process accountability and increased commitment under outcome accountability also hold true in AI systems development contexts (Doney and Armstrong 1995; Simonson

and Staw 1992). Second, our UI design elements for IDEs represented only two accountability mechanisms (cf. Vance et al. 2013, 2015). Future research could examine other accountability mechanisms (i.e., social presence and identifiability) for potential differential effects on AI developers' process versus outcome accountability perceptions. In this context, the interaction of our proposed UI design elements with other ISD tools and methods, such as AI principles or audits, could also be investigated. Third, while we focused on development processes and outcomes in both our quantitative and qualitative studies to maintain research focus, future research could explore the effects of UI design elements as accountability attributions for other phases of AI systems development, such as AI systems' operation or use, or addressing other stakeholders, such as IT managers of organizations that govern AI systems. Fourth, our scenario used in the quantitative study included a financial setting. Future research could investigate whether the intended contexts of AI systems affect AI developers' perceived process and outcome accountability differently. Finally, our research presents limitations regarding both role heterogeneity and cultural context. As part of our qualitative study, we interviewed AI developers and professionals in related roles working in Germany at the time of the interviews, while our quantitative study focused on core AI developers in the US. Although we found consistent patterns across different roles and cultural contexts – suggesting that the fundamental dynamics of process and outcome accountability transcend professional and cultural boundaries – we cannot rule out the possibility that specific manifestations of accountability perceptions vary across roles and regions. While our mixed method approach helped validate our findings across these different contexts, future research could more systematically examine how cultural, regulatory, and role-specific factors interact to shape process and outcome accountability perceptions. For instance, researchers could investigate how different regulatory frameworks affect process and outcome accountability perceptions across various roles within AI systems development teams. Such research could help organizations develop more nuanced accountability practices that account for both role-specific needs and regional requirements while maintaining consistent core principles about process and outcome accountability.

## 8 Conclusion

Our research opens up new pathways to ensure effective future governance of AI systems development, which crucially depends on AI developers' accountability perceptions. Grounded in CLT and Toulmin's model of argumentation, our research reveals both practical and theoretical insights about accountability in AI systems

development. While our quantitative findings demonstrate that process accountability arguments are generally more effective than outcome accountability arguments and that supporting evidence particularly enhances the impact of outcome accountability arguments, our qualitative investigation reveals why: process and outcome accountability emerge as distinct theoretical constructs in AI systems development, each requiring different communication approaches. Process accountability manifests as a concrete, experience-near phenomenon aligned with AI developers' daily work, while outcome accountability appears more abstract and temporally distant. Our mixed method approach thus provides practical guidelines for enhancing algorithmic accountability through appropriate governance tools and also advances theoretical understanding of how accountability manifests in AI systems development contexts. These insights shift the narrative on algorithmic accountability, moving away from treating it as a unitary concept and toward recognizing its multi-dimensional character. We hope that our findings will not only promote adherence to emerging ethical and legal standards in AI systems development but also advance the evolving landscape of AI governance, where understanding and addressing the distinct dimensions of accountability and how key stakeholders like AI developers perceive them is paramount for the responsible advancement of AI systems.

