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New Short Scale to Measure Workers' Attitudes Toward the Implementation of Cooperative Robots in Industrial Work Settings: Instrument Development and Exploration of Attitude Structure

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Abstract

The implementation of new robotic technology at workplaces is oftentimes accompanied by social and organizational change processes. A new context-specific questionnaire was developed as a diagnostic tool to measure workers' attitudes toward mobile cooperative manufacturing robots to provide a basis for managerial decisions and interventions—the "Attitudes toward Cooperative Industrial Robots Questionnaire" (ACIR-Q). Two samples, an online sample of 355 German manufacturing workers and a field sample of 201 workers from 4 local manufacturing companies were collected. For a large item pool, exploratory and confirmatory factor analysis was used to identify the attitudinal factor structure. Data showed a combined affective-behavioral factor and two cognitive factors on task-related and social-related beliefs. Based on this, the 12-item short scale ACIR-Q was derived using ant colony optimization. As attitudes can also be interpreted as networks of evaluative responses, network analysis was used for further insights. The small-world network structure (high clustering and connectivity) allows to hold complex attitudes and centrality measures indicate the most influential evaluative responses. Additionally, we explored relationships between workers' attitudes and interpersonal variables (perceived competence, perceived control, and general self-efficacy), as well as social/organizational variables (trust in management, support climate, job insecurity and job characteristics). Based on the results, practical implications are suggested to improve workers' attitudes.

Keywords Technology acceptance · Organizational change · Network analysis · Manufacturing · Human-robot interaction · Innovation

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1 Introduction: New Robots and Organizational Change

Whenever new technology is introduced into work systems, the acceptance by the staff and its support is a key requirement for successful implementation and the innovation's usage in the long run [29, 41]. If the needs of the workforce are only insufficiently taken into account, this can have negative consequences, such as greater job dissatisfaction or intentions to leave (e.g., [52]). In this respect, employee surveys can be of great managerial value during organizational change. As attitudes can predict behavior [4, 27, 34], the measurement of workers' attitudes, can serve as a diagnostic instrument in order to deduce potentials for improvement, as a basis for management decisions, as a control-function, and as guidance for possible interventions.

Advanced manufacturing technologies such as industrial robots might even be revolutionary, disruptive innovations that affect social systems to a considerable degree and require radical organizational change [58]. The measurement of workers' attitudes toward such robots and subsequent change is not a new endeavour [5, 13, 30]. However, with the trend toward mass customization, the need for higher flexibility, as well as new technological developments [45], new mobile robots are expected to be introduced into industrial work environments. This will lead to drastic changes at workplaces and a need for new instruments that can account for different evaluative responses (thoughts, emotions, or behavioral intentions toward a certain attitude object that include or are associated with a value judgment to a certain degree in a positive or negative direction). This need is also echoed in the human-robot interaction (HRI) literature calling for more properly validated scales for HRI research (e.g., [39]). To address this need, we developed a new and free to use short scale to measure workers' attitudes specifically toward mobile, cooperative industrial manufacturing robots and their implementation into work settings - the "Attitudes toward Cooperative Industrial Robots Questionnaire" (ACIR-Q). This short scale allows organizations for effective and timesaving context-specific assessment.

For the development of the ACIR-Q and the analysis of attitude structure, we collected data of two samples using a large pool of affective, cognitive and behavioral attitudinal items. This data allowed to explore the structure of the attitude construct using both, structural equation modelling and network analysis. We then derived the optimized ACIR-Q short scale using ant colony optimization.

As attitudes are influenced by other characteristics of the respondents such as their self-efficacy (e.g., [21, 44]) and by social structures in the organizations (e.g., [1, 30]), the relationship of interindividual (variables that differ in their manifestation between people, e.g., perceived control) and organizational (variables affected by organizational structures, processes or culture, e.g., trust in management) variables with workers' attitudes toward robots and their implementation was analyzed. The exploration of correlations will also allow the attitudinal construct(s) to be better located in a theoretical network – an important step in validation processes [17]. The analyses are discussed with respect to potential practical interventions.

2 Theory and Related Work

2.1 The Role of Attitudes in Technology Adaption

In order to understand how to measure and change attitudes toward robots a deeper understanding of its role in the technology implementation and organizational change processes is needed. In the history of social psychology, scholars had developed a multitude of theoretical models that try to explain empirical findings on attitudes and their influence on human behavior. In many of these models, attitudes are interpreted as associations between a given attitude object and evaluations based on cognitive, affective and behavioral information [25, 26].

As evaluative associations of a new technology are a determinant for human behavior, attitudes are also key for a successful implementation of technology and subsequent organizational change processes. Thus, frameworks that are often used in the technology adaption literature either name attitudes directly as one or more constructs, or contain constructs describing different evaluative responses that could be semantically described as attitudinal (e.g., Technology Acceptance Model or extensions thereof (see [33])). Similarly, attitudes play a key role in the organizational change literature [14, 40, 52].

However, such frameworks often do not specify how the attitudinal component is structured (e.g., Theory of Planned Behavior [3]), that is for example what evaluative responses can be clustered together into one or more attitudinal factors, and often do not allow for an in-depth understanding [6]. In other words, these models are rather generic. While their strength lies in their parsimony, this also has the disadvantage that they do not take into account specific factors in the various application contexts [6]. For example, the Technology Acceptance Model has been used in different technological domains including robotics [10] or exoskeletons [57], but factors had to be specified further to get a deeper understanding (see for example the model of Bröhl et al [10]). Important aspects of attitudes toward robots, such as people's fear about losing their jobs [24] or the concern that a heavy manufacturing robot can be a safety issue [10], are not included in simple generic models and would have to be included as an additional factor. Such aspects, however, are necessary to understand unterlying processes and can entail important information for managers to make actionable decisions. Furthermore, past social-psychological research on attitudes has established the principle of "correspondence" [4, 34]. In order to predict behavior toward a specific attitude object, high correspondence between attitudinal measures and the behavior is needed [4, 34], that is the level of specification – a concept similar to the Brunswik symmetry [11, 62].

Therefore, a more in-depth context-specific examination of attitudes is needed. It is often neglected that attitudes are complex, may involve multiple latent constructs, and that the attitude structure changes depending on the (social) context. Attitudes are "moving categories because they are related to social interactions, and thus dependent on a social matrix" [28, p. 8]. Thus, context-specific models and questionnaires are more informative compared to broader, general conceptualizations [34]. Note, the purpose here is not to test a generic model, but to develop a measurement tool that addresses specifics of the manufacturing context, and that can be used as a practical diagnostic tool.

2.2 The Measurement of Attitudes Toward Robots—Existing Questionnaires

Different studies from the last 40 years by Argote et al [5], Chao and Kozlowski [13], and Herold et al [30] found different attitudinal structures across different robots and situations indicating a dynamic, situation-sensitive and time-dependent nature of attitudes. While the content of evaluative statements in attitude questionnaires can be theoretically described as cognitive (e.g., statements describing beliefs about the attitude object), affective (e.g., statements about emotional states associated with the attitude object), and behavioral (e.g., statements concerning behavioral intentions concerning the attitude object), a factor structure does not necessarily need to reflect this theoretical three-fold nature as past empirical research demonstrated.

For example, Chao and Kozlowski [13] found four factors describing different areas of concern including "job insecurity" (e.g., "Robots seriously threaten my future with this company."), "new opportunities from robot implementation" (e.g., "Working with robots will allow me to learn more about high technology."), "general robotics orientation" (e.g., "In the long run, robots will increase the company's profits."), and "management concern" (e.g., "New automation and robots are put into place with little regard for the welfare of the employees."). Herold et al [30], in contrast, only identified a two-dimensional factor solution with a rather general negative (e.g., "Robots will create new safety problems.") and a positive factor (e.g., "Robots will increase productivity in my department"). Attitude structures might differ because of different stages of implementation, differences in culture and as a function of historical developments. Herold et al [30, p. 170] states: "With the gathering of new information, and as adoption and implementation decisions are made, more differentiated attitudes will probably develop".

In order to explain differences in attitudes, researchers also analyzed the influence of interpersonal and organizational variables (see [5]). The exploration of relationships with such concepts can help to understand attitudes within a larger social context and to develop measures that can inform implementations. For example, Argote et al [5] and Chao and Kozlowski [13] found differences between job classes. Chao and Kozlowski [13] report that line workers compared to persons with higher-skilled jobs regarded the robot as more threatening because of potential job loss or social isolation.

Herold et al [30] state that especially in early implementation phases, when attitudinal knowledge is limited, other variables might serve as possible sources of inferential beliefs and shape worker's predispositions. The study showed correlations of attitudinal factors with personal beliefs, organizational support environment and the perceived labor-management relationship. Past research thus showed that structures of attitudes toward industrial robots differ fundamentally between studies depending on the social matrix, and these differences can be partly explained by differences of job characteristics and organizational cultures. Based on the organizational change literature, such influences affecting attitudes could be organizational culture, including such aspects like support climate [22, 30], trust in management [46, 47], or perceived job insecurity (the feeling that one's job is at risk, see [7, 56, 59]) – a factor that has especially been associated with the implementation of new robots [24, 30]. As such variables can influence attitudes in organizational change processes (e.g., caused by a new robot), a validation process of a new attitude scale needs to test the relationship with such variables (e.g., [30, 48]), especially because they could also indicate possible practical implications. For example, if attitudes are associated with trust in management because workers think that the implementation of a new robot will cause chaos at work due to change managers incompetency, then steps that increase trust in management might also lead to more positive attitudes toward the implementation of a robot. Similar to organizational influences, other interindividual factors, predominantly perceived competence or perceived control in using a certain technology [2, 35, 48, 54, 55], are known to be important covariates and subsequently need to be differentiated in validation processes of technology-related attitude scales.

2.3 Attitudes from a New Perspective—On Networks of Evaluative Responses

While past research on attitudes toward robots has found different attitudinal constructs, it remains widely unclear how different constructs develop or which of workers' concerns should be tackled first. A network perspective might help in this respect.

