

The Interaction of Causal Attribution of Performance and Compliance with Decision Support Systems in Cyber-Physical Production Systems - An Empirical Study Using a Business Simulation Game

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Abstract. Supply Chains and production networks are complex sociotechnical systems whose performance is determined by system, interface, and human factors. While the influence of system factors (e.g., variances in delivery times and amount, queuing strategies) is increasingly well understood, the influence of the interface and human factors is currently insufficiently explored. Previous research has shown that decision support systems may help to enhance performance by improving the interface. In this work, we address the users' trust in a decision support system. In a user study (n = 40), using a business simulation game, we investigated how four dimensions of attribution theory relate to trust in decision support systems and further to task performance. The results show that human factors, especially trust in automation and attribution theory relate to the performance in the business simulation game. We conclude that attribution relates to job compliance and performance in material disposition tasks and supply chain management.

Keywords: Business simulation game · Industrial internet of things · Automation · Trust in automation · Attribution theory · User modelling · Human factors

1 Introduction

In the era of digitalization, decisions are no longer made by humans alone. Algorithms filter and preselect options for later decision making or - with increasing pervasiveness - decide on their own [1]. While there are many situations and contexts in which algorithms might have the better understanding of the situation and thus decide more competently and flawlessly, there are still many situations and contexts in which humans in the loop are needed due to their higher cognitive expertise and awareness for the respective situation. While both approaches might have benefits as well as drawbacks, it is pivotal to find a right balance between humans and cyber-physical systems. In

particular, countries with high wages must augment their production systems with smart algorithms to maintain their competitiveness. Despite the increasing automation, the human-in-the-loop has an irreplaceable role in these cyber-physical production systems and because of the automation, the human operators need to handle increasingly complex tasks in shorter time.

The challenge in finding this balance is to harness the “individual” capabilities of both humans and computers to their maximal extent, in order to reap benefits beyond the individual contribution [2, 3]. Computers are very suitable for tasks that involve complex mathematical operations, handling large data, or e.g., optimizing unique fitness functions. However, they are (still) blind to information not encoded in data (e.g., larger context, ethical implications [4], human perception of decisions, black swan effects [5]). This blindness is directly related to tasks where humans excel. The challenge at hand is how to harmonize the effort of both entities to maximize benefits and utility. In a cyber-physical production network—often referred to as Industry 4.0—setting, the operator must evaluate algorithm and data output to optimize the production point. This is particularly important when contextual information, unavailable to the closed world of the machine, would tip the scale in favor of a different decision. The new linchpin in this scenario is obviously the interface between machine and human, algorithm and operator, digital and analog. This crucial part must be designed to optimize the efficient application of the human resource and the transformation between the digital and analog world is most constrained by human perception (mostly visual ergonomics) and evaluation (in terms of interpretation of situational issues, cognitive ergonomics). Addressing human perception in interface design is to a large extent mapping multidimensional, highly complex data to lower dimensional information that is both comprehensible and actionable. This mapping process is mostly assumed to be governed by laws of perception and screen real-estate. Still, a large part of the uniqueness of human capability is ignored. Capabilities such as risk perception, multi-criterion decision making, success attribution [1] and other cognitive and affective factors enable human decision making, yet they are unequally distributed across individuals. Here, human factors research can play a critical role in leveraging individual differences by incorporating them in the “interface equation”. A key question is whether a one-size-fits-all approach is adequate and justified, given the diversity of human attributes [6].

In this article, we look at how individual differences in success attribution affect judgement in a decision-making task. This task is assisted by a decision support system that, depending on the experimental condition, may be helpful or defective. By investigating the associations of performance and human factors, success attribution and objective task criteria, we hope to find rules that allow allocating human resources to tasks that are both suitable and useful. The overall objective is to develop smart and targeted tools and methods for augmenting the abilities of the human-in-the-loop in these socio-technical, cyber-physical production systems. Decision Support Systems (DSS) can be a viable solution, however, we need to understand when these support systems provide a real, measurable, and sustainable benefit. Also, we need to understand if, when, and why these systems are blindly obeyed with possible disastrous consequences for the process, the companies, and the customers.