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## References

- Adam M, Werner D, Wendt C, Benlian A (2020) Containing COVID-19 through physical distancing: the impact of real-time crowding information. *Eur J Inf Syst* 29(5):595–607. <https://doi.org/10.1080/0960085X.2020.1814681>
- Aguinis H, Bradley KJ (2014) Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organ Res Meth* 17(4):351–371. <https://doi.org/10.1177/1094428114547952>
- Asatiani A, Malo P, Nagbol PR, Penttinen E, Rinta-Kahila T, Salovaara A (2021) Sociotechnical envelopment of artificial intelligence: an approach to organizational deployment of inscrutable artificial intelligence systems. *J Assoc Inf Syst* 22(2):325–352. <https://doi.org/10.17705/1jais.00664>
- Benbya H, S P, Jarvenpaa S (2021) Special Issue editorial: artificial intelligence in organizations: implications for information systems research. *J Assoc Inf Syst* 22(2):281–252. <https://doi.org/10.17705/1jais.00662>
- Benlian A (2015) Web personalization cues and their differential effects on user assessments of website value. *J Manag Inf Syst* 32(1):225–260. <https://doi.org/10.1080/07421222.2015.1029394>
- Benlian A, Klumpe J, Hinze O (2020) Mitigating the intrusive effects of smart home assistants by using anthropomorphic design features: a multimethod investigation. *Inf Syst J* 30(6):1010–1042. <https://doi.org/10.1111/isj.12243>
- Berente N, Gu B, Recker J, Santhanam R (2021) Managing Artificial Intelligence. *MIS Q* 45(3):1433–1450. <https://doi.org/10.25300/MISQ/2021/16274>
- Berente N, Kormylo C, Rosenkranz C (2024) Test-driven ethics for machine learning. *Commun ACM* 67(5):45–47. <https://doi.org/10.1145/3633455>
- Bittner EAC, Leimeister JM (2014) Creating shared understanding in heterogeneous work groups: why it matters and how to achieve it. *J Manag Inf Syst* 31(1):111–144. <https://doi.org/10.2753/MIS0742-122310106>
- Bovens M (2007) Analysing and assessing accountability: A conceptual framework. *Eur Law J* 13(4):447–468. <https://doi.org/10.1111/j.1468-0386.2007.00378.x>
- Bovens M (2010) Two concepts of accountability: accountability as a virtue and as a mechanism. *West Eur Politics* 33(5):946–967. <https://doi.org/10.1080/01402382.2010.486119>
- Collins C, Dennehy D, Conboy K, Mikalef P (2021) Artificial intelligence in information systems research: a systematic literature review and research agenda. *Int J Inf Manag* 60:102383. <https://doi.org/10.1016/j.ijinfomgt.2021.102383>
- Conboy K (2009) Agility from first principles: reconstructing the concept of agility in information systems development. *Inf Syst Res* 20(3):329–354. <https://doi.org/10.1287/isre.1090.0236>
- Corvera Charaf M, Rosenkranz C, Holten R (2013) The emergence of shared understanding: applying functional pragmatics to study the requirements development process. *Inf Syst J* 23(2):115–135. <https://doi.org/10.1111/j.1365-2575.2012.00408.x>
- Crano WD, Prislin R (2006) Attitudes and persuasion. *Ann Rev Psychol* 57:345–374. <https://doi.org/10.1146/annurev.psych.57.102904.190034>
- Cummings J, Dennis AR (2018) Virtual first impressions matter: the effect of enterprise social networking sites on impression formation in virtual teams. *MIS Q* 42(3):697–718. <https://doi.org/10.25300/MISQ/2018/13202>
- Dey S, Lee S-W (2021) Multilayered review of safety approaches for machine learning-based systems in the days of AI. *J Syst Softw* 176:110941. <https://doi.org/10.1016/j.jss.2021.110941>
- Doney PM, Armstrong GM (1995) Effects of accountability on symbolic information search and information analysis by