In connectionist models, attitudes can be seen as evaluations of objects based on automatically activated associations and additional reflective processes. An attitude thus "reflects the current processing state of the entire evaluative system" [18, p. 738].

Based on connectionist ideas, Dalege et al [19] proposed a formalized measurement model of attitudes using empirical network modeling, which has been applied to political attitudes [20] or job attitudes [12]. In the Causal Attitude Network (CAN) model by Dalege et al [19], attitudes are conceptualized as networks of interacting evaluative reactions, in which these reactions are cognitive (e.g., beliefs about an attitude object), affective or behavioral in nature. Evaluative reactions are graphically represented by nodes. These nodes are connected by edges representing the causal influence between the nodes. Edges can be described as excitatory or inhibitory and can vary in weights. The attitude construct is thus formed by these (bidirectional) interactions between nodes constituting a network [12, 19, 28].

Based on the dynamic nature and the configurations resulting from these connections, such networks have different emergent properties [28]. These properties of systems result from the interaction of connected elements, but are not properties of the elements themselves nor can these properties be predicted based on the properties of the elements. Such emergent properties are, for example, the clustering of nodes or the overall connectivity, which inevitably lead to certain structures and configurations. Thus, these properties have important implications for the description of attitudes (i.e., what are areas of major concerns), or attitude change (i.e., what evaluative nodes are most easily changed). For example, both the belief of an increased risk of job loss due to robots (node A) and the belief that the robot will just take away some of the exciting work tasks instead of monotonous ones (node B) could be directly associated with the thought that one might be less valuable as a factory worker (node C). So, since the thought of value here might be in the midst of a cluster (nodes A, C, B,...), it might be more difficult to change this evaluative response. This property is not a property of the node itself, but is only evident by its position in the network.

While a simple attitude that is generally positive or negative might result from a tightly connected network, complex attitudes can be held if a network converges into different clusters with these clusters being connected through shortcuts [12, 20]. That is, while some groups of nodes are highly connected within these groups, only a few edges connecting nodes from different groups exist. Thus, complex attitudes are expected to show high clustering and high global connectivity, also termed “small-world structure”. With such a small-world structure, an attitude can be held stable in which different aspects of the evaluative object can have different valences. For example, it is possible to hold the positive belief that robots are productive and efficient, but simultaneously hold the negative belief that robots behave in a socially unacceptable way.

Additionally, a network perspective has valuable implications for attitude change. Changes in evaluations also depend on network configurations [19]. The change in tightly connected, single-clustered networks is more difficult than loosely connected and multi-cluster networks [12]. In attitudes with a small-world structure it is unlikely that the change in a single node would result in a change of the entire network. Nodes differ in their connectivity. Changing a single node will thus most likely only affect closely connected nodes. Other nodes not belonging to the cluster and thus also having fewer bridges to the node in question will be largely unaffected by the change [12, 19]. Because of variation in connectivity and their position in the network, nodes differ in their relative importance in attitude change. This relative importance is called centrality [19]. For attitude change, this means it is easier to change nodes of low centrality, but this change will also less likely evoke changes in the whole network. Compared to this, nodes of high centrality are more difficult to change, but their change will have more effect on the attitudinal network due to a ripple effect [19].

With respect to the conceptualization of attitudes, the network perspective is often contrasted with the latent variable perspective [12, 19, 28]. However, the latent variable view and the network modeling view are not directly competing, but rather relate to and complement each other [12, 19, 28]). The clustering of network models of psychological attributes and thus the emergent properties can be interpreted as what is conceptualized as a latent variable. Based on this reasoning, it is legitimate to analyze latent variables without the underlying complex networks [28]. A network perspective can then add additional information such as centrality measures.

3 Research Questions and Research Goals

We aimed to measure workers’ attitude toward robots within the context of development and implementation of new mobile, cooperative robot technology in manufacturing companies. Robots developed for this application context typically consist of a transport platform or other mobile base and a manipulator, for example in the form of a robot arm with gripper. This allows them to perform tasks such as transporting materials, autonomous pre-assembly, or cooperative assembly work with factory workers, and more. An example of such a robot is shown in Fig. 1. Descriptions of the context in which the new scale can be applied and of corresponding robots as attitude objects can also be found in Sect. 4.1 and in Appendix A.

We therefore developed a new context-specific questionnaire (ACIR-Q). This assessment should serve as a predictor for potential future behavior, as a diagnostic tool to identify areas of concern and a basis for intervention strategies.

First, factor analysis is applied to identify communalities using a large number of different attitudinal items. Because of the mixed literature [13, 30], number and nature of these factors was unclear.

Step 1 Identifying the number and content of attitudinal factors.

While large and detailed questionnaires can give a comprehensive understanding of workers’ attitudes, such questionnaires can be time-consuming and tiresome for staff. Therefore, we constructed a short-scale using ant colony optimization.

Step 2 Short scale construction using ant colony optimization.

In network models, factors can be interpreted as emergent properties of an underlying network of evaluative responses. In such network perspective, the identified major areas of concerns are represented as clusters connected through short-

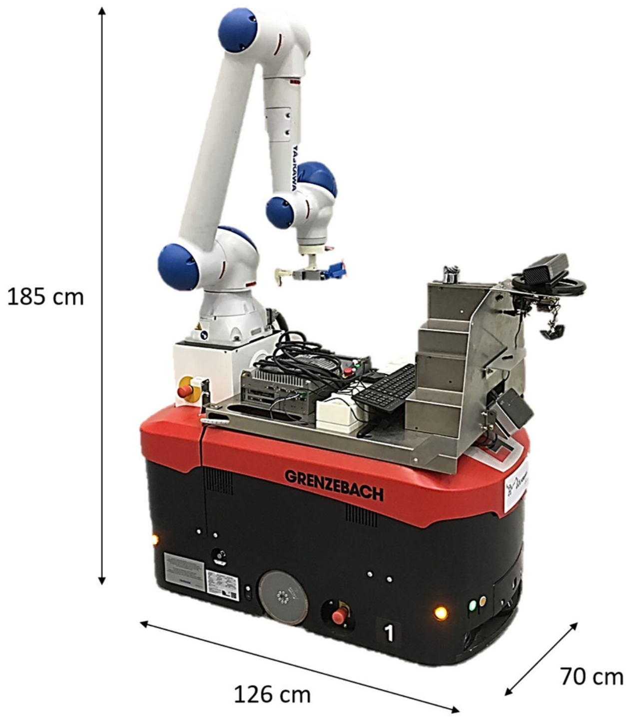

Fig. 1 Example picture of a mobile cooperative robot based on a mobile automated guided vehicle by Grenzebach and a robotic arm attached to it by YASKAWA developed by the FORobotics project consortium

cuts. We thus expect attitudes to constitute a small-world structure.

Step 3 Testing if attitude structure resembles a small world network.

Furthermore, the network models propose that nodes highest in network centrality have the highest impact on the network and are thus the most promising indicators for change.

Step 4 Identifying evaluative responses that constitute the nodes highest in network centrality.

Attitudes are moving constructs depending on a social matrix [28], and can be shaped by other interindividual and organizational constructs [30]. We thus tested the influence of different interindividual and organizational variables. On an interpersonal level, a prominent concept that had been related to attitudes is self-efficacy [3, 48].

Step 5 Testing the relationship between workers attitudes toward robots and perceived competence, perceived control, and general self-efficacy.

On the organizational level, we explored the relationship of attitudes toward cooperative industrial robots with organizational variables and job characteristics suggested by past research (see [13, 30]).

Step 6 Testing the relationship between workers attitudes toward robots and perceived support climate, workers' trust in management, and perceived job insecurity.

Step 7 Testing differences in attitudes toward robots depending on job characteristics (e.g., managerial responsibility) and affiliation to organization.

4 Methods

In this section the development of items for the new Attitudes toward Cooperative Industrial Robots Questionnaire (ACIR-Q) is described, as well as other variables and samples used for data analysis. The final ACIR-Q is available in different languages including a short manual for usage and additional material at https://osf.io/5fnr9/ [37]. The German (original) and English (translation) version is additionally attached in Appendix C. The quality of the translations of the ACIR-Q are ensured using the back-translation method.

4.1 Item Pool Development

As it is important for measurement to know for which situations a questionnaire had been developed and is thus expected to be valid, a short characterization of the context of use and a description of the basis of scale development is fundamental. The development of a new context-specific attitude questionnaire was part of a collaborative research project, in which the implementation of a new mobile and cooperative industrial robot in manufacturing workplaces should be evaluated. The new scale should thus measure the attitudes of workers in the manufacturing sector where a new manufacturing robot is planned to be implemented including the necessary change process. This means, the scale should cover attitudes toward this new technology and also take into account the social and organizational consequences that are connected to such an implementation (e.g., workers' fear of job loss due to the robot). The robot used as the attitudinal stimulus in these studies constitutes of a mobile automated guided vehicle and a robotic arm attached to it. Such robots had been used in previous ergonomic and design studies [15, 38]. Within the companies, the robot technology had the major functions of order picking, transportation of materials, pre-assembly of components, and assistance during the assembly of components in cooperation with a human worker. Of course, the scale is not developed for this specific robot only but should be usable for the implementation of mobile, cooperative manufacturing robots in general. A more detailed characterization of this type of robots based on the taxonomy by Onnasch and Roesler [51] can be found in "Appendix A".

For the new questionnaire, different items based on previous measurement items from Chao and Kozlowski [13] as well as Herold et al. [30] were used. Additionally, new items were developed to cover various potential consequences of this new technology, based on the results of qualitative work system analyses as a first step of the robot implementation process (published elsewhere by Leichtmann et al. [36]).

