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The Threats of Artificial Intelligence Scale (TAI)

Development, Measurement and Test Over Three Application Domains

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Abstract
In recent years Artificial Intelligence (AI) has gained much popularity, with the scientific community as well as with the public. Often, AI is ascribed many positive impacts for different social domains such as medicine and the economy. On the other side, there is also growing concern about its precarious impact on society and individuals, respectively. Several opinion polls frequently query the public fear of autonomous robots and artificial intelligence, a phenomenon coming also into scholarly focus. As potential threat perceptions arguably vary with regard to the reach and consequences of AI functionalities and the domain of application, research still lacks necessary precision of a respective measurement that allows for wide-spread research applicability. We propose a fine-grained scale to measure threat perceptions of AI that accounts for four functional classes of AI systems and is applicable to various domains of AI applications. Using a standardized questionnaire in a survey study (N = 891), we evaluate the scale over three distinct AI domains (medical treatment, job recruitment, and loan origination). The data support the dimensional structure of the proposed Threats of AI (TAI) scale as well as the internal consistency and factoral validity of the indicators. Implications of the results and the empirical application of the scale are discussed in detail. Recommendations for further empirical use of the TAI scale are provided.

Keywords Threat perceptions · Artificial intelligence · Fear · Scale development

1 Introduction

In recent years, applications making use of Artificial Intelligence (AI) have gained re-newed popular interest. Expectations that AI might change the face of various life domains for the better are abundant [1–3]. Be it medicine, mobility, scientific progress, the economy, or politics; hopes are that AI will increase the veracity of input, effectiveness and efficiency of procedures as well as the overall quality of outcomes. Irrespective whether changes apply to the workplace, public management, industries producing goods and services as well as private life: As usual with the diffusion of new technologies there is tremendous uncertainty as to how exactly developments will play out [4], what social consequences will manifest and to what extent respective expectations of stakeholders and societal groups will materialize. Oftentimes, there will be some people that immensely profit from socio-technological innovations, while others are left behind and cannot cope with the unfolding of events [5]. Thus, whenever new technologies bring about social change, the success of their implementation or failure depends upon the reaction of the affected people. People might happily accept new technology, they might not care nor use it at all, or they may even show severe reactance towards it [6]. There is first empirical evidence suggesting that the general public itself shows some considerable restraint when it comes to the broad societal diffusion of AI applications or robots that might even border on actual fear of such technology [7–9]. However, as fear and respective threat perceptions are presuppositional theoretical constructs, they necessitate a more fine-grained approach that goes beyond broad claims of concerns or even fear regarding autonomous systems.

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Accordingly, in this paper, we argue for an improved assessment of the perceived threats of AI and propose a survey scale to measure these threat perceptions. First, a broadly usable measurement would need to address perceived threats of AI as a precondition to any actual fear experienced. This conceptual difference is subsequently based on the literature on fear and fear appeals. Second, the perceived threat of AI would need to take into account the context-dependency of respective fears as most real-world applications of AI are highly domain-specific. AI that assists in the medical treatment of a person's disease might be perceived vastly different from an AI that takes over their job. Third, not only do perceptions hinge on the domain in which people encounter AI applications, it would also be necessary to differentiate between the extent of an AI's actual autonomy and reach in inflicting consequences upon a person. Thus, it needs to be asked to what extent the AI is merely used for analysis of a given situation, or going even further, whether the AI is used to actively give suggestions or even making autonomous decisions.

As the field of application is crucial for the mechanism and effects of threat perceptions concerning AI, any standardized survey measure needs to be somewhat flexible and individually adaptable to accommodate the necessities of a broad application that considers AI's functions and the context of implementation. That is why our scale construction opts for a design that can easily be adapted to varying research interests of AI scholars.

Consequently, we developed a scale addressing threats of AI that takes into account such necessary distinctions and subsequently tested the proposed measure for three domains (i.e. loan origination, job recruitment and medical treatment that are subject to an AI application) in an online survey with German citizens. In our proposed measure of perceived threats of AI, we aim to cover all aspects of AI functionality and make it applicable to various societal fields, where AI applications are used. Thereby, we highlight three contributions of our scale, that are addressed in the following:

(1) We underpin our scale development theoretically by connecting it with the psychological literature on fear appeals.
(2) The construction of the scale differentiates between the discrete functionalities of AI that may cause different emotional reactions.
(3) Moreover, we consider perceived threats of AI as dependent on the context of the AI's implementation. This means that any measure must pay respect to AI's domain-specificity.

The collected data supports the factorial structure of the proposed TAI scale. Furthermore, results show that people differentiate between distinct AI functionalities, in that, the extent of the functional reach and autonomy of an AI application evoke different degrees of threat perceptions irrespective of domain. Still, such distinct perceptions do also differ between the domains tested. For instance, recognition and prediction with regard to a physical ailment as well as the recommendation for a specific therapy made by an AI do not evoke substantial threat perceptions. Contrarily, autonomous decision-making in which an AI unilaterally decides on the proscribed treatment was met with relatively bigger apprehension. At the same time, the application of AI in medical treatment was generally perceived as less fearsome than situations where AI applications are used to screen applicants on a job or a financial loan.

Eventually, to measure construct validity, we assessed the effects of the *Threats of Artificial Intelligence* (TAI) scale on emotional fear. Threat perceptions are a necessary, but not sufficient prerequisite to fear. While most research directly focuses on fear, we will subsequently argue for the benefits of addressing the preceding threat perceptions. Ultimately, the threat perceptions do in fact trigger emotional fear. Lastly, we discuss the adoption and use of the TAI scale in survey questionnaires and make suggestions for its application in empirical research as well as general managerial recommendations with regard to public concerns of AI.

2 Public Perceptions of Recent Developments in Artificial Intelligence

In recent years there has been a somewhat re-newed interest in applications of AI based on recent developments in computer technology that allows for use of extensive processing power and the analysis of vast amounts of so-called Big Data applications of Machine Learning, Deep Learning and Neural Networks. Such applications gather under the label of AI, which is ascribed a huge impact on society as a whole [10]. Thereby, AI has especially seen widespread use in business and public management [11]. As a consequence, the public discourse regarding AI is mainly driven by companies that provide AI technology looking for customers and markets for their products [1,12,13]. Meanwhile, empirical evidence from survey research supports the assumption that AI is not per se perceived as entirely positive by the public. A cross-national survey by Kelley et al. [10] shows that AI is connected with positive expectations in the field of medicine, but reservations are prevalent concerning data privacy and job loss. Another concern is raised by Araujo et al. [14], who state that citizens perceive high risks regarding decision-making AI. Moreover, a representative opinion poll by Zhang and Dafoe [15] illustrates that Americans as well as citizens from the European Union (EU) believe that robots and AI could have harmful consequences for societies and should be carefully managed. Additionally, Gnambs and Appel [16] show that attitudes towards robots have recently changed for the worse in the EU. Especially, when it comes to the influence of robots in the economy and the substitution of workforce, people express fear [7,9]. On a broader level, a recent study by Liang and Lee [8] inquiring about the fear of AI even found that a considerable amount of all Americans reported fears when it comes to autonomous robots and AI.

