ADOPTION BARRIERS OF AI: A CONTEXT-SPECIFIC ACCEPTANCE MODEL FOR INDUSTRIAL MAINTENANCE

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ADOPTION BARRIERS OF AI: A CONTEXT-SPECIFIC ACCEPTANCE MODEL FOR INDUSTRIAL MAINTENANCE

Research in Progress

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Abstract

Maintenance decision support systems can be equipped with artificial intelligence capabilities. Artificial intelligence algorithms allow for automatically extracting patterns and hidden relationships from data gathered from machinery to support maintenance-related tasks such as diagnosis and prognosis. However, the adoption of such systems in industrial maintenance remains rather hesitant. Currently, research lacks independent, rigorous studies investigating barriers causing this absence of adoption. We modified the unified theory of acceptance and use of technology (UTAUT) for our research to provide a better explanation for this observation. In particular, we extended the model with the constructs of trust and system transparency. We assume that trust is a central factor for artificial intelligence technology acceptance due to the black-box character of such algorithms, which in turn is highly affected by system transparency. Our model can serve as the foundation for better understanding actions that can enable user adoption of such systems.

Keywords: Technology Acceptance, Machine Learning, System Transparency, Trust.

1 Introduction

Today a multitude of data is being generated with a multitude of possibilities for exploitation (Guidotti et al., 2018). This is noticeable in contemporary manufacturing, which is the context of our investigation. Complex production plants require sophisticated maintenance measures to guarantee human safety, low environmental risks, and high reliability (Muchiri et al., 2011). For this purpose, modern maintenance strategies rely on artificial intelligence (AI) maintenance decision support systems (AI-MDSS) (Zschech et al., 2019). Deploying AI-MDSS avoids unnecessary manual labor during the maintenance process and allows resources to be used more efficiently (Elattar et al., 2016, Zschech et al., 2019). On the downside, AI-MDSS have the disadvantage that the processing mechanisms and their results are often difficult to reproduce as these algorithms usually show black-box characteristics. While those systems are found to outperform classic MDSS, their characteristics promote technology-related anxiety and alienation of labor through a lack of understanding and trust (Mokyr et al., 2015, Siau and Wang, 2018). As a result, we observe hesitation towards the adoption of AI at the workplace (Milojevic and Nassah, 2018). It prevents the effectiveness of such systems in practice, although the performance of AI often

outperforms other analysis methods or even human decision makers (e.g., Akay, 2009, Kourou et al., 2015, Silver et al., 2016). A common means to investigate technology adoption concerns in the IS discipline are the technology acceptance model (TAM) (Benbasat and Barki, 2007) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2016).

Some acceptance studies already address the issue of adopting intelligent DSS (e.g., Choi and Ji, 2015, Nilashi et al., 2016). However, these studies are not focused on an organizational setting. In addition, the two constructs of trust and system transparency have neither been considered in parallel nor considered with the core technology adoption constructs of performance and effort. However, trust and system transparency seem to be crucial to counteract to the black-box problem of advanced AI models as they are strongly correlated in the context of hybrid intelligence (e.g., Lai and Tan, 2019, Zhang et al., 2020). Besides, performance and effort seem to be of high relevance in the context of an AI-based DSS application (e.g., Wanner et al., 2020). However, an interconnected understanding of the implications of those constructs in this context is still missing. That is, it is not yet known whether they influence each other, so that inaccurate conclusions may have been drawn in previous research.

Against this background, our research is concerned with a context-specific modification of the original UTAUT model for AI-MDSS. Explicitly, we extend the model with the constructs of trust and system transparency. With this research, we pursue the following research question:

RQ: Which constructs and measurement items can extend the UTAUT model to measure the acceptance of artificial intelligence maintenance decision support systems?

Answering this RQ implies several contributions. First, we provide a differentiated UTAUT model for AI-based acceptance research. It highlights the important constructs in the context of AI-based DSS. For the context of industrial maintenance, we further provide suggestions for measurement items. Using this model allows to derive targeted actions to improve AI-based DSS adoption readiness. Second, as derivations and conceptualization are possible, we enable variations for further AI-based DSS application domains. Third, we provide awareness for the XAI research community to conduct further socio-technical research to better understand the effect relationships between constructs.

