Designing AI-based systems to last: Identifying the enablers and inhibitors for the AI usage intentions of automotive blue-collar workers

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DESIGNING AI-BASED SYSTEMS TO LAST: IDENTIFYING THE ENABLERS AND INHIBITORS FOR THE AI USAGE INTENTIONS OF AUTOMOTIVE BLUE-COLLAR WORKERS

Research Paper

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Abstract

This study presents a research model specifically contextualised to explain and substantiate the enablers and inhibitors of automotive blue-collar workers’ AI usage intentions. The identified factors therein stem from a multiple case study approach including interviews with 24 workers from three different German car manufacturers at four different production sites. The model includes 15 different behaviour-affecting expectations, three of which have never been mentioned in the literature before and can thus be regarded as completely new in that context. The proposed model addresses research gaps in both the individual-level technology adoption research literature and the literature on the application of AI in the automotive environment. It helps to pave the way towards a lean and user-centric development of AI-based systems in the future which do not fail at the threshold of individual-level user acceptance.

Keywords: Individual-level technology adoption, artificial intelligence, car manufacturing, technology acceptance / resistance
1 Introduction

Individual-level technology adoption is a mature area of research within the information systems (IS) community, with many established theories that successfully predict and explain the adoption and use of a broad range of technologies (Davis, 1989; Venkatesh et al., 2003). Within the last decades, a huge variety of technologies and contexts have been studied under that lens. By identifying and empirically substantiating numerous different behaviour-affecting factors, the IS community has developed many valuable ideas and strategies on how organizations can address and influence employees’ reactions in their favour. This includes many insights on how IS should be designed to foster their acceptance rather than their rejection (Cenfetelli, 2004).

However, the latest boom of artificial intelligence (AI) poses a new challenge for that research area as that technology class differs quite heavily from what has been researched in the past (Venkatesh, 2021). The particular shift with AI-based systems is not only powered by the involvement of enormous amounts of autonomously created and hence mostly uncontrolled data, but also by a shift from decision support to actual decision making. With many AI-based systems, the human decision maker, i.e., the employee, is relegated to playing a secondary role. Further, the also rather uncontrolled nature and outcome of the underlying learning processes, which make up the core of most AI-based systems just as well as their value propositions, bears quite severe dangers (Crawford and Calo, 2016). A recent example therefore, which also created a lot of attention within the media, is the sexist AI recruiting algorithm from Amazon. It was ceased after the company found out that the model had taught itself that male candidates were preferable and thus discriminated female candidates for their gender (Schmalenbach and Laumer, 2020).

Contextual conditions and attributes unique to specific technologies are known to play a pivotal role in the adoption and use of those technologies and should hence already be considered when designing them (Hong et al., 2014). AI marks no exception thereof and is arguably even so different from all previously researched technologies that priorly gained adoption-related knowledge does not sufficiently apply (Venkatesh, 2021).

One industry that obviously had to learn that the hard way within the last couple of months is the car manufacturing industry. Recent surveys suggest a notable role of individual-level technology resistance within many recent AI project fails, leading to a sluggish overall adoption across the entire industry (Cam et al., 2019; Webb, 2018; Winkler et al., 2019). Besides the quite obvious industry-specific need to find out more about that phenomenon, it makes one particular group of (potential) IS users very interesting also for the general AI-centred individual-level technology adoption research (Venkatesh, 2021), namely automotive blue-collar workers. With them being the primary users for AI-based systems within that context, understanding their acceptance of such systems should allow both to solve the automotive resistance problem as well as to increase the general understanding of what makes AI special in terms of technology adoption.

In consequence, this paper dedicates itself to the following research questions: What are the expectations that enable and inhibit the usage intentions of automotive blue-collar workers towards AI-based IS? What does that mean for the design of such systems now and in the future?

It relies on the dual-factored model proposed by Cenfetelli and Schwarz (2011) as its main theoretical lens. Based on that, a contextualized research model is developed that aims to explain the usage intentions of automotive blue-collar workers towards AI-based IS. Whereas the model in its entirety is limited to that specific context, the individual elements included in it contribute to the currently emerging transcontextual discussion on the adoption of AI-based systems and how that technology is special compared to other technologies from that point of view (Venkatesh, 2021).

The results presented stem from a multiple case study approach including interviews with 24 blue-collar workers from three different German car manufacturers. This article presents that model in detail in Section 4, after outlining the theoretical background of the overall study in Section 2 and its methodology in Section 3. It closes with a discussion of the model’s impacts for theory and practice in Section 5.
2 Theoretical Background

To ensure a common understanding of the contexts and domains in which the produced results have to be seen, this article first provides a brief overview over the already published research on (AI-focused) individual-level technology adoption. It then explains what AI is used for in the context of car manufacturing and what the current status of research is in that area.

2.1 Individual-level technology adoption

When studying employees’ acceptance of or resistance to IS in organizations, research focuses either on the adoption of IS and the corresponding beliefs and behaviours of individuals (Lapointe and Rivard, 2005; Maier et al., 2012; Polites and Karahanna, 2012) or on the use of IS and its influence on work performance (Bala and Venkatesh, 2015). Research related to the former focuses on the implementation process and how individuals react to a new IS, whereas the latter focuses on individual behaviours to well-known IS. With the focus of this study on newly to implement AI-based IS for car manufacturing, this study in line with the tradition of the former research stream.