3 Measuring the Fear of Autonomous Robots and Artificial Intelligence

Using data from the Chapman Survey of American Fears, Liang and Lee [8] set out to investigate the prevalence of *fear of autonomous robots and artificial intelligence* (FARAI). They come to the conclusion that roughly a quarter of the US population experienced a heightened level of FARAI. In the respective study, participants were confronted with the question "How afraid are you of the following?". The FARAI-scale was afterwards built out of these four items: (1) "Robots that can make their own decisions and take their own actions,", (2) "Robots replacing people in the work-force", (3) "Artificial intelligence" and (4) "People trusting artificial intelligence to do work". All items were rated on a four-point Likert scale with answers ranging from "not afraid (1), slightly afraid (2), afraid (3), to very afraid (4)" [8].

While the authors shed some first light in addressing threat perceptions of artificial intelligence and generate valuable insights into various associations of FARAI with demographic and personal characteristics, there is also need for a potential enhancement of the existing measurement of FARAI. As the FARAI scale was developed out of a broad questionnaire concerning many possible fears people in the US might have, the measurement was not specifically developed for measuring the distinctive fear of robots and AI, respectively. The FARAI scale also varies in its scope. While item 3 broadly queries the fear of AI in general, item 2 specifically inquiries about its specific impacts on the economic sector. Items 1 and 4 query a specific functionality of AI, with item 4 focusing on the human-machine connection. Thus, the items are mixed in their expressiveness and aim at different aspects of AI's impact. Accordingly, the scale does not allow for distinct assessments of AI and necessary specifications concerning its domain of application and the employed functions.

Besides, the public understanding of robots and AI might be influenced by popular imaginations from pop-culture, science-fiction, and the media, as is also already implied by Liang and Lee [8] and Laakasuo et al. [17]. Due to the popularity of vastly different types of autonomous robots and AI in literature, film and comics, it is hard to pin down what exactly comes to a person's mind inquired about both terms. Delineating boundaries may not be possible when it comes to the public imagination. As a survey research in the UK by Cave et al. [18] suggests, a quarter of the British population conflates the term AI with robots. Accordingly, a conceptual clarification concerning the distinction between the terms *robot* and *artificial intelligence* is required to begin with. In the FARAI measure by Liang and Lee [8], there is a mixture between both terms as two question items focus on each term, respectively. This terminological distinction is often conflated in empirical research [19]. We believe that the mixture of the terms might lead to avoidable ambiguity and maybe even confusion, since people may think of two distinct and even completely different phenomena or might not be able to distinguish between the two constructs at all. According to the Oxford English Dictionary a robot is "an intelligent artificial being typically made of metal and resembling in some way a human or other animal" or "a machine capable of automatically carrying out a complex series of movements, esp. one which is programmable" while AI is "the capacity of computers or other machines to exhibit or simulate intelligent behaviour". There is certainly some conceptual overlap by definition, especially with regard to the capacity of intelligent behavior demonstrated by an artificial construct, hence, something that does not exist naturally, but is human-made. It also cannot be ruled out that appraisal of robots may be strongly associated with AI, especially when such robots are depicted as autonomous.

Recently, the term AI, particularly, has renewedly received widespread attention and describes techniques from computer science that gather many different concepts like *machine learning*, *deep learning* or *neural networks*, which are the basis of autonomous functionality and pervasive implementation. As a consequence, we decided to focus our measurement solely on AI as it depicts the core issue of the nascent technology, i.e. autonomous intelligent behavior, which applies to many use cases that do not necessarily include a physical machine in motion.

4 Threat Perceptions as Precondition of Fear

There is plenty of literature on the subject of fear, especially from the field of human psychology. Altogether, fear is defined as a negative emotion that is aroused in response to a perceived threat [20]. When it comes to the origins of emotion, many studies rely on the appraisal theory of emotion: "The appraisal task for the person is to evaluate perceived circumstances in terms of a relatively small number of categories of adaptional significance, corresponding to different types of benefit or harm, each with different implications for coping" [21]. Accordingly, the authors define relational themes for different emotions. According to Smith and Lazarus [21] anxiety, respectively fear, is evoked, when people perceive an ambiguous danger or threat, which is motivationally relevant as well as incongruent to their goals. Thereby, a threat is seen as an "environmental characteristic that represents something that portends negative consequences for the individuum" [22]. Furthermore, people perceive low or uncertain coping potential. In other words: Fear is the result of a persons' appraisal process, where a situation or an object is perceived as threatening and relevant as well as no avoiding potential can be seen. If theses appraisals are processed, people react with fear and try to avoid the threat [21], i.e. in turning away from the object.

Many scholars build on appraisal theory to develop more specified theories on the mechanisms of fear. Especially in health communication much work on so called fear appeal literature has been done [22,23]. In a nutshell, most fear appeal theories state that a specific object, event or situation (e.g., a disease) threatens the well-being of a person [24,25]. With the development of the Extended Parallel Process Model (EPPM), Witte [25] theorizes that this threat is at first processed cognitively. Thereby, severity and susceptibility of the threat as well as coping potential (self and general), i.e. the amount of efficacy [25] respectively control [26], is rated. Depending on the weights of these cognitive apprehensions, people react differently. Fear emerges, when the threat perception is high, while the coping perception is low. As a result, message denial arises that is mostly characterized by avoiding the threat. On the other hand, when threat as well as coping potential are perceived as high, message acceptance results. If this happens, people actively engage with the threat, for example in gathering information about the threat or actively combating potential harms. In this case, fear does not emerge. Whereas the empirical examination of the EPPM found no clear proof [27] and many suggestions for extending the model have been made [28,29], scholars agree upon the central persuasion effects of threat and coping perceptions [30]. Moreover, the EPPM commonly serves as a framework for further research [31].

