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Understanding the challenges of AI implementation: Insights from an empirical study of manufacturing companies

Research Paper

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Abstract. The increasing importance of artificial intelligence on manufacturing competitiveness is a prevalent topic in contemporary studies. Thereby, the potential of AI extends across companies of all sizes. However, small and medium-sized enterprises in particular see major challenges in AI implementation. As a result, our study determined the variations in the perceived barriers to AI realization among different company sizes and the obstacles that notably impede the willingness to implement AI. To achieve this, a factor analysis and structural equation modeling were carried out. Our findings highlight that the different challenges for AI implementation can be divided into four groups economic, technological, social, and political. Thereby the perception of economic challenges varies the most among distinct enterprise sizes, whereas the social challenges correlate extremely weakly. Regarding the willingness to implement AI, political challenges show the strongest negative correlation, while technological challenges, contrary to prior assumptions, lack significant influence.

Keywords: Artificial intelligence, Barriers, Challenges, Readiness for AI implementation

1 Introduction

The growing prevalence of artificial intelligence (AI) has a substantial impact on manufacturing companies in particular (Teerasoponpong & Sopadang 2021). Considerable potential, for example in the optimization of production processes (Cheng et al. 2021), provides these enterprises with the opportunity to improve their economic situation. On the other hand, however, there is also a risk of losing competitiveness if the new technology is not implemented (Dwivedi et al. 2019). Despite the importance of AI, studies indicated that the vast majority of manufacturing companies have not yet implement AI applications (Maslej et al. 2023). In the case of European small and medium-sized enterprises (SMEs), the adoption rate is only around 10% (Szedlak et al. 2021; Willenbacher et al. 2021). The barriers to AI implementation are defined as the main reason for this state of affairs (Bettoni et al. 2021). Various case studies and surveys showed a wide range of different challenges that businesses are confronted with (Oldemeyer et al. 2024). However, these vary substantially depending on the size of the company (Heizmann et al. 2022). On one hand, SMEs frequently contend with limited financial resources, making the risk of failure a more significant factor (Barton et al. 2022). On the other hand, their initial conditions often differ substantially. For instance, smaller companies are more likely to struggle with issues related to data availability and data quality (Chen et al. 2019). The demands for a potential AI solution also vary greatly according to business size in terms of the required complexity (Jain et al. 2021).

However, empirical studies of the challenges of AI implementation in the manufacturing sector are still limited compared to other sectors. Moreover, we conducted a factor analysis to facilitate an open and alternative approach to categorizing the identified challenges from the literature review. This differs from previous classifications that have often been based on established models such as the Organization-Environment framework (TOE) (Kinkel et al. 2022; Maslej et al. 2023). In addition, country-specific characteristics such as the degree of industrialization, the education level of the population, or legal regulations are considered because they can also influence the challenges and willingness to implement new technologies in companies (Tornatzky et al. 1990; Vagnani et al. 2019). As Kinkel et al. (2022) have already compared the perceived challenges of AI implementation in different countries, we will focus on manufacturing companies located exclusively in the industrialized nation of Germany. Germany is well-known for its broad "German Mittelstand" (Pahnke & Welter 2019), which encompasses many companies of all sizes. This leads to our first research question:

- RQ1: How does the size of German manufacturing companies influence the perceived challenges of an AI implementation?

Although many researchers perceived similar obstacles to AI implementation in their studies, there are substantial discrepancies between the assessment of the influence of the different challenges on the willingness to realize an AI project. While some studies emphasized the role of knowledge as the most substantial entry barrier (Kumar & Kalse 2021; Ulrich & Frank 2021), others highlighted the costs associated with implementation as the primary obstacle (Kim et al. 2022). Moreover, other factors such as acceptance (Garrel & Jahn 2022), or data (Bauer et al. 2020) were also deemed critical for AI implementation by some researchers. Therefore, there is no consensus on the influential factors concerning AI realization. This aligns with the research gap identified by Kinkel et al. (2022), in investigating various challenges related to the effect of readiness to introduce AI. As such, we deploy the second research question:

- RQ2: How do the various perceived challenges of AI implementation influence the willingness of German manufacturing companies to implement AI solutions?

Our study contributes to theory and practice in different ways. First, we did a data-based grouping of the various challenges for a structured overview. We anticipate that this approach will contribute added value in terms of new focal points and new perspectives on the topic of implementation barriers and their correlation with the willingness to realize. Furthermore, we were also able to identify the areas where the challenges exhibit the greatest variance across the enterprise sizes. In these, greater differentiation should be made between the sizes, both in political considerations and in the context of further research. Besides, we were able to empirically investigate the influence of the various challenge groups on the willingness to implement AI in order to identify the greatest lever for increasing the spread of AI in manufacturing companies.

2 Hypothesis Development and Research Model

The development of the following hypotheses and the research model are based on the findings of our literature review and a subsequent factor analysis, which are described in detail in section 3.

One of the primary challenges of AI implementation relates to the costs and their associated budget. Nonetheless, variations among different enterprise sizes have been emphasized. For instance, Barton et al. (2022) pointed out that financial resources represent the most substantial distinction between SMEs and larger enterprises regarding AI implementation. Similarly, studies by Szedlak et al. (2020) and Ulrich & Frank (2021) highlighted that costs and the financial risk of failure are considerably higher for smaller companies. The availability of AI solutions on the market is also perceived differently among various business sizes. While this is frequently discussed in the context of SMEs (Jain et al. 2021; Brezani et al. 2022), larger firms tend to pay less attention to this concern. In summary, we derive our first hypothesis, H1: As the **size of the company** increases, the perceived **economic** challenges of AI implementation decrease.

