How AI Developers’ Perceived Accountability Shapes Their AI Design Decisions

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Abstract

While designing artificial intelligence (AI)-based systems, AI developers usually have to justify their design decisions and, thus, are accountable for their actions and how they design AI-based systems. Crucial facets of AI (i.e., autonomy, inscrutability, and learning) notably cause potential accountability issues that AI developers must consider in their design decisions, which has received little attention in prior literature. Drawing on self-determination theory and accountability literature, we conducted a scenario-based survey (n=132). We show that AI developers who perceive themselves as accountable tend to design AI-based systems to be less autonomous and inscrutable but more capable of learning when deployed. Our mediation analyses suggest that perceived job autonomy can partially explain these direct effects. Therefore, AI design decisions depend on individual and organizational settings and must be considered from different perspectives. Thus, we contribute to a better understanding of the effects of AI developers' perceived accountability when designing AI-based systems.

Keywords: Perceived Accountability, AI Design Decisions, Perceived Job Autonomy, Scenario-based Survey

Introduction

Design decisions of AI-based systems are becoming increasingly important due to AI-based systems' growing relevance to society in more and more domains and contexts (e.g., Adam et al., 2022; Berger et al., 2021). Examples include Amazon's hiring AI-based system, whose recommendations discriminated against women (Dastin, 2022), or the recidivism assessment AI-based system COMPAS (Correctional Offender Management Profiling for Alternative Sanctions), which has discriminated against certain minorities (Brennan et al., 2009), underscore the urgency to design AI-based systems more ethically to prevent harm to AI users (e.g., Benlian et al., 2022; Novelli et al., 2023).

How an AI-based system behaves is dictated in no small part by decisions made during its development and, accordingly, by its technical design. Earlier information systems (IS) research identified three facets that characterize AI-based systems' design: The *autonomy* of an AI-based system, its *inscrutability*, and its *capability to learn* (Berente et al., 2021). Due to AI-based systems' autonomy, AI stakeholders, such as their users, can no longer or only very limited intervene in the decision-making of AI-based systems. Due to the inscrutability of AI-based systems, the functionalities of the systems are no longer comprehensible to their stakeholders. Finally, AI-based systems change over time due to their capability to learn to adapt to a dynamic and often unknown environment. Even if these facets of AI (i.e., autonomy, inscrutability, and learning) are indispensable for further development of AI-based systems for new application areas or overall performance gains (e.g., Došilović et al., 2018), they give rise to ethical problems such as the lack of explainability and transparency (e.g., Asatiani et al., 2021; Berente et al., 2021).

As a result, it is often discussed who should be obliged to justify AI-based systems and their outcomes despite these technical realities and who could be held accountable for the systems (e.g., Martin, 2019b; Shin & Park, 2019). In this discourse, accountability is often attributed to AI developers (e.g., Martin, 2019b; Novelli et al., 2023; Shin & Park, 2019). Background to this discourse is that AI developers determine the capabilities and facets of AI-based systems with their design decisions (e.g., Du Plessis, 1993; Shin & Park, 2019). Due to such attributed accountability, AI developers must justify their actions and decisions while developing AI-based systems to others (e.g., Bovens, 2007; Wieringa, 2020). Those obligations to justify often intend to ensure that AI developers follow development guidelines and ethical policies during development (e.g., Bovens, 2007; Martin, 2019b; Vaast, 2022). Accordingly, if AI developers fail to meet the corresponding accountability obligations, they can be subject to sanctions, such as job loss, disciplinary measures, and fines (e.g., Bovens, 2007; Schedler et al., 1999; Strümke et al., 2021).

These additional explanation obligations expose AI developers to another stressor in AI development projects and increase the challenges of AI developers during such projects (e.g., Asatiani et al., 2021; Benbya et al., 2021). This is particularly relevant in light of previous IS research findings that show that software development projects are inherently characterized by complex, non-routine, and knowledge-intensive tasks (Kirsch et al., 2010). Such characteristics of software development projects do not infrequently lead to behavioral changes in software developers due to the stress they induce (Benlian, 2022; Hardgrave et al., 2003; Mueller & Benlian, 2022; Windeler et al., 2017). In particular, perceived stress often negatively affects individual decision-making behavior which can be explained by the inability to consider all options for action in the decision-making process in stressful situations (Galván & Rahdar, 2013).

Accordingly, AI developers have to think about how they design their AI-based systems and which capabilities they grant them, limiting their perceived job autonomy. Moreover, they find themselves in a conflict of goals: On the one hand, they have to meet their accountability obligations. On the other hand, they have to rely on models and algorithms that are as performant as possible as the basis of their AI-based systems for many use cases (e.g., Asatiani et al., 2021). While the first goal could be achieved, for example, with a high degree of explainability of the models, this explainability decreases with increasing performance (e.g., Asatiani et al., 2021). Accordingly, the necessity of resolving these conflicting goals limits the decision-making scope of AI developers in designing AI-based systems, which can also be understood as a limitation of the perceived job autonomy of AI developers. AI developers are positioned to deal with this trade-off not least because of the growing trend of agile project management methods, whereby AI developers are increasingly involved in decision-making processes (e.g., Maruping et al., 2009). As a result, AI developers face higher job autonomy, but they must be able to justify their decisions, for which they are held accountable. Apart from this negative effect on AI developers, a high level of job autonomy is essential in Information System Development (ISD) projects to ensure high-performance levels of developed IS (e.g., Ozer & Vogel, 2015).

Despite its importance, IS research has paid little attention to how AI developers respond to the accountability attributed to them when designing AI-based systems (e.g., Schmidt et al., 2023; Shin & Park, 2019). In particular, it is unclear whether and how perceived accountability affects AI developers' AI design preferences and decisions regarding the three facets of AI mentioned at the outset, *autonomy*, *inscrutability*, and *ability to learn* (Berente et al., 2021). Additionally, it has not yet investigated how this effect can be explained by a perceived curtailment of AI developers' perceived job autonomy. Against this backdrop, we investigate how AI developers' perceived accountability shapes their AI design decisions regarding *autonomy*, *inscrutability*, and *learning*. Therefore, we pose the following research question:

RQ: How does perceived accountability affect AI developers' AI design decisions on the AI facets of autonomy, inscrutability, and learning due to limitations on perceived job autonomy?