- organizational buyers. *J Acad Mark Sci* 24(1):57–65. <https://doi.org/10.1177/00920703960240010>
- Duda S, Hofmann P, Urbach N, Völter F, Zwickel A (2024) The impact of resource allocation on the machine learning lifecycle. *Bus Inf Syst Eng* 66(2):203–219. <https://doi.org/10.1007/s12599-023-00842-7>
- European Union (2024) Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 Laying Down Harmonised Rules on Artificial Intelligence and Amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act), No. 2024/1689, European Union (2024). <http://data.europa.eu/eli/reg/2024/1689/oj>
- Feldman MS, Pentland BT (2003) Reconceptualizing organizational routines as a source of flexibility and change. *Admin Sci Q* 48(1):94–118. <https://doi.org/10.2307/3556620>
- Floridi L (2019) Establishing the rules for building trustworthy AI. *Nat Mach Intell* 1(6):261–262. [https://doi.org/10.1007/978-3-030-81907-1\\_4](https://doi.org/10.1007/978-3-030-81907-1_4)
- Gallivan MJ, Keil M (2003) The user–developer communication process: a critical case study. *Inf Syst J* 13(1):37–68. <https://doi.org/10.1046/j.1365-2575.2003.00138.x>
- Hair JF, Black WC, Babin BJ, Anderson RE (2009) Multivariate data analysis, vol 24. Prentice Hall, Upper Saddle River
- Hansen J, Wänke M (2010) Truth from language and truth from fit: the impact of linguistic concreteness and level of construal on subjective truth. *Pers Soc Psychol Bull* 36(11):1576–1588. <https://doi.org/10.1177/0146167210386238>
- Hauser DJ, Ellsworth PC, Gonzalez R (2018) Are manipulation checks necessary? *Front Psychol* 9:362650. <https://doi.org/10.3389/fpsyg.2018.00998>
- Hennel P, Rosenkranz C (2021) Investigating the “Socio” in socio-technical development: the case for psychological safety in agile information systems development. *Prof Manag J* 52(1):11–30. <https://doi.org/10.1177/8756972820933057>
- Hinz O, Spann M, Hann I-H (2015) Research note – Can’t buy me love... or can I? Social capital attainment through conspicuous consumption in virtual environments. *Inf Syst Res* 26(4):859–870. <https://doi.org/10.1287/isre.2015.0596>
- Hochwarter WA, Perrewé PL, Hall AT, Ferris GR (2005) Negative affectivity as a moderator of the form and magnitude of the relationship between felt accountability and job tension. *J Organ Behav Int J Ind Occup Organ Psychol Behav* 26(5):517–534. <https://doi.org/10.1002/job.324>
- Hochwarter WA, Ferris GR, Gavin MB, Perrewé PL, Hall AT, Frink DD (2007) Political skill as neutralizer of felt accountability – Job tension effects on job performance ratings: a longitudinal investigation. *Organ Behav Hum Decis Proc* 102(2):226–239. <https://doi.org/10.1016/j.obhdp.2006.09.003>
- Horneber D, Laumer S (2023) Algorithmic accountability. *Bus Inf Syst Eng* 65(6):723–730. <https://doi.org/10.1007/s12599-023-00817-8>
- Kautz K, Madsen S, Nørberg J (2007) Persistent problems and practices in information systems development. *Inf Syst J* 17(3):217–239. <https://doi.org/10.1111/j.1365-2575.2007.00222.x>
- Keutel M, Michalik B, Richter J (2014) Towards mindful case study research in IS: a critical analysis of the past ten years. *Eur J Inf Syst* 23(3):256–272. <https://doi.org/10.1057/ejis.2013.26>
- Kim D, Benbasat I (2006) The effects of trust-assuring arguments on consumer trust in internet stores: application of Toulmin’s model of argumentation. *Inf Syst Res* 17(3):286–300. <https://doi.org/10.1287/isre.1060.0093>
- Kim D, Benbasat I (2009) Trust-assuring arguments in B2C e-commerce: Impact of content, source, and price on trust. *J Manag Inf Syst* 26(3):175–206. <https://doi.org/10.2753/MIS0742-1222260306>