In an iterative process, $I_1 = 81$ single statements concerning robots in relation to industrial work were generated (see Appendix B for details). These items were pre-tested for comprehension and modified. The final item pool consisted of $I_{Attitude} = 57$ attitudinal items using a 5-point bi-polar scale. The attitudinal items describe evaluative responses including affective elements (items on emotions toward robots and their implementation, e.g., "I have an uneasy feeling about a new robot."), cognitive beliefs (items on beliefs about consequences due to the implementation, e.g., "New robots are a new hazard in my workplace") and behavioral intentions (e.g., "I would resist working with a new robot").

$I_{Competence} = 7$ (e.g., "I am easily able to operate a new robot.") and $I_{Control} = 7$ (e.g., "Robots are little controllable technologies.", reversed coded) items were developed to measure perceived competence and perceived control during work with a robot based on work of Neyer et al. [48]. 6-point Likert scales are used ranging from "disagree" to "agree".

At the beginning of the questionnaire, a short instruction text informed the participants about the planned implementation of the mobile robot in their workplace, about the functions and capabilities of the robot, and about its potential use within the work system.

4.2 Additional Variables

4.2.1 Demographic Variables and Job Descriptions

Demographic variables were assessed including gender, age, the educational level, the participant's job title, their main task, seniority, and managerial responsibility.

4.2.2 Robot Experience

For robot experience, a definition of robots was presented, and participants were asked if a robot was used at their workplace (yes/no) and if they had used such a robot in the past (ranging from "never seen or interacted" to "interacting on a regular basis or often" on 5 ordinal levels) (see [24]).

4.2.3 General Self-Efficacy

General self-efficacy was measured on a 5-point Likert scale using the 3-item short scale by Beierlein et al. [8].

4.2.4 Perceived Job (In)Security

Perceived job (in)security was measured using the 4-item short scale by Vander Elst et al [61] with a 5-point Likert scale ("strongly disagree" to "strongly agree").

4.2.5 Trust in Management

Trust in management was measured using the ability (6 items) and benevolence (5 items) subscales of the trustworthiness scale by Mayer and Davis [43] with a 5-point Likert scale ("strongly disagree" to "strongly agree").

4.2.6 Support Climate

For support climate, a new scale with 9 items was constructed based on the definition by Herold et al [30] in which the beliefs about the organizations training system and communication during change were assessed (e.g., "When there are innovations in the company, every person who needs training gets it.") with a 5-point Likert scale ("disagree" to "agree").

4.3 Samples

Two independent German samples were collected, one sample consisting of workers from manufacturing companies of the collaborative research project (project sample), and one sample consisting of workers from the online panel of a market research company (online sample).

The project sample consisted of $N_{project} = 202$ participants. Participants worked at four manufacturing companies in Bavaria (Germany) at five workplaces in which mobile manufacturing robots were planned to be implemented within the next years. At the time of measurement, no mobile cooperative robot was used at their workplaces. The workforce had been informed about the plans of the management to use mobile manufacturing robots in the future.

The study was conducted using paper-pencil questionnaires at the workplaces. The study complied with the tenets of the Declaration of Helsinki, was supported by the local works council, and approved by the ethics committee of the Bundeswehr University Munich. Only storage and manufacturing workers were considered for participation. One participant terminated the study early. Thus, data of $N = 201$ participants were used for analysis. The mean age was $M = 38.49$ years ($SD = 12.70$). 32 participants identified as female, 166 as male and none of any other gender. Three participants did not indicate their gender. The sample was rather unexperienced with robots (74% had never worked with a robot before). Participants were on average $M = 13.14$ years ($SD = 11.59$) working in their job.

The online sample consisted of $N_{online} = 355$ German participants. All participants were derived from an online panel by a market research company and paid for participation. Only participants, who reported to work at a company in the manufacturing branch were invited. Additional screening questions ensured that only workers participated that worked at manufacturing plants or in the warehouse and that tasks such as assembly or commissioning are part of their job, to resemble the target population of manufacturing workers. Especially in online surveys one issue is insufficient attention of respondents resulting in lower data quality [42]. Therefore, participants who incorrectly responded to 5 attention check items or who had been faster than 8 min to complete the questionnaire were considered inattentional and had been excluded.

A total of $N_{online} = 355$ complete datasets (after excluding participants who terminated the study early, who incorrectly responded to one of 5 attention check items, or who were faster than 8 min; that is 34 % from initially $N_{online} = 1041$ starting the questionnaire) were used for analysis. The mean age was $M = 44.66$ years ($SD = 11.03$). 74 participants identified as female (21%), 281 as male and none of any other gender. Participants indicated to be mostly unexperienced with robots (69% had never worked with a robot before). Participants were on average $M = 15.42$ years ($SD = 11.70$) working in their job.

In both studies, participation was voluntary and could have been terminated at any time without consequences. Informed consent was obtained from each participant.

5 Results

For data analysis, the open source statistic software R version 4.0.2 [53] was used (R-code in supplements).

5.1 Identifying Major Areas of Concern—Exploratory Factor Analysis

First, we ran an exploratory factor analysis (EFA) with all $I_1 = 57$ newly constructed items to identify attitudinal factors using the online sample ($N = 355$). Tests show that a factor analysis would lead to a meaningful solution (KMO-statistic $MSA = .96$; Bartlett's test $\chi^2(1596) = 14273$, $p < .001$, determination $det > .00001$). A parallel analysis with 100 simulations suggested $k = 5$ factors.

EFA was conducted using a principal axis factoring procedure with oblique rotation (oblimin). Eight items were deleted because of high cross loadings ($\lambda > .299$). Based on factor loadings, the factors were interpreted as follows. The first factor describes items concerning participants affect when thinking about a mobile robot and its implementation into their workplaces, as well as behavioral intentions (affect / behavior; $\omega = .94$). The second factor can be described as beliefs concerning changes of work tasks or workplaces such as the belief that robots will increase / decrease errors at work or will lead to more / less accidents (task-related beliefs; $\omega = .93$). The third factor describes beliefs about social consequences such as the belief that due to robots, human workers will have less / more contact to colleagues or robots will lead to job loss (social-related beliefs; $\omega = .92$). A fourth factor reflects beliefs about the robot's effect to one's role at work such as the belief that robots will affect responsibility (self-related beliefs; $\omega = .81$). The fifth factor describes autonomy and pressure (pressure-related beliefs; $\omega = .74$). The final EFA lead to five factors explaining a total of 42% of variance. However, because the pressure-related factor only explains 3% of variance and factor loadings are low, it was deleted for further analysis.

5.2 Identifying Major Areas of Concern—Confirmatory Factor Analysis

After identifying common attitudinal factors using the online sample data, we tested whether the project sample fits this hypothesized factor structure. The confirmatory factor analyses are based on maximum likelihood estimation. We consider models with goodness of fit indices of Comparative Fit Index $CFI \geq .95$, Tucker Lewis Index $TLI \geq .95$, Standardized Root Mean Square Residual $SRMR \leq .08$, and Root Mean Square Error of Approximation $RMSEA \leq .06$ as good [31].

First, single-factor models were tested based on the EFA and modified based on factor loadings and modification indices by deleting single items and adding residual correlations to improve fit. The affect and behavioral intention factor reached acceptable fit ($\chi^2(52) = 111$, $p < .001$, $CFI = .95$, $TLI = .94$, $RMSEA = .08$, $SRMR = .05$). The internal consistency was good ($\omega = .91$). The single-factor model of task-related beliefs reached overall acceptable fit ($\chi^2(136) = 1591$, $p < .001$, $CFI = .92$, $TLI = .90$, $RMSEA = .07$, $SRMR = .06$) and good internal consistency ($\omega = .91$). The social-related beliefs factor reached overall good model fit ($\chi^2(33) = 65$, $p = .001$, $CFI = .96$, $TLI = .95$, $RMSEA = .07$, $SRMR = .05$) and good internal consistency ($\omega = .89$). The self-related beliefs factor reached only moderate fit ($\chi^2(10) = 240$, $p < .001$, $CFI = .94$, $TLI = .84$, $RMSEA = .14$, $SRMR = .05$) and moderate internal consistency ($\omega = .74$). In total 1 item (affect / behavior) was deleted, and 8 residual correlations were added. The single-factor models are depicted in Fig. 2.

After testing the fit of the single factors, a model of correlated attitudinal factors was tested. The fit was moderate ($\chi^2(888) = 1617$, $p < .001$, $CFI = .83$, $TLI = .82$, $RMSEA = .07$, $SRMR = .09$). To improve fit, the self-related factor and one item from the task-related belief factor were deleted (decisions based on modification indices). The model fit improved but remained moderate ($\chi^2(655) = 1097$, $p < .001$, $CFI = .88$, $TLI = .87$, $RMSEA = .06$, $SRMR = .07$). The latent factors correlated highly with each other - the two cognitive factors ($r_{task-social} = .60$), but especially the cognitive factors and the affective-behavioral factor ($r_{task-affect} = .76$, $r_{social-affect} = .77$). The model is depicted in Fig. 3. The 38 items used for this model can