To answer our research question, we conducted a scenario-based survey (Teubner & Flath, 2019) with 132 AI developers and asked how they tend to design a new AI-based system for credit scoring while perceiving accountability. The findings demonstrate that perceived accountability leads AI developers to design AI-based systems that are less autonomous and inscrutable but more capable of learning. In addition, we can partially explain these effects by job autonomy mediating the direct relationship between AI developers' perceived accountability and the three facets of AI (i.e., autonomy, inscrutability, and learning) reflecting their AI design decisions.

With our research, we thus contribute to ISD research in two ways: First, we show that AI developers possess preferences over designing AI-based systems when perceiving accountability. AI developers tend to make less autonomy- and inscrutability-related and more learning-related design decisions to meet their accountability obligations. Therefore, AI design decisions are shaped not only by technical constraints and objectives but also by the individual and organizational settings in which they are made. Second, we partially explain these effects through AI developers' job autonomy, providing transparency about the relationship between their perceived accountability and AI design decisions. Therefore, we contribute to a better understanding of how and why AI design decisions are affected.

Theoretical Framework

AI Development and AI Facets

AI development involves designing and implementing AI-based systems (Gao et al., 2019), whereby such systems can be characterized by three interdependent facets of AI: Autonomy, inscrutability, and learning (Berente et al., 2021) (see Table 1). *Autonomy* describes how AI-based systems can act without or with less human involvement within a given interaction space. Autonomy can, therefore, range from no decision being made without human interaction to humans cannot intervene (Citron & Pasquale, 2014; Danaher, 2016), meaning that humans can or cannot correct a decision made by AI-based systems. *Inscrutability* describes the opacity of AI-based systems, making their operations incomprehensible to humans at a fine-grained level. For example, AI-based systems can be understood on a macro level (e.g., which AI algorithm is used), but humans can no longer comprehend outputs on a micro level (e.g., how and why an AI algorithm arrives at a specific decision). To address the problem of the inability to comprehend AI-based systems by humans, AI-based systems can be designed and developed more transparently (Asatiani et al., 2021; Berente et al., 2021). The third facet, *learning*, refers to "the ability to inductively improve automatically through data and experience..." (Berente et al., 2021, p. 1437). Therefore, learning minimizes current errors and bugs over time. However, learning challenges AI developers' design and development process, as it requires closed data feedback loops to guarantee AI-based systems' continued accuracy over time (e.g., Ngiam & Khor, 2019).

Facet of AI	Definition/Explanation	Example
Autonomy (e.g., Baird & Maruping, 2021; Berente et al., 2021)	AI-based systems are allowed to act without human intervention, enabling AI-based systems to make independent decisions that do not require human confirmation.	AI-based systems independently determine customers' creditworthiness on their own, without the decision being reviewed by a bank employee.
Inscrutability (e.g., Asatiani et al., 2021; Berente et al., 2021)	AI-based systems are unintelligible to AI stakeholders (e.g., users, managers, and developers), and the exact functioning of AI-based systems can only be conjectured and assumed. A detailed understanding of how AI-based systems come to decisions is no longer comprehensible by humans.	AI-based systems decide on customers' creditworthiness and do not explain the exact criteria for why the customer gets a loan or not.
Learning (e.g., Berente et al., 2021; Berger et al., 2021)	AI-based systems improve themselves by analyzing new data and experiences. Improvement implies that AI-based systems do not follow a static concept but can reshape themselves and react flexibly to environmental changes.	AI-based systems receive new credit data from customers and update the creditworthiness score accuracy based on that.

Table 1. Facets of AI

Through these facets, AI development projects face particular ethical challenges concerning the fairness, transparency, and accountability of AI-based systems on the one hand (e.g., Jobin et al., 2019) and challenges in terms of achieving an acceptable performance on the other (Asatiani et al., 2021). Achieving a good performance of AI-based systems tends to come at the cost of transparency (Asatiani et al., 2021). Thus, ethical issues arise that AI developers must consider when designing such systems (e.g., Asatiani et al., 2021; Berente et al., 2021). With over 80 different ethical guidelines (e.g., Statement on Algorithmic Transparency and Accountability, Ethics Guidelines for Trustworthy AI), there is no consensus on designing AI-based systems ethically (Jobin et al., 2019). Consequently, AI developers cannot draw on dedicated and standardized ethical guidelines to monitor and mitigate all ethical issues. Therefore, AI developers must choose individual ways of responding to imposed accountability because it is only known on a case-by-case basis what they have to justify to others. Accordingly, AI developers must decide for themselves how to deal with ethical challenges and achieve good performance within their individual AI design decisions.

Accountability in AI Development Projects

Perceived accountability implies the perceived need to justify one's behavior to others and should be considered and addressed in ISD projects right from the beginning, as it affects decisions and judgments carried out in the face of impending sanctions and rewards (Bovens, 2007; Schmidt et al., 2023; Vance et al., 2015; Wieringa, 2020). This sense of justification leads to increased use of cognitive abilities within decision-making processes and, simultaneously, to more restrained and less risk-affine behavior (Staw, 1976; Weigold & Schlenker, 1991). Within decision-making, *systematic processing* explains this behavior of individuals (Crano & Prislin, 2006), as it refers to the thorough and intensive processing of all available information through systematic thinking to make well-considered decisions (e.g., Adam, 2022; Wirth et al., 2007). Encouraging systematic processing can improve judgment quality, promote information sharing, and increase the understanding of a considered topic (Scholten et al., 2007) but requires high cognitive effort (Adam, 2022; Vance et al., 2015). To shape perceived accountability, four mechanisms can be used: (1) identifiability, (2) expectation of evaluation, (3) awareness of monitoring, and (4) social presence (e.g., Adam, 2022; Vance et al., 2015). Identifiability describes the determination of the actor performing actions. The expectation of evaluation ensures that the actor cannot perform actions without restrictions. Therefore, the actions will be scrutinized by others, and the actor has to justify his actions. Awareness of monitoring causes the actors' actions to be recorded and viewed transparently. Finally, social presence implies that actors do not have to perform actions by themselves but see whether and which other people are available from whom actors can obtain support in case of doubt (e.g., Adam, 2022; Vance et al., 2015).