- Lapierre LM (2007) Supervisor trustworthiness and subordinates’ willingness to provide extra-role efforts. *J Appl Soc Psychol* 37(2):272–297. <https://doi.org/10.1111/j.0021-9029.2007.00160.x>
- Leiner DJ (2019) Too fast, too straight, too weird: Non-reactive indicators for meaningless data in internet surveys. *Surv Res Meth* 13(3):229–248. <https://doi.org/10.18148/srm/2019.v13i3.7403>
- Lerner JS, Tetlock PE (1999) Accounting for the effects of accountability. *Psychol Bull* 125(2):255–275. <https://doi.org/10.1037/0033-2909.125.2.255>
- Levine SS, Schilke O, Kacperczyk O, Zucker LG (2023) Primer for experimental methods in organization theory. *Organ Sci* 34(6):1997–2025. <https://doi.org/10.1287/orsc.2023.18093>
- Lewin K (1936) Principles of topological psychology. McGraw-Hill
- Lewis MW, Grimes AI (1999) Metatriangulation: building theory from multiple paradigms. *Acad Manag Rev* 24(4):672–690. <https://doi.org/10.5465/amr.1999.2553247>
- Liberman N, Trope Y (2008) The psychology of transcending the here and now. *Sci* 322(5905):1201–1205. <https://doi.org/10.1126/science.1161958>
- Lindberg SI (2013) Mapping accountability: core concept and subtypes. *Int Rev Admin Sci* 79(2):202–226. <https://doi.org/10.1177/0020852313477761>
- Lings B, Lundell B (2004) On transferring a method into a usage situation. In: Kaplan B et al (eds) Information systems research: Relevant theory and informed practice. Springer, Boston, pp 535–553
- Lowry PB, Moody G, Vance A, Jensen M, Jenkins J, Wells T (2012) Using an elaboration likelihood approach to better understand the persuasiveness of website privacy assurance cues for online consumers. *J Am Soc Inf Sci Technol* 63(4):755–776. <https://doi.org/10.1002/asi.21705>
- Martin K (2019) Designing ethical algorithms. *MIS Q Exec* 18(2):129–142. <https://doi.org/10.2139/ssrn.3056692>
- Maruping LM, Matook S (2020) The evolution of software development orchestration: current state and an agenda for future research. *Eur J Inf Syst* 29(5):443–457. <https://doi.org/10.1080/0960085X.2020.1831834>
- Matus KJ, Veale M (2022) Certification systems for machine learning: lessons from sustainability. *Regul Gov* 16(1):177–196. <https://doi.org/10.1111/regg.12417>
- Mikalef P, Conboy K, Lundström JE, Popović A (2022) Thinking responsibly about responsible AI and ‘the dark side’ of AI. *Eur J Inf Syst* 31(3):257–268. <https://doi.org/10.1080/0960085X.2022.2026621>
- Miles MB, Huberman AM (1994) Qualitative data analysis: An expanded sourcebook, 2nd edn. Sage
- Mingers J (2001) Combining IS research methods: towards a pluralist methodology. *Inf Syst Res* 12(3):240–259. <https://doi.org/10.1287/isre.12.3.240.9709>
- Mittelstadt B (2019) Principles alone cannot guarantee ethical AI. *Nat Mach Intell* 1(11):501–507. <https://doi.org/10.1038/s42256-019-0114-4>
- Mökander J, Juneja P, Watson DS, Floridi L (2022) The US algorithmic accountability act of 2022 versus The EU artificial intelligence act: what can they learn from each other? *Minds Mach* 32(4):751–758. <https://doi.org/10.1007/s11023-022-09612-y>
- Myers MD, Newman M (2007) The qualitative interview in IS research: examining the craft. *Inf Organ* 17(1):2–26. <https://doi.org/10.1016/j.infoandorg.2006.11.001>
- Oates BJ, Fitzgerald B (2007) Multi-metaphor method: organizational metaphors in information systems development. *Inf Syst J*



- 17(4):421–449. <https://doi.org/10.1111/j.1365-2575.2007.00266.x>
- Oppenheimer DM, Meyvis T, Davidenko N (2009) Instructional manipulation checks: detecting satisficing to increase statistical power. *J Exp Soc Psychol* 45(4):867–872. <https://doi.org/10.1016/j.jesp.2009.03.009>