Transferred to the subject of perceived threats of AI, we belief that AI is best described as an environmental factor that might cause fear. However, AI should not be treated as a specific fear itself. In our view, fear may be a result of a cognitive appraisal process, where AI depicts a potential threat origin. Thus, we explicitly focus on threats of AI, not fear of AI. This idea becomes more prevalent in thinking about an actual situation. For example, a person is confronted with an AI system that decides over an approval of a credit. This person most likely will not be afraid of the computer system, but will rather evaluate cognitively the threat that such a system might pose to its well-being. The person then rates the probability of the system causing harm (e.g., if it denies the credit). If the outcome of this process ends in a negative evaluation for the person, fear will be evoked. However, this fear is based on the threat the AI systems poses and not on the AI system itself. This is crucial for our understanding of threats of AI.

5 Context Specificity of Threat Perceptions

It is also important to address the social situation, in which a threat is perceived. Smith and Lazarus [21] already stated that an "appraisal can, of course, change (1) as the person-environment relationship changes; (2) in consequence of self-protective coping activity (e.g. emotion-focused coping); (3) in consequence of changing social structures and culturally based values and meanings; or (4) when personality changes, as when goals or beliefs are abandoned as unservicable". Furthermore, Tudor [32] proposed a sociological approach for the understanding of fear. He developed a concept, in which he distinguishes parameters of fear including environments, cultures as well as social structures.

Thereby, contexts can vary in manifold ways. A rather simple example for what Tudor [32] refers to as an environmental context is the case of the wild animal: for instance, a tiger could face a human being; however, arguably there is a huge difference in fear reaction if one is confronted with the tiger in a zoo or in its natural habitat. Thus, the environmental factor "cage" does have a huge impact on the incitement of fear. Additionally, cultural backgrounds can affect the way threats are perceived: "If our cultures repeatedly warn us that this kind of activity is dangerous, or that sort of situation is likely to lead to trouble, then this provides the soil in which fearfulness may grow" [32]. Lastly, social structures described that the societal role of an individual might influence threat perceptions. For instance, that could be the job position of an employee or just the belonging to a specific societal group.

Furthermore, different social actors are able to influence the social construction of public fears, i.e. if and how environmental stimuli are treated as threats [26]. According to Dehne [26], the creation of fear, among other factors, is dependent upon transmission of information in a society. In that, especially scientific, economic, political and media actors affect the social construction of threats. However, depending on the actors that take the highest share in the public discourse, different threat perceptions might emerge. For instance, given an AI application in medicine, we assume that science as well as media lead the debate. On the other hand, an AI application in the field of recruiting will probably be led by economic actors. It is plausible that there are specific context dependencies (who informs the public about a specific AI application) that have an influence on (threat) perceptions.

In summary, there are many (social) factors that shape the way emotions are elicited leading to the conclusion that threat perceptions heavily rely on the context in which an individual encounters AI. Of course, we are not able to cover all possible contexts of AI related threats. However, we distinguish two context groups, which are important for the understanding of TAI: AI functionality and distinct domains of AI applications.

5.1 Distinct Dimensions of AI Functionality

What an AI is capable or supposed to do may have a decisive effect on the appraisal of AI applications. However, AI is a generic term that unites many different functionalities. In the scientific community, there are manifold definitions on the term AI and what can and what cannot be counted as an AI system. Whereas there is not one definition, most scholars agree upon central functionalities AI systems can perform. Nevertheless, there is no consensus upon how to group these functionalities. For example, Hofmann et al. [33], identify perceiving, identification, reasoning, predicting, decision-making, generating and acting as AI functions. Though, we base our approach on the periodic systems of AI [34] and group AI functionalities into four categories, which undoubtedly intersect each other: recognition, prediction, recommendation and decision-making.

Noteworthy, our approach is quite similar to Hofmann et al. [33]: however, we subsumed generating and acting into the category of decision-making as we focus on AI that act autonomously in that category. Additionally, we added perceiving and identification into one category: This decision was based upon the results of a pre-test of the scale, which we conducted with 304 participants. Our results show that participants could not differentiate between the perceiving and identification function.

In the following, we elaborate on our proposed AI function classes:

5.1.1 Recognition

Recognition describes the task of analyzing input data in various forms (e.g., images, audio) and recognizing specific patterns in the data. Depending on the application, these patterns can vary hugely. In a health application, AI recognition is used to detect and identify breast cancer [35]. In the economic sector AI systems promise to detect (personal) characteristics and abilities of potential employees via their voices and / or faces [36].

5.1.2 Prediction

In prediction tasks, AI applications prognose future conditions on the basis of the analyzed data. It differentiates from recognition in forecasting developments of specific states, whereas recognition mostly classifies the given data. In the medical sector, a AI applications are able to calculate the further development of diseases on basis of medical diagnoses and (statistical) reports [37].

5.1.3 Recommendation

Recommendation describes a task in the field of human-computer interaction. Thereby, AI systems directly engage with humans, mostly decision makers, in recommending specific actions. These actions are again highly dependent on the actual application field. For the medical example this could mean that the AI application, which takes into account all given data, proposes a medical treatment to the doctor [38]. Noteworthy, the decision to accept or decline this suggestion is still made by the physician or the patient, respectively.

5.1.4 Decision-Making

Ultimately, the functionality decision-making refers to AI systems that operate autonomously. Oftentimes, these applications are also called algorithmic decision-making (ADM) systems. Hereby, AI systems learn and act autonomously after being carefully trained by developers. The most prominent application is with no doubt autonomous driving [39]. However, decision-making tasks can also be found in other domains of application. For example, in medicine AI systems could directly decide over medical treatments of patients; in the higher education sector ADM could decide about the admissions of students' applications to university [40]. Concerning the human-computer interaction an ADM substitutes the human task completely.

Noteworthy, two points are important to mention. Firstly, the functionalities can depend on each other and are thus not completely separable. Secondly, AI applications in specific fields do not necessarily have to fulfill all AI functionalities. Mostly, AI systems just perform one task while not providing the other ones. We stress that threat perceptions of AI - in technical terms - should not be treated as a second-order factor. Rather our scale deploys a toolbox which can be used to cover threat perceptions of the different functionalities. However, we expect that there are significant correlations between the functionalities. In conclusion, we pose the following research question:

RQ1: Do respondents have distinct threat perceptions regarding the different functions AI systems perform?