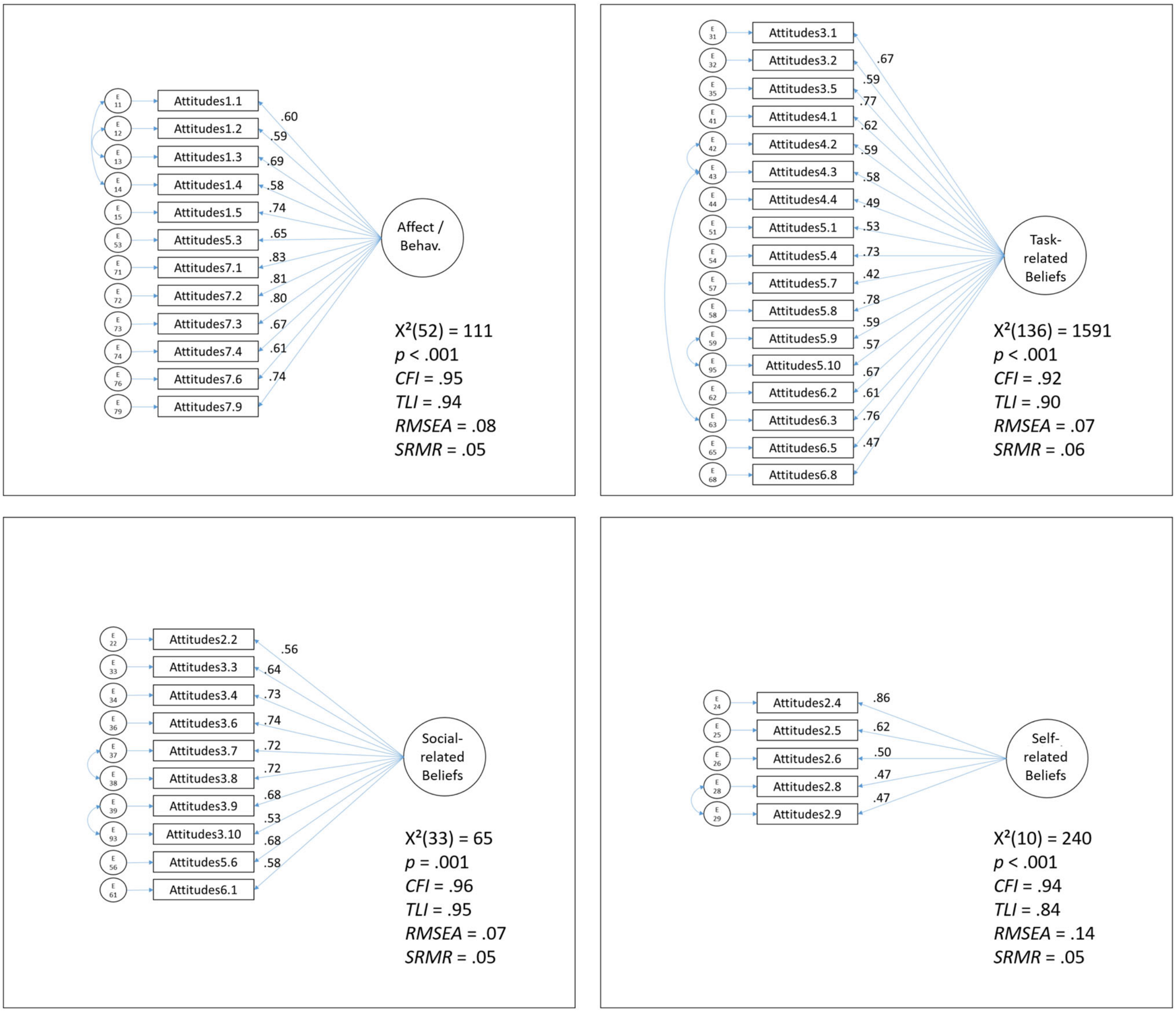

Fig. 2 Single-factor models for each of the attitudinal factors, based on the project sample ($N = 201$). The model for the attitudinal affect factor is in the upper left, for the task-related beliefs in the upper right, for the social-related beliefs in the bottom left and for the self-related beliefs in the bottom right

be downloaded at https://osf.io/5fnr9/ [37]. Taken together the results of the factor analyses, attitudes toward robots can generally be described by three factors resembling affective / behavioral, task-related, and social-related concerns (Step 1).

5.3 Short Scale Construction Using Ant Colony Optimization

Based on the three-factor model, we constructed the short scale ACIR-Q to allow for a more time-efficient measurement in future studies. We used ant colony optimization (ACO, [49, 50]) to identify the (approximately) best possible solution. Ant colony optimization is a search heuristic inspired by the behavior of ants, which use pheromones attracting other ants to find the shortest path to a food source. Similarly, "ACO uses virtual pheromones to increase the attractiveness of item sets that yield better psychometric properties" [50, pp. 402–403].

For ACO we aimed to optimize CFI and RMSEA, as well as Mc Donald's omega simultaneously in a solution consisting of four items for each of the attitudinal sub-factors ("affect / behavior", "task-related beliefs" and "social-related beliefs"). As recommended by Olaru et al. [50], a maximum number of 40 iterations, 60 ants per iteration, and an evaporation parameter of.99 were chosen. Because ACO is a probabilistic search procedure, the analysis was run 10 times with identical settings (see [50]).

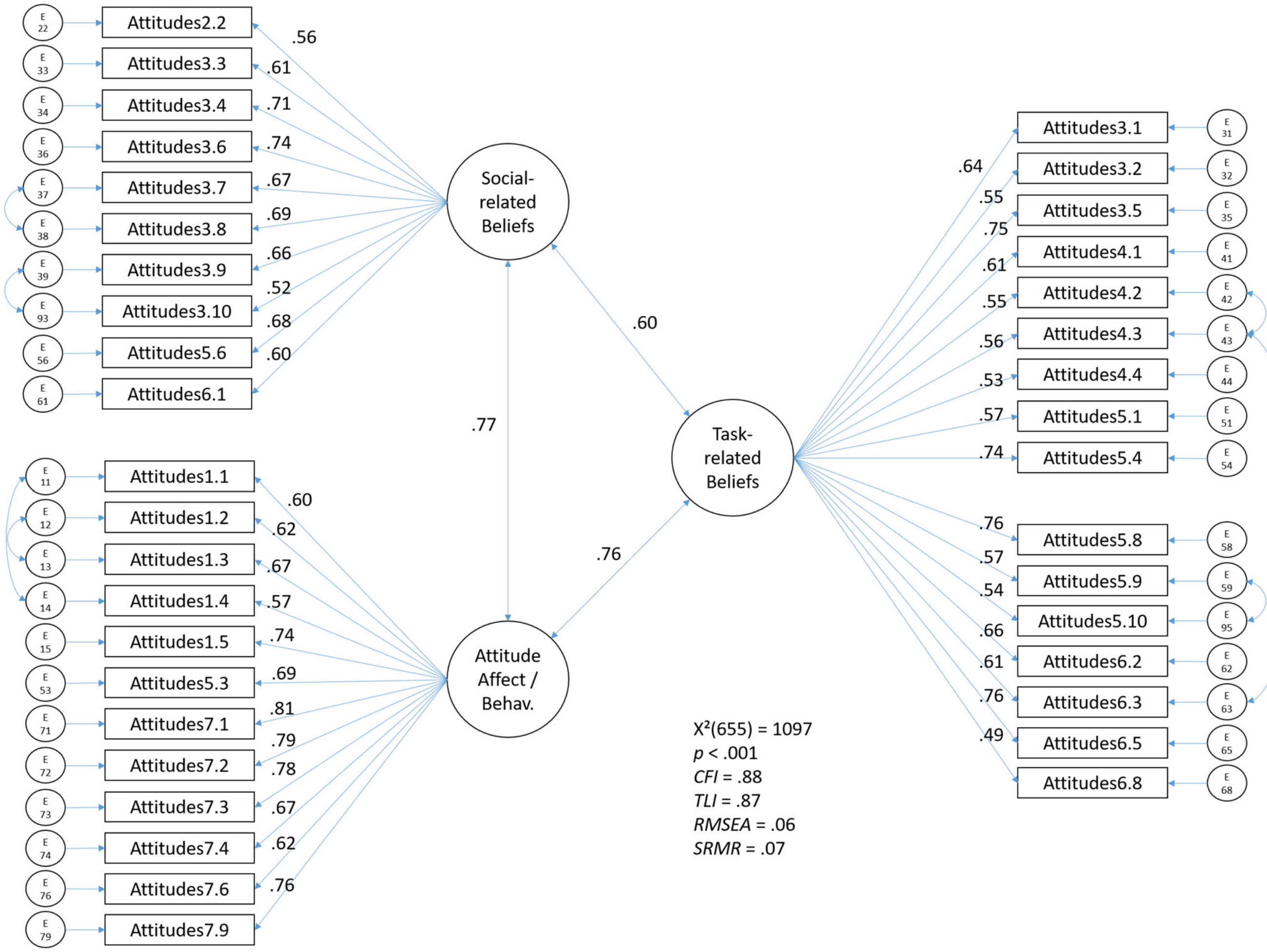

Fig. 3 Attitudinal factor model including three correlated factors on affective/behavioral attitudes, task-related beliefs and social-related beliefs, based on the project sample ($N = 201$). Goodness of fit: $\chi^2(655) = 1097$, $p < .001$, $CFI = .88$, $TLI = .87$, $RMSEA = .06$, $SRMR = .07$

The algorithm resulted in the best solution of 12 items with indices $CFI \approx 1$, $RMSEA \approx 0$, $\omega_{task} = .81$, $\omega_{social} = .84$, $\omega_{affect-behavior} = .83$ (Step 2). The high correlations between factor scores of the 12-item ACIR-Q and factor scores based on the longer 38-item version ($r_{affect(short,long)} = .95$, $r_{task(short,long)} = .92$, $r_{social(short,long)} = .94$) indicate that the 12-item ACIR-Q represents the factors equally well.

Overall ($N = 556$), based on a bipolar 5-point scale, affective attitudes and behavioral intentions are moderate to slightly positive ($M = 3.41$, $SD = .87$). Cognitive beliefs concerning task-related changes due to new robots were also moderate to slightly positive ($M = 3.47$, $SD = .78$), and cognitive beliefs concerning social changes were slightly negative to moderate ($M = 2.80$, $SD = .89$).

5.4 Network Modeling

As explained in the theoretical section, network analysis was expected to give further insights on attitude structure and change. Network models are estimated using regularized partial correlations. Regularization techniques in network estimation lead to sparse models by penalizing complexity [23]. Thus, we used the "least absolute shrinkage and selection operator" (= "lasso", [60]). The Extended Bayesian Information Criterion (EBIC) is minimized to select the best fitting model. The hyperparameter $\gamma = 0.5$ is chosen as recommended by Epskamp and Fried [23].

