Evaluating Strategies to Restore Trust in Decision Support Systems in Cross-Company Cooperation

Ralf Philipsen(✉), Philipp Brauner, André Calero Valdez, and Martina Ziefle

Human-Computer Interaction Center, RWTH Aachen University, Campus-Boulevard 57, 52074 Aachen, Germany
{philipsen,brauner,calero-valdez, ziefle}@comm.rwth-aachen.de

Abstract. Advancing automation in many technical areas (mobility, production, medicine, etc.) is accompanied by new challenges for the interaction between humans and technical systems. Trust in automation is a key element for the use of technology and for compliance with its recommendations. This also applies to decision support systems (DSS) in the production domain. These can make the increasing complexity of production processes and networks manageable but can lead to serious financial losses in case of error as well. The present study addresses the restoring of trust in those DSS after a failure. In an exploratory two-stage approach, interviews were used to identify user requirements for trust restoring measures, followed by a questionnaire study including a business simulation game to quantify those measures in an exemplary manner. Preliminary results suggest that trust can only be restored to a very limited extent by specific intervention measures, but that systems must laboriously rebuild trust by long-term error-free functioning.

Keywords: Repairing trust in automation · Decision Support Systems
Failure management · Cyber-physical production systems · Human factors

1 Introduction

The increasing complexity of modern products and the underlying production networks also complicate the decisions that managers in production planning and control have to make. Simultaneously, more detailed, heterogeneous, and up-to-date information on production and delivery processes is available due to the digitization of production. This information must be recorded, evaluated and weighed up for making efficient and effective decisions. Many of these decision-making processes can now be automated, but for reasons of strategic, ethics and corporate policy, people cannot entirely be relieved of their responsibilities in the foreseeable future. Providing the decision-makers with the appropriate tools to support them in shaping complex production contexts and in making the flood of information manageable, thus making it easier to make correct decisions, poses a major challenge.

© Springer International Publishing AG, part of Springer Nature 2019
W. Karwowski et al. (Eds.): AHFE 2018, AISC 793, pp. 115–126, 2019.
https://doi.org/10.1007/978-3-319-94196-7_11

Decision support systems (DSS) provide computer-based decision aids for operative, tactical, or strategic decision processes by automating the programmable part of decision problems [1, 2].

These systems are both light and shadow in terms of corporate success and efficiency. In the case of functioning, the likelihood of blatant human error decreases, while defective DSS can cause damage when they provide a faulty basis for decision-making. Previous studies have shown that defective DSS are also detrimental if the malfunction is not recognized by people working with the systems and they consequently continue to blindly follow the DSS [3, 4].

Trust is an essential prerequisite for effective and sustainable relationships between people, organizations, and technology. Consequently, studies have shown that trust in the automated system is crucial for performance [5] and depends on a reasonable calibration between *under*- and *overtrust* in the automated system [6]. Thus, the *use*, *misuse*, *disuse*, or *abuse* [7] of decision support systems and automated processes relates to the correctness of the support system and the users' trust in these systems declines after critical incidents or errors [3, 8]. Understanding which factors influence confidence in a DSS and how trust can be restored once lost, e.g., after a repaired defect, is pivotal for the development and reasonable use of such systems.

2 Related Work and Questions Addressed

The current research regarding the repair of trust can be divided into three areas: Interpersonal trust [9–11], trust in organizations [12, 13] and trust in technical systems [14]. While a broad understanding of the first two subject areas is already available, it is still unclear to what extent findings on human-human trust and trust repair strategies can be applied to technical systems [15].

In particular, there is a lack of detailed knowledge on how the automated system must react after an error in the interaction with the user and on how these interventions of the system must be designed. In accordance with Kim et al.'s results for organizational trust [16], Quinn et al. expected apologies to be more effective for competency-based errors of a technical system and denials for integrity-based errors. However, currently, only preliminary results are available [17]. Promises or apologies can also be effective for robot interaction if the timing is right. The moment the error occurs is not necessarily the ideal time for this, the next time the human user has to rely on the system might be better [18]. This also raises the question of whether the system should take the blame for an error at all, or whether someone else should. According to Buchholz, Kulms and Kopp, both strategies have no influence on the perceived competence of virtual agents, but self-blaming does lead to a higher perceived trustworthiness [19]. However, it is questionable whether the same effects can be demonstrated for simple DSS with a lower tendency to anthropomorphization.