IS research that focuses on the adoption process (e.g. Cooper and Zmud, 1990) revealed several insights into why and how individuals accept or resist a new IS that is implemented in an organization. In general, when a new IS is implemented, users decide to accept or resist it based on their evaluation of the change associated with the system (Kim and Kankanhalli, 2009; Laumer and Eckhardt, 2010; Laumer et al., 2016a). That overall research stream has thereby produced various research models that are known and acknowledged all around the globe by now, for instance, the technology acceptance model (TAM) (Davis, 1989) or the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). Embedded within such models, an extensive number of different behaviour-affecting factors has been identified and researched by now, reaching from rather universally applicable elements to some heavily technology-specific ones (see e.g. DeLone and McLean, 1992 or Laumer et al., 2016b for thorough reviews).

In this context, Cenfetelli (2004) proposes the dual-factored model and two types of influencing factors: enablers and inhibitors. He does so, as most of the aforementioned IS research at many points implicitly assumes that the inhibitors of usage are merely the opposite of the enablers. In contrast thereto, the dual-factored model theorises about the existence, nature, and effects of factors that are fundamentally different from being simply the opposite or lack of factors that enable usage and so solely discourage use. Thereby, enablers refer to “those external beliefs regarding the design and functionality of a system that either encourage or discourage usage, dependent on valence. For example, systems that are perceived to be reliable are used; unreliable ones are not.” (Cenfetelli 2004, p. 475). Inhibitors, in contrast, are “perceptions held by a user about a system’s attributes with consequent effects on a decision to use a system. They act solely to discourage use” (Cenfetelli, 2004, p. 475). Inhibitors and enablers are independent of one another and can coexist. Building up on that rationale, Cenfetelli and Schwarz (2011) propose a research model that splits these two elements for the context of IS into four major groups: system quality, system inhibitors, information quality, and information inhibitors. System and information quality thereby function in the sense of enablers. Further, they contextualise that model for the contexts of e-business websites, personal digital assistants (PDAs), and e-mails and empirically test 16 different factors.

Looking at all the aforementioned peculiarities of AI-based systems, especially inhibitors play a crucial role against the background of this study. This is the main rationale behind the choice for the dual-factored model as the main theoretical lens. In consequence, avoiding those when designing AI-based IS might already be more than half of the battle, especially as humans by nature tend to disproportionally value negative experiences higher than positive ones (Samuelson and Zeckhauser, 1988).

After all, this study therefore relies on the dual-factored research model proposed by Cenfetelli and Schwarz (2011) as its first-level theoretical backbone. Further, it refers to the many different behaviour-affecting factors identified in the past (DeLone and McLean, 1992; Laumer et al., 2016b) as the
theoretical fundament when identifying and shaping the second-level contextual constructs from the interview data.

2.2 Previous AI-focused individual-level technology adoption research

Despite a steep increase of attention for AI during the last couple of years, within the aforementioned literature stream on the adoption of new IS in organizations and the corresponding beliefs and behaviours of individuals AI is still an underrepresented topic (Venkatesh, 2021).

AI-focused individual-level technology adoption studies with quantitatively substantiated outcomes can only be found for two very specific sub-groups of AI technologies, namely chatbots (Laumer et al., 2019) and voice-based conversational agents, e.g. Amazon’s Alexa or Apple’s Siri (Fernandes and Oliveira, 2021; Pitardi and Marriott, 2021). Explorative studies are also still very rare and can only be found with a clear application focus, e.g. to healthcare (Reis et al., 2020) or knowledge-intensive work (Zhang et al., 2020). For the adoption of AI in general, not a single suchlike study can be found, not to speak of one specifically addressing the (automotive) manufacturing industry (unlike as for the adoption of AI on the organisational level, e.g. Demlehner and Laumer, 2020a or Jöhnk et al., 2021).

Within his latest work, Viswanath Venkatesh (2021) comes to the same result and uses that as an opportunity to issue a call for counteraction. In his article, he carves out what makes AI-based IS and other AI-based systems and tools special from an adoption perspective, leading to a list of six different AI-specific technology characteristics (cf. Table 1).

<table>
<thead>
<tr>
<th>Number</th>
<th>Peculiarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Model is blackboxed</td>
</tr>
<tr>
<td>2</td>
<td>Model errors</td>
</tr>
<tr>
<td>3</td>
<td>Model learning takes time</td>
</tr>
<tr>
<td>4</td>
<td>Model bias</td>
</tr>
<tr>
<td>5</td>
<td>Human biases and greater trust in human judgment</td>
</tr>
<tr>
<td>6</td>
<td>(Human) algorithm aversion</td>
</tr>
</tbody>
</table>

Table 1. Adoption-relevant technological peculiarities of AI-based systems (Venkatesh, 2021)

He proposes UTAUT, which was developed by himself about 20 years ago (Venkatesh et al., 2003), as the theoretical fundament to build a newly to build research stream on AI-focused individual-level technology adoption on it. Although this research does not follow that particular suggestion, it amply adopts his assessment that AI is rather special compared to all previously researched IS and hence deserves particular attention and work to find out what drives people when deciding to accept or resist it within their professional environment.