In addition to increasing the perception of one's accountability, accountability in ISD projects can be supported by a transparent organization of systems and procedures that includes precise tasks for specific actors (Nguyen, 2006; Weitzner et al., 2008). Hence, accountability establishes clear rules and guidelines to monitor ISD projects (e.g., Merchant & Otley, 2006). This is particularly important in developing AI-based systems, where assigning accountability is often challenging: Due to the facets of AI (i.e., autonomy, inscrutability, and learning), AI-based systems are no longer static but are instead subject to dynamics (e.g., Berente et al., 2021; Mistry & Koyner, 2021), so new ethical issues can arise anytime (Martin, 2019a). Consequently, accountability ensures that AI developers consider ethical issues that can arise based on the facets of AI and make well-considered decisions that minimize ethical issues. With such decisions, AI developers can also reduce their own risk, as they do not have to justify themselves for ethical issues and thus risk personal sanctions that arise from accountability. As a result, accountability limits AI developers' scope of action, limiting their job autonomy.

Self-Determination Theory

Self-determination theory (SDT) builds on fulfilling three basic psychological needs of autonomy, competence, and relatedness, which result in "...high-quality performance and wellness" (Deci et al., 2017, p. 19). For this purpose, SDT distinguishes between autonomous and controlled motivation: While autonomous motivation arises based on interest, controlled motivation results from external incentives and specifications (Gagné & Deci, 2005). In this context, autonomous motivation leads individuals to more outstanding commitment and better work performance as individuals identify with the given goals and adopt them (Gagné & Deci, 2005). In contrast, controlled motivation tempts the individual to poorer performance and well-being (e.g., Deci et al., 2017). If, for example, people explicitly perform or refrain from acting only to avoid negative consequences, this indicates the existence of controlled motivation (Gagné & Deci, 2005). Hence, SDT describes the decision behavior of individuals, which can lead to explorative and restrained decisions, depending on the elicited motivation (e.g., Ramamoorthy et al., 2005; Shalley et al., 2000).

Previous IS research has drawn on SDT primarily to explain user and developer behavior (e.g., Khan et al., 2020; Menard et al., 2017; Tobon et al., 2020). For example, SDT was used to shed light on why IS users tend to be more responsible in the information security context (Menard et al., 2017). It also explains how users of gamified systems can be encouraged to use them (Tobon et al., 2020). In particular, previous IS research used SDT to demonstrate that promoting the three basic psychological needs (i.e., autonomy, competence, and relatedness) increases project success and developers' invested time in development projects (e.g., Khan et al., 2020; Von Krogh et al., 2012). This indicates that fulfilling the three basic psychological needs, according to SDT, positively affects individuals' behavior. Therefore, one can assume that interventions on those needs also affect AI developers' decision-making behavior. In particular, we assess the relevance of the basic psychological need of autonomy in the form of perceived job autonomy as high, as this need can be curtailed by perceived accountability and systematic processing.

Research Model and Hypotheses Development

Drawing on SDT (Ryan & Deci, 2000) and literature on accountability (e.g., Bovens, 2007; Wieringa, 2020), we develop our research model that investigates the effects of AI developers' perceived accountability on their intended AI design decisions (H1a-c). In addition, we examine whether the effects can be explained by a mediation effect of perceived job autonomy (H2a-c). Figure 1 shows our research model with the hypotheses. In addition, it indicates the expected direction of the path coefficients in brackets, which are explained in detail below.

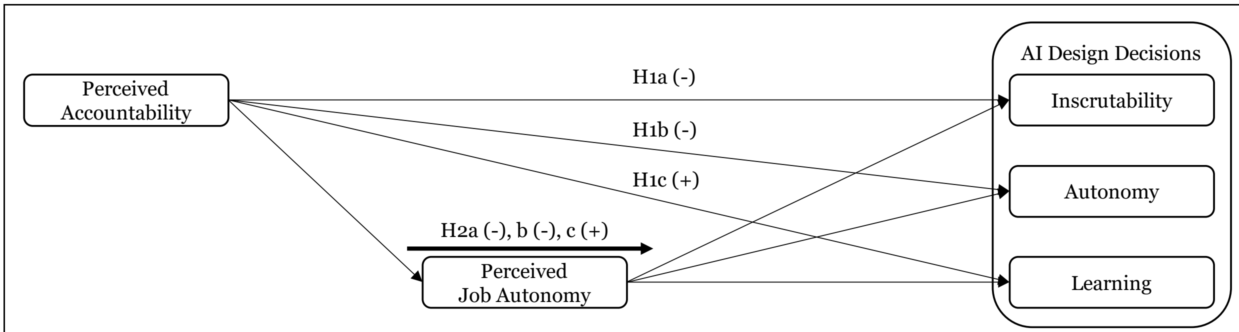


Figure 1. Research Model

Effects of Perceived Accountability on AI Developers' AI Design Decisions

Due to systematic processing, AI developers collect and evaluate all available information before making a decision (e.g., Crano & Prislin, 2006; Vance et al., 2013, 2015; Wirth et al., 2007). Such collection and evaluation of available information allow AI developers to justify their actions and decisions to others, thus fulfilling accountability obligations. However, systematic processing places high mental demands on AI developers (e.g., Crano & Prislin, 2006; Vance et al., 2015; Wirth et al., 2007). Nevertheless, imposing high mental demands on AI developers can be justified to avoid potentially harmful consequences for users (e.g., Berente et al., 2021; Martin, 2019b; Wieringa, 2020). As AI developers need to justify themselves for the AI-based systems they develop, they must consider the consequences that arise through their design (e.g., Martin, 2019b; Wieringa, 2020). Such consequences include failing to fulfill the AI-based system's desired performance or ethical issues resulting from errors and bugs. Therefore, AI developers must weigh the consequences of their AI design decisions related to their risk perception as they need to decide whether they want to justify themselves for not reaching a desired performance or the presence of ethical issues. Based on this decision, AI developers have to fear personal consequences present through the potential rewards and sanctions associated with accountability, as estimating rewards and sanctions can help individuals anticipate any subsequent negative consequences (e.g., Bovens, 2007; Wieringa, 2020). While rewards should represent extrinsic motivation to motivate AI developers to excel in their AI development projects (e.g., Qiao et al., 2021), sanctions define the space for actions where AI developers can feel confident in their risk perception. When AI developers are involved in AI design decisions, this individual trade-off between personal costs and benefits should lead to reflecting these in their AI design decisions.

