Accountability-Based User Interface Design Artifacts and Their Implications for User Acceptance of AI-Enabled Services

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ACCOUNTABILITY-BASED USER INTERFACE DESIGN ARTIFACTS AND THEIR IMPLICATIONS FOR USER ACCEPTANCE OF AI-ENABLED SERVICES

Research Paper

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Abstract

Although services empowered by artificial intelligence (AI) have been demonstrated to provide reliable advice, users are often reluctant to follow this advice. One promising means to reduce this reluctance is increasing the degree to which users perceive accountability of the AI-enabled service (i.e., the system of AI, providers, and developers) for the provided advice. Drawing on the four core components of accountability theory (i.e., identifiability, expectation of evaluation, awareness of monitoring, and social presence), we designed four user-interface (UI) design artifacts. The results of a scenario-based factorial survey (N = 629) reveal that each UI design artifact raises users’ perceived accountability of the AI-enabled service, which in turn influences users’ intentions to follow the AI-enabled service’s advice. These findings provide important theoretical and practical insights, as they demonstrate that accountability-based UI design artifacts can increase user acceptance of AI-enabled services via the degree to which users perceive the AI-enabled services accountable.

Keywords: Accountability, User Interface, Following Advice, Factorial Survey.

1 Introduction

Artificial intelligence (AI) refers to machines performing cognitively demanding tasks, such as analyzing and deriving insights from large data sets, at a speed and accuracy that is similar to or even surpasses the levels of humans (e.g., Tschang and Mezquita, 2020, Jain et al., 2021, Rai et al., 2019). Moreover, the introduction of AI is often associated with, for example, higher performance, fewer errors, and lower costs (e.g., Glikson and Woolley, 2020, Daugherty and Wilson, 2018). As such, it is no surprise that half of businesses implemented some form of AI in 2020 and that AI is deployed in various applications, such as robots, autonomous vehicles, facial recognition, natural language processing, and virtual agents (e.g., Balakrishnan et al., 2020). Particularly in the context of healthcare, AI and related AI-enabled services, such as Pharmabot (Comendador et al., 2015), Mandy (Ni et al., 2017), and Babylon (NHS, 2021), are already recognized for providing accurate, reliable, and efficient medical advice directly to patients.

While the outlook of AI is promising, the related AI-enabled services (i.e., the system comprising of AI, providers, and developers) also pose unprecedented challenges and, thus, have yet to reach widespread acceptance, particularly from their users. One of the most considerable tensions that users face with AI-enabled services is that the AI’s processes are often invisible and incomprehensible, in that the AI does not and often cannot provide their users understandable explanations for its black-box-like processes and outcomes, sometimes not even to their providers and/or developers (e.g., Lindebaum et al., 2020, Ziewitz, 2016, Pasquale, 2015). Most critically, users cannot perceive to what degree the AI acts according to the intentions of the providers and/or developers and thus whether the AI-enabled services’ advice is in the
interest of the users, making it especially difficult if users are supposed to follow and realize the AI-enabled services’ advice. Hence, users often hesitate to follow the advice or even to accept the AI-enabled services at all, so that identifying how to master these challenges has become crucial for both research and practice.

Current approaches for raising user acceptance of AI-enabled services are mainly based on educational input to persuade users of the qualities (e.g., accuracy, reliability) of AI-enabled services (e.g., Longoni et al., 2019, Longoni and Cian, 2020). Yet, these educational approaches seem rather time-consuming and exhausting for users. One recently highly discussed means to thwart these downsides is to address the design of AI and of related AI-enabled services, particularly regarding the accountability for actions and outcomes (e.g., Martin, 2019, Berente et al., 2021, Mikalef et al., 2022). Accountability can hereby be defined as “the implicit or explicit pressure to justify one’s beliefs and actions to others” (Tadmor and Tetlock, 2009, p. 8). Indeed, previous studies demonstrated that users’ own accountability perceptions can influence their behaviors with information technologies (e.g., Stout et al., 2014, Vance et al., 2013, Vance et al., 2015). In the context of AI-enabled services, a user may be more inclined to accept an AI-enabled service’s advice if the user’s perceived accountability of that AI-enabled service increases. Yet, it is often unclear which entity involved in the AI-enabled service (e.g., provider, developer, AI) a user considers accountable for the AI’s processes and decisions (e.g., Baird and Maruping, 2021, Berente et al., 2021). Given the current expert consensus that AI (and technologies in general) is considered unable to be held accountable for its actions, the providers and/or developers of the AI are usually considered accountable (e.g., Rahwan et al., 2019, Benbya et al., 2021). This responsibility results from the fact that the providers and/or developers define how the AI and the related AI-enabled service are designed, implemented, and controlled and on what rationale the AI’s processes and decisions are built on (e.g., Martin, 2019). Yet, users do not necessarily consider providers and/or developers in interactions with AI, even perceiving AIs as agentic and mindful and thus potentially accountable on their own (e.g., Nass and Moon, 2000, Baird and Maruping, 2021). To account for these perceptual ambiguities from a user’s perspective, we apply a broad approach and focus on users’ perceived accountability of the overall AI-enabled service, defined as the system of all entities involved in the offering of the AI-enabled service (e.g., provider, developer, AI), and how users’ perceived accountability of the AI-enabled service affects users’ willingness to follow the AI-enabled service’s advice.