2 Related Work

The following sections present a brief overview on Decision Support Systems and Human Factors in Decision Support Systems. The second section summarizes the theory of causal attribution and illustrates its relationship with the design of interactive systems.

2.1 Decision Support Systems

The development of decision support systems has its roots in the 1950's and aimed at providing workers assistance in decision making tasks by using the capabilities of upcoming computer systems [7]. Industrial and military tasks were the primary fields of application where operational, tactical, or strategic decision problems were (and still are) subject to growing task and information complexity. The idea was to split decision tasks into a computational part that is solved by machine, by implementing knowledge, models, and decision rules into a computational form [8], and a part that is still carried out by human, who then can use the support in terms of recommendations, reports, or visualizations.

Today, modern DSS cover a broad range of methods and deployment scenarios, e.g., data warehousing [9], online analytical processing (OLAP) [10], or data-mining [11]. The growing data complexity is accompanied with an increasing importance of data-centric approaches and artificial intelligence that is able to handle large amounts of fuzzy information [12].

However, as long as decision-making is not fully automated and the human is still in the loop due to responsibility, ethical, political, or organizational reasons, it is necessary to study the effects of human factors on the use of decision support systems [13, 28]. Next to user interface issues, the compliance in terms of accepting or neglecting the assistance of a DSS is crucial for successful decision making, especially if the DSS is defective and should be overruled by human. In this context, the perceived effectiveness, the perceived usefulness and the trust in the system are likely to influence the acceptance and thereby the compliance with DSS [14–16]. Two companion papers on this study have investigated the influence of the Decision Support System's defectiveness on attained performance, compliance and trust in automation [16, 28]: In general, a correctly working DSS yields higher trust in automation, higher compliance with the system, and higher overall company profit than a defective system. A further finding is that the subjective evaluations are basically consistent with the measurements from the underlying simulation model, meaning that the participants have a good perception of their own performance in the game.

However, to better understand humans' perception of both flawless and defective decision support systems, we need to gain deeper insights into the attribution of success and failure to these systems.

2.2 Theory of Causal Attribution

In the social sciences, the theory of causal attribution is defined as “[a] theory designed to explain how people perceive, infer, or ascribe causes of their own and other people’s behavior” [17]. Weiner, as a key scientist in this field, argued that attribution is subdivided into the four dimensions *Locus Of Control*, *Stability*, *Controllability* and *Globality* [18]: *Locus of control* addresses if an individual attributes the cause for the outcome of their actions to their own abilities (internal) or external factors (external). For example, the same good performance in a math exam might be attributed to oneself (“I am good at math”) or to external factors (“The exam was easy”). *Stability* as a dimension captures how much the cause for the outcome of one’s actions is considered to be just temporary (unstable) or rather constant (stable). For example, the exam performance can be attributed to luck (temporary) or as stable (stable). *Controllability* addresses whether the cause of the outcome is modifiable (controllable vs. not controllable). For example, the good performance in the aforementioned math exam can be attributed as controllable (“I am good at math because I have practiced a lot”) or as stable (“I can’t help it. I am just good at math”). *Globality* captures how much the cause for outcomes of one’s actions are specific to a certain domain or how much they also affect other domains (domain specific vs. generic; “I am good at math” vs. “I am good at school”). Figure 1 shows the theory of causal attribution and its dimensions.

Attribution Theory—though well-known in the social science as a major driver of human well-being [17, 19]—is currently gaining importance in human-computer interaction research. For example, Niels et al. [20] successfully linked the four dimensions locus, stability, controllability, and globality from the attribution theory to the evaluation of a product on the User Experience Questionnaire (UEQ), or used attribution theory to study gamified supermarket checkouts [21].

Also, sub-dimensions of attribution theory and related constructs have been identified as a key player in human-computer interaction: Bandura’s self-efficacy theory is strongly related to locus of control and locus of control has been identified as a key predictor of efficiency, effectivity, and learning to use interactive technology in variety of different domains [22–24].