Consequently, this raises the question of the AI developers' choices in designing AI. Based on the facets of AI-based systems (Berente et al., 2021) that can also be understood as available characteristics of its design, AI developers can affect their AI-based systems' autonomy, inscrutability, and learning. However, AI developers who grant AI-based systems the autonomy to act independently from humans need to expect a loss of control over the AI-based systems (e.g., Berente et al., 2021). AI developers must, therefore, ensure that AI-based systems and their decisions do not cross ethical boundaries and cause harm to AI users (e.g., Citron & Pasquale, 2014; Danaher, 2016). Therefore, they have to implement, for example, adequate control mechanisms, which rules increase the complexity of AI-based systems (e.g., Asatiani et al., 2021). This increase in complexity leads to an inevitable increase in the complexity and inscrutability of AI-based systems because AI developers must consider more mechanisms. Additionally, while implementing monitoring functions is fundamentally essential to identify and resolve hidden errors and bugs (e.g., Finucane et al., 2005), their implementation comes at the cost of being able to thoroughly evaluate AI-based systems through the increased number of mechanisms to oversee. It becomes challenging to control the AI-based system over unethical behavior (e.g., Asatiani et al., 2021). Finally, designing AI-based systems to be capable of learning allows AI developers to enable their AI-based systems to improve themselves and correct occurring errors and bugs in the long run without constant human intervention (e.g., Berente et al., 2021; Berger et al., 2021). As a result, it should be expected that the longer an AI-based system capable of learning is deployed, the fewer errors and bugs will occur in the long run. Such errors and bugs lead to ethical issues like being unfair or biased. Reducing errors and bugs suggests reducing ethical issues like being biased. Consequently, AI developers need to justify themselves less often because of the reduced amount of unfair or biased outcomes.

Accordingly, through systematic processing, AI developers must weigh between and make decisions regarding the facets of AI when designing their AI-based systems. In addition, they might have the required knowledge to evaluate the possible consequences of a specific design of AI-based systems while meeting the desired performance criteria of the AI-based system. When held accountable, AI developers may find themselves in situations where they must either justify why their AI-based systems behave in an undesirable manner (e.g., being unfair or biased) or do not meet desired performance criteria. Accordingly, perceived accountability limits the AI developers' potential scope of action. In such situations, individuals tend to be risk averse and decide more conservatively (e.g., Maner et al., 2007; Tom et al., 2007). Therefore, we hypothesize a connection between AI developers' perceived accountability and their subsequent AI design decisions to reduce or avoid potential personal negative consequences. Accordingly, AI developers should tend to be more conservative in designing AI-based systems to reduce potential harm to AI users.

Conversely, this implies that AI developers who perceive themselves as accountable should prefer designing AI-based systems to act less autonomously and inscrutable but more capable of learning. Such behavior would be justified as it would decrease the probability of errors and bugs in advance (by reducing AI-based systems' *autonomy* and *inscrutability*). At the same time, it also suggests increasing the AI-based systems' ability to identify and correct occurring errors and bugs by *learning* from new data. Therefore, the underlying assumption of our study is that perceived accountability directly affects AI developers' AI design decisions. We state the first hypotheses:

H1a: *Perceived accountability negatively affects autonomy-related AI design decisions.*

H1b: *Perceived accountability negatively affects inscrutability-related AI design decisions.*

H1c: *Perceived accountability positively affects learning-related AI design decisions.*

Mediation Effect of Perceived Job Autonomy

Systematic processing restricts the self-determined decision-making space of AI developers. Consequently, systematic processing as the underlying cognitive process of perceived accountability prevents decisions without collecting and evaluating all information beforehand (e.g., Crano & Prislin, 2006; Wirth et al., 2007). That is why AI developers are obligated by perceived accountability to collect and evaluate all information, which restricts their self-determined decisions on how much information they want to collect and evaluate. This constraint results from balancing potential AI design decisions against the potential harm for AI users, for what AI developers would have to expect sanctions. Therefore, perceived accountability restricts their perceived job autonomy. They cannot freely evolve their AI design decisions during their AI development without perceiving the threat of sanctions for undesired outcomes. For example, suppose that AI developers want to develop an AI-based system aligned closely to the "frontier of computation" (Berente et al., 2021, p. 1434). Due to this orientation of the AI-based system, the AI developers cannot estimate the consequences that arise from their AI-based system as it opens up new possibilities in developing such systems. However, they must justify the consequences to others, which prevents AI developers from acting autonomously in their jobs if they perceive themselves as accountable. Perceived accountability thus cannot be reconciled with high perceived job autonomy. Hence, we argue for a negative relationship between AI developers' perceived accountability and job autonomy. Adjacent to the negative relationship, SDT explains the effects between AI developers' perceived accountability and the three AI design decisions autonomy, inscrutability, and learning based on AI developers' perceived job autonomy.

Further and following SDT, perceived job autonomy leads to autonomous motivation by fulfilling the basic psychological need of autonomy, while controlled motivation is constrained (Gagné & Deci, 2005). As a result, individuals with higher autonomous motivation tend to behave more creatively and innovatively (e.g., Ramamoorthy et al., 2005; Shalley et al., 2000) on the costs of their risk perception (e.g., Stone et al., 2009). Creative and innovative behavior in designing AI-based systems can also be reflected in decisions concerning designing the three facets of AI. For example, innovative AI-based systems can be seen as systems that automate previously human activities, allowing AI developers to address various use cases (e.g., Berente et al., 2021). Such previously human activities that AI developers can automate using creative and innovative design of AI-based systems might include driving a car (e.g., Asatiani et al., 2021) and involve the explicit design of autonomous AI-based systems, which is why autonomous motivation encourages the design of such systems. Consequently, AI developers with high perceived job autonomy should tend to grant their developed AI-based systems higher autonomy.