Because users receive their information and thus perceptions of the AI-enabled services primarily through user interfaces (UI), we focus on the accountability-based UI design for AI-enabled services. Previous IS research has already focused on the design of UIs, such as recommendation presentation (e.g., set size, sorting cues) (e.g., Tam and Ho, 2005, Komiak and Benbasat, 2006) and avatar features (e.g., anthropomorphism, explanation facility) (e.g., Qiu and Benbasat, 2009, Wang and Benbasat, 2007). Yet, scarce research on UI design shaping users’ accountability perceptions exists, whereby the existing few mainly focus on shaping users’ perceived own accountability and not that of others (i.e., the AI-enabled service) (e.g., Vance et al., 2013, Vance et al., 2015). Therefore, more research on accountability-based UI design is of theoretical interest and practical importance, particularly for AI-enabled services. In our study, we thus investigate how accountability-based UI design artifacts for AI-enabled services can be used to noninvasively increase users’ perceived accountability of the AI-enabled service and thus encourage users to follow the AI-enabled service’s advice. In particular, we intend to answer the following research question:

**RQ:** How can accountability-based UI design artifacts for AI-enabled services increase users’ perceived accountability of an AI-enabled service and thus users’ intentions to follow its advice?

To answer this research question, we drew on accountability theory (e.g., Tadmor and Tetlock, 2009) and tested accountability-based UI design artifacts for AI-enabled services based on the theory’s four core components: identifiability, expectation of evaluation, awareness of monitoring, and social presence. Through a scenario-based factorial survey method (N = 629), we show that all four accountability-based UI design artifacts individually raise users’ perceived accountability of the AI-enabled service, which increases users’ likelihood to follow the AI-enabled service’s advice.
With our insights, we answer several recent calls for research on the user acceptance and the design of AI and related AI-enabled services (e.g., Martin, 2019, Berente et al., 2021, Mikalef et al., 2022) and thus contribute to the usage and implementation of UI designs. The results extend previous research on UI design by showing that accountability theory can be applied to UI design to increase users’ perceived accountability of the AI-enabled service. Moreover, our research yields new insights into user acceptance of AI-enabled services and opens new directions for further developing UI design artifacts.

2 Accountability Theory

Accountability theory describes how the abstract need to justify one’s behavior to another party causes accountability for decisions and judgments (e.g., Tadmor and Tetlock, 2009). This perceived accountability, in turn, triggers systematic thinking about one’s behaviors, known as systematic processing (Crano and Prislin, 2006). Systematic processing involves deep cognitive processing and elaboration to make decisions (Lowry et al., 2012). When thinking systematically about decisions, people are more likely to consider multiple information sources to come to the optimal conclusion. This “thorough, in-depth, complete, and well-advised processing of all given information” (Wirth et al., 2007, p. 780) consequentially increases the priority on creating optimal outcomes for which one is held accountable. The increased awareness for the decision process caused by systematic processing has been linked to many positive outcomes, such as prosocial behaviors (e.g., Fandt and Ferris, 1990), conformity to expected behaviors (e.g., Tetlock et al., 1989), and conservatism (e.g., Staw, 1976).

In IS research, users’ perceived own accountability has been demonstrated, for example, to influence users to reduce their own accountability by delegating tasks to technologies, thus relying more on these technologies (e.g., Stout et al., 2014). We argue that AI-enabled services can use accountability-based UI design artifacts to signal that the AI-enabled service accounts for the AI and related AI-enabled service’s processes, actions, and decisions, so that users are more likely to follow the AI-enabled service’s advice. Accountability theory hereby proposes several components that each may increase perceived accountability (e.g., Tadmor and Tetlock, 2009), whereby four components are particularly core: (1) identifiability, (2) expectation of evaluation, (3) awareness of monitoring, and (4) social presence. Previous studies showed that these four core components could increase users’ perceived own accountability of their own actions and thus reduce misbehavior intentions in the context of access-policy violations (e.g., Vance et al., 2013, Vance et al., 2015). As such, it is promising and interesting to examine whether and how the four core components of accountability theory can be leveraged as UI design artifacts to influence users’ perceived accountability of others, namely the AI-enabled service. As a result, users’ increased perceived accountability of the AI-enabled service may decrease the tension around the question of responsibility and consequentiality for the black-box-like decision-making of AI and related AI-enabled services (e.g., Lindebaum et al., 2020, Benbya et al., 2021), so that the users’ increased perceived accountability of the AI-enabled service raises users’ intentions to follow the AI-enabled service’s advice. In the following, we present each of the four core components of accountability theory and subsequently derive the related hypotheses, respectively.