For that reason, it makes sense to take one step back and develop possible system interventions for decision support systems using a user-centered approach, both in terms of design and content. How such interventions must be designed, and how they affect the repair of trust, are therefore the central questions in the present study.

3 Methodology

To address the aforementioned research questions, a two-stage mixed-method approach was applied. For this an explorative procedure using qualitative interviews was followed by a subsequent quantification using a questionnaire. Both studies used a DSS in a previously developed business simulation game as technological context.

3.1 Business Simulation Game as Research Framework

For the experimental research on decision-making in production and supply chain management, the web-based Q-I-Game was developed [20, 21]. In this business simulation game, the player has the role of decision maker. Each round the player has to make decisions on the order of supplier parts for his own company's production, as well as on the investment in the incoming goods inspection, and the production quality itself. Maximizing the company's profit and increasing its own product quality are the central goals of the game. The game includes a DSS which gives recommendations for ordering parts. In the event of a defect, the recommendations are too low and there is a risk of production downtime and penalties if the player does not override the system and deviate from the recommendations.

3.2 Preliminary Qualitative Work

In the first step, guideline-based interviews were conducted, and the derived transcripts were evaluated by content analysis. The interviews aimed to identify general aspects of trust in technology, general requirements for interventions/error messages following a system error, and concrete elements that should be included in such interventions. During the interviews, the participants also had to play the aforementioned game twice, once with a functioning DSS and once with a defective DSS. The participants were asked questions to indicate their trust in the system and to give suggestions for restoring trust. Participation was voluntary and there was no incentive. A total of 15 interviews were conducted by trained interviewers. Nine participants were female, six were male. The average age was 25.3 years (SD = 1.7) and varied between 22 and 28 years.

First, the participants specified general requirements for error messages or interventions after a system failure. Such interventions should be as short as possible, but should still be detailed: "*Short and to the point. No continuous text, so you do not have to read a lot; short and precise*" (female, 25 years). Furthermore, by showing exemplary error messages, it became evident that the information embedded in the use of language and design must convey a seriousness accordant with the context of use, as several participants stated:

> *The visual setup with this "Oops" is not an adequate answer to such a mistake in an economical system. And, yeah, I thought the error message was kind of dubious.* (male, 28 years)

In addition, the participants also felt like friendliness (*"It was very kind…. I almost pardoned the system."*, female, 23 years) and conspicuousness were important aspects to ensure that the message is not missed. Regarding the requested elements that an error message or intervention should contain in order to restore the trust in the system, a distinction was made between:

- the **indication of an error** as the basic condition: *"And if there was such a defect, then I would really like the software or the decision support system to point this out, so that you can plan more thoroughly for the next month."* (female, 26 years)
- the **indication of the cause of error**: *"I think it's important to know why such a mistake happened, why this could happen and why it won't happen again in the future."* (female, 26 years)
- the **information about whether the error has been corrected**
- an **excuse or taking responsibility for the error**: *"Yes, perhaps not necessarily an apology but just a statement that the error was unintentional, that it doesn't happen anymore and that one is doing the most possible to work on fixing the problem."* (male, 28 years)
- and an optional **contact option for human support**: "*Maybe you also have an e-mail address or phone number stored somewhere, so that if you really don't know where to go, you also know that you can contact someone."* (female, 25 years)

In summary, the participants wanted an openly communicating and transparent system:

> *Very important is an open communication because otherwise I think, that I can do that much better and I don't need the system at all and then I probably wouldn't use the software anymore.* (female, 26 years)

While most of the participants asked for a detailed report on the occurred errors, as was described above, there was also the contrary opinion that minor bugs which are fixed quickly and have limited consequences should perhaps not be mentioned, in order not to actively reduce confidence.