The small-worldness measure S, based on a global clustering coefficient and the average shortest path length, is used to determine if the network can be classified as small-world network. An index of $S > 1$ indicates a small-world structure [16, 32]. Centrality statistics were calculated in order to identify the most central nodes of the network.

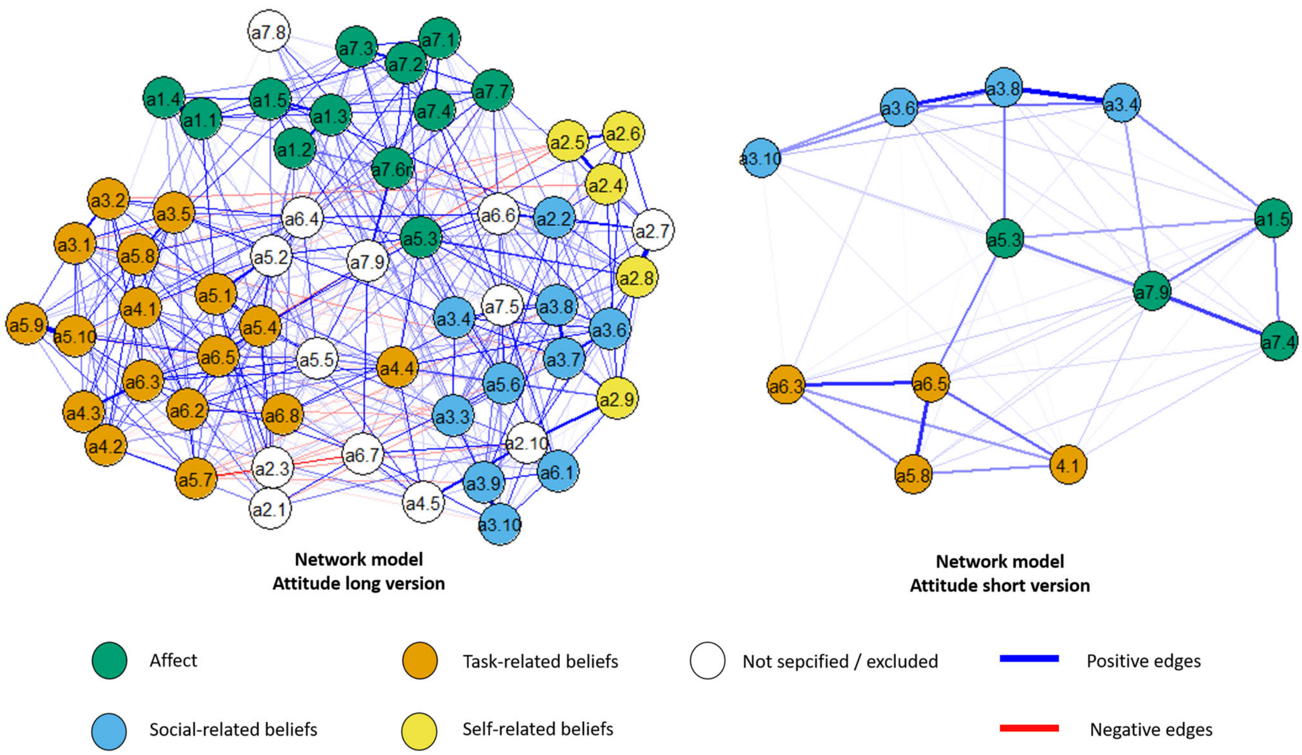

Fig. 4 Network structure of attitudes toward robots of all evaluative responses ($k_{all} = 57$ items) and the evaluative responses included in the ACIR-Q ($k_{ACIR-Q} = 12$) using both samples. Evaluative responses are represented as nodes (a1.1–a7.9), bi-directional causal influences as edges

Two network models were calculated, one network model including all attitudinal items, and one model including the 12 item ACIR-Q. Both models are depicted in Fig. 4, in which evaluative reactions are depicted as nodes connected by edges. Excitatory or inhibitory connections are coded with different colors. These connections can also vary in strengths (weights), depicted as color saturation and the width of the edges with more saturated and wider edges corresponding to higher weights (stronger connections). The strength is also indicated by the distance of the nodes of which stronger connected nodes are closer to each other compared to less strongly connected nodes. Additionally, nodes are colored to indicate groupings based on the factor analysis.

Because both, factor analysis and network modeling are based on commonalities, those items reflecting one factor are visible as clusters within networks, that is a number of evaluative responses within a group are more closely connected compared to evaluative responses clustered within other groups.

The small-worldness statistic for the model including all items $S_{all} = 1.26$ and for the model including only the 12 ACIR-Q items $S_{ACIR-Q} = 1.02$ indicate that the data can be described by a small-world structure (Step 3). As such, networks allow to hold complex attitudes, in which for example social-related beliefs are more negative while task-related beliefs may be more positive.

For attitude change, the most influential nodes can be identified through centrality measures. As recommended by Epskamp and Fried [12, p. 18], strength centrality (= number of neighbors of a node) was used to identify items that are most influential in the network.

The nodes with the highest strength centrality based on the network including all items, represent concerns about changes in work organization ($C_D(i) = 1.31$), changes in the complexity of the work tasks ($C_D(i) = 1.24$), their confidence with the robot ($C_D(i) = 1.23$), their feeling of being needed or being superfluous ($C_D(i) = 1.21$), and the impact on their work skills ($C_D(i) = 1.19$) (see Appendix D).

The nodes highest in centrality of the ACIR-Q differ only slightly, concerning workers' feeling of confidence ($C_D(i) = 1.11$), the worries of the robot's effect on work organization ($C_D(i) = 1.08$), and their concerns on the value of human work ($C_D(i) = 1.06$) being most central.

A change in these evaluative responses is predicted to lead to change of other nodes in the network as a ripple effect. The centrality measures give additional information for attitude change that cannot be obtained by factor analysis as the nodes highest in centrality do not necessarily represent the factors very well.

Table 1 Goodness of fit indices for factor models for each of the co-variates

Model	M	SD	χ^2	Df	CFI	TLI	$RMSEA$	$SRMR$	ω	Final / Excluded items
Perceived competence	4.20	1.24	47	2	.95	.86	.20	.04	.85	4/3
Perceived control	3.08	0.79	22	9	.97	.95	.07	.03	.80	6/1
General self-efficacy	4.15	0.59	–	–	–	–	–	–	.86	3/0
Job security	2.53	0.68	38	2	.97	.92	.18	.03	.89	4/0
Trust-ability	3.38	1.03	5967	55	.97	.97	.08	.03	.95	6/0
Trust-benevolence	2.94	0.99	5967	55	.97	.97	.08	.03	.93	5/0
Support climate	3.43	0.93	4061	36	.94	.92	.13	.04	.94	9/0

No fit indices are reported for general self-efficacy as this model is just identified (zero degree of freedom). The fit indices are based on the improved scales after item exclusion. Goodness of fit indices for the two trust factors are the same as a correlated two-dimensional factor model was calculated

Table 2 Fit indices for models including correlated attitudinal factors (ACIR-Q) and different interpersonal and organizational co-variates

Model (covariate, ACIR-Q)	χ^2	DF	CFI	TLI	$RMSEA$	$SRMR$	$r_{cov-affect}$	$r_{cov-task}$	$r_{cov-social}$
Perceived competence, ACIR-Q	155	98	.99	.98	.03	.04	.34	.28	.24
Perceived control, ACIR-Q	177	129	.99	.98	.03	.04	.59	.55	.50
General self-efficacy, ACIR-Q	98	84	1	1	.02	.03	.18	.18	.02
Job security, ACIR-Q	187	98	.98	.98	.04	.04	-.44	-.22	-.44
Trust (ability/benevolence), ACIR-Q	383	220	.98	.98	.04	.03	.22/.28	.20/.18	.10/.27
Support climate, ACIR-Q	437	183	.96	.96	.05	.03	.24	.19	.14

Attitudes consist of the correlated sub-factors affect / behavior (affect), task-related beliefs (task) and social-related beliefs (social). Both samples were used for the calculation of all parameters and correlations between the attitudinal factors and the covariates ($r_{cov-factor}$)

5.5 Relationships with Interpersonal and Organizational Variables

The interindividual and organizational influences on attitudes were tested using both samples. First, factor analysis for each of the co-variables was run and internal consistencies (Mc Donald's ω) were calculated (see Table 1). Single-factor models were calculated except trust in management, for which a two-dimensional factor model with correlated latent sub-factors on ability and benevolence was tested ($r_{ability,benevolence} = .72$). If the deletion of items led to improved model fit or higher internal consistency items were excluded for further analysis. All variables reached acceptable to good model fit (except general self-efficacy which was just identified), and acceptable to good internal consistency (see Table 1).

For each co-variate a model was calculated in which the co-variate was correlated with each of the attitudinal factors. The attitudinal factors were modeled based on the ACIR-Q items (see Table 2).

Perceived control and perceived competence are positively and moderately correlated with attitudinal variables. General self-efficacy showed only small relationships to attitudinal factors (Step 5). Among organizational variables (Step 6), job-insecurity correlated most highly with attitudes toward robots. Correlations of all other organizational variables with attitudinal variables are low with $|r| < .30$. However, workers who trust their management and feel supported by the organization during change, also showed more positive attitudes toward the robot.

Furthermore, we tested differences in attitudes between organizations and workplace characteristics for the 12-item ACIR-Q (Step 7). The affiliation to companies in the project sample can be understood as a multi-group situation. We thus tested a model including workplace affiliation as a manifest effect coded variable additionally regressing on the three correlated attitudinal factors (“affect / behavior”, “task-related beliefs” and “social-related beliefs”). The model fit was very good ($\chi^2(87) = 84$, $p < .58$, $CFI = 1$, $TLI = 1$, $RMSEA < .001$, $SRMR = .04$). Model intercepts showed that workers' attitudes differed between organizations significantly (Appendix E).