Additionally, due to the growing popularity of AI-based systems, new state-of-the-art machine learning techniques (e.g., deep neural networks and generative artificial networks) are continuously being developed, which provide increasingly improved performance at the cost of transparency and explainability (e.g., Asatiani et al., 2021). Exploring these new techniques and possibilities for AI-based systems is a creative and innovative task for AI developers as they try new algorithms that replace former algorithms. For example, AI developers might creatively and innovatively explore deep neural networks instead of decision trees, thereby exploring new opportunities in designing AI-based systems. Accordingly, autonomous motivation supports AI developers' explorative engagement with new state-of-the-art techniques and helps them to accept their AI-based systems' higher inscrutability.

The situation is different concerning AI developers' AI design decisions to enable AI-based systems to learn. While AI-based systems capable of learning can resolve emerging errors and bugs due to their continuous improvements (e.g., Berger et al., 2021), this requires developing and implementing appropriate rules and controls that govern the learning process. These rules and controls include continuous monitoring of the AI-based systems to ensure that they do not internalize biases or other undesirable behaviors due to learning on biased data (e.g., Berente et al., 2021). However, appropriate continuous monitoring cannot be considered a creative and innovative activity, as AI developers should define criteria under which their AI-based systems are allowed to learn. AI developers need to adjust these criteria as the environment in which their AI-based systems operate might change (e.g., Berente et al., 2021; Mistry & Koyner, 2021), leading to a recurring and often manual task. Accordingly, the continuous monitoring of AI-based systems' capability of learning should not be stimulated by autonomous motivation, according to SDT.

In summary, perceived accountability through threatened sanctions and rewards (e.g., Bovens, 2007; Merchant & Otley, 2006) provides a framework for how much autonomy AI developers perceive in their jobs. In this respect, SDT may explain the effects on AI developers' AI design decisions through autonomous motivation. The hypotheses are, accordingly:

H2a: Lower perceived job autonomy due to higher perceived accountability reduces autonomy-related AI design decisions, mediating the effects.

H2b: *Lower perceived job autonomy due to higher perceived accountability reduces inscrutability-related AI design decisions, mediating the effects.*

H2c: *Lower perceived job autonomy due to higher perceived accountability increases learning-related AI design decisions, mediating the effects.*

Method

Survey Design

We conducted a scenario-based survey to examine our research model. This method is appropriate for answering the stated hypotheses as scenarios can query hypothetical patterns of action and decision-making behavior without considering participants' concerns in their situations (Harrington, 1996). In the designed scenario, participants were to develop a financial application for banks to decide on customer loan applications. Since the creditworthiness of natural persons is calculated by relying on AI-based systems, the scenario thus represents the development of a future high-risk application (European Commission, 2021). Moreover, the scenario reflects a current and realistic problem from practice (e.g., Strich et al., 2021; Townson, 2020). We pointed out to the participants that the AI-based system should be implemented on reviewed, unbiased data and from scratch to reduce AI developers' mental complexity with the scenario. This limitation also aimed at preventing the so-called *many-hands problem*, describing the lack of clear attributable accountability from occurring (e.g., Cooper et al., 2022). This procedure allowed us to consider individual AI developers in isolation, as accountability was clearly attributed to them.

Additionally, the scenario followed the current accountability understanding of a relationship between an actor and a forum, in which the actor faces possible sanctions and rewards imposed by the forum (Bovens, 2007; Wieringa, 2020). The scenario defined the forum as the AI developers' supervisors and the possible sanctions and rewards as potential bonus payments that may or may not be achieved depending on the forum's assessment. We have decided not to provide clear success criteria leading to rewards from the forum's point of view, as we believe that this could strongly interfere with our survey design and define the results in advance. We believe this because if we define how AI-based systems should be designed to receive rewards, the AI developers might choose the respective facets of AI accordingly. Therefore, it remains open for them what the forum requires, which implies they have to decide what they feel comfortable with to justify it to the forum. Further, we told them to perform the task independently from colleagues to prevent the many-hands problem from occurring in the scenario (e.g., Cooper et al., 2022). Due to the possible sanctions and rewards, the scenario is eligible for AI developers perceiving externally controlled motivation (Gagné & Deci, 2005).

As the explicitly given task for the AI developers was to decide to what extent the facets of the AI-based system should be designed, we questioned dedicated AI design decisions in this scenario. To ensure that AI developers perceive accountability and not only rely on a fictive scenario, we have also designed the scenario to include all four accountability mechanisms (*identifiability*, *expectation of evaluation*, *awareness of monitoring*, *social presence*) (e.g., Adam, 2022; Vance et al., 2013, 2015). We implemented these mechanisms by clearly defining AI developers as selected actors (*identifiability*) and pointing to a forum that decides on possible sanctions and rewards by evaluating the AI developer's activities (*expectation of evaluation* and *awareness of monitoring*). Finally, we embedded the AI developer in an organization and a team (*social presence*), even if the development task was to be completed independently. Thus, we increased AI developers perceived accountability by drawing on previous IS research to increase AI developers' perceived accountability (e.g., Adam, 2022; Vance et al., 2013, 2015).

Measurement of the Constructs

After the scenario, we asked participants to complete a questionnaire based on their assessment and perception of the scenario. The questionnaire comprised the five reflective constructs: *Perceived Accountability*, *Perceived Job Autonomy,* and *AI Design Decisions: Autonomy, Inscrutability,* and *Learning*. Thereby, we define *Perceived Accountability* as the degree to which AI developers perceive themselves as accountable during their AI development projects and *Perceived Job Autonomy* as the degree to which AI developers believe they can decide on their own during AI development projects. Further, we define *AI Design Decisions: Autonomy*, *Inscrutability*, and *Learning* as the degree of autonomy, inscrutability, and the capability of learning that AI developers intend to grant to the AI-based system within the scenario. To measure these constructs, we adapted items of established scales (Hochwarter et al., 2007; Moore, 2000; Rutner et al., 2008; Santhanam et al., 2008) to the study's context (see Appendix A). However, to our knowledge, no adaptable scale exists yet to measure the third facet of AI, namely *AI Design Decisions: Inscrutability*. Therefore, we leaned on respective IS literature (Berente et al., 2021) while developing corresponding items. We primarily focused on the properties of the inscrutability AI facet (Berente et al., 2021). The properties of *inscrutability* are described by the "black-box problem..., explainable AI..., AI accountability..., or algorithm tractability" (Berente et al., 2021, p. 1437). Accordingly, the items addressed those characteristics. To finally test whether the adapted items measure the intended constructs, we conducted three expert interviews and explored whether the constructs apply to the survey. As they confirmed that the adapted constructs and items were applicable to the survey, we used them.