> *At the moment, if there had been no error message, you wouldn't have known anything about it. Accordingly, if you do not want to break the trust at all, you should not note anything.* (male, 28 years)

The opinion of some participants, who attached little value to a message/intervention and regarded the system's behavior after the repair as decisive, also aimed in a similar direction: *"If I notice that the system will show me same values again which I calculate in my head, then you can say, okay, I trust in it again."* (female, 24 years)

In conclusion, the interviews essentially gave rise to two questions for further investigation. First, it is unclear what effect an intervention portrayed as an (error) message has on the trust in a DSS, and whether this trust is restored without extra intervention when the user continues to interact with the repaired system in the same way he used to. Furthermore, it must be explored which components of an intervention have which effect on the trust in and reliance on automated systems. The assurance that the error has been corrected and does not recur, which was demanded in the interviews, seemed to be a suitable first focus of investigation.

3.3 Questionnaire Design and Experimental Setting

Based on both the state of the art in research and the interview studies, a large questionnaire study was designed in the second step to address a larger sample. The experimental design is shown in Fig. 1. Every participant had to play the Q-I-Game twice. The first game run consisted of 12 rounds and was solely played as a means of training in order to get the participants acquainted to the game. In this session the DSS was fully functional and there were no interventions. The training was followed by the main game, which comprised twice the number of rounds (24). The game started with a functioning DSS, the system then broke down after round four and started to give wrong, in terms of too low, recommendations for part ordering. Halfway through the game, after twelve rounds, the DSS was repaired and continued to give correct recommendations for the remainder of the game. The participants were randomly assigned to a group, whose affiliation decided whether and in what way there was an information about the prior defect of the DSS between rounds 12 and 13. For this between-group factor, a distinction was made between no intervention, an error message that only indicated that an error occurred in the past, and a message that additionally contained the information that the error had been corrected and that the DSS is functioning normally again.

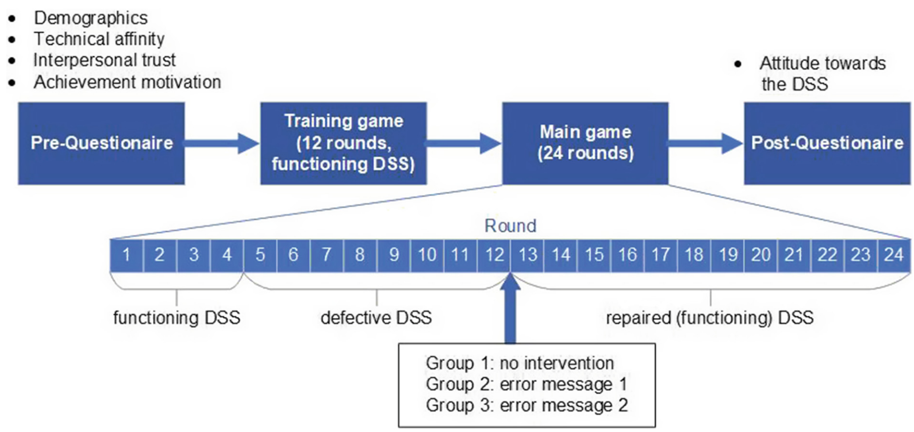

Fig. 1. Overview of the experimental setting

The games were embedded in a questionnaire, which was divided into a pre- and a post-part. In the pre-part, in addition to the usual demographics (i.e., age, gender, level of education) the affinity for technology [22], the disposition to interpersonal trust [23] and the achievement motivation [24] of the participants were assessed. In the post part, the participants had to state how much they trusted the DSS, how much they relied on the recommendations and how well they understood the system's functionality. A 6-point Likert scale answer format was used for all approval and evaluation questions (0 = no agreement at all, 5 = full agreement).