2.3 Use of AI for car manufacturing purposes

Unfortunately, the increasing popularity of AI in recent years has not yet brought a uniform and commonly accepted definition with it. Typically, AI is used as a collective term for computer systems that show capabilities that are perceived as intelligent when performed by humans, thereby at their core not relying on precisely foreordained, hand-coded rules (Harfouche et al., 2017). This includes for instance, among many other things, perception mechanisms like natural language processing and computer vision, or self-learning entities like neural networks and reinforcement learning algorithms (Russell and Norvig, 2016). This research refers to the term AI in the sense of a computer system having the ability to perceive, learn, judge, or plan without being explicitly programmed to follow predetermined rules or action sequences throughout the whole process (Demlehner et al., 2021).

Although many people predict AI to have a bright future within the domain of car manufacturing (Luckow et al., 2018; Webb, 2018; Winkler et al., 2019), the existing body of scientific literature on that topic is still rather fragmented. Currently, there is only one paper drawing a bigger picture of the
applicability and use of AI within that context (Demlehner et al., 2021). The other works existing mostly present concrete AI application scenarios and algorithms for specific tasks within the automotive production environment, presented in a mainly technical manner (Demlehner and Laumer, 2019, 2020b). Popular use cases for AI in that context are, for instance, quality control and prediction tasks on the basis of either visual or non-visual input data or the prediction of upcoming maintenance needs based on changes within the machine data over time (Demlehner et al., 2021).

But as most of the discussed AI-based systems find their place directly at the shop floor next to human workers, either nudging them in their decisions or taking them over completely (Venkatesh, 2021), they have to be seen as socio-technical systems. Therefore, it is not enough to just look at their technical details. Instead, it is also necessary to study their behavioural elements, ultimately looking for answers to questions like why still often “personal judgement overrides AI-based decision making” (Webb, 2018, p. 6) or why only 16% of the interviewed employees trust AI-generated results and 45% fear impending personal privacy infractions due to the use of AI at their workplace (Cam et al., 2019). This is especially relevant for the design phase of a new system as at that point in time the main system features, which shape its use in practice in the following years, are defined. Besides the direct value of the contextualised model for the automotive industry and all individuals trying to overcome the obviously existing AI acceptance issues within the same (Cam et al., 2019; Webb, 2018; Winkler et al., 2019), that overall contextual setting is the ideal environment to (co-)kick off the aforementioned transcontextual AI-centred individual-level technology adoption research stream for the upcoming years (Venkatesh, 2021).

3 Research Design

As this research aimed at exploring previously unknown ground by developing a research model that explains the usage intentions of automotive blue-collar workers towards AI-based applications, an explorative research design in the form of a qualitative multiple case study approach was the obvious choice. On the one hand, an explorative research design is the most suitable and most common approach when trying to create first insights on a novel topic (Yin, 2008). On the other hand, a qualitative research design is indicated as soon as one is mainly looking for answers to why- and what-questions that cannot (yet) be answered quantitatively because the necessary constructs are not yet known (Miles et al., 2014).

3.1 Interviewee sampling

A purposeful sampling strategy in line with the research objectives and the multiple case study design was chosen (Yin, 2008). Therefore, semi-structured interviews with 24 blue-collar workers from three different German car manufacturers at four different sites were conducted. That setting eliminates the possibility of any company- or site-specific biases. To further control for process-specific biases, it was made sure that never more than two of the interviewees were working within the same procedural environment. Furthermore, only workers that either worked directly at the production line or in a maintenance team were interviewed.

At none of the four factories visited, an AI-based system productively supporting the active car manufacturing operations was in place. As a result, no workers with previous experiences on the industrial application of AI were to be found, which is in line with the low overall diffusion rate of AI within the automotive manufacturing environment as reported by Winkler et al (2019). However, this is no obstacle to the overall goal of this work but rather a further indicator towards its necessity in order to avoid vast amounts of development expenditures being wasted on AI-based systems failing at the threshold of individual-level user acceptance in the near future. To make clear already at first sight that the research model presented in this article relies on the interviewees’ expectations rather than their experiences, it adds the word ‘expectations’ to all of their four categories of enablers and inhibitors all along the course of this study (Venkatesh et al., 2003).

The interviewees were acquired via contacts to managers at the factories from the personal networks of the research team. All interviews were conducted face-to-face in the course of visits at the respective
four factories in January and February 2020. They took between 13 and 33 minutes each. All interviews were completely audio-recorded and transcribed directly after their completion in order to ensure that no thematic aspects were lost. The interview language was German. Thus, as soon as extracts from those interviewees are reported in this study, they are translated without any exception. The data collection was ended as soon as only redundant aspects were identified and it became obvious that additional interviews would not provide any new insights (Lapointe and Rivard, 2005). Additionally, the sample is double the recommended number of twelve interviews for a homogenous group of interviewees overall and hitting each twelve for assembly line workers and maintenance workers (Guest et al., 2006). Table 2 provides an overview of the interviewees in an anonymized fashion.