3 Accountability-based UI Design Artifacts and Hypotheses

Identifiability, “the participant’s knowledge that [their] outputs can be linked to [them]” (Williams et al., 1981, p. 309), is often considered the opposite to anonymity and an important deterrent of antisocial behavior (e.g., social loafing). Suppose a person is distinguishable from a group. In that case, the identifiability of the person to a powerful party increases the likelihood of the powerful party to practice resistance if the person engages in antisocial behavior (Reicher and Levine, 1994).
When an individual seeks advice from another human (e.g., a patient contacting a physician), the individual can recognize identifiers (e.g., name, face). If any issue occurs, the individual knows who is to be held accountable and can use the identifiers to refer to them. This is different from user-system interactions because the AI usually has no physical form and is thus disembodied. The AI-enabled service can use design elements in the UI (e.g., display of a unique registration number for the AI) to make the AI-enabled service identifiable to the users, empowering users to differentiate between various AI. If identifiability is integrated as a UI design artifact, users can explicitly refer to the AI and know that the AI-enabled service can identify the AI, thus increasing users’ perceived accountability of the AI-enabled service.

**H1: Identifiability raises users’ perceived accountability of the AI-enabled service.**

*Expectation of evaluation* refers to the expectation “that [one’s] performance will be assessed by another [party] according to some normative ground rules and with some implied consequences” (Lerner and Tetlock, 1999, p. 255). Typically, the expectation of evaluation creates accountability in an individual-level context and is named as a stressor in, for example, workplace situations due to evaluation apprehension (e.g., Hochwarter et al., 2007).

Current regulations propose that the actions and decisions of an AI can be evaluated with implicit consequences as “evaluation by internal and external auditors, and the availability of such evaluation reports, can contribute to the trustworthiness of the technology” (European Commission, 2020). An AI comprises several complex algorithms and can be perceived as a black-box by users. Users often cannot follow the decision process of the AI in contrast to a human whose decision process is easier and more intuitive for an individual to follow and relate to. Hence, to increase user compliance, a user needs to get the sense that the AI-enabled service can grasp and evaluate the processes of the AI somehow. For example, the AI-enabled service can use the UI to indicate that the AI is measured and evaluated based on its accuracy or reliability of the AI, so that an AI with bad decision-making can be adjusted or removed. Any neglect to deal with a badly behaving AI can thus be accounted back to the AI-enabled service. To give the user the sense that the AI-enabled service evaluates the AI and thus bears the consequences of its actions, the AI-enabled service can signal users the expectation of evaluation through UI design (e.g., dates and testimonies of previous evaluations). As such, we hypothesize that if the expectation of evaluation is integrated as a UI design artifact, users’ perceived accountability of the AI-enabled service increases.

**H2: Expectation of evaluation raises users’ perceived accountability of the AI-enabled service.**

*Awareness of monitoring* consists of a “supervisor’s physical or electronic presence” (Griffith, 1993, p. 551) that observes an individual’s activities. Especially an awareness of electronic or computer-based monitoring can be effective because activities can be recorded to a detailed level. Although *expectation of evaluation* and *awareness of monitoring* are listed separately in this paper, they complement each other (e.g., Griffith, 1993, Vance et al., 2015). Evaluation of an action can only occur if this action is monitored, and monitoring actions are ineffective if no consequences follow the recorded behavior. In practice, individuals who are aware of monitoring and subsequent evaluations have been found to have increased perceived accountability (e.g., Boss et al., 2009).

An AI-enabled service can use visual indicators in the UI (e.g., transaction logs, breadcrumb trails) to signal non-intrusively that the AI-enabled service monitors the AI and related processes and decisions and that it can use these records for later evaluations. If users perceive that the AI-enabled service monitors the AI, the user can expect that the AI-enabled service can be held more accountable for the provided advice. Overall, we hypothesize that if awareness of monitoring is integrated as a UI design artifact, users’ perceived accountability of the AI-enabled service increases.

**H3: Awareness of monitoring raises users’ perceived accountability of the AI-enabled service.**
**Social presence**, “the feeling, that other actors are jointly involved in … interactions” (Walther, 1992, p. 54), is often referred to as the perceived presence of another social being. This concept is closely related to *awareness of monitoring* as it consists of the expectation that another being observes the happenings (Lerner and Tetlock, 1999). Individuals usually tend to conform to public standards or norms when another person is present, even if the other person is not physically present (e.g., Guerin, 1986, Vance et al., 2013). Individuals perceiving a high degree of social presence assume that they may have to justify their actions to the other social beings and, consequently, may be held accountable for their behavior (Lerner and Tetlock, 1999). As such, social presence usually increases individuals’ perceived accountability.