- Palan S, Schitter C (2018) Prolific.ac – A subject pool for online experiments. *J Behav Exp Fin* 17:22–27. <https://doi.org/10.1016/j.jbef.2017.12.004>
- Palinkas LA, Horwitz SM, Green CA, Wisdom JP, Duan N, Hoagwood K (2015) Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Admin Policy Ment Health Ment Serv Res* 42(5):533–544. <https://doi.org/10.1007/s10488-013-0528-y>
- Paolacci G, Chandler J, Ipeirotis PG (2010) Running experiments on Amazon Mechanical Turk. *Judgm Decis Mak* 5(5):411–419. <https://doi.org/10.1017/S1930297500002205>
- Patton MQ (1990) *Qualitative evaluation and research methods*, 2nd edn. Sage
- Pitts MG, Browne GJ (2007) Improving requirements elicitation: an empirical investigation of procedural prompts. *Inf Syst J* 17(1):89–110. <https://doi.org/10.1111/j.1365-2575.2006.00240.x>
- Podsakoff PM, MacKenzie SB, Lee J-Y, Podsakoff NP (2003) Common method biases in behavioral research: a critical review of the literature and recommended remedies. *J Appl Psychol* 88(5):879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Pogarsky G (2004) Projected offending and contemporaneous rule-violation: implications for heterotypic continuity. *Criminol* 42(1):111–136. <https://doi.org/10.1111/j.1745-9125.2004.tb00515.x>
- Ravn JE, Moe NB, Stray V, Seim EA (2022) Team autonomy and digital transformation: disruptions and adjustments in a well-established organizational principle. *AI Soc* 37(2):701–710. <https://doi.org/10.1007/s00146-022-01406-1>
- Robinson SL (1996) Trust and breach of the psychological contract. *Admin Sci Q* 41:574–599. <https://doi.org/10.2307/2393868>
- Rosenkranz C, Charaf MC, Holten R (2013) Language quality in requirements development: tracing communication in the process of information systems development. *J Inf Technol* 28:198–223. <https://doi.org/10.1057/jit.2012.33>
- Rosenkranz C, Vranešić H, Holten R (2014) Boundary interactions and motors of change in requirements elicitation: a dynamic perspective on knowledge sharing. *J Assoc Inf Syst* 15(6):2. <https://doi.org/10.17705/1jais.00364>
- Rosenkranz C, Stray V, Wiesche M (2023) Call for Papers, Issue 1/2025. *Bus Inf Syst Eng* 65(4):483–486. <https://doi.org/10.1007/s12599-023-00819-6>
- Saffarizadeh K, Keil M, Maruping L (2024) Relationship between trust in the artificial intelligence creator and trust in artificial intelligence systems: the crucial role of artificial intelligence alignment and steerability. *J Manag Inf Syst* 41(3):645–681. <https://doi.org/10.1080/07421222.2024.2376382>
- Sarker S, Xiao X, Beaulieu T, Lee AS (2018) Learning from first-generation qualitative approaches in the IS discipline: An evolutionary view and some implications for authors and evaluators (Part 1/2). *J Assoc Inf Syst* 19(8):752–774. <https://doi.org/10.17705/1jais.00508>
- Sawyer S, Guinan PJ, Coopridge J (2010) Social interactions of information systems development teams: a performance perspective. *Inf Syst J* 20(1):81–107. <https://doi.org/10.1111/j.1365-2575.2008.00311.x>
- Schulte-Derne D, Gnewuch U (2024) Translating AI ethics principles into practice to support robotic process automation implementation. *MIS Q Exec* 23(2):205–221. <https://doi.org/10.17705/2msqe.00095>
- Seidel S, Berente N, Lindberg A, Lyytinen K, Nickerson JV (2019) Autonomous tools and design: a triple-loop approach to human-machine learning. *Commun ACM* 62(1):50–57. <https://doi.org/10.1145/3210753>
- Shadish WR, Cook TD, Campbell DT (2002) *Experimental and quasi-experimental designs for generalized causal inference*. Houghton, Mifflin