3.4 Data Acquisition, Preparation and Analysis

The study was designed as an online survey. The participants were acquired in specialist forums for production and supply chain management as well as in the university environment. Participation was voluntary, anonymous and there was no form of incentive. Participants who did not complete all games were excluded from the analysis as dropouts. The same applies to speeders and participants with a conspicuously inconsistent, dubious response behavior. The remaining data were analyzed using both parametric and non-parametric methods, where either was applicable. The level of significance was set to $\alpha = .05$. In supplement to frequentist statistics, Bayesian-based methods were used with a Cauchy distribution ($r = .707$) as prior [25].

3.5 Sample

In total, the sample consisted of 72 (N) data sets. 56.9% of the participants ($n = 41$) were male, 43.1% female ($n = 31$). The age varied between 20 and 52 years with an average of 27.1 years ($SD = 6.9$). The participants were rather educated. More than half of them had a university degree (54.1%, $n = 39$) and more than a third graduated from high school (36.1%, $n = 26$). On average, the sample showed a rather high interpersonal trust ($M = 3.7$ out of 5 max, $SD = 0.5$) and technical affinity ($M = 4.0$ out of 5 max, $SD = 0.7$), as well as a high achievement motivation ($M = 4.2$ out of 5 max, $SD = 0.9$).

Due to the subsequent quality-related exclusion of data sets from the analysis, the participants were not evenly distributed among the three intervention groups. 30 participants did not receive any information about the defective DSS and its repair, while 18 participants were only informed that an error had occurred. The remaining 24 participants additionally received the information that the error had been corrected and the recommendations of the DSS would be correct in the future.

4 Results

The results of the study are presented below. A distinction was made between the behavior of the participants during the game and the subsequent evaluation of the (decision support) system, as users often have difficulties calibrating their trust accurately because of their reliance on the system [26].

4.1 Decision Behavior

Three aspects regarding the in-game decision-making were focused on: the time required per round; the absolute deviations, in terms of ordered parts, from the recommendations of the DSS per round; and the percentage of rounds in which deviations from the recommendation were made, as a deviation from the recommendation of the DSS indicates that the participant trusted him- or herself rather than the system. Furthermore, the analysis differentiated between three phases of the game: First, the start of the game with a functioning DSS, second, the middle phase in which the DSS gave false recommendations, and finally the game phase after a possible intervention in which the DSS was repaired and fully functional again.

Looking at the needed time, no significant influence of the intervention was found for the average round times. Except for two peaks in round 5 after the failure of the DSS and in round 13 due to the appearing of the error message, the round time decreased continuously as the game progressed, regardless of the DSS's state.

A different picture emerges regarding the deviations from the recommendations of the DSS (see Fig. 2). A repeated measures Friedman test revealed that the phases differed significantly with regard to the absolute deviations of the ordered quantities from the recommendation ($\chi^2(2) = 35.4$, $p < .001$, $BF_{10} = 7.812 \times 10^5$). Pairwise comparisons (Durbin-Conover) showed that the deviations from the recommendation of the DSS differed significantly between the first functioning phase and the defective phase ($p < .001$, $BF_{10} = 5.723 \times 10^4$) of the DSS. The deviations in the first game phase with correct recommendations are much lower than the ones in the game phase with defective DSS recommendations. The same applies for the first phase and the last phase with the repaired DSS ($p < .001$, $BF_{10} = 4.984 \times 10^3$). In contrast, the deviations from the recommendation did not differ significantly between the defect and repaired DSS condition. For these two conditions, the deviations for the groups with error messages remained approximately at the same level. Deviations for the group without intervention, on the other hand, increased again in the final phase of the game.