Computer-mediated communication is usually considered low in social presence in contrast to face-to-face communication (e.g., Walther, 1992, Hassanein and Head, 2007). For instance, in the medical context, patients who are used to communicating face-to-face with their doctors might experience deprivation of social presence when interacting with an AI, resulting in a perception that the AI may act more disinhibited and careless. Moreover, there are no witnesses of the human-computer interaction or someone to turn to if the AI acts in undesired or unexpected ways. By including social presence as a UI design artifact (e.g., displaying green lamps to indicate that other users are online), an AI-enabled service can increase users’ perceived accountability of the AI-enabled service.

**H4: Social presence raises users’ perceived accountability of the AI-enabled service.**

What happens once the accountability-based UI artifacts have raised users’ perceived accountability of the AI-enabled service? We hypothesize that if accountability measures are implemented, users perceive that the AI-enabled service “ensure[s] responsibility and accountability for AI systems and their outcomes, both before and after their development, deployment and use” (European Commission, 2020). In conclusion, users’ perceived accountability of the AI-enabled service causes users to trust and rely on the AI-enabled service, resulting in users’ intentions to follow the AI-enabled service’s advice.

**H5: An increase in users’ perceived accountability of the AI-enabled service raises users’ intentions to follow the AI-enabled service’s advice.**

Finally, we propose a mediation hypothesis in that the effect of UI design artifacts on users’ intentions to follow the advice is mediated by users’ perceived accountability of the AI-enabled service. Previous studies have shown that attitude formation drives persuasion and forms intentions, which is the foundation of mainly all information processing models (e.g., Crano and Prislin, 2006). The mediation via accountability should exist because identifiability, expectation of evaluation, awareness of monitoring, and social presence individually impact users’ perceived accountability of the AI-enabled service, which consecutively impacts users’ intentions to follow (Lerner and Tetlock, 1999).

**H6: Users’ perceived accountability of the AI-enabled service mediates the effects of each of the UI design artifacts on users’ intentions to follow the AI-enabled service’s advice.**

Figure 1 depicts the hypotheses in the proposed accountability research model.
4 Research Methodology

4.1 Method

The factorial survey is a special form of the scenario method (Rossi, 1979). It especially fits for testing accountability theory because it combines the advantages of experimental designs with advantages of survey methods and considers heterogeneous respondent samples. From all possible factor combinations, which are called vignettes, a subset of vignettes is obtained. This subset of vignettes is then given to and rated by participants.

4.2 Experimental Design

Firstly, we created the scenario. We used patient consulting in healthcare as our context, as the employment of AI-enabled services in patient consulting can profoundly influence patients’ satisfaction with medical services, ranging from federal reimbursements to long-term financial sustainability (e.g., Longoni et al., 2019). We used the existing AI-enabled service Babylon (NHS, 2021) as inspiration to assure realism and generalizability. Babylon aims to offer quick and convenient medical care by automatically checking the patient’s symptoms and/or connecting patients with doctors.

We chose the scenario of a skin cancer prevention service because it is an important and necessary procedure for people of every age and gender, so that most people are familiar with this service. We did not vary the scenario during the study because previous research has already investigated the influence of different medical scenarios on the patient’s decision with no significant differences in the scenarios (e.g., Longoni et al., 2019). The scenario instructed the participants to imagine that they discovered an unusual-looking mole on their arm. Because their dermatologist had a month-long waiting time for an appointment, they would decide to use the free-of-charge skin cancer prevention AI their health insurance provides. This AI-enabled service consisted of a website where the participants were told that they had uploaded pictures of the worrying mole. The AI would then evaluate the pictures and try to identify harmful moles. Finally, the AI would give participants the advice to get the mole removed and to find a dermatologist close to them.

Secondly, following previous IS research on accountability (e.g., Vance et al., 2015, Vance et al., 2013), we developed the UI design artifacts for the graphical vignettes according to the core components of accountability theory: (1) identifiability, (2) expectation of evaluation, (3) awareness of monitoring, and (4) social presence (Figure 2). We used these four core components as independent variables in our study. In the graphical vignette, each of the components could be either present or not present. This resulted in a 2 x 2 x 2 x 2 – design and therefore 16 different graphical vignettes. All UI design artifacts were consistent
across the participants and only varied in their background color and positioning on the website. We implemented this variation to facilitate the distinction between the UI design artifacts and embedded each graphical vignette in a website design that simulated the scenario. In line with previous studies (e.g., Vance et al., 2013, Vance et al., 2015), we added labels on the side of the website design to facilitate recognition of the vignettes and related UI design artifacts. Each respondent received a pack of four randomly assigned vignettes and subsequently rated the accountability of the AI-enabled service and the participant’s intention to follow the AI-enabled service’s advice.