We used 7-point Likert-type scales to measure all items, including scores from 1 = *strongly disagree* to 7 = *strongly agree* (Vagias, 2006). In addition, we recorded participants' socio-demographic data like *Gender*, *Age*, and *AI Development Experience* in years.

Data Collection and Sample Demographics

We surveyed 150 AI developers via the online platform *Prolific* (`https://www.prolific.co/`), as previous studies show that *Prolific* offers high data quality (e.g., Peer et al., 2017). Additionally, we pre-selected participants by ensuring that survey participants are older than 25 years, are U.S. citizens, speak fluent English, have experience in software development techniques, and are employed. Based on the Relative Speed Index (RSI) criterion of lower than 2.0 (Leiner, 2019), which relates the time required by a single participant to complete the survey to the completion time of all participants, we removed ten records. Attention checks and filtering on non-AI developers required excluding an additional eight records, leaving 132 records for analysis. Accordingly, the valid response rate is 88%.

The socio-demographic analysis shows that 84% of the participating AI developers identified themselves as male and, on average, 38.14 years old (std = 9.89). In addition, 86% of the participants have a university degree, and 76% work in a team of up to ten people. Finally, participants indicated an average of 3.50 years (std = 2.89) of AI developing experience.

Measurement Validation

After examining the socio-demographics, we tested the constructs concerning their indicator reliability, internal consistency reliability, and convergent validity in the first step (see Table 2). Therefore, we measured internal consistency reliability using Rho_A. Rho_A goes beyond Rho_C and Cronbach's alpha as it is based on the construct's weights and reflects the off-diagonal elements (Dijkstra & Henseler, 2015). While evaluating the measurement validation, we focused primarily on the self-created construct *AI Design Decisions: Inscrutability*, which met all necessary validity criteria. In addition, all remaining constructs also achieved the necessary validity criteria. Thus, all indicator loadings were above 0.7 (Hair et al., 2011). The measured Rho_A values were in the interval ranging from 0.736 to 0.882, thus fulfilling the internal consistency reliability (Dijkstra & Henseler, 2015). Last, the Average Variance Extracted (AVE) values all exceeded 0.5, satisfying convergent validity (Hair et al., 2011).

Construct	**Indicator Loadings**	**Indicator Reliability**	**Rho_A**	**AVE**
Perceived Accountability	0.848 - 0.906	0.720 - 0.821	0.882	0.787
Perceived Job Autonomy	0.811 - 0.940	0.659 - 0.884	0.867	0.764
AI Design Decisions: Autonomy	0.859 - 0.906	0.738 - 0.820	0.736	0.779
AI Design Decisions: Inscrutability	0.813 - 0.863	0.661 - 0.746	0.796	0.700
AI Design Decisions: Learning	0.822 - 0.842	0.675 - 0.709	0.858	0.700

Table 2. Results of the Indicator Reliability, Internal Consistency Reliability, and Convergent Validity

In the second step, we tested discriminant validity using the Heterotrait-Monotrait Ratio of Correlations (HTMT) criterion (see Table 3). All HTMT values reached a value of less than 0.79, thus meeting the requirements of values below 0.85 (Henseler et al., 2015). Finally, to exclude Common Method Bias (CMB) from affecting the subsequent results, we checked the data using Harman's one-factor test with principal axis factoring and restricting factors. As the test showed that the results are below the critical value of 50% with a value of 20%, it is unlikely that CMB occurred in our survey and affected our results significantly (Podsakoff et al., 2003).

	I.	II.	III.	IV.	V.
I. Perceived Accountability					
II. Perceived Job Autonomy	0.312				
III. AI Design Decisions: Autonomy	0.198	0.238			
IV. AI Design Decisions: Inscrutability	0.412	0.297	0.750		
V. AI Design Decisions: Learning	0.344	0.378	0.499	0.789	

Table 3. Results of the Discriminant Validity

Results

After systematically testing the reflective measurement model, we analyzed the data using Partial Least Squares Structural Equation Modeling (PLS-SEM). We chose PLS-SEM as the study required the simultaneous consideration of all three *AI Design Decisions* in a single model. Other analysis approaches, such as regression analysis, would have been contrary to the understanding of the literature on the interdependent facets of AI (Berente et al., 2021), which allows the consideration of only one facet of AI as a dependent variable. We conducted the PLS-SEM analysis using *SEMinR* (Ray et al., 2022). As our research model hypothesizes a mediation effect of *Perceived Job Autonomy*, we calculated two separate models, M1 and M2 (Baron & Kenny, 1986). While M2 included the entire research model, we removed the mediator *Perceived Job Autonomy* in M1 to test the direct effect in the first step. In addition, we examined the significance of the measured control variables (i.e., *Gender*, *Age*, *Education*, *AI Development Experience*, and *Team Size*). For statistical robustness of the significances, we conducted a sufficiently large bootstrapping (n = 10,000) to calculate the corresponding confidence intervals (Hair et al., 2011).

Effects of Perceived Accountability on AI Developers' AI Design Decisions

Table 4 shows the results of M1, where we found significant effects in all three *AI Design Decisions: Autonomy, Inscrutability,* and *Learning*. The relations reached a significance level of at least $p < 0.05$, supporting the hypotheses H1a-c. As hypothesized in H1a and H1b, the path coefficients are negative between *Perceived Accountability* and *AI Design Decisions: Autonomy* and *AI Design Decisions: Inscrutability*. H1c suggests an adverse effect between *Perceived Accountability* and *AI Design Decisions: Learning*, which is also supported ($\beta = 0.325$; $p < 0.01$).