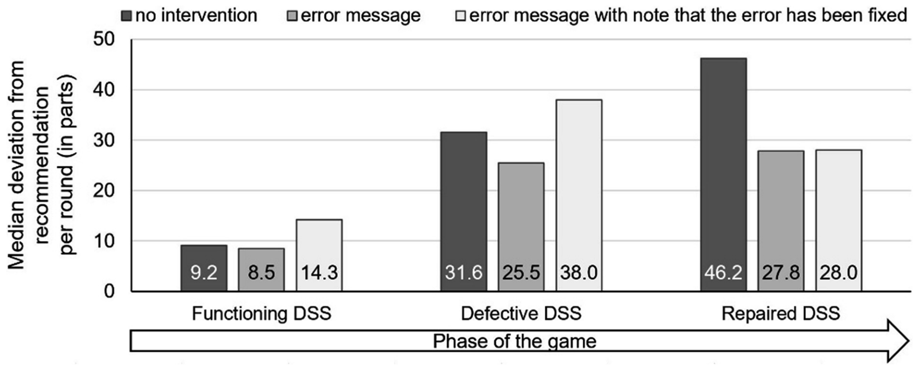

Fig. 2. Median deviation from DSS recommendation in the different phases of the game distinguished between the type of intervention

Although the deviations of the group without intervention in absolute numbers are clearly higher than those of the groups that received an error message, this difference is not significant ($p > .05$, $BF_{10} = 20.781$). In all groups the low starting level of the deviations at the beginning of the game was not achieved again after the failure.

As can be seen in Fig. 3, a similar picture was obtained for the relative number of rounds with deviations from the DSS. Again, an increase in the number of rounds with deviations in the phase with the defective DSS can be observed. Afterwards, fewer rounds with deviations from the recommendations occurred, and the level of the game start was reached again. Accordingly, there is a main effect of game phase on the relative number of rounds with deviations ($F(2, 138) = 11.623$, $p < .001$, $\eta^2 = .139$, $BF_{10} = 706.339$). Post-hoc tests revealed that the phase with the defective DSS differed significantly from the first ($p < .001$, $BF_{10} = 5.474 \times 10^3$) and the last game phase ($p = .012$, $BF_{10} = 7.109$), whereas there was no significant difference between both phases with a functioning DSS ($p < .05$, $BF_{10} < 1$) regarding the number of rounds with deviations. Variations between groups can be found for all phases of the game, but a significant effect of the intervention could not be determined.

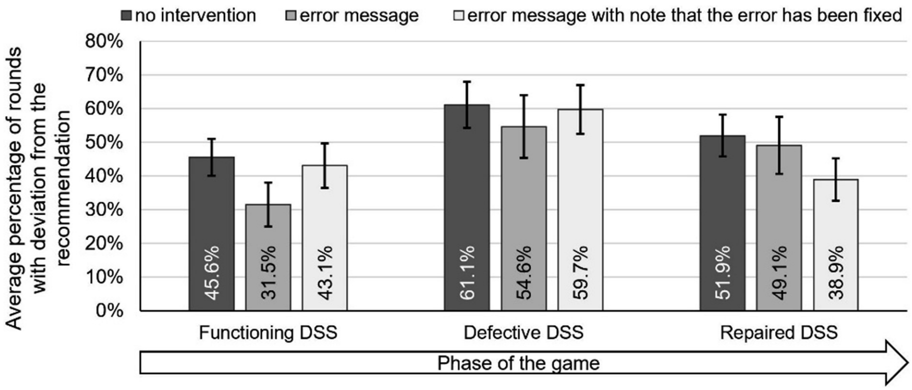

Fig. 3. Average rounds with deviation from DSS recommendation (and standard errors) in the different phases of the game distinguished between the type of intervention

4.2 System Evaluation

After presenting the participants' actual behavior during the game, the participants' attitudes towards the decision support system are presented in the following. To assess these attitudes, a factor analysis of the individual items was carried out and the following dimensions were identified: the participants understanding of the system (Cohen's $d = 0.834$), reliance on the system during the game (Cohen's $d = 0.773$), and the trust in the system (Cohen's $d = 0.830$). As can be seen in Fig. 4, the participants' agreement with each of the dimensions was rather low.

Both for understanding the system and for relying on it, the participants' agreement (absolute means) increased with the level of detail of the intervention. The group without intervention showed the lowest agreement, while the group that received the information that the error was repaired expressed the highest approval. However, this effect was not significant ($p < .05$, $BF_{10} < 1$). The same applies to the trust in the system, where there was no pattern comparable to the other two dimensions.