<table>
<thead>
<tr>
<th>Interviewee</th>
<th>Company</th>
<th>Job</th>
<th>Gender</th>
<th>Age</th>
<th>Interview duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Car manufacturer A</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>24</td>
<td>14 minutes</td>
</tr>
<tr>
<td>2</td>
<td>Car manufacturer A</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>24</td>
<td>13 minutes</td>
</tr>
<tr>
<td>3</td>
<td>Car manufacturer A</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>28</td>
<td>13 minutes</td>
</tr>
<tr>
<td>4</td>
<td>Car manufacturer A</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>29</td>
<td>23 minutes</td>
</tr>
<tr>
<td>5</td>
<td>Car manufacturer A</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>33</td>
<td>18 minutes</td>
</tr>
<tr>
<td>6</td>
<td>Car manufacturer B</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>28</td>
<td>20 minutes</td>
</tr>
<tr>
<td>7</td>
<td>Car manufacturer B</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>50</td>
<td>13 minutes</td>
</tr>
<tr>
<td>8</td>
<td>Car manufacturer B</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>26</td>
<td>18 minutes</td>
</tr>
<tr>
<td>9</td>
<td>Car manufacturer B</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>28</td>
<td>16 minutes</td>
</tr>
<tr>
<td>10</td>
<td>Car manufacturer B</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>38</td>
<td>23 minutes</td>
</tr>
<tr>
<td>11</td>
<td>Car manufacturer B</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>33</td>
<td>30 minutes</td>
</tr>
<tr>
<td>12</td>
<td>Car manufacturer B</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>53</td>
<td>33 minutes</td>
</tr>
<tr>
<td>13</td>
<td>Car manufacturer B</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>36</td>
<td>26 minutes</td>
</tr>
<tr>
<td>14</td>
<td>Car manufacturer C</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>28</td>
<td>18 minutes</td>
</tr>
<tr>
<td>15</td>
<td>Car manufacturer C</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>22</td>
<td>18 minutes</td>
</tr>
<tr>
<td>16</td>
<td>Car manufacturer C</td>
<td>Maintenance worker</td>
<td>Female</td>
<td>24</td>
<td>17 minutes</td>
</tr>
<tr>
<td>17</td>
<td>Car manufacturer C</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>36</td>
<td>20 minutes</td>
</tr>
<tr>
<td>18</td>
<td>Car manufacturer C</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>38</td>
<td>22 minutes</td>
</tr>
<tr>
<td>19</td>
<td>Car manufacturer A</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>31</td>
<td>20 minutes</td>
</tr>
<tr>
<td>20</td>
<td>Car manufacturer A</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>31</td>
<td>26 minutes</td>
</tr>
<tr>
<td>21</td>
<td>Car manufacturer A</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>27</td>
<td>22 minutes</td>
</tr>
<tr>
<td>22</td>
<td>Car manufacturer A</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>58</td>
<td>28 minutes</td>
</tr>
<tr>
<td>23</td>
<td>Car manufacturer A</td>
<td>Maintenance worker</td>
<td>Male</td>
<td>33</td>
<td>30 minutes</td>
</tr>
<tr>
<td>24</td>
<td>Car manufacturer A</td>
<td>Assembly line worker</td>
<td>Male</td>
<td>38</td>
<td>31 minutes</td>
</tr>
</tbody>
</table>

Table 2. Overview over interviewees

3.2 Interview guide

The interviews were orientated along a high-level interview guideline with open-ended questions (cf. Table 3). They were divided into three sections. In the first part, general information like age, job, and a detailed description of the respondent’s working process were collected. Right at the beginning of the second section, the interviewees were asked regarding their understanding of the term “artificial intelligence”, aiming at a common comprehension of AI between the interviewees and the interviewer. This is a necessary prerequisite for any valid qualitative study (Yin, 2008). As soon as that common understanding was reached, they were asked whether any AI application had already been implemented or announced either at their personal working environment or at any person’s to whom they might have talked in the past. With the fourth question of the second part, the experiences on AI stemming from the interviewees’ private lives were identified. In the third part, it was examined what changes they associate
with the introduction of AI into their working environment in order to identify the enablers and inhibitors for their AI usage intentions. With the subquestion of “How would those affect you?” an attempt was made to make sure that no inhibitor would be mistaken for an enabler and vice versa.

<table>
<thead>
<tr>
<th>Part 1: Personal information</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1 How old are you?</td>
</tr>
<tr>
<td>1.2 What is your function?</td>
</tr>
<tr>
<td>1.3 Can you describe the process that takes place within your area of responsibility?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Part 2: Individual experiences with AI</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1 What do you personally understand under the term “artificial intelligence”?</td>
</tr>
<tr>
<td>2.2 Is AI already used or announced (even unofficially) in your personal working environment?</td>
</tr>
<tr>
<td>2.3 Is AI already used or announced (even unofficially) in the working environment of one of your friends/colleagues? If yes, have you heard anything from them about the new system?</td>
</tr>
<tr>
<td>2.4 Where have you already come into contact with AI in your private environment? Could you please describe the experiences you have made with it so far? What gut feeling does the term trigger in you personally when you hear it?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Part 3: Enablers and inhibitors of AI usage intentions</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1 Assuming that AI would find its way into your work area, could you please describe the three most important positive changes you expect to see? How would those affect you? Based on what information or experience do you think that this change will happen?</td>
</tr>
<tr>
<td>3.2 Assuming that AI would find its way into your work area, could you please describe the three most important negative changes you expect to see? How would those affect you? Based on what information or experience do you think that this change will happen?</td>
</tr>
</tbody>
</table>