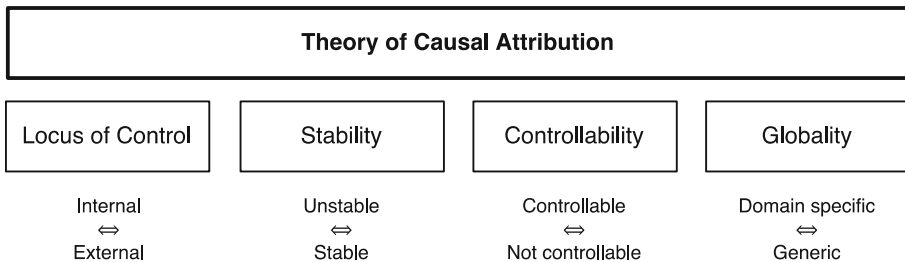


Fig. 1. Illustration of the four considered dimensions of the theory of causal attribution.

3 Research Design

To evaluate the relationship between human factors in a scenario with both correct and defective decision support systems in cyber-physical production systems, we applied an exploratory experimental approach. We looked at four larger constructs in both human performance and attitudes: (1) trust in automation, (2) compliance, (3) performance, and (4) attributional factors.

The participants interacted for two rounds with the “*Quality Intelligence Game*” business simulation game [25] that combines material disposition tasks from Sterman’s Beer Distribution Game [26] and quality management aspects from Goldratt’s game [27]. Here, the objective of the participants is to carefully balance costs of purchasing and stock-keeping supplies on one side with the investments into inspection of incoming goods and production quality on the other side—all in the setting of a simulated company. After each of the two rounds, a post-questionnaire captured the participant’s evaluation of the decision support system. A more verbose elucidation of the method can be found in our companion paper [16].

Within-subject factor: The *Correctness* of the Decision Support System (DSS) for ordering supplies is modified as a within-subject factor. This means that we adjust whether the DSS is helpful or leads the user astray. In the case of a correct DSS, the suggested number of supplies that should be ordered is near the optimum (only very experienced players might find slightly better order levels). In the case of the defect DSS, the suggested orders are correct for the first six turns of the game, then the system turns defective and suggests values 50% below the optimum; the defectiveness of this value is directly sensible from within the user interface (lower than the number of requested orders by the customer) and indirectly through dramatically increasing penalty costs in the subsequent turns of the game. The other tasks - investments in production quality - are not supported by a decision support system. Each round of the game consists of 18 turns (i.e., 18 months of the simulated company).

Dependent variables: After each of the two rounds, the following dependent variables were measured either with log files in the game or by a survey.

Compliance: The compliance with the Decision Support System is measured with the item “*How often did you follow the suggestion of the DSS during the game?*”.

Performance: Following Goldratt and Cox the *Company’s Profit* is calculated as the overall objective performance metric as the cumulated net profit for each turn of the game [27]. In addition, the participants also reported their *Perceived Performance*.

Attribution styles: After each round the participants reported on the perceived causes of their performance. The four attribution dimensions *Locus of Control*, *Stability*, *Controllability*, and *Globality* were captured with one item each (see Table 3).

The subjective measures are captured on 6-point Likert scales and rescaled to 0–100% for reasons of legibility. Subjective *Compliance* was directly captured on a scale from 0–100%. Figure 2 illustrates the experimental setup of this study.

Repeated Measure:
Correctness of the DSS (Correct vs. Defect) as randomized within-subject variable

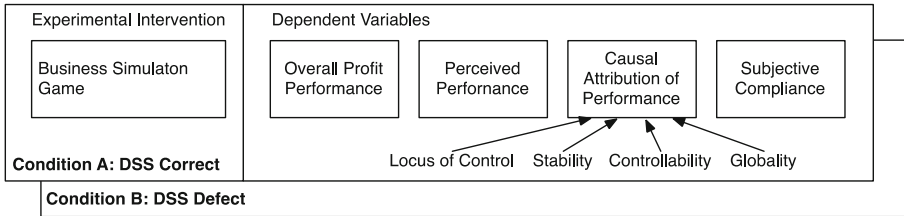


Fig. 2. Illustration of the experimental setup.