5.2 Distinct Domains of AI Application

As usual, social science research addresses the social change induced by technological phenomena and artifacts in various domains of public and private life. Depending on the domain of application, AI may be wholeheartedly welcomed or seen as a severe threat [19,41]. For instance, imagining to hand over certain decisions to an AI may appear rather innocuous for certain lifestyle choices such as buying a product or taking a faster route to a destination, but may lead to reactance when perceived individual stakes are high, e.g. when AI interferes in life altering decisions that affect one's health or career decisions. As applications of AI are expected to get implemented in manifold life domains, research will need to address the respective perceptions of the people affected. The domain specificity of effects is already an established approach in social science research; for instance Acquisti et al. [42] as well as Bol et al. [43] found that distinct application domains do matter in terms of online privacy behavior. Additionally, Araujo et al. [14] analyzed perceptions of automated decision-making AI in three distinct domains. Thus, we believe that a measurement of threat perceptions also needs to be adaptable to a multi-faceted universe of AI related phenomena, some of which might not even be known to date. Concludingly, we propose a measurement that is adaptable to every AI domain. As follows, the proposed TAI scale is tested in three different domains, namely loan origination, job recruitment, and medical treatment.

5.2.1 Loan Origination: Assessing Creditworthiness

AI technologies are already applied in the finance sector, i.e. in credit approval [44]. As credit approval is a more or less mathematical problem, it is reasonable that AI based algorithms are applied for this purpose. The algorithms used analyze customer data and calculate potential payment defaults - and finally can decide, whether a credit is approved. As individual goals greatly depend on such decisions, it may pose a threat for individuals, who believe that their input data might be deficient or assume that the processing biased.

5.2.2 Job Recruitment: Assessing the Qualification and Aptitude of Applicants

Recently, AI applications have been applied to the field of human resource management, i.e. recruiting [45]. More specifically, AI can be used to analyze and predict performance of employees. Furthermore, AI based systems are able to recommend or select potential job candidates [46]. However, there are several potential risks of the use of AI systems in human resource management. For instance, algorithms based on existing job performance data may be biased and lead to discrimination of specific population groups [45,47].

5.2.3 Health: Medical Treatment of Diseases

One of the most important fields of AI development and implementation is with no doubt health care/medicine [48]. Especially, in fields where imaging techniques are applied (e.g., radiology) AI applications are frequently used [49]. Recent works show that AI applications are especially appropriate to detect and classify specific diseases, for example breast or skin cancer, in X-ray images [48,49]. Moreover, another AI application can identify gene-related diseases in face images of patients [50]. Generally, people tend to have optimistic perceptions of the use of AI in medicine [10].

Summing up, it may be assumed that distinct domains of AI application cause different threat perceptions. As mentioned earlier, a possible explanatory approach is that the public discourse, through which individuals are mostly confronted with AI, is led by different actor groups. Another reason to believe that domains do vary is the actual tasks AI systems perform and which severity individuals ascribe to them. Presumably, also personal relevance appraisals play a major role in the level of threat individuals ascribe to distinct domains. An individual, who does not plan to apply for a credit will probably rate the use of an AI system for credit approval as less threatening than a person who is in dire need of a loan. Arguably, we can only focus on a small sample of potential AI domains. In conclusion, we formulate the following hypothesis:

H1: Threat perceptions of AI differ between distinct domains of AI application.

6 Fear Reactions Towards AI

As outlined in Sect. 4, perceived threats of AI are a precondition of emotional (fear) reactions. Thus, we assume that threat perceptions concerning AI actually trigger fear reactions. Accordingly, hypothesis 2 reads as followed.

H2: Threat perceptions of AI induce fear among respondents.

As threat perceptions of AI functionalities and domains may differ vastly from each other, we are interested in whether the amount of perceived fear (if any) that is explained by our proposed measure also differs by context. Arguably, not all threat perceptions necessarily need to cause the same fear reactions. For instance, if subjects perceive high levels of efficacy in dealing with the potential threat, a far less strong emotional reaction is likely to occur [25]. This becomes particularly obvious, when comparing the recommendation and the decision-making functionality. Decision-making AI takes control away from the individual, whereas in recommendation at least an (other) human still has control over the process.

Therefore, we test whether the measure is able to capture induced fear reactions across the different contexts and whether these differ. Accordingly, we pose and address the following research question:

RQ2: Does the influence of threat perceptions of AI on fear differ between contexts?

7 Method

Accordingly, we set out to develop a measurement scale for the application in survey research on AI that addresses the threat perceptions of people that are confronted with various forms of AI implementation. Here, we explicitly emphasize that the proposed scale addresses the *perceptions* of individuals. Hence, it is not of much concern what an AI system actually does on a technical level, but how different ideal functionalities are seen in the eyes of respondents that usually do not have much knowledge about AI technology. The scale must be applicable with regards to the respondents and their individual imaginations of AI to show validity when it comes to threat perceptions. Again, this must not be coherent with the "technical"/"mathematical" level of actual AI systems. Rather respondents need only to differentiate between the observable functions AI systems perform.

Thus, the aim is to reliably and validly assess the extent to which respondents perceive autonomous systems as a threat to themselves. Moreover, the scale needs to be standardized allowing for comparisons between samples from various populations, but flexible enough allowing for application in distinct domains of AI research. It thus needs to be as concise as possible affording to be included in brief questionnaires.

We tested our scale using a non-representative German online access panel. We used an online questionnaire with a split survey design comparing the threat perceptions towards AI in the three sectors loan origination, job recruitment, and medical treatment. Participants were randomly assigned to one of the three groups. We chose the method of matching urns after completion of the questionnaire to ensure an even distribution among the different questionnaire groups.

8 Sample

Participants were recruited from the SoSci Open Access Panel between the 30th September and 14th October 2019 [51]. All in all, 917 subjects completed the questionnaire. In the data cleaning process, we had to drop 26 cases from our data set. Data elimination was based on two criteria: minus scores deployed by the access panel as well as time for completing the questionnaire. The minus scores are calculated on basis of the sum of the deviations from the average time for answering individual questionnaire pages in order to identify respondents' inattentiveness. For our data cleaning process, we chose the access panel's recommended value for a conservative cut-off criterion to ensure a high-quality data set. Moreover, we checked the overall time score participants needed to fill out the questionnaire. We excluded all data from participants with an answering time below five minutes, since we defined this minimum value after a pre-test of our questionnaire. Thus, our final sample consists of n=891 participants.