Table 3. High-level interview guide

This approach ensured that there is a) a common understanding between all involved parties and b) that the workers are given sufficient freedom to express all their thoughts, concerns, and expectations regarding the use of AI on the automotive shop floor (Yin, 2008). This made it possible to not just analyse factors already known from previous studies but also to identify new ones (Hong et al., 2014).

### 3.3 Interview analysis

The transcripts from the 24 interviews were collected within a single case protocol. This protocol ultimately accounted for 216 pages of text with almost 70,000 words. The protocol was then coded and structured with the help of the software MAXQDA. To systematically analyse and categorise the information from the interviews, qualitative content analysis was chosen. This was done for the simple reason that it allows to build on existing acceptance research but also to generate new propositions (Demlehner and Laumer, 2020a; Mayring, 2014).

As already indicated in Section 2.1, the study relied on the dual-factored model proposed by Cenfetelli and Schwarz (2011) as its first-level theoretical backbone. Further, it refers to the many different behaviour-affecting factors identified in the past (DeLone and McLean, 1992; Laumer et al., 2016b) when identifying and shaping the second-level contextual constructs from the interview data. Therefore, the interviews were coded in a parallel deductive and inductive approach. In a first step, all behaviour-affecting factors mentioned and hence present within the case protocol were marked. Then deductive coding was used to carve out whether the underlying mechanism was that of an enabler or of an inhibitor.

In a second coding round the approach then aimed for identifying our second-level contextual constructs. Thereby, where an overlap with a previously identified behaviour-affecting element from the literature was obvious, the term used to describe that factor in the past by the respective author(s) was used as the code in a deductive approach. For instance, statements like “If the system is very reliable, that would of
course be a plus.” were coded as reliability (Cenfetelli and Schwarz, 2011). In parallel, inductive coding was used to identify factors that explain the usage intentions of automotive blue-collar workers regarding AI-based systems and have not been covered by research yet. For example, statements like “At some point, you realize that the more technology comes into it and the more is done for you by a machine, the more of your thinking ability is lost at some point. So, many people then think that they don’t have to worry about anything anymore. They more or less become dull over time.” were coded as new factors (here: dulling of the employees).

The statements coded as new factors were then grouped afterwards and once again compared to the known factors from previous research to avoid oversights. As soon as the chance of an oversight could be ruled out, they were then assigned a new label in an inductive fashion. Ultimately, the 15 different identified contextual factors were once again reviewed, sorted into one of the four first-level groups of the research model and then further processed towards the form present in this article as Figure 1.

4 Results

With this approach, ultimately 15 expectations impacting the usage intentions of automotive blue-collar workers towards AI-based systems were identified. Clustered into the four groups proposed by Cenfetelli and Schwarz (2011), with the two on the left side representing the enablers and the two on the right the inhibitors, they constitute a new contextualized research model explaining the usage intentions of automotive blue-collar workers towards AI-based IS, as it is to be seen in Figure 1.

![Figure 1. Enablers and inhibitors for AI usage intentions of automotive blue-collar workers](image)

4.1 System quality expectations

Within two of the interviews, the respondents stated that a high degree of autonomy of an AI-based system would positively influence their usage intentions towards the same and vice versa. Both respective interviewees were involved in maintenance. Whereas the first expects a high degree of system autonomy to be positive for his personal operations in the sense of the system being able to fix minor problems on its own, the second (a team leader) emphasised the expected positive implications for him as a leader and, in consequence, the entire team.
Until now, this factor has been completely left out in the literature dealing with traditional IS and other technologies and can only be found within the very recent AI-focused article of Reis et al. (2020). It can thus be considered as being specific for the element of AI. After all, the first proposition is as follows:

**P1:** The higher (lower) the expected autonomy of an AI-based system, the higher (lower) the usage intentions of automotive blue-collar workers towards the same.

13 mentions can be counted for the reliability of such systems, a factor that has frequently been identified and confirmed in previous studies (Cenfetelli and Schwarz, 2011). When discussing that element, the dual-sided nature of enablers became especially apparent as the following statement shows:

“If the system is very reliable, that would of course be a plus. Else, such technology also poses the threat of breaking down at any time. That is in turn negative, of course.” (Interviewee 14)

**P2:** The higher (lower) the expected reliability of an AI-based system, the higher (lower) the usage intentions of automotive blue-collar workers towards the same.

The element of usefulness was the most mentioned one with overall 22 statements. It had thereby two different facets. On the one hand, eight workers expected an AI-based IS to make their jobs easier/harder and, on the other hand, 15 interviewees expected it to reduce/increase their workload. That (perceived) usefulness is a behaviour-affecting element is thereby neither new to the adoption literature as such nor under the label of system quality features (DeLone and McLean, 1992). Nevertheless, the exclusive contextual focus on job difficulty and workload is an interesting side note in the AI-specific context.