Our paper is structured as follows. In Section 2, we describe theoretical foundations and related work. We derive our context-specific UTAUT model by reviewing previous trust and system transparency extensions from adoption research and hypothesizing the constructs’ connections in Section 3. In Section 4, we form our final measurement model in several test iterations. Finally, we present our research model and summarize to offer concluding remarks in Section 5.

2 Foundations and Related Work

2.1 Industrial Maintenance and Explainable Artificial Intelligence

Industrial maintenance is intended to maintain and restore the operational readiness of machinery (Delen and Demirkan, 2013). AI-based MDSS are a promising novel approach to support and execute maintenance tasks (Carvalho et al., 2019). Such systems cover a variety of machine learning techniques and have the advantage of automatically exploiting hidden insights in vast amounts of observed data (Elattar et al., 2016, Peng et al., 2010). Currently, deep learning algorithms (Janiesch et al., 2021) based on artificial neural networks outperform other machine learning techniques, rendering them the state-of-the-art in the field of data-driven maintenance (Khan and Yairi, 2018). However, due to their black-box nature, the missing transparency makes it impossible for humans to comprehend decision logic and results (Adadi and Berrada, 2018, Samek et al., 2017). Several authors highlight that explaining the rationale behind a decision is a prerequisite for establishing a trustworthy relationship (Hayes and Shah, 2017, Hoff and Bashir, 2015, Mercado et al., 2016). The missing transparency, thus, negatively affects the user’s confidence in the recommendations given by the AI-MDSS (Adadi and Berrada, 2018, Sheridan and Hennessy, 1984). This lack of trust can even lead to inefficaciousness of the system (Dam et al., 2018).
The research field of explainable AI (XAI) tries to counter this effect by providing additional explanations and, thus, enabling the application of black-box models even in a critical high-stake situation (Adadi and Berrada, 2018, Wanner et al., 2020). Therefore, while it is reasonable to assume that system transparency and the related trust play a central role when investigating socio-technical aspects of technology acceptance, it is not evident to what extent these factors lead to an increased acceptance of AI-MDSS, nor if there are side-effects of and with other adoption factors.

2.2 Technology Acceptance Research

Technology acceptance has been widely studied in the context of several theoretical frameworks. Davis (1989) used the theory of reasoned action to propose the TAM model that explains the actual use of a system through the perceived usefulness and perceived ease of use. Many more theoretical models were defined over the years, for example the theory of planned behavior. To synthesize existing models and help researchers avoid having “to ‘pick and choose’ constructs across the models, or choose a ‘favoured model’ and largely ignore the contributions from alternative models”, Venkatesh et al. (2003) reviewed and tested existing models, and incorporated them into the unified theory of acceptance and use of technology (UTAUT). As such, core components of TAM, that is the perceived usefulness and perceived use are included in UTAUT via performance expectancy and effort expectancy. UTAUT has been used extensively to explain and predict acceptance and use in a multitude of scenarios (Williams et al., 2015).

The UTAUT model has been subject to several augmentations concerning its constructs and measurement items to fit the model to a specific use case (Oliveira et al., 2014, Slade et al., 2015). Typically, a modification or extension is applied in three different ways and achieved by multiple iteration cycles (Venkatesh et al., 2012, Williams et al., 2015): (1) the evaluation of new technologies or new cultural settings (e.g., Gupta et al., 2008), (2) adding new constructs to expand the investigation scope (e.g., Baishya and Samalia, 2020), or (3) including exogenous predictors for the proposed UTAUT variables (e.g., Neufeld et al., 2007). Furthermore, many contributions combine multiple ways to construct a new context-specific acceptance model (e.g., Albashrawi and Motiwalla, 2017, Esfandiari and Sokhanvar, 2020).

2.3 Technology Acceptance in AI-based Industrial Maintenance

Only a few insights on technology acceptance exist for industrial applications such as studies on the acceptance of intelligent robots in production processes (e.g., Bröhl et al., 2016, Lotz et al., 2019). In addition, there is the intent to understand the acceptance of augmented reality (Jetter et al., 2018).