4.3 Technical Affinity, Interpersonal Trust, and Achievement Motivation

Analogous to the type of intervention, no influence on the decision behavior or the system evaluation after the breach of trust could be determined for most user factors.

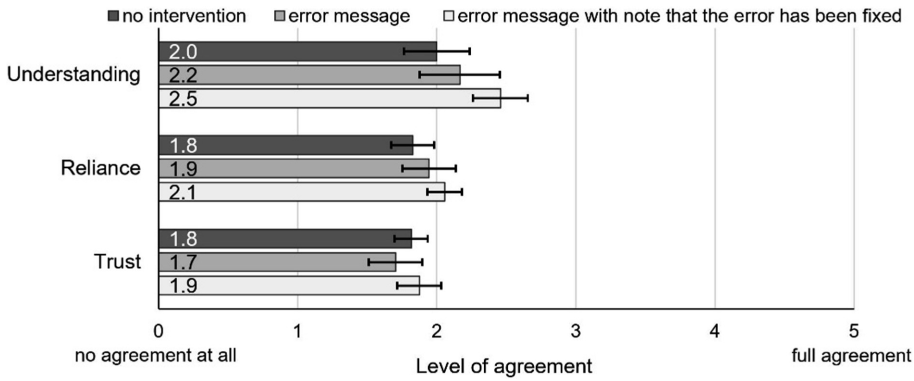

Fig. 4. Agreement to different (means and standard errors) distinguished by the type of intervention.

Neither a high affinity for technology nor a strong inclination to interpersonal trust resulted in a quicker or stronger recovery of trust in the system after it had been repaired. A significant negative correlation could only be found for achievement motivation (r_s = .364, p = .002, BF_{10} = 2.928). Participants with a high motivation for performance did not deviate as much from the recommendations during the last phase of the game with repaired DSS. However, the relation was rather weak. In addition, no significant effect of the user factors could be observed in interaction with the type of intervention.

5 Discussion, Limitations and Outlook

The present exploratory study provides a first glimpse into the recovery of trust in decision support systems on the route towards a more complete trust-recovery model that is needed to explain confidence in and compliance with automated systems. Based on the qualitative interviews, it was possible to identify requirements for the reaction of the system after a failure. In particular, a transparent communication of the status, including potential errors and their correction, of the automated system was demanded by the participants. While some participants had already noted that the behavior of the system may be more important than its messages or apologies, a majority of participants considered such interventions to be important for building sustainable trust.

However, deviating from the expectations based on the interviews, no significant effect of the intervention on the participants' decision-making behavior or trust in the system could be found. Although there were tendencies, such as the greater deviations from the recommendation in the group without intervention after the repair of the system, these differences were not large and systematic enough to speak of significant effects. It is noteworthy that there was neither a significant difference between the different interventions, nor between the baseline with no intervention at all on the one hand and an arbitrary message on the other, in terms of restoring trust.

One possible explanation could be the small sample size. A test power analysis showed that, given the sample size, only effects with a size above *.380* can be found. Accordingly, it can be assumed that an intervention such as the one implemented in this study has no or only a very weak effect. Therefore, further studies with larger sample sizes and more trained participants are required to reduce noise in the data and to identify possible effects with smaller sizes. The present results also support another hypothesis: Trust in DSS after errors have occurred can only be repaired to a very limited extent by interventions and must be restored by long-term correct functioning. Trust has to be earned. In order to verify this, the next step would be to implement long-term studies which must include repeated failures of the system, but also significantly longer intact phases.

If trust is restored over the long term and interventions are only marginally supportive in the sense of a transparent technology, a deeper insight into influencing user characteristics is necessary. Although the user factors considered in this study had no influence on the decision-making behavior, there could be other user profiles whose regaining of trust could at least be accelerated by appropriate user-specific intervention measures. A possible difference in the effect of apologies and denials, such as Quinn et al. anticipated [17], could also be significantly influenced by user factors. It would be of interest, for example, to consider the influence of human persuasion on whether a technical system can improve or whether error susceptibility is something stable, analogous too [27]. Therefore, a more complete picture of interdependencies between user characteristics and trust repair is imperative.