**P3:** The higher (lower) the expected usefulness of an AI-based system, especially in its effect on job difficulty and workload, the higher (lower) the usage intentions of automotive blue-collar workers towards the same.

4.2 **Information quality expectations**

Moving over to the expectations regarding the traits of the information presented and processed by an AI-based system instead of the system’s traits itself, seven of the respondents proposed a connection between the completeness of the information presented by an AI-based system and their willingness to use the same. Here, it became quite clear that the contrast between the existing system and the potentially to be adopted one plays a severe role in such settings (Polites and Karahanna, 2012):

“When I need information, then I always expect that it is correct and that it is correct. However, I expect that it is also complete. If there is an error, I would expect that, when the message comes up, it would tell that right away, too.” (Interviewee 3)

Completeness is another factor that is already well known and researched within the existing literature (Cenfetelli and Schwarz, 2011; DeLone and McLean, 1992; Wixom and Todd, 2005).

**P4:** The higher (lower) the expected completeness of the information given by an AI-based system, the higher (lower) the usage intentions of automotive blue-collar workers towards the same.

The element that was second most frequently mentioned (19 out of 24) was the decision effectiveness. Thereby the decision’s correctness was the overarching element (16 mentions) but not the only one. Also, the time to make a decision and thus a potential acceleration of the affected process and also the neighbouring ones were mentioned (3 mentions). Again, it became apparent that expectancy is heavily influenced by the contrast between the current system and the potential new one (Polites and Karahanna, 2012). In the setting at hand, seven interviewees stated that they would expect a decision making improvement through an AI-based system mainly because it would most likely replace human involvement for repetitive and detail-focused tasks like quality inspections of always-the-same parts:

“With artificial intelligence, it does not matter if 1,000 parts have to be checked per hour or just ten. But with humans, you’ll notice a big difference as soon as the numbers go up. Then the factor of stress comes in and people get sloppy and make mistakes.” (Interviewee 2)
Again, this factor is not really new to the IS literature (DeLone and McLean, 1992). However, the study’s results support the assumption from Venkatesh (2021) that it will heavily gain in importance with AI in comparison to traditional technologies (Reis et al., 2020).

P5: The higher (lower) the expected decision effectiveness of an AI-based system, the higher (lower) the usage intentions of automotive blue-collar workers towards the same.

A more up-to-date format of the presented information is, according to two out of 24 interviewees, closely associated with their usage intentions towards AI-based systems. They especially mentioned the use of touch displays and iconized menus, which are standard in the consumer world of today. This factor has i.a. also been recognised within the work of Cenfetelli and Schwarz (2011) for their context.

P6: The expectably more (less) appealing the format of the information presented by an AI-based system, the higher (lower) the usage intentions of automotive blue-collar workers towards the same.

A very AI-specific and further completely new element ends the list of information quality expectations. 13 out of 24 blue-collar workers stated that if an AI-based system would bring some kind of knowledge to the process that a human worker barely or not at all could bring to it, this would significantly increase their usage intentions towards this system. They thereby all argued in the direction of detecting interdependencies and correlations that are by now unknown, as obvious in the following statement:

“We have our quality issues from time to time and if there was artificial intelligence in it, which tells me, there was now three times this error, which occurred with this specific combination, boy, that would be a huge step ahead.” (Interviewee 1)

In such explicitness, that factor has to be regarded as completely new to the adoption literature. Hence, it also has to be argued that it is highly AI-specific, potentially enforced by the latest “hero tales” on AI within public media and marketing in recent years (Demlehner et al., 2021; Fast and Horvitz, 2016).

P7: The more (less) an AI-based system expectably adds value that lies beyond the possibilities of humans, the higher (lower) the usage intentions of automotive blue-collar workers towards the same.

4.3 System inhibitor expectations

On the inhibitor side, six of the interviewees mentioned that the expected complexity of an AI-based system might lower their intention to use the same. As none of these six mentioned that a (surprisingly) low degree of complexity would positively influence them, that element has to be refereed to as an inhibitor. Whereas the underlying factor as such is not really new to the literature (DeLone and McLean, 1992; Wixom and Todd, 2005), its unidimensional role as an inhibitor is.

P8: The higher the expected complexity of an AI-based system, the lower the usage intentions of automotive blue-collar workers towards the same.

Four of the respondents stated their expectation that the introduction of AI might lead to the dulling of the affected employees in the long-term. Thereby, they especially fear a weakening of the human workforce as a long-term consequence of this technological development, as the following quote shows:

“At some point, you realize that the more technology comes into it and the more is done for you by a machine, the more of your thinking ability is lost at some point. So, many people then think that they don’t have to worry about anything anymore. They more or less become dull over time.” (Interviewee 18)

This inhibiting factor is thereby completely new to the literature. It can further be regarded as specific for the context of AI.