Turning to the distribution by questionnaire groups, 296 participants were assigned to the 'loan origination' group, 294 to the 'job recruitment' group and 301 to the 'medical treatment' group. Of all participants 445 identify as female (50.0%) and 438 as male (49.2%), while seven (0.8%) respondents identify as non-binary. The average age of the participants is approximately 46 years (SD=15.66). Because of the demographic structure of the access panel, 82 percent of our participants have the highest German school leaving certificate. Arguably, our data is not representative for the German population, which should be acknowledged when interpreting the descriptive results. However, our primary interest of introducing a valid scale remain unchallenged by this limitation.

9 Measurement

9.1 Threat Perceptions of Artificial Intelligence

We propose a measurement for threat perceptions concerning AI based on the specific functionality that AI systems can perform. We identified 'recognition', 'prediction', 'recommendation' and 'decision-making' as the core functions of current AI systems performance from a user's perspective. The phenomenon AI was firstly explained to the participants with a short text, which also contained the information that AI currently draws widespread public attention. Furthermore, a broad definition of AI systems and functionality was given in a neutral tone as well as an explanation of how AI systems could be used in the specific context presented to the respondents.

To achieve context independence, we then developed formal items with clozes for the specific thematic foci, which can be seen as a toolbox that is customizable for distinct areas of application. Altogether, participants had to rate twelve statements on 5-point Likert scales (1="non-threatening" to 5="very threatening"). The question block with the statements was introduced with the following text: "If you now think of the use of AI in [specific context], how threatening do you think computer applications of artificial intelligence are that...". The items for the specific functionalities reads as follows:

Recognition: "(…) detect (object)" (RCG1), "(…) record (object)" (RCG2) and "(…) identify (object)" (RCG3).

Prediction: "(…) forecast the development of (object)" (PDC1), "(…) predict the development of (object)" (PDC2) and "(…) calculate the development of (object)" (PDC3).

Recommendation: "(…) recommend (action)" (RCM1), "(…) propose (action)" (RCM2) and "(…) suggest (action)" (RCM3).

Decision-making: "(…) decide on (action)" (DSM1), "(…) define (action)" (DSM2) and "(…) preset (action)" (DSM3).

The brackets for *object* were filled with the terms I) "diseases", II) "suitability of applicants/work performance", and III) "probability of default of credits/creditworthiness". The brackets for *action* were filled with the terms I) "medical treatment", II) "hiring applicants", and III) "granting of credits". An example sentence reads as follows: "(…) how threatening do you think computer applications of artificial intelligence are that recommend a medical treatment."

9.2 Emotional Fear Reaction

Lastly, emotional responses towards the use of AI in the respective domain of application were retrieved. Participants had to rate how strongly they experience the emotion of fear on 5-point Likert scales (1="non at all" to 5="very strong"). Fear was measured through the items "afraid" (FEAR1), "frightened" (FEAR2), and "anxious" (FEAR3) [52].

10 Results

To test our measurement, we performed confirmatory factor analyses (CFA) with the *lavaan* package [53] in R (version 4.0) as well as several test statistics with the *semTools package* [54]. For visualization we used the *semPlot* package [55]. Firstly, we calculated a CFA with configural invariance. To check, if the factor loadings differ between the applications, we secondly calculated a model with measurement invariance. Thirdly, we constrained the intercept of the measurement to check for scalar invariance, i.e. to analyze whether threat perceptions are different between application areas. Lastly, we set one intercept free to gain our final model; that is, our results suggest the TAI scale as a measurement with partial scalar invariance. To check the influence of the TAI scale on emotional fear, we built a structural equation model (SEM) with emotional fear as dependent variable. We will further elaborate on our findings.

10.1 Descriptives

We first calculated descriptive statistics (mean, standard deviation, skewness and kurtosis) for all scale items separately for each domain (Table 1). The descriptive values for each threat perception of the distinct AI functionalities are quite equal between the domains but differ considerably between different functionalities of AI. For example, we see that the decision-making functionality provoked the highest threat perceptions in all domains.

To check the reliability and factorial validity of the latent variables, we first calculated several test indices (Cronbach's alpha, omega, omega2, omega3 and average variance extracted; Table 2). Cronbach's alpha values are good, varying between .80 and .92, indicating a satisfactory reliability of the latent variables. The average variance extracted varies between min=.598 and max=.798, with values >.50 regarded as good [56].

In combination with considerable covariance among the latent factors this raises questions concerning the discriminant validity of the latent factors of the specified model [57]. Thus, a Fornell-Larcker test was performed for each model, separately. For this test the squared correlation between two factors is compared with the average variance extracted for each factor. Here, the former needs to show a lower value than the latter. As this was the case for all factors in the three domains of application, the results suggest discriminant validity between the latent factors within each group.

10.2 Measurement Invariance

Before addressing the hypotheses, we need to check for measurement invariance, i. e. whether the measurement of the construct can be considered invariant between groups. Only then a mean comparison of the construct between groups is viable. A first CFA model addresses configural invariance. In our model, the four latent factors are measured with the three respective manifest indicators described in the measurement section. Furthermore, we assume covariances between all latent factors as every dimension reflects a special aspect of perceptions regarding threats of AI. The chi-square test of model fit reaches significance, $\chi^2(144)=207.091$, $p < .001$. In addition, the approximate fit indices results show good fit for the model, TLI=.989, RMSEA=.038 (.026, .050), SRMR=.026. Following the suggestion by Vandenberg [58], we do not automatically reject the present model with high degrees of freedom and a considerable sample size on the basis of the strict chi-square test, but look into the reasons for any misspecification. Results show that the unexplained variance in the specified model stems from cross-loadings of items RCG2 and RCG3 on the dimension of prediction in the finance condition. While freeing the respective parameters would improve model fit, at this point no such action is taken.

In a first modification step, we calculated a CFA-model with measurement invariance. Thus, we constraint the factor loadings of all items assuming that the factors load equally on the latent factors in each group. We compared the measurement invariance model with the original model with configural invariance. The chi-square difference test shows that the measurement invariance model does not fit the data worse than the configural invariance model, $\Delta\chi^2(16)=26.152$, p=.052. Accordingly, our data support the assumption of measurement invariance, i. e. that the factor loadings are equal across different domains of application.