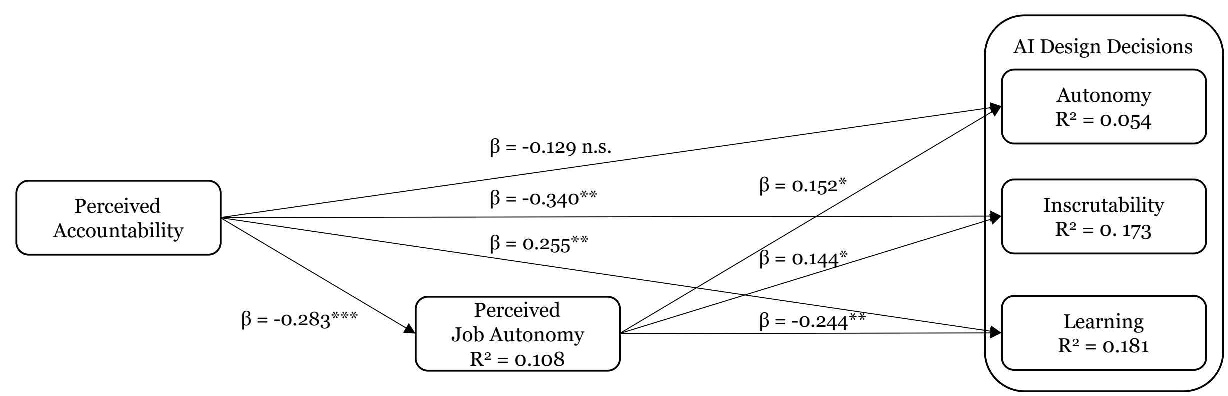
	Path Coefficient (β)	**R^2**
Perceived Accountability → AI Design Decisions: Autonomy	-0.184*	0.041
Perceived Accountability → AI Design Decisions: Inscrutability	-0.379***	0.153
Perceived Accountability → AI Design Decisions: Learning	0.325**	0.126
Note: * p < 0.05, ** p < 0.01, *** p < 0.001; n = 132		

Table 4. Path Coefficients of the PLS-SEM Model M1

Analysis of the Mediation Effects of Perceived Job Autonomy

In the next step, we examined M2 to test the entire research model. Figure 2 shows the results of M2. First, we considered the collected control variables. We observed a significant effect of *AI Development Experience* on *Perceived Job Autonomy* (β = 0.163; p = 0.032) and of *AI Development Experience* on *AI Design Decisions: Inscrutability* (β = 0.153; p = 0.032). We consider these correlations justifiable as we assume that *Perceived Job Autonomy* increases with higher professional experience, that is, *AI Development Experience*. We argue that with increasing professional experience, higher professional positions are generally reached. These positions are usually associated with greater scope for action and, thus, more *Perceived Job Autonomy*. Additionally, we suggest that increasing professional experience reduces AI developers' need for supervisors' instructions, leading to more *Perceived Job Autonomy*. Further, we explain that as AI developers gain professional experience, their confidence in their abilities increases, and so does their self-perceived decision scope regarding the design of AI-based systems. To measure the effects of *AI Development Experience* in terms of explanatory power, we computed the model again, excluding this control variable, and calculated the difference in the R^2 values. Results showed a difference of 0.022 in *Perceived Job Autonomy* and 0.018 in *AI Design Decisions: Inscrutability*. These results indicate that AI experience has little explanatory power and is unlikely to affect the overall results tremendously.

H2a-c exhibits statistical validity due to the significant relationships between *Perceived Accountability* and *Perceived Job Autonomy* and between *Perceived Job Autonomy* and all three *AI Design Decisions*. To test the mediation effect, we calculated the indirect effect and the respective confidence intervals (CI). We observed a full mediation with an indirect effect of −0.043 (CI [-0.096; -0.002]) between *Perceived Accountability* and *AI Design Decisions: Autonomy*. Indirect effects of −0.041 (CI [-0.089; -0.013]) and 0.069 (CI [0.022; 0.129]), respectively, and significant direct relationships revealed partial mediations of *Perceived Accountability* and the *AI Design Decisions: Inscrutability* and *Learning*. Based on the directions of the path coefficients, we assess the partial mediations as complementary. Therefore, we find support for hypotheses H2a-c.



Note: * p < 0.05, ** p < 0.01, *** p < 0.001, n.s. = not significant; n = 132

Figure 2. PLS-SEM Model M2

Discussion

Our study examined how perceived accountability shapes AI developers' AI design decisions in the direction of autonomy, inscrutability, and learning. Additionally, our study aimed to explain these effects through possible mediation effects of perceived job autonomy.

The results of our study show that perceived accountability affects AI developers' AI design decisions regarding the three facets of autonomy, inscrutability, and learning. When AI developers perceive themselves as accountable, they tend to shape AI-based systems to be less autonomous and inscrutable but more capable of learning. Moreover, we demonstrate that the mediation effects of perceived job autonomy can partially explain the effects on AI developers' AI design decisions. We explain the results with fewer occurring errors and bugs in such designed AI-based systems, for which AI developers perceive themselves as accountable and have to justify themselves to others. Thus, perceived accountability leads to AI-based systems being developed more conservatively and, therefore, less in the direction of the "frontier of computation" (Berente et al., 2021, p. 1434).

Theoretical Contributions

Our study adds to ISD research, especially AI development projects, in two ways. First, we increase the understanding of how AI developers' perceived accountability affects their AI design decisions. Previous ISD research focused mainly on the effects of perceived accountability on IS users (e.g., Adam, 2022; Vance et al., 2013, 2015). More specifically, previous ISD research addressed the effects of perceived accountability on users' intentions to follow the advice of AI-based systems and their intention to violate access policies. Therefore, while previous ISD research highlighted perceived accountability's diversity and importance in ISD research, it neglected the effects of perceived accountability on AI developers' decision-making behavior so far. However, previous ISD research examined the effects of decision-making behavior concerning the complexity of ISD projects (e.g., Hardgrave et al., 2003; Windeler, 2017), although perceived accountability of decision-makers was not considered. Accordingly, we contribute to ISD research by investigating the effect of perceived accountability on AI developers' AI design decisions. Our results suggest that AI developers who perceive themselves as accountable for AI-based systems are affected by this in their design decision behavior. Moreover, AI developers who feel accountable tend to favor AI design decisions that grant their AI-based systems greater autonomy and inscrutability but diminish their learning. It can be assumed that AI developers thus try to minimize their risk of having to justify themselves to others for errors and bugs when later operating their AI-based systems. This insight is important because AI developers are getting more involved in designing their AI-based systems (e.g., Maruping et al., 2009). Accordingly, AI design decisions are subject to the AI developers' balancing of potential rewards and sanctions, which is why they are exposed to AI developers' rational thinking and decision-making processes. Against this background, AI design decisions should be understood not only as technical decisions but also as decisions affected by individual and organizational conditions.