Additionally, workers ($N = 556$) felt more positive about the robot if they had managerial responsibility ($t(370) = 2.89$, $p = .01$; $d = .26$, $CI95\% = [.09, .44]$, and if they already use a robot at work ($t(432) = 3.22$, $p < .01$; $d = .28$, $CI95\% = [.11, .46]$).

6 Discussion

In this article, we described the development of a new context-specific questionnaire—the ACIR-Q—to measure workers' attitudes toward cooperative manufacturing robots and their implementation into industrial work systems. The goal was to identify major areas of concern and to create a basis for the development of intervention strategies and managerial decision making. In doing so, this work also addresses the need for more scale validation in HRI research [39].

6.1 The Structure of the Attitude Construct

We used exploratory and confirmatory analysis to identify different areas of concerns based on a large item pool. Three major areas of concern were identified including a factor based on affective evaluations and behavioral intentions, as well as two cognitive factors including a factor based on task-related beliefs, and a factor based on social-related beliefs (Step 1).

Based on a model including these three attitudinal factors, we were able to construct our new 12-item short scale ACIR-Q using ant colony optimization for an efficient measurement of attitudes toward cooperative industrial robots and their implementation (Step 2). The analysis showed good model fit and good internal consistencies. The short scale is comparable to longer questionnaires with more items.

We additionally analyzed the data from a network perspective. The data showed a small-world structure of attitudes that is high clustering and high overall connectivity (Step 3). This means that one could hold complex attitudes including different areas of concern. For example, with such a small-world structure, it is possible for workers to have positive task-related beliefs, while social-related beliefs can be more negative. A change in valence of one cluster might not cause a change in other clusters.

In a network conceptualization of attitudes, nodes as evaluative responses differ in centrality and thus in relative importance for attitude change as nodes with higher centrality are more likely to affect other nodes in the network [12, 19]. We thus identified nodes highest in strength centrality (Step 4), which can be used for implications on attitude change.

The structure of the attitudes in this study differed compared to other past studies. Herold et al [30] found two rather vague factors describing a general negative and positive factor and Chao and Kozlowski [13] found four specific but different factors (e.g., a factor on expected new opportunities). These differences may have various reasons.

One reason is the dynamic time- and context-dependent nature of attitudes as attitudes are moving constructs embedded in different social systems [28]. The phase of the implementation is crucial in this respect [30] as attitudes develop from rather new and loosely coupled networks to more complex networks with several clusters [19]. Additionally, studies also differ in historical embeddedness (i.e. robots are becoming more standard over time) and social contexts. This is especially relevant for early stages of attitude formation because responses to attitudinal items are expected to be shaped by such influences [19, 30].

A second reason for differences in factor structures, are of methodological nature. The scale development and analysis process depends on several subjective decisions and is thus not as objective as the mathematical process makes it seem [9]. Researchers developed the attitudinal questionnaires and decided which items to pick for the study. In the studies of Chao and Kozlowski [13], Herold et al [30] and the study reported in this article, questionnaires differed in the total number of items, in content and the number of items tapping on each content. This can be explained by a process that Block [9] called "prestructuring" meaning items might have been already pre-selected by subjective decisions. Questionnaires force participants to give an answer on a certain evaluative statement even if this questionnaire item does not really correspond to any attitudinal element held by individuals. As a result, some concerns might get artificially overblown just because more items were formulated on a certain aspect. Such a deletion and inclusion of items can lead to a different factor structure. In conclusion, "a small factor can be made large, a large factor can be made small, residuals can be made into "factors"" [9, p. 189]. Subjective decisions like pre-structuring, the choice of statistical cut-of criteria and others thus lead to different attitudinal structures.

6.2 Interpersonal and Organizational Influences on Attitudes

Another goal of this study was to analyze the relationships of attitudinal factors with other interpersonal and organizational variables. These variables can be used to explain differences in attitudes and can subsequently be considered when planning strategies to change attitudes.

Other studies and models (e.g., [48]) highlight the importance of perceived control and perceived competence. Our results confirm this importance especially for perceived control. However, general self-efficacy on the contrary was almost uncorrelated with attitudes (Step 5).

As attitudes are embedded in a social matrix, organizational factors can shape workers' attitudes. Our study showed that workers' attitudes differed significantly between companies, indicating that differences in organizational characteristics would cause differences in attitudes. Across organizational variables, job (in)security had the highest influence on workers' attitudes with a moderate effect. Although other organizational variables such as trust in management and organizational support climate were positively correlated with attitudes toward mobile robots confirming results of Herold et al [30], the magnitude of this influence was rather small (Step 6).

Differences in workers' attitudes are also caused by job characteristics. Workers with higher managerial responsibility had more positive views on the implementation of new robots confirming findings of Chao and Kozlowski [13]. Additionally, workers who already had experience with robots also reported a more positive attitude. Clear expectations based on past experience might lead to this more positive affect. These results emphasize the importance of the social context for attitudes and thus attempts of attitude change need to take into account the organizational and job context of workers.

6.3 Practical Implications

The article showed that the newly developed, context-specific, short, time efficient and free to use ACIR questionnaire was able to identify differences in attitudes toward robots and to identify major areas of concerns specifically for industrial work settings. The questionnaire can thus be recommended for use in organizational practice and might be preferred to broader and more general instruments in diagnosing attitudes in change processes and as a basis for intervention strategies. For example, it can be used as an initial screening tool to capture a broad picture in the workforce and it can be used longitudinally to monitor the progression and changes in attitudes during the change process. From a research perspective the results show that the new context-specific factors reflect worker concerns that are currently not reflected in more generic models such as the Technology Acceptance Model. Thus, these attitudinal constructs could be used to extend and adapt existing models for very specific contexts by predicting existing constructs and thus providing deeper understanding [6, 10, 57], for example, predicting behavior beyond self-efficacy-related constructs. The ACIR-Q is accessible in Appendix C in German and English. Additional materials are available at https://osf.io/5fnr9/ [37].

Based on the data presented in this article, workers' attitudes toward robots and the implementation tend to be positive. However, attitudes varied between individuals and organizations. Especially, concerns such as fear of being isolated at the workplace or the fear of job loss need to be addressed in organizational change carefully. Different strategies derived from the results of factor analysis, centrality measures of network analysis, and the influence of other interindividual and organizational variables, are expected to improve workers' attitudes.

1. Robotic technology design: The results showed that attitudes were highly correlated with perceived control over the robot. Such a perceived controllability can be established, for example, by adding possibilities to interact with the technology in its design.
2. Training for workers: Another implication is to provide appropriate training for workers in using the robot. The results showed a correlation between perceived competence and the affective-behavioral attitude factor. Additionally, demographic analysis showed that workers who have experience in using a robot at work had more positive attitudes toward the mobile robot. Thus, earlier or longer training with robots could be helpful, which would need to be investigated in intervention studies.
3. Job and work design strategies: A major fear of workers were social-related concerns including isolation. Such an isolation of workers can eventually be prevented by rearranging the workplace or by job redesign (e.g., job enlargement). These job design strategies can have additional positive effects. An increase in managerial responsibility and a decrease of the feeling of being superfluous (a feeling with high centrality) might lead to more positive attitudes toward the robot.
4. Managerial strategies: As the relationships with other organizational variables suggest, a more indirect strategy to improve attitudes toward robots might be managerial interventions such as the improvement of organizational support or workers' trust in management.

To briefly sketch an example, if it emerges that a certain number of plant workers no longer feel valued enough due to the introduction of a robot (item "With new robots I lose value as a worker"), this could be a sign of low trust in management, or it could also mean that their perceived own value is lower due to shifts in work tasks. Therefore, efforts could be made to increase workers' value perception through measures that increase trust in the company (e.g., communicating change processes more transparently) and changes in job design (e.g., by assigning new tasks that are more meaningful).

6.4 Limitations

As for every study, several limitations need to be addressed. Attitudes are described as dynamic and time-dependent [30]. For example, with the rapid development of robots, the attitude stimulus might change raising new concerns resulting in a different networks and factor structures. Because of these dynamics, validation processes are difficult. A questionnaire being valid in one situation might not be valid in another situation. Thus, the questionnaire must be adapted. However, we tried to cover a wide range of work-related concerns. This breadth is likely to be beneficial when transferring the questionnaire into other contexts.

The breadth of possible attitude content and its dynamic nature also poses another challenge to measurement. In the exploratory analysis where many items with high diversity in attitudinal content were tested, the three-factor solution explained 39% of variance in the data. However, adding more factors would explain little further variance, and it would take a large number of hard-to-interpret factors to better explain the variance in the data. We think this property is inherent and natural to the field of attitudes. This is not necessarily a problem, it just requires a well-considered decision by applicants of attitude scales on how to decide in the trade-off between exhaustivity and measurement accuracy. A quantitative survey by means of questionnaires cannot capture attitudes in full depth, but for diagnostic purposes it is sufficient to capture central indicators accurately in sufficient depth to derive meaningful and actionable measures. We have developed a scale with a three-factor solution as an adequate middle ground. Thus, three factors can be captured with good construct validity and represent a good starting point on which to build further.

A similar limitation regarding the breadth-accuracy trade-off can be pointed out for the development of the short scale via ACO. Of course, a short scale always has the risk that a construct cannot be measured in an all-encompassing way but only represents an estimator. However, such short scales can nevertheless capture constructs efficently and still provide a good estimate. Here, too, it was decided to reduce the number of items on the basis of the available data so that the three-factor solution can still be estimated well. If one looks at the items, they still show a certain breadth in content even within the factors. For example, the social cognitive factor does not only contain the fear of losing one's job as in Chao and Kozlowski [13], but also aspects of the meaningfulness of the work or the social contact to colleagues. Nonetheless, short scales could of course be developed that optimize aspects other than a certain factor structure, such as optimizing a breadth of content, alternatively in future work.