3.1 Methods

We analyzed the data using parametrical and non-parametrical methods, such as bivariate correlations (Pearson’s r or Spearman’s ρ), Wilcoxon tests, single and repeated multi- and univariate analyses of variance (M/ANOVA), and multiple linear regressions. We set the type I error rate (level of significance) to $\alpha = .05$ (findings $.05 < p < .1$ are reported as marginally significant). Pillai’s value is considered for the multivariate tests and effect sizes are reported as η^2 . If the assumption of sphericity is not met, Greenhouse-Geisser–corrected values are used, but uncorrected dfs are reported for legibility. The whiskers in diagrams represent the standard error (SE) of the point estimate, arithmetic means are reported with standard deviations (denoted \pm).

3.2 Description of the Sample

In total, 40 people in the age range from 20–56 years ($M = 28.5 \pm 8.6$, $Md = 25$) participated voluntarily in the study (23 male, 17 female). Age and gender were not correlated in our sample ($\rho = .200$, $p = .215 > .05$, $n.s.$).

4 Results

The results section is structured as follows. First, we look at the effect of playing the business simulation game twice for each player, guided by the question, if players improved their success in a second run of the game. We then look on the influence of the DSS. Here, the crucial question is whether a defective DSS changes the compliance and the performance for each player and how this changes the attribution of success for the player.

4.1 Effect of Repetition

Our study revealed no significant increase on overall attained profit increased from the first ($M = -2,622.5 \pm 25,672$, $Md = 12,275$) to the second round of the game ($M = 3,557.69 \pm 20,789$, $Md = 11,650$) ($Z = -.132$, $p = .895 > .05$). Yet, there is a

strong correlation between the performance attained in the first and the second round of the game ($\rho = .751, p < .001$). Both these findings indicate that some players consistently attain higher performances than others. As previous studies have reported an increase in performance [25], we conclude that the absence of this effect in this study is based on the influence of the correctness of the decision support system.

For both rounds of the game, there is a strong correlation between the actual Company Profit attained in the game and the Perceived Performance ($\rho = .470, p = .002 < .05$ for round 1 and $\rho = .577, p < .001$ for round 2). Thus, the participants from the study are able to judge their performance in line with their actual performance.

The reported Compliance with the Decision Support System was $36.9 \pm 30.0\%$ in the first round of the game and $42.9 \pm 28.7\%$ in the second round. However, a repeated measures ANOVA with Round as within-subject variable and Compliance in round 1 and 2 as dependent variable revealed no significant differences ($V = .029, F_{1,33} = .977, p = .330, \eta^2 = .029$). This means that players at least report to follow the suggestions by the decision support system to a similar extent in both rounds. Thus, further investigation on the evaluation of attribution regarding the DSS seems reasonable. If players would not have followed the DSS, no such conclusions could be drawn.

Regarding the performance attribution, a repeated measures MANOVA with the four dimensions Locus of Control, Stability, Controllability, and Globality revealed no significant overall effect of repetition across both rounds of the game ($V = .146, F_{4,35} = 1.492, p = .226 > .05, \eta^2 = .146$). Hence, the participant's performance attribution does not change significantly during both rounds. Merely for the dimension Stability, a small and marginally significant difference emerges ($F_{1,38} = 3.755, p = .060 > .05, \eta^2 = .090$) and the participants' perceived stability of the performance increases from $56.9 \pm 29.2\%$ to $68.2 \pm 19.9\%$). This means that the attribution of success—or lack thereof—becomes more stable after playing a second round of the game.

A correlation analysis revealed that the attributed Locus of Control ($\rho = .037, p = .819 > .05$) and the Stability ($\rho = -.007, p = .968 > .05$) of the performance is not stable over the two repetitions of the game, whereas the perceived Controllability ($\rho = .692, p < .001$) and the perceived Globality ($\rho = .508, p = .001 < .05$) of the performance remains stable (see Table 2, left).