P9: The higher the expected dulling of the employees through an AI-based system, the lower the usage intentions of automotive blue-collar workers towards the same.
And again, six respondents described that if they would perceive a risk of losing control over the machine or the situation through the introduction of an AI-based system, this would significantly lower their willingness to use that system. The factor of loss of control as such cannot be regarded as new to the literature (Bhattacheree and Hikmet, 2007). However, the circumstance that this negatively associated expectation is heavily affected by the display of AI in Hollywood movies definitely can:

“Let me put it to you in the extreme. I think most people have seen the movie ‘The Terminator’, right? I mean, the underlying idea as such was well-intentioned, but if it gets out of hand, if you lose control at some point, you’re going to have a huge problem.” (Interviewee 24)

P10: The higher the expected risk of a loss of control over an AI-based system, the lower the usage intentions of automotive blue-collar workers towards the same.

Based on the responses of 15 of the interviewees, the fear of job loss does also have an inhibiting effect on the usage intentions of automotive blue-collar workers towards AI-based systems. Again it was notable within several of the interviews that the public perception of AI in general, and the stigmatization of AI as a job killer in particular (Fast and Horvitz, 2016), play a substantial role that has yet barely been mentioned in the literature whereas the factor as such has (DeLone and McLean, 1992).

P11: The higher the expected risk of a loss of jobs due to an AI-based system, the lower the usage intentions of automotive blue-collar workers towards the same.

Also already known (DeLone and McLean, 1992) and even contentwise similar to the previous element, despite being a bit less severe in terms of the expected impact on one’s personal (working) life, is the fear of a loss of status which was mentioned by six of the 24 automotive blue-collar workers interviewed. One statement from the interviews illustrates that inhibiting factor perfectly:

“If someday things become so simple that everyone can do the job, there won’t be any need for an experienced and trained guy like me and I would have to start over at some new meritless task again.” (Interviewee 15)

P12: The higher the expected risk of a loss of status due to an AI-based system, the lower the usage intentions of automotive blue-collar workers towards the same.

Another inhibiting element that was raised by only one single interviewee is the fear of being (indirectly) surveilled by the new AI-based IS. He argued in that way as in his expectation an AI-based IS would collect and process far more data than any conventional system with the overall intention of using this data as the basis for its decision making. Thinking that trait ahead, he stated his fear that a lot of this data might as well allow to draw interferences about the machinist’s behaviour to an unprecedented extent which would him then leave with the feeling of being surveilled. This would, in turn, negatively influence his usage intentions towards that system.

This inhibitor is the third completely new behaviour-affecting element identified in the course of this study. Again, it has to be regarded as AI-specific and further most likely initiated or at least enforced by the coverage of AI in public media (Fast and Horvitz, 2016).

P13: The higher the expected perceived surveillance by an AI-based system, the lower the usage intentions of automotive blue-collar workers towards the same.

A point that was raised by only two older interviewees was the obligation to be trained on the new technology, which they reported to be an inhibitor for them. Despite being questionable in its overall significance, this factor in this contextual manifestation is however rather unusual to find in the literature. From a theoretical perspective, the underlying factor is typically covered by the concept of transition costs as it can be found in various previous studies (Polites and Karahanna, 2012).

P14: The higher the expected transition costs of switching to an AI-based system, especially in the form of obligations for training, the lower the usage intentions of automotive blue-collar workers towards the same.
4.4 Information inhibitor expectations

The last element is a well-known problem within the context of AI: the black box decision making of most AI algorithm types. This means that, although many AI models have a high predictive quality far beyond any other technology, it is not comprehensible to humans based on which rationales the system makes its predictions (Ochmann et al., 2021). This is elucidated by the following statement:

“I would always like to know what is happening in the background and how. If I don’t know that, I am not sure whether I would want to use such a system, regardless of its qualities.
(Interviewee 20)

The fact that eleven of the interviewees mention that as an inhibiting element strongly supports the assumption of Venkatesh (2021) that this behaviour-affecting factor is strongly AI-specific.

P15: The higher the explainability of the decisions presented by an AI-based system, the higher the usage intentions of automotive blue-collar workers towards the same.

5 Discussion and Conclusion

After having unveiled the expectations that shape automotive blue-collar workers’ usage intentions towards AI-based systems in the previous section, the following section is dedicated to the implications and conclusions that can be derived from these results for research and practice. For the latter, the focus lies on the second research question, i.e. what those results mean for the design of such systems in order to ensure their acceptance by the users.

On the one hand, within this study, a new contextualized research model that explains the usage intentions of automotive blue-collar workers towards AI-based applications is presented (cf. Figure 1). Therein, 15 different expectations that enable and inhibit these usage intentions are revealed. Many factors from that list have already been identified in the past as being relevant for individual-level user acceptance, e.g. factors like reliability and usefulness (Cenfetelli and Schwarz, 2011; DeLone and McLean, 1992; Laumer et al., 2016b; Williams et al., 2009; Wixom and Todd, 2005). However, as in sum a three-digit number of different factors has been identified over the last decades, this work helps all those individuals trying to overcome the currently existing AI acceptance issues within the car manufacturing environment (Cam et al., 2019; Webb, 2018; Winkler et al., 2019) by narrowing down the numbers regarding which factors might be the (most) relevant ones. In consequence, they would do well to refer to the fifteen factors identified here already during the design phase for any new AI-based system in order to craft it in a way that fosters its acceptance rather than its rejection.