- Shidende NH, Aanestad M, Igira F (2016) The role of context in the co-evolution of work and tools: a case from the primary health sector in Tanzania. *Inf Technol People* 29(4):850–875. <https://doi.org/10.1108/ITP-12-2013-0218>
- Siegel-Jacobs K, Yates JF (1996) Effects of procedural and outcome accountability on judgment quality. *Organ Behav Hum Decis Proc* 65(1):1–17. <https://doi.org/10.1006/obhd.1996.0001>
- Simonson I, Staw BM (1992) Deescalation strategies: a comparison of techniques for reducing commitment to losing courses of action. *J Appl Psychol* 77(4):419–426. <https://doi.org/10.1037/0021-9010.77.4.419>
- Srivastava SC, Chandra S (2018) Social presence in virtual world collaboration: an uncertainty reduction perspective using a mixed methods approach. *MIS Q* 42(3):779–804. <https://doi.org/10.25300/MISQ/2018/11914>
- Stray V, Moe NB (2020) Understanding coordination in global software engineering: a mixed-methods study on the use of meetings and slack. *J Syst Softw* 170:110717. <https://doi.org/10.1016/j.jss.2020.110717>
- Streiner DL (2003) Starting at the beginning: an introduction to coefficient alpha and internal consistency. *J Pers Assess* 80(1):99–103. [https://doi.org/10.1207/S15327752JPA8001\\_18](https://doi.org/10.1207/S15327752JPA8001_18)
- Strich F, Mayer AS, Fiedler M (2021) What do I do in a world of artificial intelligence? Investigating the impact of substitutive decision-making AI systems on employees' professional role identity. *J Assoc Inf Syst* 22(2):304–324. <https://doi.org/10.17705/1jais.00663>
- Sturm T, Gerlach JP, Pumplun L, Mesbah N, Peters F, Tauchert C, Nan N, Buxmann P (2021) Coordinating human and machine learning for effective organizational learning. *MIS Q*. <https://doi.org/10.25300/MISQ/2021/16543>
- Ter Hofstede AHM, Verhoef TF (1997) On the feasibility of situational method engineering. *Inf Syst* 22(6–7):401–422. [https://doi.org/10.1016/S0306-4379\(97\)00024-0](https://doi.org/10.1016/S0306-4379(97)00024-0)
- Tóth Z, Caruana R, Gruber T, Loebbecke C (2022) The dawn of the AI robots: towards a new framework of AI robot accountability. *J Bus Ethics*. <https://doi.org/10.1007/s10551-022-05050-z>
- Toulmin S (1958) *The uses of argument*, 1st edn. Cambridge University Press
- Toulmin S (2003) *The uses of argument*, 2nd edn. Cambridge University Press
- Trope Y, Liberman N (2003) Temporal construal. *Psychol Rev* 110(3):403–421. <https://doi.org/10.1037/0033-295X.110.3.403>
- Trope Y, Liberman N (2010) Construal-level theory of psychological distance. *Psychol Rev* 117(2):440. <https://doi.org/10.1037/a0018963>
- Urbach N, Ahlemann F, Böhm T, Drews P, Brenner W, Schaudel F, Schütte R (2019) The impact of digitalization on the IT department. *Bus Inf Syst Eng* 61(1):123–131. <https://doi.org/10.1007/s12599-018-0570-0>
- Vaast E, Pinsonneault A (2021) When digital technologies enable and threaten occupational identity: the delicate balancing act of data scientists. *MIS Q*. <https://doi.org/10.25300/MISQ/2021/16024>
- van den Broek E, Sergeeva A, Huysman M (2021) When the machine meets the expert: an ethnography of developing AI for hiring. *MIS Q* 45(3):1557–1580. <https://doi.org/10.25300/MISQ/2021/16559>
- Vance A, Lowry PB, Eggett D (2013) Using Accountability to reduce access policy violations in information systems. *J Manag Inf*

- Syst 29(4):263–290. <https://doi.org/10.2753/MIS0742-1222290410>
- Vance A, Lowry PB, Eggett D (2015) Increasing accountability through user-interface design artifacts. *MIS Q* 39(2):345–366. <https://doi.org/10.25300/MISQ/2015/39.2.04>
- Venkatesh V, Brown SA, Bala H (2013) Bridging the qualitative-quantitative divide: guidelines for conducting mixed methods research in information systems. *MIS Q* 37(1):21–54. <https://doi.org/10.25300/MISQ/2013/37.1.02>