4.2 Effect of the Decision Support System

The overall attained Company Profit as the key performance metric for the defect and correct DSS are strongly correlated ($\rho = .777, p < .001$), which indicates that some players are consistently more successful than others. On average, the Company Profit gained with a correct DSS is higher ($M = 7,110.3 \pm 12,599.2, Md = 13,100$) than the Company Profit gained with a defect DSS ($M = -6,086.3 \pm 29,269.2, Md = 11,350$). A Wilcoxon test attests that this difference is significant ($Z = -2.647, p = .008 < .05$). Again, the Perceived Performance is related to the objectively measured Company Profit for both the defect ($\rho = .442, p < .05$) and the correct DSS ($\rho = .389, p < .05$).

Next, the relationship between the attained performance and the compliance with the support system is evaluated. First, for the correct DSS, then for the defective DSS:

For the correct DSS, there is a marginally significant positive correlation between the Compliance with the DSS's suggestions and the Perceived Performance ($\rho = .284$, $p = .08 > .05$) but no significant relationship between the objective Company Profit and the Compliance ($\rho = -.174$, $p = .295 > .05$). However, for the case of the defective support system, there is a strong negative relationship between Compliance and measured Company Profit ($\rho = -.668$, $p < .001$) as well as between Compliance and Perceived Profit ($\rho = -.339$, $p < .05$). Therefore, the compliance with the support system is a strong determinant for performance, but the influence of compliance can either be positive or negative, depending on the correctness of the support system.

For the first round of the game, a MANOVA with the Correctness of the DSS as independent variable and the four attribution items revealed no significant overall effect of Correctness on Attribution ($V = .056$, $F_{4,34} = .509$, $p = .730 > .05$). As argued in the companion paper [16], the results from the first round of the game might not provide a clear view on differences in attribution, as the participant's internal reference frame is not yet established after the first round of playing.

However, significant overall differences in attribution based on Correctness emerge for the second round of the game ($V = .272$, $F_{4,35} = 3.271$, $p = .022 < .05$, $\eta^2 = .272$). Specifically, significant differences are found for the dimensions Locus of Control ($p = .027 < .05$, $\eta^2 = .122$) and Controllability ($p = .030 < .05$, $\eta^2 = .118$), whereas Stability ($p = .329 > .05$) and Globality ($p = .295 > .05$) are not affected. This means that those aspects of attribution that are innate to the player are—as expected—unaffected by the experiment, while the two dimensions depending on the immediate context do change in our scenario. This is expected as the conditions between rounds change.

As Table 1 and Fig. 3 illustrate, the participants with the correct decision support system experienced a significantly higher external locus of control than participants with the defect system (54.3 ± 29.1 vs. $33.7 \pm 27.5\%$). However, participants with the correct decision support system perceive their performance as much more controllable than the participants with the defective system (68.6 ± 28.7 vs. $47.4 \pm 30.7\%$).

A correlation analysis shows that the performance attribution of defective and correct support systems is not related for the dimensions Locus of Control ($\rho = .033$, $p = .841 > .05$) and Stability ($\rho = -.002$, $p = .992 > .05$). But again, the dimensions Controllability ($\rho = .718$, $p < .001$) and Globality ($\rho = .526$, $p < .001$) are strongly related (see Table 2, right).

Table 1. Effect of the DSS's correctness on the four dimensions of causal attribution for the first and second round of the game.

Correctness	External Locus		High Stability		High Control		High Globality	
	Round 1	Round 2	Round 1	Round 2	Round 1	Round 2	Round 1	Round 2
Correct	44.2 ± 19.5	54.3 ± 29.1	63.3 ± 24.0	71.4 ± 24.1	53.7 ± 27.5	68.6 ± 28.7	47.4 ± 27.7	52.4 ± 27.2
Defect	45.7 ± 27.7	33.7 ± 27.5	51.4 ± 32.6	65.3 ± 13.1	61.9 ± 26.8	47.4 ± 30.7	46.7 ± 23.9	44.2 ± 20.6