Another limitation is the explicit measurement method. Especially in situations in which workers only hold weak attitudes a questionnaire with many items covering a wide range of topics can lead to artificially overblown unstable results. In such situations, qualitative interviews can be less prone to this problem of quantification (see [5]). Other methodological limitations such as the subjectivity of analysis had been outlined above to explain differences between studies.

Finally, a limitation is the study design. All variables had been measured only at one point in time. We were thus not able to analyze the process of attitude formation during the change process. This is a limitation especially because attitudinal factors and attitudinal networks can change over time. Furthermore, only two German samples had been used in this validation process. The scale has to be continuously tested with new samples to confirm the suggested structure, also within new contexts and cultural backgrounds. The scale also needs to be tested in longitudinal studies during change processes in the future. Additionally, the effect of these attitudes on actual behavior (e.g., turn-over) still needs to be tested.

7 Conclusion

In organizational change processes following the implementation of new technologies such as mobile robots, it is essential to take into account the needs and concerns of factory workers. In this article, we reported the development of a new context-specific questionnaire to measure workers' attitudes toward mobile manufacturing robots and their implementation serving as a basis for managerial intervention strategies. We showed how network theory can be used to identify the attitude structure and how other organizational factors can shape these attitudes. However, future studies need to further explore the predictive power of such attitude measures for actual behavior such as turn-over in longitudinal studies or multi-level analyses across different cultures. For such endeavors, the 12-item ACIR-Q short scale can be used to measure workers' attitudes effectively.

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Author Contributions All authors contributed to the study conception and design. Benedikt Leichtmann prepared the material, collected data, analyzed data, and wrote the first draft of the manuscript. Additionally, Benedikt Leichtmann and Johanna Hartung both collected items for the initial item pool for the questionnaire development. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data Availability Data from the online sample and additional materials are available at https://osf.io/5fnr9/ [37]. Data from the online sample is additionally available in the supplements. Data from the field sample is available upon request.

Declarations

Competing Interests The authors have no competing interests to declare that are relevant to the content of this article.

Ethical approval The study complied with the tenets of the Declaration of Helsinki, was supported by the local works council, and approved by the ethics committee of the Bundeswehr University Munich.

Consent to participate Study participants were given all necessary information about the study before participation and gave their informed consent. Participation in the study was voluntary and could be terminated at any time without consequences.

Code availability The R-Code used for the analysis of data is available in the supplements.

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Appendix A: Context Description Using a HRI Taxonomy

Using the HRI taxonomy by Onnasch and Roesler [51], possible contexts and robots with corresponding tasks for which the use of ACIR-Q was developed will be described in this Appendix. This description is only intended to sketch an outline, not to be exhaustive. This categorization is based on qualitative work [36].

Field of Application industry, manufacturing sector, including tasks such as assembly, pre-assembly, setup/operation/monitoring of machines/equipment, work on machines/equipment (e.g. insertion/removal of parts), quality control/assurance, intralogistics, transportation of materials, order picking, management of incoming/outgoing goods, inventory management in the warehouse, packaging and shipping, maintenance of machines.

Description of Robot Type and Tasks Mobile cooperative manufacturing robot, for example consisting of a mobile automated guided vehicle and a manipulator attached to it such as a robotic arm with a gripper. Typical tasks of such mobile cooperative robots are order picking, transportation of materials and goods in the warehouse and assembly area, autonomous pre-assembly, cooperative work tasks with human workers such as cooperative assembly. Furthermore they can collect, process and provide certain information via sensors and communication channels. The FORobotics mobile cooperative robot and its tasks are described as an example in Sect. 4.1 and in previous ergonomic and design studies [15, 39] and is depicted in Fig. 1.

Human Roles Mobile cooperative robots may be developed as flexible tools for different tasks. Thus, depending on the task, the role of the human worker differs. For example, human worker and robot might work in the same workplace for order picking in the material warehouse and are responsible for transporting materials (see [39]). In such a scenario human workers may be bystanders or collaborators. When human workers and the mobile cooperative robot have to cooperate in an assembly task, such as mounting motors on a steel ring as in the study by Colceriu et al [15], the human worker has the role of a cooperator or even also supervisor.

Proximity Proximity can also be different depending on the current task [36] which is very close in cooperative assembly tasks [15] or distant in storage corridors in a warehouse where human worker and mobile robot transport materials independently from each other [39].

Appendix B: Item Development Process Details

Items were developed in an iterative process. First, items of existing context-specific scales (i.e., attitudes toward robots in manufacturing contexts) by Herold et al [30], Chao and Kozlowski [13] and based on work by Argote et al [5] were collected. Second, additional items were formulated based on qualitative, structured, guide-based work-system analyses with observational interviews that had been conducted in four different work systems in manufacturing contexts [36] to identify potential work-related effects of robot implementations. The new items aimed to cover such potential work-related effects of new robots that had not been covered by other items. Such new items were developed by two researchers independently to ensure diversity in the item pool. In a third step, the large item pool was checked based on general diagnostic quality criteria, for example items should avoid terms like "everyone", "no one", "never", or "always", should avoid covering two different aspects in one item combinded, such as "robots are dangerous and boring", and should avoid complex, long sentences (e.g., "Robots will perform tasks that no one wants to do because they are too dangerous or too boring for humans."). Thus, items were reformulated or seperated into different items. This process resulted in $I_1 = 81$ items.

These items were pretested for comprehension using a qualitative thinking aloud method and interviews (people were instructed to speak out their thoughts while reading and answering the questionnaire and were interviewed about their comprehension of the items) with four different participants with diversity in gender, age (20, 30, 54 and 59 years), and educational level. Furthermore, one manufacturing worker was asked to provide further content-related feedback on the scale. Based on the thinking aloud interviews and feedback, the item pool was modified resulting in $N_{Attitude} = 57$ items. Finally, the questionnaire including the newly developed items was also reviewed by local works councils, workers' representatives from the companies from the field sample, as well as an ethics committee, and approved.

Appendix C: ACIR-Q Items in German and English Language

Table 3 shows all 12 items in German original and English translation of the ACIR-Q, on which factors they mainly load, and item codes used for network modeling to name nodes.

The questionnaire ACIR-Q has been developed mainly to diagnose attitudes of factory workers toward new cooperative robots that are going to be implemented in industrial work contexts. In order to obtain a valid measurement, it is recommended to communicate a description of the robot to be used, its location and purpose, as well as its capabilities before applying the questionnaire.

The ACIR-Q has been developed as a bipolar scale, that means each item consists of a negative and a positive pole. In our studies participants were able to rate their degree of agreement with one of the statements by crossing one of five boxes between the opposing statements. An example how the scale could look like on paper can be seen in Fig. 5. We recommend using the following or similar instructions for particpants:

Table 3 Attitudes toward cooperative industrial robots questionnaire (ACIR-Q) in the German original and English translation

Item code	German original items	English translation	Factor
Attitudes1-5	"Die Einführung neuer Roboter finde ich insgesamt schlecht."—"Die Einführung neuer Roboter finde ich insgesamt gut"	"I generally find the implementation of new robots bad."—"I generally find the implementation of new robots good"	Affect/ Behavior
Attitudes3-4	"Durch neue Roboter habe ich Angst meinen Arbeitsplatz zu verlieren."—"Durch neue Roboter wird mein Arbeitsplatz auf lange Sicht gesichert"	"I'm afraid of losing my job because of new robots."—"New robots will secure my job for the long term"	Social beliefs
Attitudes3-6	"Durch neue Roboter verliert meine Arbeit zunehmend an Sinn."—"Durch neue Roboter erhält meine Arbeit neuen Sinn"	"New robots make my work increasingly meaningless."—"New robots make my work more meaningful"	Social beliefs
Attitudes3-8	"Durch neue Roboter verliere ich als Arbeiter an Wert."—"Durch neue Roboter gewinne ich als Arbeiter an Wert"	"With new robots I lose value as a worker."—"With new robots I gain in value as a worker"	Social beliefs
Attitudes3-10	"Durch neue Roboter werde ich weniger mit meinen Kollegen in Kontakt sein."—"Durch neue Roboter werde ich mehr mit meinen Kollegen in Kontakt sein"	"Because of new robots I will be less in contact with my colleagues."—"Because of new robots I will be more in contact with my colleagues"	Social beliefs

Table 3 continued

Item code	German original items	English translation	Factor
Attitudes4-1	"Durch neue Roboter werden die Arbeitsabläufe undurchsichtiger."—"Durch neue Roboter werden die Arbeitsabläufe übersichtlicher"	"New robots make work processes more opaque."—"New robots make the work processes clearer"	Task beliefs
Attitudes5-3	"Neue Roboter werden meine Arbeitssituation verschlechtern."—"Neue Roboter werden meine Arbeitssituation verbessern"	"New robots will make my work situation worse."—"New robots will improve my work situation"	Affect/ Behavior
Attitudes5-8	"Neue Roboter werden zu schlechteren Arbeitsergebnissen bei uns führen."—"Neue Roboter werden zu besseren Arbeitsergebnissen bei uns führen"	"New robots will lead to worse work results in our company."—"New robots will lead to better work results in our company"	Task beliefs
Attitudes6-3	"Neue Roboter sind ein neues Risiko für Gefahren an meinem Arbeitsplatz."—"Neue Roboter geben Potenzial für mehr Sicherheit an meinem Arbeitsplatz"	"New robots are a new hazard in my workplace."—"New robots offer potential for more safety at my workplace"	Task beliefs
Attitudes6-5	"Neue Roboter werden in unserer Arbeit vieles durcheinanderbringen."—"Neue Roboter werden zu mehr Ordnung in der Arbeit führen"	"New robots will mess up a lot at work."—"New robots will lead to more organized work"	Task beliefs
Attitudes7-4	"Ich möchte mich in meiner Arbeit für einen neuen Roboter nicht umstellen müssen."—"Ich würde mich für einen neuen Roboter in der Arbeit auch umstellen"	"I do not want to have to change my work for a new robot."—"I would change for a new robot at work"	Affect/ Behavior
Attitudes7-9	"Bezüglich eines neuen Roboters habe ich ein mulmiges Gefühl."—"Bezüglich eines neuen Roboters bin ich zuversichtlich"	"I have an uneasy feeling about a new robot."—"I am confident about a new robot"	Affect/ Behavior

The codes in this table are the codes used in this paper. The column "Factors" indicates the corresponding factor

"In the following you will find statements about robots and their effects on your work. In each line you will find two opposing statements at the respective ends. Please indicate for each line which of the two statements you rather agree with by putting a cross between the statements. The more you agree with a statement, the closer your cross should be to that statement. We are interested in your personal opinion. There are no right or wrong answers. So please answer honestly."