Wang et al. (2016) use TAM to highlight the importance of ease of use and usefulness for a successful implementation of augmented reality technology in aviation maintenance. Amadi-Echendu and De Wit (2015) use a TAM model extended by system characteristics, usefulness, and training to reveal that the level of user training influences the ease of use, usefulness, and system characteristics, which, in turn, influences user acceptance. Kluge and Termer (2017) examined the acceptance of a mobile fault-finding application, conducting a field study that revealed the importance of usefulness and ease of use.

In summary, knowledge about the technology acceptance of AI-based maintenance is still limited. In particular, trust and system transparency have not been considered in conjunction as potential factors for technology acceptance of black-box AI systems. Despite this fact, existing research consciously relies on TAM, although UTAUT offers the more comprehensive research model.

3 Research Design

3.1 Research Methodology

Figure 1 provides an overview of the development of our modified UTAUT model design. It corresponds to the procedure presented by Šumak et al. (2010) with some proper modifications.
Figure 1: Research Methodology and Positioning

The focus of our research problem is AI-MDSS adoption. Hence, our research is located at the intersection of technology acceptance, industrial maintenance, and XAI (cf. Section 2). To address this with a context-specific UTAUT model, our kernel constructs are derived from the related research on UTAUT as well as trust and transparency. Thus, in the theorizing section (THEO), we derive a suitable model from existing adoption research on (a) trust and (b) transparency. We then (c) hypothesize the derived measurement model constructs and connection based on empirical findings, and we (d) collect potential measurement items (cf. this section). In the evaluation section (EVAL), we (e) test our model in an exemplary application case in industrial maintenance, and (f, g) iteratively adapt it with the help of empirical studies (Section 4). The (h) final result of the main study is not part of this research-in-progress paper as we conclude this research with the planned test set (cf. Section 5).

3.2 Research Constructs

In the following, we give an overview of relevant, previous technology acceptance research related to trust and system transparency, regardless of its theoretical modeling. This enables us to use the reliable basis that UTAUT offers in the best possible way and extend it to our context.

<table>
<thead>
<tr>
<th>Inclusion Type</th>
<th>Dependent Variables</th>
<th>Determinants</th>
<th>Example References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Endogenous</td>
<td>Behavioral Intention</td>
<td>None</td>
<td>Alaiad and Zhou (2013), Carter and Belanger (2005), Oh and Yoon (2014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Personal Propensity to Trust</td>
<td>Oliveira et al. (2014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Trust Integrity, Trust Ability</td>
<td>Komiak and Benbasat (2006)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Trust Property, Satisfaction</td>
<td>Kim (2014)</td>
</tr>
<tr>
<td>Exogenous</td>
<td>Performance Expectancy</td>
<td>Trust Benevolence, Trust Integrity, Trust Ability</td>
<td>Cheng et al. (2008), Lee and Song (2013)</td>
</tr>
<tr>
<td></td>
<td>Perceived Usefulness</td>
<td>Perceived Ease of Use, Consumer Decision Making</td>
<td>Xiao and Benbasat (2007)</td>
</tr>
<tr>
<td>Exogenous/Endogenous</td>
<td>Perceived Risk, Behavioral Intention</td>
<td>None</td>
<td>Slade et al. (2015)</td>
</tr>
</tbody>
</table>

Table 1: Summary of Trust-based Technology Acceptance Model Modifications

In terms of trust-based model components (cf. Table 1), we found i) several theoretical approaches to describe trust itself, ii) multiple determinants of the embedded trust construct (determinants), and iii) several different ways of embedding trust into existing technology acceptance models such as TAM or UTAUT (inclusion type/dependent variable).