Table 1 Descriptives

Item	Loan origination				Job recruitment				Medical treatment			
	M	SD	Skewness	Kurtosis	M	SD	Skewness	Kurtosis	M	SD	Skewness	Kurtosis
RCG1	3.041	1.229	– 0.066	– 1.004	3.173	1.133	– 0.075	– 0.740	1.841	0.974	1.185	0.914
RCG2	3.057	1.230	– 0.022	– 0.965	3.088	1.188	0.000	– 0.931	2.033	1.146	0.930	– 0.107
RCG3	3.162	1.233	– 0.103	– 0.960	3.235	1.204	– 0.175	– 0.980	1.887	1.020	1.165	0.695
PDC1	2.865	1.214	0.009	– 1.003	3.765	1.140	– 0.595	– 0.602	2.349	1.090	0.619	– 0.354
PDC2	2.774	1.179	0.195	– 0.815	3.626	1.143	– 0.412	– 0.765	2.216	1.054	0.739	– 0.043
PDC3	2.666	1.176	0.281	– 0.758	3.684	1.150	– 0.492	– 0.716	2.236	1.123	0.796	– 0.100
RCM1	3.098	1.216	– 0.074	– 0.927	3.214	1.083	– 0.077	– 0.688	2.302	1.085	0.629	– 0.330
RCM2	3.078	1.181	– 0.064	– 0.893	3.167	1.131	– 0.061	– 0.777	2.326	1.099	0.686	– 0.164
RCM3	3.132	1.190	– 0.134	– 0.928	3.330	1.079	– 0.339	– 0.559	2.432	1.125	0.554	– 0.468
DSM1	4.135	1.081	– 1.232	0.766	4.439	0.875	– 1.762	3.102	4.023	1.078	– 0.984	0.151
DSM2	3.986	1.098	– 0.952	0.117	4.333	0.881	– 1.534	2.491	3.844	1.134	– 0.759	– 0.330
DSM3	3.963	1.112	– 0.827	– 0.213	4.235	0.922	– 1.156	0.960	3.635	1.157	– 0.456	– 0.808

Table 2 Reliability values

Item	Loan origination				Job recruitment				Medical treatment			
	RCG	PDC	RCM	DSM	RCG	PDC	RCM	DSM	RCG	PDC	RCM	DSM
alpha	0.896	0.919	0.913	0.921	0.865	0.865	0.868	0.858	0.806	0.889	0.854	0.870
omega	0.898	0.919	0.915	0.922	0.867	0.869	0.869	0.859	0.817	0.890	0.855	0.872
omega2	0.898	0.919	0.915	0.922	0.867	0.869	0.869	0.859	0.817	0.890	0.855	0.872
omega3	0.900	0.919	0.915	0.923	0.867	0.872	0.869	0.858	0.829	0.890	0.855	0.874
avevar	0.745	0.790	0.781	0.798	0.685	0.689	0.689	0.671	0.598	0.729	0.662	0.696

In a second modification step, we calculated a CFA model with scalar invariance. Accordingly, we constrained the intercepts of the items and compared the fit of the model with the measurement invariance model. The chi-square difference test suggests, that the scalar invariance model performs significantly worse than the measurement invariance model, $\Delta\chi^2(16)=32.642$, p=.008. To detect non-invariant intercepts across the groups, we referred to the modification indices. These suggest that the intercept of item DSM3 is non-invariant (modind = 7.44). Accordingly, we freed the intercept constraint of item DSM3 and calculated a partial scalar invariance model. A chi-square difference test for the model with partial scalar invariance fits the data not worse than the measurement invariance model, $\Delta\chi^2(14)=21.311$, p=.094.

In a third modification step, we also constraint the residuals and hence calculated a model with strict invariance. According to our results, the strict invariance model performs relatively poorly, $\Delta\chi^2(24) = 123.12$, $p < .001$. Thus, the assumption of strict invariance is rejected.

Consequently, the model with partial scalar invariance will be discussed. The strict chi-square test for this model reaches significance, $\chi^2(174)=254.555$, $p < .001$. Again, the approximate fit indices show good fit for the model, TLI=.988, RMSEA=.039 (.028, .050), SRMR=.037. Once more, allowing for cross-loadings and correlated error terms of indicators from the same latent factor would improve model fit. However, no action for respecification is taken at this point.

Results suggest that the measurement in the first group from the domain of loan origination appears to be somewhat problematic. Not only did the estimated model suggest that there are unanticipated cross-loadings of indicators from the recognition function to the latent factor of prediction, but also one item intercept of the factor of decision-making is non-invariant. This serves as indication that the measurement in the loan origination group did not work as optimal as intended. However, model fit as indicated by the approximate fit indices was still satisfactory.

Turning towards RQ1, we detect that individuals in fact have different threat perceptions regarding distinct AI functionalities. Across all tested domains respondents perceived recognition, prediction, recommendation and decision-making as different, yet related, functionalities of AI systems. This confirms our proposed measurement. However, irrespective of the slightly problematic values in the loan origination domain, the distinction between the functionalities proves to be quite stable and consequently appears to be feasible.

10.3 Mean Differences of AI Functions Between Conditions

After having established partial scalar invariance, the next step is to address the mean comparisons between the three domains to test H1. H1 states that there are differences regarding the threat perception of each function between the domains of AI application. The first domain regarding the application of AI in loan origination serves as a reference group. Accordingly, the means of the four latent factors of the four functions in this group are constrained to zero.

Results show that compared with the domain 2 ('job recruitment') prediction (Δ M=.918, $p < .001$) and decision-making (Δ M=.327, $p < .001$) appeared to be significantly more threatening in the job recruitment domain, while recognition (Δ M=.082, p=.355) and recommendation (Δ M=.137, p<.116) did not differ between both conditions. Thus, the job recruitment domain was perceived as more threatening in two out of four functionalities than the loan origination condition.

Compared with domain 3 ('medical treatment') the recognition (Δ M=-1.190, $p < .001$), prediction (Δ M=-.501, $p < .001$) and recommendation (Δ M=-.763, $p < .001$) were perceived as significantly less threatening in the medical treatment domain, while with regard to decision-making (Δ M=-.125, p=.139) there was no difference. Here, the loan origination domain was perceived as more threatening in three out of four functionalities.

When comparing domain 2 ('job recruitment') with domain 3 ('medical treatment') the results indicate that the recognition (Δ M=-1.273, $p < .001$), prediction (Δ M=-1.419, $p < .001$), recommendation (Δ M=-.900 , $p < .001$), and decision-making (Δ M=-.452, $p < .001$) all differed significantly between both groups. In other words, the AI application for the treatment of health problems was deemed less threatening than an AI that was deployed to assess candidates for a job.