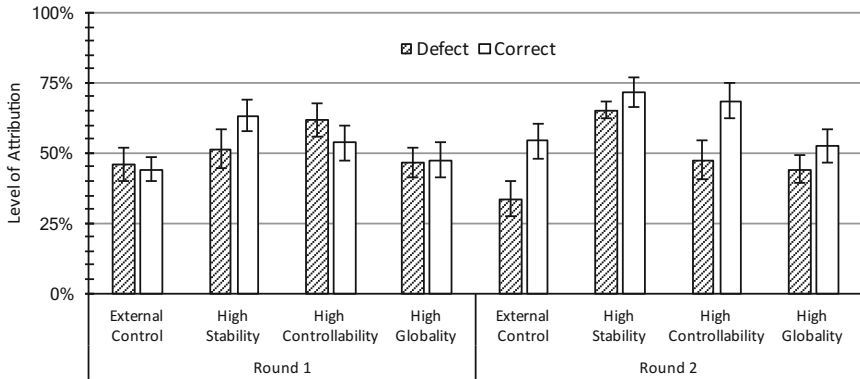


Fig. 3. Attribution of the attained performance for both rounds for the correct and defective Decision Support System. Differences emerge for the second round (sig. for External Locus of Control and Controllability), as no reference frame has been established in the first round.

Table 2. Autocorrelations of the dimensions Locus of Control (Loc), Stability (Stab), Controllability (Cont), and Globality (Glob) from attribution theory based on repetition (left) and DSS correctness (right) (** $p < .001$, * $p < .05$, + $p < .1$, () *n.s.*).

	Repetition (R1 – R2)				Correctness (Correct – Defect)				
	Loc _{R2}	Stab _{R2}	Cont _{R2}	Glob _{R2}	Loc _D	Stab _D	Cont _D	Glob _D	
Loc _{R1}	-0.037	(-.200)	(-.147)	-.285 ⁺	Loc _C	-0.033	(-.018)	(-.117)	-0.207
Stab _{R1}	(-.136)	(-.007)	(-.052)	(-.157)	Stab _C	(-.183)	(-.002)	.279 ⁺	-0.259
Cont _{R1}	-0.01	-0.045	.692**	.302 ⁺	Cont _C	-0.017	(-.244)	.718**	-0.233
Glob _{R1}	-0.104	-0.175	.266+	.508**	Glob _C	(-.225)	(-.218)	.355*	.526**

5 Discussion and Conclusion

The digitalization that is transforming manufacturing in high-wage countries and cyber-physical production systems benefits from increased automation. At the level of cross-company cooperation, supply chain disruptions are a major threat for manufacturing companies and suitable decision support systems are a viable method to mitigate these disruptions. However, previous studies found that operators are easily deflected by defective decision support systems and are misguided by insufficient or wrong information [16, 27].

The present study addressed the root of this issue and tried to understand if, when, and why people comply with support systems that are working correct, provide guidance, and offer support, and if, when, and why they are obeyed, even when they are misleading, defective, or deflected. The study found evidence that compliance with a correctly working system is beneficial for subjective performance. However, obedience with a defective DSS is thoroughly linked to a decrease in subjective performance as well as a significant decrease in the objective company performance.

The key question addressed in this study was to identify the causes for compliance and system obedience based on Weiner's attribution theory. In general, the presented results show that attribution theory can indeed be applied in this context, as some of the captured constructs could successfully be linked to the experimental conditions from the study. Specifically, the dimensions locus of control and controllability were influenced by the experimentally varied correctness of the DSS, whereas the dimensions stability and globality remained unaffected.

Obviously, a study focused on understanding the applicability of attribution theory in the context of decision support in cyber-physical production systems cannot provide definite and conclusive guidelines on how this theory can be harnessed in the design of support systems. Yet, even these focused findings presented here hint at locus of control and controllability as the key determinants for compliance with correct systems and obedience of faulty systems. Hence, shifting the locus of control to an internal attribution and increasing the perceived controllability of the situation, despite a defective support system, is crucial.

This can be addressed either by adequately designed and implemented support systems that not only make the required tasks easier but also provide the rationale for their suggestions and thereby increasing the operators' understanding, ability, and confidence in their own capability. This will likely increase the compliance with correctly working systems and likewise will reduce the blind obedience with defective systems. In addition, an increased understanding of the underlying principles might be facilitated through trainings specifically addressing the control perception. Serious business simulation games—such as the one used here in the study—might be a valuable component of these knowledge and ability dissemination strategies.