Note: Expectation of evaluation in the upper left quadrant; social presence in the upper right quadrant; awareness of monitoring in the lower left quadrant; and identifiability in the lower right quadrant

Figure 2. A Sample Graphical Vignette

Thirdly, the survey consisted of general items, pre-vignette items, and post-vignette items. Figure 3 shows the specified timeline of the survey. First, participants answered demographic and control questions (general items). Following, they rated their general perceptions of accountability of AI-enabled services, which was not closer specified (pre-vignette items). Next, they read and saw a graphical vignette. Then, they rated statements about the accountability of the AI-enabled service in the vignette they just saw and their intentions to follow the AI-enabled service’s advice (post-vignette items). This step was repeated four times.

Figure 3. Experimental Procedure
4.3 Measurement for Mediator and Dependent Variable

We used and adapted existing scales to measure our constructs. We measured perceived Accountability of the AI-enabled service (e.g., Hochwarter et al., 2005, Vance et al., 2015) and the Intention to Follow Advice from the AI-enabled service (McKnight and Chervany, 2001). See Appendix A for the exact items. We measured all items on a 7-point Likert-type scale, ranging from 1 (strongly disagree) to 7 (strongly agree). The final questionnaire consisted of 12 items (presented in Appendix A). Additionally, we measured demographics (i.e., gender, age, and education) and control variables, namely AI Knowledge (Flynn and Goldsmith, 1999), Personal Innovativeness (Agarwal and Prasad, 1998), Organizational Trust (Robinson, 1996), and Impulsivity (Pogarsky, 2004).

4.4 Data Collection and Sample

We conducted two pilot tests to ensure functionality and understanding of the scenarios and UIs. We collected the final dataset with Prolific (prolific.co), a crowdsourcing platform specifically designed for behavioral research and experiments. Research has demonstrated that Prolific exhibits high reliability and provides high-quality data (Palan and Schitter, 2018, Peer et al., 2017). Participants had to be U.S. citizens to ensure a good understanding of the English language and received monetary compensation for their participation. The data collection resulted in 200 participants. For the factorial survey, the level of interest was not the participant but the vignette. Hence, 200 participants rated 800 vignettes. Of those, participants correctly identified 629 in our attention checks. We used these 629 in the final data set to assure data quality. This resulted in a 78.63% rate of usable vignettes. The mean age of participants was 33.45 (12.563 standard deviation), 46% were females, and 60.5% had a Bachelor’s degree or higher.

4.5 Measurement Validation

To test the discriminant and convergent validity of the items, we performed a principal component analysis (PCA) with varimax rotation. It was of critical interest how the variables in each distinct stage of the causal model covary because we expected that the variables would correlate with their antecedents (Straub et al., 2004). Therefore, we did not include items that belonged to the dependent variable Intention to Follow Advice in the PCA analysis. Appendix B provides the results of the PCA analysis. Components with Eigenvalues greater than 1 were extracted, leading to five components matching the number of theoretical components we expected. All items loaded above 0.75 on their intended construct and hence showed strong convergent validity (Hair, 2009). Similarly, all items demonstrated excellent discriminant validity: Items did not cross load higher than 0.50 on any component they did not belong to. Finally, we tested the internal reliability of the items using Cronbach’s α. All constructs exhibited reliabilities of at least 0.80, indicating high reliability (Streiner, 2003). The results, along with the means, standard deviations, and bivariate correlations for the latent constructs, are in Appendix C.

5 Analysis

We conducted all analyses with the statistic software R. Each participant rated four graphical vignettes sequentially. Consequently, we correlated the four ratings with each other, resulting in a fixed individual effect. To account for the fixed and random effects in the data, we analyzed the data as a mixed effects model. We estimated the mixed effects models using a maximum likelihood estimation with the function lmer() from the library lme4. Of interest for the analyses was not the absolute value of accountability in the post-vignette measurement, but the margin of the post-vignette accountability value and the pre-vignette accountability value and is referred to in the following analysis as Delta Accountability.
5.1 Testing the Main Effects Model

We first tested H1–H4. These hypotheses stated that implementing the four core components of accountability theory as corresponding UI design artifacts raises Accountability and thus each integration of a UI design artifact increases Delta Accountability. This was tested by entering Delta Accountability as the dependent variable and the four UI design artifacts simultaneously as independent variables into a mixed effects model. Table 1 summarizes the results of the model. All four UI design artifacts displayed highly significant (p < 0.01) positive effects on Delta Accountability. Expectation of Evaluation displayed the highest effect, whereas Social Presence displayed the lowest effect. Thus, the findings support H1–H4.