With regard to i), besides describing trust as one factor that can be determined by either trust-based determinants or by other variables in technology acceptance research models (e.g., system transparency...
as in Choi and Ji, 2015), there are approaches where trust is split into several constructs, such as trust benevolence, integrity, and ability, to express that trust can rely on different features of the potential system (Mayer et al., 1995). Thus, the ability of a system would not alone be sufficient to build trust with the user (Cheng et al., 2008). Concerning ii), we found that trust is usually made up of some a-priori measure such as propensity to trust or trust ability that is rooted in human nature (Komiak and Benbasat, 2006, Oliveira et al., 2014). Regarding iii), the trust is usually embedded in simplified versions of technology acceptance models. For example, by the constructs performance expectancy (PE) and effort expectancy (EE) as endogenous determinants of attitude towards technology (ATT) and behavioral intention (BI) in UTAUT. We adopt the multi-level trust approach of McKnight et al. (2002) using trust ability (TA) as a determinant for trusting beliefs (TB) since a system does not exhibit qualities of trust benevolence or trust integrity comparable to humans. Trusting belief is then designed as an exogenous influence of BI.

<table>
<thead>
<tr>
<th>Inclusion Type</th>
<th>Dependent Variables</th>
<th>Determinants</th>
<th>Example References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exogenous/Endogenous</td>
<td>Trust, Behavioral Intention</td>
<td>None</td>
<td>Brunk et al. (2019), Choi and Ji (2015), Hebrado et al. (2011), Hebrado et al. (2013), Slade et al. (2015)</td>
</tr>
<tr>
<td></td>
<td>Trust, Behavioral Intention</td>
<td>Explanation</td>
<td>Nilashi et al. (2016)</td>
</tr>
<tr>
<td></td>
<td>Attitude towards Features, Trust, Behavioral Intention</td>
<td>None</td>
<td>Peters et al. (2020)</td>
</tr>
<tr>
<td></td>
<td>Trust, Behavioral Intention</td>
<td>Accuracy, Completeness</td>
<td>Shahzad et al. (2020)</td>
</tr>
<tr>
<td></td>
<td>Understanding, Users' Privacy Concerns, Behavioral Intention</td>
<td>None</td>
<td>Zhao et al. (2019)</td>
</tr>
<tr>
<td></td>
<td>Trust Beliefs, Understanding, Competence, Acceptance</td>
<td>None</td>
<td>Cramer et al. (2008)</td>
</tr>
<tr>
<td></td>
<td>Effort Expectancy, Trust Beliefs</td>
<td>None</td>
<td>Wang and Benbasat (2016)</td>
</tr>
</tbody>
</table>

Table 2: Summary of System-Transparency-based UTAUT Extensions

Comparable to trust, system transparency (ST) has been adopted as a construct in previous technology acceptance research (see Table 2). It is typically modeled as a sole exogenous influence. However, some related work suggests that ST itself is determined by factors such as accuracy, completeness, or explanatory quality. In turn, this reflects its importance for our context of black-box AI as those factors represent common information given by explanations of AI models using XAI techniques. Regarding the dependent variables, ST is predominantly found to influence the UTAUT-core elements of BI, PE, and EE. In addition, a relationship to TB and TA has also been recognized (e.g., Cody-Allen and Kishore, 2006, Cramer et al., 2008). Again, this highlights the strong correlation between trust and ST that has been proven in user studies several times (e.g., Zhang et al., 2020). In conclusion, we propose that ST is a candidate determinant for all of the above constructs.

3.3 Research Model and Hypothesis

As a result of the construct derivation (cf. Section 3.2), we present our modified UTAUT research model for AI-MDSS along with the hypotheses and their respective direction (- or +) in Figure 2. The measurement model can be divided into three major parts: i) UTAUT core research (PE, EE, BI, and ATT), ii) UTAUT black-box research (TA, TB, ST), and iii) moderators (SE and interactions). For each of the three parts, we formulate an exemplary hypothesis:

**H1**: Performance Expectancy (PE) positively affects Behavioral Intention (BI).

**H8**: Trusting Beliefs (TB) positively affects Performance Expectancy (PE).

**H15**: System Explainability (SE) positively affects all other measurement constructs.
The derivation of the hypotheses from i) UTAUT core research is primarily based on general research on UTAUT (e.g., Dwivedi et al., 2019, Venkatesh et al., 2003). Nevertheless, these construct interrelations can also be found in UTAUT studies on trust or system transparency (e.g., Lee and Song, 2013, Wang and Benbasat, 2016). The hypotheses for TA, TB, and ST are primarily based on references from Table 1 and Table 2 (e.g., Choi and Ji, 2015, Nilashi et al., 2016). System explainability (SE) as a global moderator is derived from the preliminary works of Cramer et al. (2008) and Herlocker et al. (2000). While ST is the user-perceived transparency level of the system, SE represents the technical circumstances to enable transparency by appropriate means, such as accuracy scores or confidence scores using augmentation frameworks. The consideration of the interaction factors age, gender, and experience follows the original UTAUT model according to Venkatesh et al. (2003).

![UTAUT Research Model](image)

**Figure 2:** Modified UTAUT Research Model for the Context of AI-MDSS

From the foundations set by Davis (1989), Moore and Benbasat (1991), and Venkatesh et al. (2003), we adopt the measurement items for the model constructs PE, EE, and BI, as well as the interaction moderation gender, age, and experience. Likewise, we used the items for the ATT construct from Davis et al. (1992), Thompson et al. (1991), and Compeau et al. (1999). For TA we adopted the items of McKnight et al. (2002) and Cheng et al. (2008). For TB we used the items of Lee and Turban (2001) and the modifications by Cheng et al. (2008) and Wang and Benbasat (2007). Finally, for ST we used the items of Cramer et al. (2008) and Madsen and Gregor (2000).

## 4 Research Evaluation

### 4.1 Use Case of Industrial Maintenance

Rolling bearings must be maintained in many production scenarios since they show signs of wear over time (Pawellek, 2016). We focus on bearings for high-speed conveyor belts in a production process that is monitored by several sensors (e.g., noise, vibration, and temperature). In the case of anomalous data patterns, an AI-MDSS system issues warnings and errors with concrete recommendations for action. To create awareness and support for the potential application of such a system, we introduce a specific maintenance decision scenario to the participants of the survey(s). Here, despite the optical condition of the conveyor belt bearings being perceived as good by the participant, the AI-MDSS recommends that the conveyor belt must be switched off immediately. We provide reliability information for the system and hint at high follow-up costs in case of wrong decisions to emphasize decision criticality.

### 4.2 Model Item Reduction by Experts

To achieve context-specific suitability of the measurement constructs for the exemplary application, we have taken two steps to select appropriate measurement items. First, we discussed the appropriateness of each measurement item within the team of authors. The team members merge knowledge in the respective domains of industrial maintenance, technology acceptance, and XAI research. Special attention was paid to the duplication of potential item questions and their feasibility for the exemplary use case. Ultimately, we reduced the total number of measurement items for the model’s constructs from 71 to 24.
Second, we conducted an expert survey with practitioners and researchers from the field of industrial maintenance (n=10). The expert study had two goals: the reduction of the remaining measurement items and the understanding of the prototypical AI-MDSS system explainability. For the former, each of the model measurement constructs was briefly explained to the experts. Subsequently, the experts had to select the most appropriate remaining item questions for the exemplary use case per construct. They were given at least one vote and at most votes for half the items. The final measurement items were then selected based on a majority result. For the latter, we presented the experts four different AI-MDSS dashboards as snapshots adapted from typical AI-MDSS (e.g., Aboulian et al., 2018, Moyne et al., 2013). They only differed in the type of system explainability, for example AI decision rules. Here, the experts rated their perceived level of AI-based MDSS explanation goodness on a seven-point Likert scale and chose their favorite dashboard. This enabled to differentiate the SE level per dashboard.

4.3 Model Refinement by Pre-Testing

We conducted a pilot study to examine our questionnaire and research design critically (Brown et al., 2010). The testing includes checks for internal consistency, convergent reliability, indicator reliability, and discriminant validity. The pre-test conducted contained 116 (A: 56; B: 60) valid responses. Here, we ensured representative respondents, that is maintenance professionals holding a potential position to use an AI-MDSS for their job-related tasks (e.g., personal experience in maintenance). We provided the participants with a description of the exemplary use case (cf. Section 4.1) and screenshots of the AI-MDSS. In accordance with our underlying research design, we split the study into two groups. Participants of group A were provided with an AI-MDSS dashboard that did not explain its recommendation, while participants of group B received an AI-MDSS dashboard that explained its recommendation using the best choice from the expert survey (cf. Section 4.2). This includes a graphical illustration of sensor data readings and rule-based explanations.