For the analysis of the questionnaire, scale means and standard deviations can be calculated for each of the three subscales.

$$Affect/Behavior = \{attitudes1.5, attitudes5.3, attitudes7.4, attitudes7.9\}$$

$$Task = \{attitudes4.1, attitudes5.8, attitudes6.3, attitudes6.5\}$$

$$Social = \{attitudes3.4, attitudes3.6, attitudes3.8, attitudes3.10\}$$

More information on how to use the scale can be found online at https://osf.io/5fnr9/ [37].

I generally find the implementation of new robots bad.	☐	☐	☐	☐	☐	I generally find the implementation of new robots good.
I'm afraid of losing my job because of new robots.	☐	☐	☐	☐	☐	New robots will secure my job for the long term .
New robots make my work increasingly meaningless.	☐	☐	☐	☐	☐	New robots make my work more meaningful.
With new robots I lose value as a worker.	☐	☐	☐	☐	☐	With new robots I gain in value as a worker.
Because of new robots I will be less in contact with my colleagues.	☐	☐	☐	☐	☐	Because of new robots I will be more in contact with my colleagues.
New robots make work processes more opaque.	☐	☐	☐	☐	☐	New robots make the work processes clearer.
New robots will make my work situation worse.	☐	☐	☐	☐	☐	New robots will improve my work situation.
New robots will lead to worse work results in our company.	☐	☐	☐	☐	☐	New robots will lead to better work results in our company.
New robots are a new hazard in my workplace.	☐	☐	☐	☐	☐	New robots offer potential for more safety at my workplace.
New robots will mess up a lot at work.	☐	☐	☐	☐	☐	New robots will lead to more organized work.
I do not want to have to change my work for a new robot.	☐	☐	☐	☐	☐	I would change for a new robot at work.
I have an uneasy feeling about a new robot.	☐	☐	☐	☐	☐	I am confident about a new robot.

Fig. 5 Example how the bipolar ACIR-Q could look like on paper

Appendix D: Centrality Measures

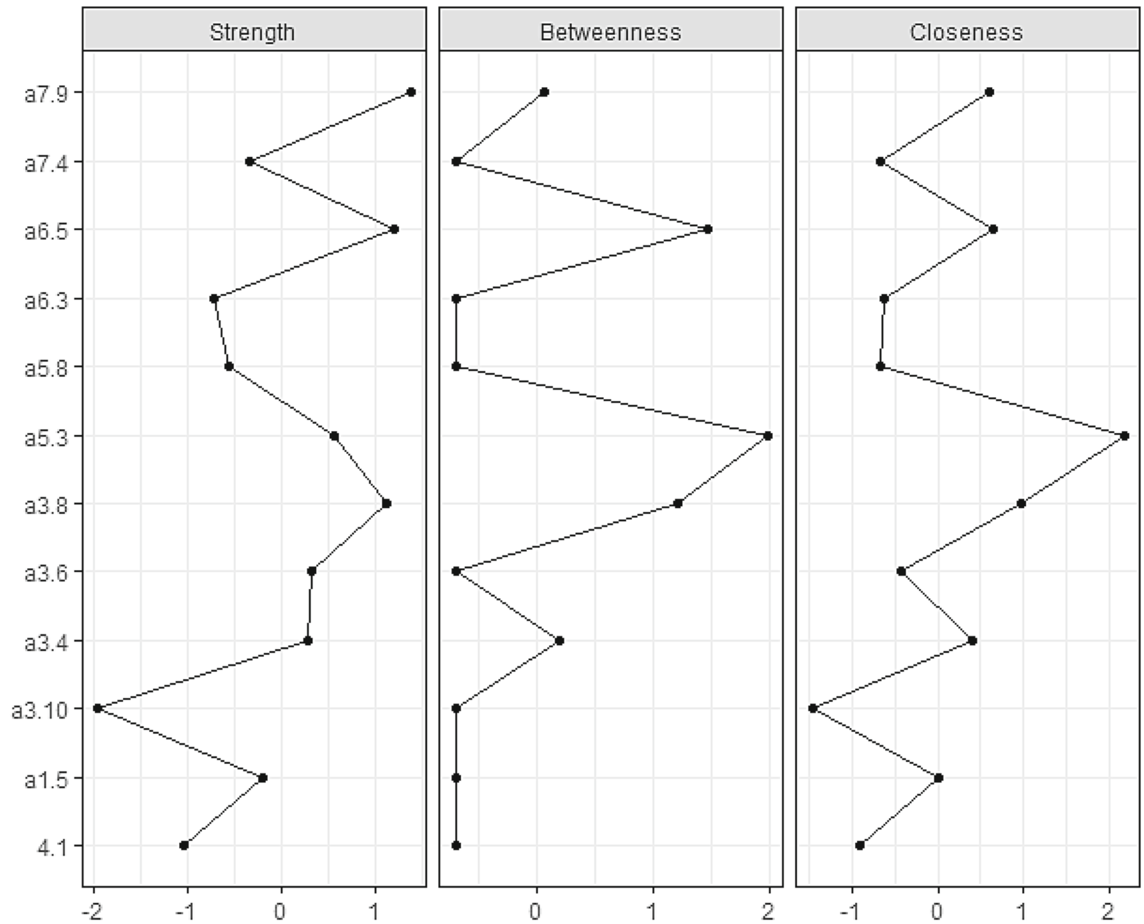

Fig. 6 Centrality measures for a network including the 12 ACIR-Q items

Appendix E: Attitudinal Factor Model with Company Affiliations

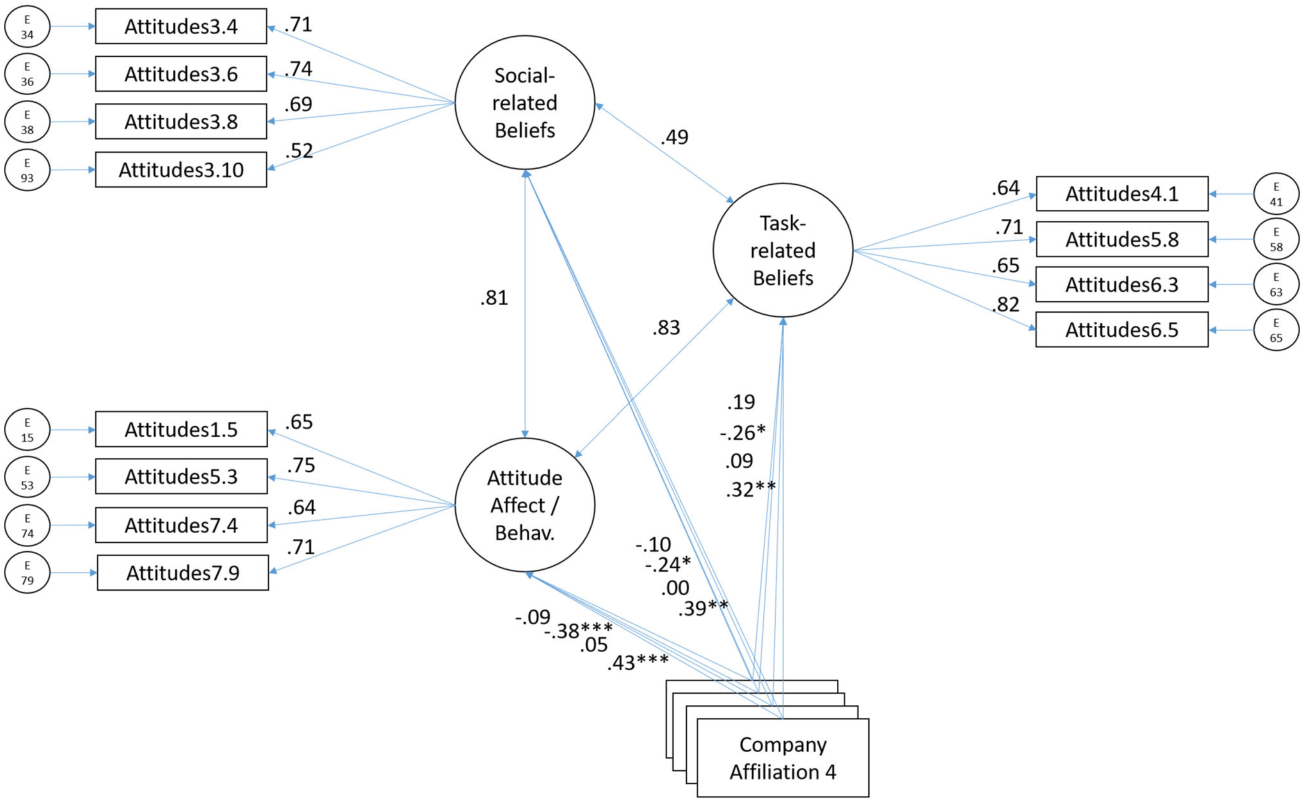

Fig. 7 Attitudinal factor model including three correlated factors company affiliation as manifest effect coded variable. Goodness of fit: $\chi^2(87) = 84$, $p < .58$, $CFI = 1$, $TLI = 1$, $RMSEA < .001$, $SRMR = .04$. Analysis based on the project sample ($N = 201$) and the 12-item ACIR-Q

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