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<th>Std. Error</th>
<th>t-value</th>
<th>Coefficient</th>
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Note: *p < 0.05, **p < 0.01, ***p < 0.001, n.s. = not significant; degrees of freedom: intercept = 200; all others = 629

Table 1. Effects of UI Design Artifacts on Delta Accountability

H5 stated that users’ perceived accountability of the AI-enabled service increases users’ intentions to follow the AI-enabled service’ advice. To model the effects, Intention to Follow Advice was entered as dependent variable and Delta Accountability as independent variable into the mixed effects model. Table 2 display the results of this model. As can be seen, Delta Accountability significantly increased the Intention to Follow Advice (p < 0.001), supporting H6.

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<td>-0.501 n.s.</td>
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<tr>
<td>AI knowledge</td>
<td></td>
<td></td>
<td></td>
<td>0.438</td>
<td>0.150</td>
<td>2.924**</td>
</tr>
<tr>
<td>Impulsivity</td>
<td></td>
<td></td>
<td></td>
<td>0.066</td>
<td>0.154</td>
<td>0.428 n.s.</td>
</tr>
<tr>
<td>Organizational trust</td>
<td></td>
<td></td>
<td></td>
<td>0.5327</td>
<td>0.174</td>
<td>3.028**</td>
</tr>
<tr>
<td>Marginal R²</td>
<td>0.246</td>
<td></td>
<td>0.275</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conditional R²</td>
<td>0.772</td>
<td></td>
<td>0.768</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>2879.830</td>
<td></td>
<td>2874.526</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p < 0.05, **p< 0.01, ***p < 0.001, n.s. = not significant; degrees of freedom: intercept = 200; all others = 629

Table 2. Effects of Delta Accountability on Intention to Follow Advice
5.2 Testing for Mediation

H6 states that Delta Accountability mediates the effects of the UI design artifacts on Intention to Follow Advice. We tested this hypothesis by using bootstrapping to construct confidence intervals of the mediation effects. Bootstrapping has a great statistical power and does not assume a normal distribution which are key advantages of this method. For the bootstrapping method, we evaluated three paths: Path a from the independent variables to the mediator, path b from the mediator to the dependent variable and path c from the independent variables to the dependent variable. Path a*b thereby depicts the mediation effect whereas path c depicts a direct effect without mediation.

The bootstrapping process involved resampling the collected data 5,000 times. In each resample, the coefficients of path a where multiplied with the coefficient of path b. The product is the estimate for the mediated effect on the dependent variable. Based on these resampled values, confidence intervals are calculated. If zero is not included in the path a*b confidence interval, it can be concluded with a 95% confidence that the effect is mediated. Next, path c is examined. If zero is not included in path c, it can be concluded with a 95% confidence that the independent variables have a direct effect on the dependent variable. Table 3 summarizes the results of the bootstrapping analysis.

The results show that Delta Accountability mediates all four effects of UI design artifacts on Intention to Follow Advice. Therefore, the effects of Identifiability, Expectation of Evaluation, Awareness of Monitoring, and Social Presence are explained by Delta Accountability, supporting H6.

<table>
<thead>
<tr>
<th></th>
<th>Path a*b</th>
<th>Path c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.5% lower bound</td>
<td>97.5% upper bound</td>
</tr>
<tr>
<td>Identifiability</td>
<td>0.231</td>
<td>0.617</td>
</tr>
<tr>
<td>Expectation of Evaluation</td>
<td>0.807</td>
<td>1.204</td>
</tr>
<tr>
<td>Awareness of Monitoring</td>
<td>0.471</td>
<td>0.864</td>
</tr>
<tr>
<td>Social Presence</td>
<td>0.113</td>
<td>0.502</td>
</tr>
</tbody>
</table>

Table 3. Bootstrapped Confidence Interval Tests for Mediation

6 Discussion

AI-enabled services promise various benefits but often face resistance from users. Little is known about how UI design artifacts can address users’ perceived accountability of an AI-enabled service and thus users’ intentions to follow the AI-enabled service’s advice. Our findings demonstrate that installing the four accountability-driven UI design artifacts (i.e., identifiability, expectation of evaluation, awareness of monitoring, and social presence) individually increases users’ perceived accountability of the AI-enabled service and thus the user’s intention to follow the AI-enabled service’s advice. Hereby, expectation of evaluation displayed the highest effect whereas social presence displayed the lowest effect. Thus, expectation of evaluation is likely the most important core component of accountability theory for the accountability-based UI design for AI-enabled services. Furthermore, a positive change in users’ perceived accountability significantly increased users’ intentions to follow the AI-enabled service’s advice, so that perceived accountability mediates the effects of each of the UI design artifacts on users’ intentions to follow the AI-enabled service’s advice.
6.1 Contributions to Theory and Practice

The present work makes two major research contributions, particularly to user acceptance and design of AI-enabled services (e.g., Martin, 2019, Berente et al., 2021, Mikalef et al., 2022).