Furthermore, attention must be paid to decision support systems which consequences are difficult to recognize or extremely time-delayed. As can be seen from the users' deviations from the DSS at the beginning of the defect, the participants quickly identified the wrong recommendations. On the one hand, this characteristic of a DSS is helpful because blindly obeying is reduced, on the other hand it allows a quick assessment of whether a system is functioning again without relying on a related error message. In this case, the system could indeed have been too transparent in terms of its functioning, which cannot always be achieved in real-world scenarios with more complex decisions. Therefore, further studies with less transparent DSS are needed. Basically, however, the use of the business simulation game has turned out to be suitable for studying the reliance on automated systems.

In the future, trade-offs and contexts will also have to be further focal points of research. In the current study, for example, there was no time pressure. A system error, although time-consuming, could be compensated for by manual calculation with the appropriate competence. It is unclear how the costs (time, accuracy) of a human decision affect the willingness to trust the system. It can be assumed that the higher these costs compared to automated decisions are, the faster the user relies on the system again after a failure. This could also play a role in other contexts where the perceived benefits of automation are small compared to the possible damage caused by failure of automation. The present study only dealt with virtual financial losses and even here no effect of short-term trust-building interventions could be determined. A more difficult context could be, e.g., automated driving, where wrong decisions are life-threatening, and many users still think that they can handle the vehicle at least as well as the automated system. In this case, it cannot be assumed that single interventions or apologies are sufficient to restore trust, but that, as previously mentioned, only positive achievements of the system, directly through interaction with the user or indirectly through social influence, can repair trust. A possible transferability of strategies for restoring trust to other technical contexts must therefore be another research objective.

Acknowledgements. This research was funded by the German Research Foundation (DFG) within the Cluster of Excellence „Integrative Production Technology for High-Wage Countries" (EXC 128) and the Integrated Cluster Domain "Self-Optimizing Production Networks" [28] (ICD D1). The authors thank all participants for sharing opinions on a novel technology. Furthermore, thanks go to Christin Gatzka, Felix Glawe, Susanne Gohr, Nils Plettenberg, Lisanne Simons, and Jacqueline Bialas for their research support.

References

1. Gorry, G.A., Morton, M.S.S.: A framework for management information systems. Sloan Manag. Rev. **13**, 50–70 (1971)
2. Burstein, F., Holsapple, C.: Handbook on Decision Support Systems 1. Springer, Heidelberg (2008)
3. de Vries, P., Midden, C., Bouwhuis, D.: The effects of errors on system trust, self-confidence, and the allocation of control in route planning. Int. J. Hum Comput Stud. **58**, 719–735 (2003)
4. Brauner, P., Calero Valdez, A., Philipsen, R., Ziefle, M.: Defective still deflective – how correctness of decision support systems influences user's performance in production environments. In: HCI in Business, Government, and Organizations: Information Systems, pp. 16–27. Springer, Cham (2016)
5. Rovira, E., McGarry, K., Parasuraman, R.: Effects of imperfect automation on decision making in a simulated command and control task. Hum. Factors **49**(1), 76–87 (2007)
6. Lee, J.D., See, K.A.: Trust in automation: designing for appropriate reliance. Hum. Factors **46**, 50–80 (2004)
7. Parasuraman, R., Riley, V.: Humans and automation: use, misuse, disuse, abuse. Hum. Factors J. Hum. Factors Ergon. Soc. **39**, 230–253 (1997)
8. Brauner, P., Calero Valdez, A., Philipsen, R., Ziefle, M.: How correct and defect decision support systems influence trust, compliance, and performance in supply chain and quality management. LNCS, pp. 333–348 (2017)
9. Schweitzer, M.E., Hershey, J.C., Bradlow, E.T.: Promises and lies: restoring violated trust. Organ. Behav. Hum. Decis. Process. **101**(1), 1–19 (2006)
10. Vasalou, A., Hopfensitz, A., Pitt, J.V.: In praise of forgiveness: ways for repairing trust breakdowns in one-off online interactions. Int. J. Hum Comput Stud. **66**(6), 466–480 (2008)
11. Tomlinson, E.C., Mryer, R.C.: The role of causal attribution dimensions in trust repair. Acad. Manag. Rev. **34**(1), 85–104 (2009)
12. Tschannen-Moran, M.: Collaboration and the need for trust. J. Educ. Adm. **39**(4), 308–331 (2001)
13. Gillespie, N., Dietz, G.: Trust repair after an organization-level failure. Acad. Manag. Rev. **34**(1), 127–145 (2009)
14. Johnson, J.D., Sanchez, J., Fisk, A.D., Rogers, W.A.: Type of automation failure: the effects on trust and reliance in automation. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting, vol. 48, no. 18, pp. 2163–2167. SAGE Publications Sage CA, Los Angeles (2014)