Second, we shed light on the underlying mechanisms explaining why AI developers' perceived accountability shapes their AI design decisions. Previous ISD research showed that perceived job autonomy could lead to unethical behavior (e.g., Lu et al., 2017; Zhou, 2020). These findings indicate the risk that AI developers can behave unethically in their AI design decisions while perceiving job autonomy. Especially in the context of AI-based systems, whose recommendations and outcomes potentially affect many users and are increasingly used in sensitive areas of life, unethical behavior is problematic (e.g., Berente et al., 2021; Martin, 2019a). In contrast, prior IS research emphasizes that perceived accountability can counteract unethical behavior (Martin, 2019b; Novelli et al., 2023; Vaast, 2022), indicating a trade-off between perceived job autonomy and perceived accountability concerning the effects of unethical behavior. Our study illustrates that perceived job autonomy depends on perceived accountability and can thus partially explain how AI developers' perceived accountability shapes their AI design decisions. Therefore, we show that AI developers' perceived accountability interferes with their self-determination and leads them to choose restrained AI design decisions. This finding is important, as it highlights that AI developers' perceived accountability affects their AI design decisions in a way that restricts creative and innovative behavior in designing AI-based systems. While this can help avoid ethical problems using AI-based systems, it also limits the technical progress that would expand the "frontier of computation" (Berente et al., 2021, p. 1434).

Practical Implications

Besides our theoretical contributions to ISD research, our study also offers practical implications. First, the results demonstrate that AI developers' perceived accountability is an essential factor affecting their AI design decisions and can serve as a control and governance mechanism in implementing ISD projects (Saunders et al., 2020). Nevertheless, it should be considered that this comes at the expense of creative and innovative behavior, which is why such goals might not be achieved. Organizations that want to design autonomous AI-based systems should limit their AI developers' accountability. Consequently, companies need to reconsider their decision-making processes and the responsibilities assigned to their AI developers to balance the trade-off between AI-based systems that should behave conservatively and systems that are close to the „frontier of computation" (Berente et al., 2021, p. 1434).

Second, accountability becomes increasingly important considering ethical aspects when developing AI-based systems, as AI developers' AI design decisions can be affected by their perceived accountability. The intention of AI developers to design their AI-based systems to be less inscrutable is important from an ethical perspective, as AI-based systems should become more transparent and explainable. In addition, AI developers tend to design their AI-based systems less autonomously, implying that their systems must be supervised by at least one human. Finally, AI developers advocate that their AI-based systems can learn to correct errors and bugs (e.g., ethical issues) independently. Thus, perceptions of accountability can contribute to companies developing more ethical AI-based systems by holding AI developers accountable for their AI-based systems. The demand for such systems is already part of regulatory requirements that companies can proactively address by increasing the perceived accountability of AI developers (e.g., European Commission, 2016).

Limitations and Further Research

Our study cannot be considered without the following limitations, which at the same time offer starting points for future research: First, we conducted a scenario-based survey. It should be mentioned that scenario-based surveys are limited in showing hypothetical behavior (e.g., Harrington, 1996; Teubner & Flath, 2019). Future studies should, therefore, extend this research by conducting field experiments in which real-world effects of AI developers' perceived accountability on their AI design decisions can be explored. Second, we addressed only the direct effects of the SDT's basic psychological need for autonomy. Therefore, examining the moderation effects between perceived accountability and perceived job autonomy could be part of further research to better understand the relationship between the two constructs. Third, our study examined a scenario of creating an AI-based system for banks to decide on customer loan applications. Thus, we only investigated a specific use case of AI-based systems. Future research could adapt the revealed effects shown in different application domains and contexts to highlight potential differences. This future research might also address how companies effectively balance AI developers' perceived accountability to address the trade-off between conservative and explorative AI-based systems. As a result, our study offers a starting point for further investigations to examine the effects of perceived accountability on AI developers' AI design decisions. Doing so would give ISD research and companies a more vital understanding of the significant effects of AI developers' perceived accountability.

Conclusion

This study illuminated how AI developers' perceived accountability affects their AI design decisions. The results indicate that AI developers tend to design conservative AI-based systems (i.e., less autonomous and inscrutable but more capable of learning) when they perceive themselves as accountable for their AI-based systems, and how their perceived job autonomy can explain this. These findings are important for ISD research as they explain why AI developers choose and want to develop a specific AI design.

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Appendix

Construct	Items
Perceived Accountability (Hochwarter et al., 2007)	I often have to explain why I do certain things regarding AI development. Top management holds me accountable for all of my AI development decisions. I am held accountable for the performance of the AI.
Perceived Job Autonomy (Rutner et al., 2008)	I expect from developing [AI-Name] ... ...that I will generally not have to refer matters to my direct supervisor for final AI development decisions. ... that my direct supervisor will usually do not have to approve my AI development decisions before I can act. ... that rather than asking my direct supervisor, I usually make my own AI development decisions about what to do on a job.
AI Design Decisions: Autonomy (Moore, 2000)	If [AI-Name] is to make suggestions for actions or decisions, it should be easy for humans to intervene. If [AI-Name] is to make an important decision that could impact humans, it should seek human feedback before.
AI Design Decisions: Inscrutability (Self-Created)	[AI-Name] should be transparent so that it can be scrutinized anytime. [AI-Name] should show humans the most important factors influencing a particular decision. I want to be able to trace the path to a particular decision based on [AI-Name's] code.
AI Design Decisions: Learning (Santhanam et al., 2008)	The opportunity for [AI-Name] to learn new things is important. The opportunity for [AI-Name] to evolve over time is important. The opportunity for [AI-Name] to extend its abilities is important. [AI-Name] should be designed to learn new concepts constantly.

Appendix A. Constructs and Items Used