First, we tested UI design artifacts based on the four core components of accountability theory to increase users’ perceived accountability of AI-enabled services. Previous research on the design of UIs has looked at, for example, recommendation presentation (e.g., set size, sorting cues) (e.g., Tam and Ho, 2005, Komiak and Benbasat, 2006) and avatar features (e.g., anthropomorphism, explanation facility) (e.g., Qiu and Benbasat, 2009, Wang and Benbasat, 2007). Some of these investigated how UI design can increase users’ own accountability perceptions (e.g., Vance et al., 2013, Vance et al., 2015). Our research extends and departs from previous research on UI design by reinforcing the idea that accountability-based UI design artifacts can effectively increase users’ perceived accountability of AI-enabled services. Moreover, contrary to previous education-based approaches requiring users to cognitively process and deliberate about potential benefits against their original attitude, the UI design artifacts are minimally intrusive, marginally time-consuming, and function as visual cues that do not require extensive reading. Moreover, our UI design artifacts can be implemented in many kinds of UIs, thereby having a vast scope of possible implementation use cases. We thus contribute to a better understanding of how UI design artifacts can increase users’ perceived accountability of others, demonstrating that accountability theory can be successfully transferred to the context of designing UIs for AI-enabled services.

Second, we revealed that users’ perceived accountability of an AI-enabled service increases users’ intentions to follow the AI-enabled service’s advice. Moreover, we demonstrate that users’ perceived accountability of the AI-enabled service mediates the effects of the UI design artifacts on users’ intention to follow the AI-enabled service’s advice. This aspect was crucial because we needed to determine whether the UI design artifacts influence the intention to follow advice via the construct of accountability or whether they influence intentions directly or through alternative explanations (e.g., media richness). The mediation analysis validates the central role of accountability as the key mechanism fostered by the four UI design artifacts. We, therefore, increase our understanding of how the users’ perceived accountability of an AI-enabled service can shape users’ intentions to follow the AI-enabled service’s advice. Hence, accountability-based UI design artifacts are compelling means to increase user acceptance of AI-enabled services.

Regarding practical implications, the implementation of accountability UI design artifacts increased users’ intentions to follow an AI-enabled service’s advice. This plays an immense role for the successful implementation of AI-enabled services. Besides higher performance and cost-efficiency, AI-enabled services promise to improve user satisfaction if users accept the AI-enabled service. This is particularly true in the context of healthcare-related services, where the implementation of AI-enabled services can improve several critical outcomes for institutions, such as federal reimbursements or long-term financial sustainability. Yet, AI-enabled services still struggle to realize their full potential because of users’ resistance and hesitation to use these services. Issues remain regarding unclear responsibilities for actions, lack of responding mechanisms to unintended AI actions, and “no-fault” policies in cases of AI making wrong and even harmful decisions (e.g., Mikalef et al., 2022). By providing actionable and easily implementable accountability-based UI design artifacts, we provide providers and developers of AI-enabled services tools to overcome existing challenges regarding user acceptance and design of AI-enabled services. Moreover, these accountability-based UI design elements can function as inspiration on how to make AI-enabled services generally more accountable beyond mere UI design.


6.2 Limitations and Directions for Future Research

Despite the promising methods and data of the study, our research is not without limitations. First, we examined intentions rather than actual behaviors. Hence, future research should conduct a field study measuring users’ behaviors to test and validate the presented model. Furthermore, the actual realization of the accountability-based UI design artifact should be investigated and how users react once an incident or violation happens. Second, the UI design artifacts should be tested for potential interaction effects on both users’ perceived accountability of the AI-enabled service and their intentions to follow the given advice. Third, future research may investigate whether a differentiation between the accountabilities of the individual entities in the AI-enabled service (e.g., provider, developer, AI) are relevant and whether the implementation of these UI design artifacts even influences these entities’ actual (ethical) behaviors. In the same vein, the ethics of boosting perceived accountability through UI design artifacts should be fleshed out. This is important as the presented accountability UI design elements should not only be presented visually to maximize user acceptance but actually technically realized and enforced to guarantee their implicit ethical promises. Fourth, our participants were U.S. citizens. Thus, further research might want to investigate whether cultural differences play a role in users’ perceived accountability and acceptance of AI-enabled services. Moreover, the group of participants largely consisted of young and presumably healthy people. Since older people have a higher chance of getting ill and hence place a greater burden on the healthcare system, it should be examined whether a more specific target group of patients has significantly different values of accepting advice from AI-enabled services. Lastly, the study was conducted in a medical scenario. Thus, future research could use accountability theory to counteract issues of user acceptance of AI-enabled services in and beyond medical contexts, such as autonomous vehicles or smart home assistants.
Appendix

Construct | Items
--- | ---
Perceived Accountability of the Service (Hochwarter et al. 2005; Vance et al. 2015) | I believe that the AI-based service is accountable for its actions.
I believe that the AI-based service would be accountable for its actions.
I would hold the AI-based service accountable for its actions.
The health insurance would hold the AI-based service accountable for its decisions.
If things in the AI-based service do not go the way that they should, I would likely hear about it from the health insurance.
Doctors and the health insurance would closely scrutinize the AI-based service's efforts.