15. Lewandowsky, S., Mundy, M., Tan, G.: The dynamics of trust: comparing humans to automation. J. Exp. Psychol. Appl. **6**(2), 104 (2000)
16. Kim, P.H., Dirks, K.T., Cooper, C., Ferrin, D.L.: When more blame is better than less: the implications of internal vs. external attributions for the repair of trust after a competence- vs. integrity-based trust violation. Organ. Behav. Hum. Decis. Process. **99**, 49–65 (2006)
17. Quinn, D.B., Pak, R., de Visser, E.J.: Testing the efficacy of human-human trust repair strategies with machines. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting, vol. 61, no. 1, pp. 1794–1798. SAGE Publications Sage CA, Los Angeles (2017)
18. Robinette, P., Wagner, A.R., Howard, A.M.: Investigating human-robot trust in emergency scenarios: methodological lessons learned. In: Robust Intelligence and Trust in Autonomous Systems, pp. 143–166. Springer, Boston (2016)
19. Buchholz, V., Kulms, P., Kopp, S.: It's (Not) Your Fault! Blame and Trust Repair in Human-Agent Cooperation. Kognitive Systeme 1 (2017)
20. Philipsen, R., Brauner, P., Stiller, S., Ziefle, M., Schmitt, R.: The role of human factors in production networks and quality management. In: International Conference on HCI in Business, pp. 80–91. Springer, Cham (2014)
21. Brauner, P., Philipsen, R., Fels, A., Fuhrmann, M., Ngo, Q.H., Stiller, S., Schmitt, R., Ziefle, M.: A game-based approach to raise quality awareness in ramp-up processes. Qual. Manag. J. **23**, 55–69 (2016)
22. Karrer, K., Glaser, C., Clemens, C., Bruder, C.: Technikaffinität erfassen – der Fragebogen TA-EG. Mensch Mittelpunkt techn. Syst. **8**, 196–201 (2009)
23. Beierlein, C., Kemper, C., Kovaleva, A.J., Rammstedt, B.: Interpersonales Vertrauen (KUSIV3). In: Zusammenstellung sozialwissenschaftlicher Items und Skalen (2014)
24. Schuler, H., Prochaska, M.: Entwicklung und Konstruktvalidierung eines berufsbezogenen Leistungsmotivationstests. Diagnostica **46**(2), 61–72 (2000)
25. Wagenmakers, E., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau, Q.F., Šmíra, M., Epskamp, S., Matzke, D., Rouder, J., Morey, R.: Bayesian inference for psychology. part I: theoretical advantages and practical ramifications. Psychon. Bull. Rev. **25**(1), 35–57 (2018). https://doi.org/10.3758/s13423-017-1343-3
26. Chavaillaz, A., Wastell, D., Sauer, J.: System reliability, performance and trust in adaptable automation. Appl. Ergon. **52**, 333–342 (2016)
27. Haselhuhn, M.P., Schweitzer, M.E., Wood, A.M.: How implicit beliefs influence trust recovery. Psychol. Sci. **21**(5), 645–648 (2010)
28. Schlick, C., et al.: Cognition-enhanced, self-optimizing production networks. In: Integrative Production Technology, pp. 645–743. Springer International Publishing, Heidelberg (2017)