Summing up the results, the usage of AI in medical treatment is perceived as less threatening in nearly all functionalities compared to the usage of AI for loan origination or job recruitment. On the other hand, the job recruitment domain was rated as most threatening compared to the other domains - at least regarding the prediction and the decision-making functionality.

Consequently, H1 that assumed differences in the threat perceptions between the different domains of AI application was partially accepted. Threat perceptions regarding AI functionalities appear to be widely domain-dependent.

10.4 Effects on Fear

To assess whether threat perceptions are able to predict reported fear of the respondents, a structural regression model was specified. Here the three items that served as indicators of fear loaded on a latent factor that is modeled as an endogenous dependent variable. The four latent factors of threat perceptions of AI systems functions are modeled as exogenous independent variables. Fig. 1 displays the model.

Before addressing the analysis, measurement invariance of the fear construct was assessed. The results suggest that measurement of the fear construct is non-invariant between the three groups. Especially, the loading of item FEAR1 is considerably non-invariant. Consequently, the equality constraints for the loadings and intercept of this item were freed for the analysis. The chi-square difference test indicates that this model with partial invariance still fits significantly worse compared to the configural model, $\Delta\chi^2(4) = 11.95$, p = .018. However, there is a substantial improvement in the comparative fit indices between the model with measurement invariance and scalar invariance, ΔTLI = .003. While the actual measurement of the fear construct is not optimal, we still rely on this previously tested measurement of fear from the literature for the purpose of an analysis of the connection between threat perceptions and self-reported fear.

Concerning the eventual analysis, in a first step, a model was estimated where the regressions coefficient of threat perceptions on the induced fear could vary freely, $\chi^2(274)=376.578$, $p < .001$. Again, the approximate fit indices show good fit for the model, TLI=.987, RMSEA=.036 (.026, .044), SRMR=.039. However, as the threat perceptions are highly correlated this inflates the standard errors of the estimated parameters and it needs to be tested whether their respective effects actually differ between each other [59,60]. Accordingly, due to high inter-correlations of the four latent factors in the respective groups, a second model was specified in which the effect of each latent factor on fear was constrained to be equal. The chi-square difference test for the first unconstrained model and the model with equality constraints shows that the second model does not fit the data significantly worse, $\Delta\chi^2(9) = 12.976$, $p = .164$.

The model with equality constraints for the threat perceptions within each group still suggests good fit, $\chi^2(283) = 389.555$, $p < .001$, TLI =.987, RMSEA =.036 (.026, .044), SRMR =.041. The parameter estimates show a small effect of the threat perceptions of AI on fear for group 1 ('loan origination'), B(SE)=.184(.014), $p < .001$, group 2 ('job application'), B(SE)=.189(.018), $p < .001$, and group 3 ('medical treatment'), B(SE)=.188(.017), $p < .001$, respectively. The effect size ranges from β_{min}=.135 to β_{max}=.203. Accordingly, H2 was accepted.

Eventually, RQ2 asks about differences of the effect of threat perceptions on fear between the domains. The simi-

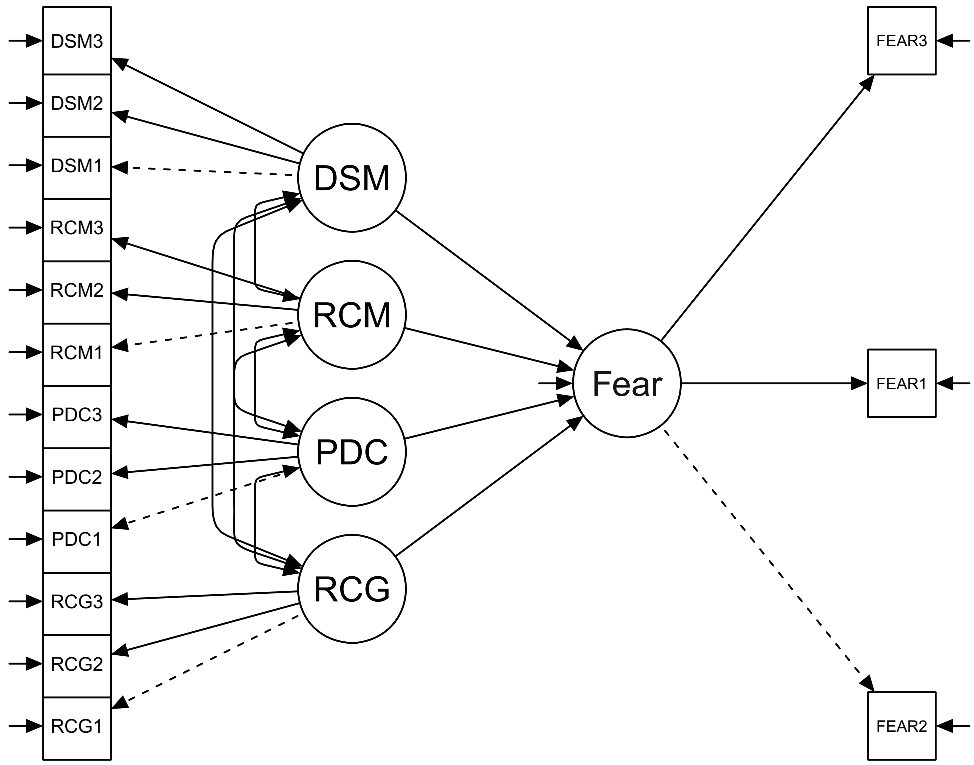

Fig. 1 SEM model

larity of the parameter estimates suggests that the effect of threat perceptions of AI on fear appears to be equal between the groups. Consequently, a model was specified where the effect of the latent factors of threat perceptions on fear were not only equal across threat perceptions of the functions of AI within the respective groups, but also did not differ between the domains. Therefore, it was tested whether the effect of the threat perceptions on fear was equal across the groups by using equality constraints. The chi-square difference test for the first unconstrained model and the model with equality constraints shows that the second model does not fit the data significantly worse, $\Delta\chi^2(2)$=0.059, p=.971.

The model with equality constraints for the effect of threat perceptions of AI on perceived fear within and between each domain still suggests good fit, $\chi^2(285)$=389.614, p $<$ .001, TLI=.987, RMSEA=.035 (.026, .044), SRMR=.041. The parameter estimates show that threat perceptions of AI have a small significant effect on reported fear for group 1 ('loan origination'), group 2 ('job application'), and group 3 ('medical treatment'), respectively, B(SE)=.186(.010), p $<$ .001. The effect size ranges from β_{min}=.133 to β_{max}=.202.