As humans by nature tend to disproportionately value negative experiences higher than positive ones (Samuelson and Zeckhauser, 1988), especially the identification and substantiation of the inhibiting factors in this study might be a key insight for the practical development of such successful and lasting AI-based systems. The reason for that is that, in contrast to enablers, which can function both positively and negatively when shaping employees’ behaviour-inducing beliefs and opinions, inhibitors solely discourage use (Cenfetelli, 2004). Hence, consequently avoiding those might rather be the most reasonable and efficient thing to do in order to ensure user acceptance instead of striving for perfection within any dimension that functions as an enabler. For the latter, at least as far as the underlying behavioural theory is concerned (Cenfetelli, 2004), identifying the threshold of acceptability and developing a minimum viable product based on that should be the most efficient thing to do.

Further, individuals with an interest in the successful implementation of such AI-based systems should also be aware of the circumstance that individual-level technology adoption is not necessarily always based on pure rationality. In fact, IS research has already proven that within that context bounded rationality on account of the employees’ cognitive limitations can play a huge role (Kim and Kankanahalli, 2009; Lee and Joshi, 2017). Especially for the factors of dulling of the employees and loss of control, it became quite clear during the interviews that the respective workers were well aware of the fact that their fears might most likely be arbitrary (cf. first and foremost the “Terminator” statement...
Automotive Workers’ AI Usage Intentions

in Section 4.3). However, they stated that those would anyway play a role within their assessments. Unfortunately, the role of irrationality in such scenarios in general and with regard to AI in particular is so far heavily under-researched within the IS community and might thus be a promising field of action for the future (Lee and Joshi, 2017).

On the other hand, this study and its results are highly relevant for IS theory, thereby especially for the research stream on individual-level technology adoption. This research stream is currently being challenged by the steep development of AI. Due to the rather unique technological features of that technology group it is unclear how far the results from previous studies can be transferred and applied to AI adoption scenarios or how heavily AI-specific technological traits dominate (Venkatesh, 2021).

This research is therefore one of the very first that give tangible indications on that question. It was able to identify three factors that have not yet been mentioned at all within the literature and can thus be regarded as rather specific for the element that distinguishes this study from most of its predecessors, i.e. the element of AI. When talking about enablers, 13 interviewees stated that they would expect an AI-based IS to bring some kind of value to the table that a traditional machine can’t but also one that humans can’t deliver. In the course of that, they all argued in the direction of detecting interdependencies and correlations in the production data that are by now unknown. This factor thereby incorporates a completely new addition to the literature. On the inhibiting side, two new factors were identified in the course of this study, i.e. dulling of the employees and perceived surveillance. After all, all three factors embody completely new additions to the aforementioned literature stream of individual-level technology adoption. For those three, future research in other contexts to substantiate the suspicion that those elements are AI-specific might be worthwhile (Venkatesh, 2021).

Although they are not completely new to the literature (Bhattacherjee and Hikmet, 2007; DeLone and McLean, 1992; Reis et al., 2020; Venkatesh, 2021), the results gained in this study suggest that the elements of autonomy, decision effectiveness, loss of control, loss of jobs, and black box decision making can be expected to heavily increase in relevance with AI-based systems compared to conventional ones. For autonomy, decision effectiveness, and black box decision making that assessment is based on the nature of systems that AI is typically used for in recent years (Demlehner et al., 2021; Venkatesh, 2021). Most of them are designed to improve and automate decision making tasks that used to be done by humans in the past. And for the factors of loss of control and loss of jobs, the portrayal of AI in public media, press, and even Hollywood movies seems to take a toll on AI’s acceptability for a notable number of people and employees (Fast and Horvitz, 2016).

Naturally, apart from these implications and contributions, this work is also accompanied by some limitations. As its results were not quantitatively tested, they cannot be counted as empirically validated. Also, they stem from interviews conducted within companies that had not yet announced any kind of AI-based system to be implemented to their employees. It has therefore to be acknowledged that the resulting research model relies on the interviewees’ expectations rather than their experiences. Although this is completely in line with previous works who have (later) empirically proven that these early expectations already have the potential to shape the future behaviour to a significant extent (e.g. Venkatesh et al., 2003), one cannot conclusively anticipate for the moment how the employees’ beliefs will change as soon as the company moves further towards an actual implementation. Both these limitations thereby incorporate further issues that require and deserve future research.

Ultimately, after investigating the usage intentions of blue-collar workers in the car manufacturing industry towards AI-based systems within the course of a multiple case study approach at four different German automotive factories, the major contribution of this paper is the provision of a new contextualized research model containing 15 different enablers and inhibitors that shape the workers’ acceptance of such systems. It is thereby one of the very first studies investigating individual-level technology acceptance towards AI-based IS in organizations in general and within the context of car manufacturing in particular. Further, three out of these 15 different factors have never been mentioned in the literature until now and can hence be regarded as completely new in this context. This study and its results thus help to pave the way towards a lean and user-centric development of AI-based systems for organisational use which do not fail at the threshold of individual-level user acceptance.
References


Automotive Workers’ AI Usage Intentions