In summary, this study has shown that attribution theory can offer valuable insights on compliance with and obedience of correct and defect decision support in cyber-physical production systems. A profound understanding of how attribution theory relates to compliance, obedience, and performance will enable us to find the right balance between automation in cyber-physical production systems on one side and inclusion of the human-in-the-loop with their unique capabilities on the other side.

6 Limitations

The present study allows some valuable insights on the link between attribution theory and the compliance with correct and defect decision support systems in the context of supply chain and quality management. However, the generalizability of the findings from this study is limited because of the small sample, the missing calibration of subjective evaluations in the first round of the game, and the possible confounding effects of practice and correctness. The experiment is based on a sample of just over 40 participants, which limits the analysis of between-subject effects. Also, the companion study found that the participants' evaluations are not calibrated at the beginning of the study, which limits the permissibility of repeated measures analysis. Furthermore, the effect of the DSS's correctness reported for the second round of the game is tainted by the effect of the previous round: People's trust in automation and performance attribution may vary depending on whether they experienced a correct or defective DSS in

the beginning of the game. Thus, future studies should build on a larger sample and must more clearly separate the factors of repetition and correctness of the Decision Support System.

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Appendix

The item texts of the constructs can be seen in Table 3.

Table 3. Items for capturing the participant’s performance attribution (based on [20]).

Dimension	Text
Locus of control	“The performance was mostly determined by external factors (such as the game and the support system)”
Stability	“I will achieve a similar performance the next time I play this game”
Controllability	“I think the degree of my success is adjustable (for example, by putting more effort into solving the problem)”
Globality	“For different games, I would have attained a similar performance”

References

1. Nguyen, T.T., Maxwell, P.H.F., Loren, H., Joseph, T.: Exploring the filter bubble: the effect of using recommender systems on content diversity. In: Proceedings of the 23rd International Conference on World Wide Web, pp. 677–686. ACM (2014)
2. Calero Valdez, A., Brauner, P., Schaar, A.K., Holzinger, A., Ziefle, M.: Reducing complexity with simplicity - usability methods for industry 4.0. In: 9th Triennial Congress of the International Ergonomics Association (IEA 2015), Melbourne, Australia (2015)
3. Holzinger, A.: Interactive machine learning for health informatics: when do we need the human-in-the-loop? *Brain Inform.* **3**, 119–131 (2016)
4. Moor, J.H.: The nature, importance, and difficulty of machine ethics. *IEEE Intell. Syst.* **21**, 18–21 (2006)
5. Aven, T.: On the meaning of a black swan in a risk context. *Saf. Sci.* **57**, 44–51 (2013)
6. Calero Valdez, A., Brauner, P., Ziefle, M., Kuhlen, T.W., Sedlmair, M.: Human factors in information visualization and decision support systems. In: Workshop Human Factors in Information Visualization and Decision Support Systems Held as Part of the Mensch und Computer 2016. Gesellschaft für Informatik (2016)
7. Shim, J.P., Warkentin, M., Courtney, J.F., Power, D.J., Sharda, R., Carlsson, C.: Past, present, and future of decision support technology. *Decis. Support Syst.* **33**(2) 111–126 (2002)