11 Discussion

In this paper we introduced a scale to measure threat perceptions of artificial intelligence. The scale can be used to assess citizens' concerns regarding the use of AI systems. As AI technologies are increasingly introduced into everyday life, it is crucial to understand under what circumstances citizens might feel themselves to be threatened. Threats can be understood as a pre-condition of fear. Subsequently, according to fear appeal literature, being frightened can lead to denial and avoidance of the threatening object. Thus, if people perceive AI as a serious threat, it could cause a non-adoption of the technology.

However, AI is an umbrella term for a huge variety of different applications. AI applications can fulfill various functions and applications are used in almost every societal field. Arguably, there are huge variances in threat perceptions of different functions and domains of application. With the TAI-scale we propose a measurement to account for this context-specificity.

First, the results suggest that threat perceptions of distinct AI functions can be reliably differentiated by respondents. Recognition, prediction, recommendation and decision-making are indeed perceived as different functions of AI systems. However, depending on the context evaluated the measure showed diverging factorial validity. In one case the indicator items had significant shared variance with more than one dimension. This impairment of discriminatory power indicates that thorough pre-testing of the adapted measures and data quality control are of utmost importance when devising the survey instrument in subsequent study designs. In doing so, researchers need to make sure that respondents fully comprehend the item wording and that the object of potential threat is clearly recognizable. Especially, this becomes important when respondents are confronted with new and technically sophisticated AI systems, for which there not yet exists enough direct personal experience.

Second, threat perceptions are shown to vary between different domains, in which AI systems are deployed. This suggests that the notion of a general fear of AI needs to enhanced in favor of a broader conception not only of what actions AI is able to perform, but also what exactly is at stake in a given situation. In cases where AI systems seem useful and the consequences of its application appear insubstantial, the introduction of AI in another domain might evoke entirely opposite reactions. Thus, while general perceptions such as general predispositions concerning digital technology certainly do play a role when it comes to the evaluation of innovative AI systems, a more fine-grained approach is necessary and appears to be fruitful with the developed measurement. Respondents' threat perceptions in this study varied considerably between domains. Especially, the use of AI in medical treatment was only perceived as lightly threatening, whereas threat perceptions were quite higher in the domains of job recruitment and loan origination. Regarding the levels of threat perceptions concerning the functionalities, it is evident that the decision-making function is perceived as most threatening within all three domains. Arguably, this might be based on the loss of humans' autonomy. As this is only a hypothesis at this point, further studies should elaborate on these findings. Future applications of the TAI scale will yield further insights concerning the items' and scales' sensitivity with regards to different domains of AI applications.

Third, threat perceptions are reliable predictors of self-reported fear. As the measurement of actual fear is rather complicated via the means of a survey instrument, the inquiry of threat perceptions appears not only to be preferable. It also suggests that it is reasonably well connected to individual self-reports of experienced fear. Further studies should elaborate on these findings and focus on the behavioral impact of AI-related threat perceptions. As the fear appeal literature suggests, one might expect that high levels of AI-induced fear lead to rejection of the technology or even protest behavior.

Highlighting the good fit of our scale, we encourage researchers to implement the TAI scale in research focusing on public perceptions of AI systems. As outlined earlier, the TAI scale can be seen as a toolbox. Hence, it is possible to integrate only those functional dimensions in a survey that actually fit the AI system under research. Anyhow, we also advise researchers to be mindful when using the scale. In practice, there is a lot of confusion about the terminology of AI - even within the scientific community. Researchers using the scale have to make sure that the AI system under research actually performs AI tasks. Given the fact that usually non-experts serve as respondents, scholars have the responsibility to inform them rightfully about what the specific AI system under consideration is and what it is able to do. Otherwise, researchers would make claims about a threat of AI perceptions without actually examining AI.

Future studies should test the TAI scale in surveys employing representative sampling to make statements over the actual level of threat perceptions regarding the different functionalities of AI systems in various domains. With that, it would be possible to grasp the public threat perception of AI systems and draw conclusions for further implementation of AI in society. However, such research needs to be thoroughly theorized, as the mere information concerning levels of threat perceptions of AI with the public is of little academic value.

Another promising future direction of research could focus on the role of knowledge in attitude building. Knowledge about AI technology could influence the way individuals feel threatened by AI. Additionally, with this extension of research one may test, whether the perceptions of what an AI system is capable of do in fact match the technical level. It may be possible that the imagination of individuals and the real performance of AI systems might not correspond.

12 Limitations

As this study attempts to develop a more fine-grained approach to measuring threat perceptions regarding AI, its focus lay on scale construction and testing the application of the scale in an online survey. The results are thus limited to German online users from a non-representative online access panel. Further research should extend the scope of the domain of AI applications as well as addressing further groups of stakeholders and, especially, behavioral consequences of perceived threats of AI.

Furthermore, a translation of the scale to other languages appears as another promising avenue. As Gnambs and Appel [16] showed, based on longitudinal data from the Eurobarometer attitudes towards robots and autonomous systems vary between countries and might be subject to cultural influences that warrant research illuminating divergent perceptions and their antecedents.

Finally, we point out that, although we refer to the periodic system of AI [34] and the study of Hofmann and colleagues [33], the functional classes may be considered somewhat arbitrary. As AI is a very broad term, there might be other possibilities for dimensional structures of a scale focusing on public threat perceptions. However, our results give support for the dimensional structure we proposed.

13 Conclusion

The public perception of Artificial Intelligence will become increasingly important as applications that make use of AI technologies will further proliferate in various societal domains. A populace that perceives AI as threatening and that in consequence fears its proliferation may prove as detrimental as a blind trust in the benevolence of actors that implement AI systems as well as a general overestimation of the veracity of assertions and decisions made by AI. Consequently, the survey of threat perceptions of various AI systems is of great research interest. In this paper, we proposed and constructed a measurement of threat perceptions regarding AI that is able to capture various functions performed by AI systems and that is adaptable to any context of application that is of interest. The developed TAI scale showed satisfactory results in that it reliably captured threat perceptions regarding the distinct functions of recognition, prediction, recommendation, and decision-making by AI. The results also suggest that the developed scale is able to elucidate differences in these threat perceptions between distinct domains of AI applications.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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