For both groups, we estimated the structural equation model using consistent partial least squares regression to assess our measurement model. As this pre-test has a relatively low sample size and can be seen as an exploratory study, we follow Chin (1998) and Urbach and Ahlemann (2010) by setting a lower indicator loading threshold of 0.5 rather than the commonly suggested threshold of 0.7 (e.g., Hair et al., 2011) for item loadings. See Table 3 for the assessment of measurement items.

<table>
<thead>
<tr>
<th>Constr.</th>
<th>CA</th>
<th>AVE</th>
<th>CR</th>
<th>FL Criterion</th>
<th>Cross-Loadings</th>
<th>Item Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>PE</td>
<td>0.95</td>
<td>0.86</td>
<td>0.78</td>
<td>0.57</td>
<td>0.95</td>
<td>0.87</td>
</tr>
<tr>
<td>EE</td>
<td>0.83</td>
<td>0.74</td>
<td>0.55</td>
<td>0.44</td>
<td>0.83</td>
<td>0.75</td>
</tr>
<tr>
<td>ST</td>
<td>0.88</td>
<td>0.67</td>
<td>0.79</td>
<td>0.51</td>
<td>0.88</td>
<td>0.67</td>
</tr>
<tr>
<td>TB</td>
<td>0.73</td>
<td>0.74</td>
<td>0.44</td>
<td>0.47</td>
<td>0.74</td>
<td>0.76</td>
</tr>
<tr>
<td>TA</td>
<td>0.92</td>
<td>0.74</td>
<td>0.80</td>
<td>0.52</td>
<td>0.92</td>
<td>0.76</td>
</tr>
<tr>
<td>ATT</td>
<td>0.85</td>
<td>0.67</td>
<td>0.65</td>
<td>0.43</td>
<td>0.85</td>
<td>0.67</td>
</tr>
<tr>
<td>BI</td>
<td>0.94</td>
<td>0.83</td>
<td>0.84</td>
<td>0.61</td>
<td>0.94</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Table 3: Assessment of Measurement Items

We conclude that the measurement items for the constructs TA, TB, EE, ATT, and ST need to be reviewed. The items for EE are well-chosen as they have been tested and verified in many UTAUT studies. As the performance of the measurement items for ST is significantly better in group A, the items are, in principle, well-chosen. Nevertheless, we conclude that an additional measurement item for ST must be added in case an item performs subpar in the main study. Hence, we extend our items by ST3, which is derived Cramer et al. (2008). Generally, we deem items for TB to be satisfactory as loadings are higher than or slightly below the 0.5 threshold. We see item TB4 as problematic, as the reverse wording suggested by Cheng et al. (2008) as well as Wang and Benbasat (2007) causes convergence
reliability issues. Removing TB4 leads to a higher AVE (0.58) in group A. Because using reversed wording is not advised (Van Sonderen et al., 2013, Zhang et al., 2016), we plan to follow Lee and Turban (2001) and use the original wording in line with the other items for the main study (TB5). Construct TA exhibits discriminant validity issues as it fails the FL criterion and the item TB3 shows cross-loadings. Because this is only the case in group B, we retain the measurement items for the main study. As ATT1 and ATT2 perform subpar in terms of discriminant validity, additional items must be added, which are not influenced as much by other constructs and lead to a higher validity. Thus, we added ATT4 and ATT5 following Taylor and Todd (1995). It was recently used in a similar context by Peters et al. (2020). Table 4 provides a summary of our measurement items for the main study to follow.