8. Gorry, G.A., Morton, M.S.S.: A framework for management information systems. *Sloan Manag. Rev.* **13**, 50–70 (1971)
9. Kimball, R., Ross, M.: *The Data Warehouse Toolkit: The Complete Guide to Dimensional Modelling*. Wiley, New York (1996)
10. Codd, E., Codd, S., Salley, C.: *Providing OLAP to User-Analysts: An IT Mandate* (1993)
11. Bra, A., Lungu, I.: Improving decision support systems with data mining techniques. In: *Advances in Data Mining Knowledge Discovery and Applications*. InTech (2012)
12. Phillips-Wren, G.: Ai tools in decision making support systems: a review. *Int. J. Artif. Intell. Tools* **21**(02), 13 pages (2012)
13. Shibl, R., Lawley, M., Debus, J.: Factors influencing decision support system acceptance. *Decis. Support Syst.* **54**, 953–961 (2013)
14. Althuisen, N., Reichel, A., Wierenga, B.: Help that is not recognized: harmful neglect of decision support systems. *Decis. Support Syst.* **54**, 719–728 (2012)
15. Ben-Zvi, T.: Measuring the perceived effectiveness of decision support systems and their impact on performance. *Decis. Support Syst.* **54**, 248–256 (2012)
16. 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 – a behavioral study using business simulation games. In: *HCI in Business, Government, and Organizations (HCIGO)*, Held as Part of HCI International. Springer (2017, in press). doi:[10.1007/978-3-319-58484-3_26](https://doi.org/10.1007/978-3-319-58484-3_26)
17. Colman, A.M.: *Oxford Dictionary of Psychology*. Oxford University Press, Oxford (2015)
18. Weiner, B.: An attributional theory of achievement motivation and emotion. *Psychol. Rev.* **92**, 548–573 (1985)
19. Graham, S., Folkes, V.S.: *Attribution Theory: Applications to Achievement, Mental Health, and Interpersonal Conflict*. Lawrence Erlbaum Associates, Hillsdale (1990)
20. Niels, A., Guczka, S.R., Janneck, M.: The impact of causal attributions on system evaluation in usability tests. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 3115–3125. ACM (2016)
21. Niels, A., Zagel, C.: Gamification: Der Einfluss von Attributionen auf die Motivation [The Influence of Attributions on Motivation]. In: Prinz, W., Borchers, J., Jarke, M. (eds.) *Mensch und Computer 2016 - Tagungsband*. Gesellschaft für Informatik e.V. (2016)
22. Arning, K., Ziefle, M.: Understanding age differences in PDA acceptance and performance. *Comput. Hum. Behav.* **23**, 2904–2927 (2007)
23. Brauner, P., Leonhardt, T., Ziefle, M., Schroeder, U.: The effect of tangible artifacts, gender and subjective technical competence on teaching programming to seventh graders. In: Hromkovic, J., Kráľovič, R., Vahrenhold, J. (eds.) *Proceedings of the 4th International Conference on Informatics in Secondary Schools (ISSEP 2010)*, Zurich, Switzerland. LNCS, vol. 5941, pp. 61–71. Springer, Heidelberg (2010)
24. Wittland, J., Brauner, P., Ziefle, M.: Serious games for cognitive training in ambient assisted living environments – a technology acceptance perspective. In: Abascal, J., Barbosa, S., Fetter, M., Gross, T., Palanque, P., Winckler, M. (eds.) *Proceedings of the 15th INTERACT 2015 Conference*. LNCS, vol. 9296, pp. 453–471. Springer, Cham (2015)
25. Stiller, S., Falk, B., Philipsen, R., Brauner, P., Schmitt, R., Ziefle, M.: A game-based approach to understand human factors in supply chains and quality management. *Procedia CIRP* **20**, 67–73 (2014)
26. Sterman, J.D.: Modeling managerial behavior: misperceptions of feedback in a dynamic decision making experiment. *Manag. Sci.* **35**, 321–339 (1989)
27. Goldratt, E.M., Cox, J.: *The Goal: A Process of Ongoing Improvement*. North River Press, Great Barringtons (1992)

28. Brauner, P., Calero Valdez, A., Philipsen, R., Ziefle, M.: Defective still defluctive – how correctness of decision support systems influences user’s performance in production environments. In: Nah, F.F.-H., Tan, C.-H. (eds.) *HCI in Business, Government, and Organizations (HCIGO)*, Held as Part of HCI International 2016, pp. 16–27. Springer, Cham (2016)
29. Schlick, C., et al.: Cognition-enhanced, self-optimizing production networks. In: Brecher, C., Özdemir, D. (eds.) *Integrative Production Technology - Theory and Applications*, pp. 645–743. Springer, Heidelberg (2017)