Intention to Follow Advice (McKnight and Chervany 2002) | I would feel comfortable acting on the information given to me by the AI-based service.
I would not hesitate to use the information the AI-based service supplied me.
I would confidently act on the information I was given by the AI-based service.
I would feel secure in using the medical information from the AI-based service.
When an important medical issue arises, I would feel comfortable depending on the information provided by the AI-based service.
I feel that I could count on the AI-based service to help with a medical problem.
I can rely on the AI-based service in a tough medical situation.

Appendix A. Construct Measures of Main Variables

<table>
<thead>
<tr>
<th>Items</th>
<th>Components</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Delta Accountability 1</td>
<td>0.758</td>
</tr>
<tr>
<td>Delta Accountability 2</td>
<td>0.926</td>
</tr>
<tr>
<td>Delta Accountability 3</td>
<td>0.898</td>
</tr>
<tr>
<td>Delta Accountability 4</td>
<td>0.884</td>
</tr>
<tr>
<td>Delta Accountability 5</td>
<td>0.861</td>
</tr>
<tr>
<td>AI Knowledge 1</td>
<td>0.852</td>
</tr>
<tr>
<td>AI Knowledge 2</td>
<td>0.899</td>
</tr>
<tr>
<td>AI Knowledge 3</td>
<td>0.768</td>
</tr>
<tr>
<td>AI Knowledge 4</td>
<td>0.887</td>
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<tr>
<td>Impulsivity 1</td>
<td>0.869</td>
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<tr>
<td>Impulsivity 2</td>
<td>0.870</td>
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<tr>
<td>Impulsivity 3</td>
<td>0.657</td>
</tr>
<tr>
<td>Impulsivity 4</td>
<td>0.884</td>
</tr>
<tr>
<td>Organizational Trust 1</td>
<td>0.893</td>
</tr>
<tr>
<td>Organizational Trust 2</td>
<td>0.865</td>
</tr>
<tr>
<td>Organizational Trust 3</td>
<td>0.888</td>
</tr>
<tr>
<td>Innovativeness 1</td>
<td>0.842</td>
</tr>
<tr>
<td>Innovativeness 2</td>
<td>0.748</td>
</tr>
<tr>
<td>Innovativeness 3</td>
<td>0.875</td>
</tr>
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Appendix B. Results of Principle Components Analysis

<table>
<thead>
<tr>
<th>Latent construct</th>
<th>Mean</th>
<th>SD</th>
<th>α</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intention to Follow Advice (1)</td>
<td>4.074</td>
<td>1.610</td>
<td>0.959</td>
<td>*</td>
<td></td>
<td></td>
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<tr>
<td>Delta Accountability (2)</td>
<td>0.467</td>
<td>1.885</td>
<td>0.923</td>
<td>0.142**</td>
<td>0.867</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Impulsivity (3)</td>
<td>3.224</td>
<td>1.251</td>
<td>0.845</td>
<td>0.001</td>
<td>0.081*</td>
<td>0.825</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational Trust (4)</td>
<td>5.058</td>
<td>1.125</td>
<td>0.872</td>
<td>0.165**</td>
<td>-0.049</td>
<td>-0.116**</td>
<td>0.882</td>
<td></td>
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</tr>
<tr>
<td>Personal Innovativeness (5)</td>
<td>4.897</td>
<td>1.334</td>
<td>0.817</td>
<td>0.081*</td>
<td>-0.121**</td>
<td>-0.029</td>
<td>-0.261**</td>
<td>0.823</td>
<td></td>
</tr>
<tr>
<td>AI Knowledge (6)</td>
<td>4.552</td>
<td>1.451</td>
<td>0.906</td>
<td>0.129**</td>
<td>-0.264**</td>
<td>-0.057</td>
<td>0.190**</td>
<td>0.439**</td>
<td>0.853</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01; α = Cronbach’s alpha; SD = Standard deviation; square root of AVE in bolded cells

Appendix C. Means, Standard Deviations, Cronbach’s Alpha and Construct Correlations
References


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*Adam / Accountability-Based User Interface Design Artifacts

Thirtieth European Conference on Information Systems (ECIS 2022), Timisoara, Romania*