<table>
<thead>
<tr>
<th>Cons.</th>
<th>Measurement Item</th>
<th>Reference(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PE</td>
<td>PE1 Using this system in my job would enable me to accomplish tasks more quickly.</td>
<td>Davis (1989)</td>
</tr>
<tr>
<td></td>
<td>PE2 Using this system would improve my job performance.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PE3 Using this system would make it easier to do my job.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>PE4 I would find this system useful in my job</td>
<td>Moore and Benbasat (1991)</td>
</tr>
<tr>
<td></td>
<td>PE5 Using this system would increase my productivity.</td>
<td></td>
</tr>
<tr>
<td>EE</td>
<td>EE1 Learning to operate this system would be easy for me.</td>
<td>Davis (1989)</td>
</tr>
<tr>
<td></td>
<td>EE2 I would find it easy to get this system to do what I want it to do.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>EE3 My interactions with this system would be clear and understandable.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>EE4 I would find this system easy to use.</td>
<td></td>
</tr>
<tr>
<td>ATT</td>
<td>ATT1 The actual process of using this system would be pleasant.</td>
<td>Davis et al. (1992)</td>
</tr>
<tr>
<td></td>
<td>ATT2 This system would make work more interesting.</td>
<td>Thompson et al. (1991)</td>
</tr>
<tr>
<td></td>
<td>ATT3 I would like working with this system.</td>
<td>Compeau et al. (1999)</td>
</tr>
<tr>
<td></td>
<td>ATT4 Using the system would be a bad/good idea.</td>
<td>Peters et al. (2020), Taylor and Todd (1995)</td>
</tr>
<tr>
<td></td>
<td>ATT5 Using the system would be foolish/wise move.</td>
<td></td>
</tr>
<tr>
<td>BI</td>
<td>BI1 If this system was available to me, I would intend to use this system in the future.</td>
<td>Venkatesh et al. (2003)</td>
</tr>
<tr>
<td></td>
<td>BI2 If this system was available to me, I predict I would use this system in the future.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>BI3 If this system was available to me, I would plan to use this system in the future.</td>
<td></td>
</tr>
<tr>
<td>ST</td>
<td>ST1 I would understand how this system will assist me with decisions I have to make.</td>
<td>Madsen and Gregor (2000)</td>
</tr>
<tr>
<td></td>
<td>ST2 I would understand why this system provided the decision it did.</td>
<td>Cramer et al. (2008)</td>
</tr>
<tr>
<td></td>
<td>ST3 I would understand what this system bases its provided decision on.</td>
<td></td>
</tr>
<tr>
<td>TA</td>
<td>TA1 This system would be competent in providing maintenance decision support.</td>
<td>Cheng et al. (2008), McKnight et al. (2002)</td>
</tr>
<tr>
<td></td>
<td>TA2 This system would perform maintenance decision support very well.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TA3 In general, this system would be proficient in providing maintenance decision support.</td>
<td></td>
</tr>
<tr>
<td>TB</td>
<td>TB1 It would be easy for me to trust this system.</td>
<td>Cheng et al. (2008), Lee and Turban (2001), Wang and Benbasat (2007)</td>
</tr>
<tr>
<td></td>
<td>TB2 My tendency to trust this system would be high.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TB3 I would tend to trust this system, even though I have little or no knowledge of it.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TB4 Trusting this system would be difficult for me.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TB5 Trusting this system would not be difficult for me.</td>
<td></td>
</tr>
</tbody>
</table>

Table 4: Measurement Items

5 Conclusion and Outlook

High-performance deep learning models dominate maintenance research on AI-MDSS. However, in practice, adoption still lacks. Rationalizations of this phenomenon are scarce. We assume that complex and untraceable algorithmic decision making is the key issue, which hamper AI-MDSS acceptance and, thus, use. With this research, we propose a modified UTAUT model to measure and explain how trust and system transparency influence the technology acceptance of AI-based DSS. Our model can serve as a foundation for a better understanding of the necessary actions to ensure user adoption as it describes and explains the innate factors that influence AI adoption. Our final results will enable scientists to better understand the interrelation of factors and we offer insights into how XAI may improve this process. Further, our model can be a means of rationalization for practitioners to reduce barriers and to have confidence in the superhuman abilities of AI-MDSS to diagnose and predict machine faults.
References