- Venkatesh V, Brown SA, Sullivan Y (2016) Guidelines for conducting mixed-methods research: an extension and illustration. *J Assoc Inf Syst* 17(7):435–495. <https://doi.org/10.17705/1jais.00433>
- Vial G, Rivard S (2022) Conceptualizing information systems development as an organizational routine: Implications and avenues for research. *ACM SIGMIS Database Database Adv Inf Syst* 53(3):91–107. <https://doi.org/10.1145/3551783.3551790>
- Vokinger KN, Gasser U (2021) Regulating AI in medicine in the united states and Europe. *Nat Mach Intell* 3(9):738–739. <https://doi.org/10.1038/s42256-021-00386-z>
- Wendt C, Werner D, Adam M, Benlian A (2022) Influencing crowding at locations with decision support systems: the role of information timeliness and location recommendations. *Decis Support Syst*. <https://doi.org/10.1016/j.dss.2022.113817>
- Ye LR, Johnson PE (1995) The impact of explanation facilities on user acceptance of expert systems advice. *MIS Q* 19(2):157–172. <https://doi.org/10.2307/249686>
- Zhang Z, Hummel JT, Nandhakumar J, Waardenburg L (2020) Addressing the key challenges of developing machine learning AI systems for knowledge-intensive work. *MIS Q Exec* 19(4):221–238. <https://doi.org/10.17705/2msqe.00035>
- Adam M (2022) Accountability-based user interface design artifacts and their implications for user acceptance of AI-enabled services. In: ECIS 2022 proceedings, Timisoara
- EU-US Trade and Technology Council (2022) Strengthening our renewed partnership in turbulent times. [https://ec.europa.eu/commission/presscorner/detail/en/IP\\_22\\_3034](https://ec.europa.eu/commission/presscorner/detail/en/IP_22_3034).
- Frink DD, Klimoski RJ (1998) Toward a theory of accountability in organizations and human resource management. In: Ferris GR (ed) *Research in personell and human resources management*, vol 16. Elsevier Science/JAI Press, pp 1–51
- Martin K (2022) Ethics of data and analytics: Concepts and cases. Auerbach
- Meckenstock J-N, Hirschlein N, Schlauderer S, Overhage S (2022) The business value of agile software development: Results from a systematic literature review. In: ECIS 2022 Proceedings, Timisoara
- Raji ID, Smart A, White RN, Mitchell M, Gebru T, Hutchinson B, Smith-Loud J, Theron D, Barnes P (2020) Closing the AI accountability gap: defining an end-to-end framework for internal algorithmic auditing. In: FAccT 2020 Proceedings, Barcelona, pp 33–44
- Russell SJ, Norvig P (2021) *Artificial intelligence: a modern approach*, 4th edn. Pearson
- Schneider D, Lins S, Grupp T, Benlian A, Sunyaev A (2017) Nudging users into online verification: the case of carsharing platforms. In: ICIS 2017 Proceedings, Seoul
- Seguel P, Vaast E (2021) Repertories of evaluation in AI ethics: plurality in professional responsibility and accountability. In: ICIS 2021 Proceedings, Austin
- Stray V, Moe NB, Bergersen G, Kirkerud J (2024) Behavioral aspects of agile software development: a case study on meeting practices. In: HICSS 2024 Proceedings, Hawaii
- VerLinden JG (1998) Verifiers in everyday argument: an expansion of the Toulmin model. In: 84th Annual Meeting of the National Communication Association
- Wieringa M (2020) What to account for when accounting for algorithms: A systematic literature review on algorithmic accountability. In: FAccT 2020 Proceedings, Barcelona. <https://doi.org/10.1145/3351095.3372833>
- Wu-Gehbauer M, Rosenkranz C (2024) Towards a framework for developing artificial intelligence systems for human-artificial intelligence augmentation. In: ECIS 2024 Proceedings, Paphos