Even though data availability and quality are widely acknowledged as barriers in AI implementation for both smaller and larger companies, it is apparent that smaller enterprises are more affected by these challenges. Mittal et al. (2018) also recognized this observation in their study, attributing this to lower maturity levels in smaller firms. Jain et al. (2021) additionally noticed technical barriers in SMEs primarily due to the lack of an IT infrastructure. This context leads to the formulation of our second hypothesis, H2: As the **size of the company** increases, the perceived **technological** challenges of AI implementation decrease.

Knowledge is a major barrier to the utilization of AI, especially for companies with lower revenues and a smaller workforce. In a survey of experts conducted by Hansen & Bøgh (2021), none of the respondents from SMEs concurred with the statement that their firms possessed sufficient knowledge and expertise in AI. This challenge exerts a more pronounced impact on smaller companies compared to their larger counterparts. Furthermore, research on management also revealed a correlation between the size of enterprises and the perceived barriers to the introduction of AI. Consequently, a greater number of SMEs did not identify a potential application area for AI within their company (Husson et al. 2021; Iftikhar & Nordbjerg 2021). In addition the review of Lu et al. (2022) showed that SMEs face other ethnic challenges than lager enterprises as these companies have often no expertise in this area and are more dependent on external data exchange. These findings from various perspectives on the social challenges emerge our third hypothesis, H3: As the **size of the company** increases, the perceived **social** challenges of AI implementation decrease.

Research conducted has also found disparities between companies of different sizes concerning the political challenges, chiefly about regulations and the lack of government support. SMEs, facing limited resources and a deficit in expertise, encounter greater challenges when it comes to understanding and complying with legal requirements (Bettoni et al. 2021; Jain et al. 2021). In this regard, but also advice on how to get started, small companies often find themselves lacking the required support (Hansen & Bøgh 2021). Consequently, our fourth hypothesis, H4, is: As the **size of the company** increases, the perceived **political** challenges of AI implementation decrease.

Furthermore, prior research has delved into the connection between perceived challenges and the willingness to realize an AI solution. In consideration of the economic barriers, such as the quandary of the monetary valuation (cost-benefit-effect) of a prospective AI application (Kaymakci et al. 2022), or the lack of a budget (Sharma et al. 2022b), many studies often presented these as frequent obstacles to a company's willingness to implement an AI solution. In addition, the often unpredictable durations and the uncertainty regarding a successful introduction of the project, as they often follow a trial-and-error approach, diminish the readiness to initiate such solutions (Prem 2019). Hypothesis H5 is thus formulated as follows: As the perceived **economic** challenges increases, the **willingness** of AI implementation decreases.

Especially with regard to AI, data is a particularly critical factor and often represents a major challenge in the realization process. Some researchers even have identified data as the most substantial problem in this context (Bauer et al. 2020). This encompasses concerns related to data availability, data quality, and data flow (Kim et al. 2022). Neglecting these aspects during the implementation process carries a considerable risk of failure. Given that decision-makers are also aware of this, the quality and availability of data are substantial factors in the willingness to AI implementation. Also, in the case where an enterprise lacks an adequate IT infrastructure, decision-makers are frequently hesitant to embark on potential AI projects. This is often even the reason why the subject is not explored in greater depth (Kumar & Kalse 2021). This leads to the formulation of the sixth hypothesis, H6: As the perceived **technological** challenges increases, the **willingness** of AI implementation decreases.

Although, as already shown, the lack of knowledge among SMEs is perceived as a greater obstacle to the adoption of AI compared to larger companies, research has indicated that this barrier has an adverse effect on the readiness to implement AI for companies of all sizes (Bencsik 2020). Apart from knowledge, management, and decision-makers also have a significant influence on realization. In this context, Iftikhar & Nordbjerg (2021) pointed out that, management is the biggest hurdle to realize an AI project in a business. Other researchers instead presented acceptance and trust in AI solutions as the biggest determinant of the willingness to implement AI (Garrel & Jahn 2022). However, the ethnical aspects of an AI implementation are also a frequently identified challenge that influences the readiness (Chalmers et al. 2021; Zang et al. 2024). Consequently, we propose the following hypothesis, H7: As the perceived **social** challenges increases, the **willingness** of AI implementation decreases.

Analogous to the barrier of knowledge, regulatory requirements are often perceived as a more significant challenge by SMEs. Yet they also negatively influence the willingness of larger businesses to implement AI, as noted by Prem (2019). Furthermore, there is a shared criticism among companies of all sizes regarding the lack of research in this area. Smaller firms are particularly impacted by the scarcity of use cases that are specifically designed to cater to their initial situation and their needs (Husson et al. 2021). Conversely, larger companies are more affected by the frameworks. Government incentives are deemed necessary to mitigate financial risk, as pointed out by Davila Delgado et al. (2020). Consequently, this current lack has a major impact on the companies' willingness to implement AI. This remark extends also to advisory offers. The dearth of free or low-cost government alternatives further dampens companies' readiness to embark on AI realization (Lu et al. 2022). This results in the final hypothesis, H8: As the perceived **political** challenges increases, the **willingness** of AI implementation decreases.

A summary of the included challenges of the four groups can be taken from the factor analysis in the following section. From the conducted hypotheses we designed our model in the next step, which is depicted in Figure 1. For each group of challenges, we created a formative construct. The individual items, representing the identified barriers, constitute the basis of these constructs.

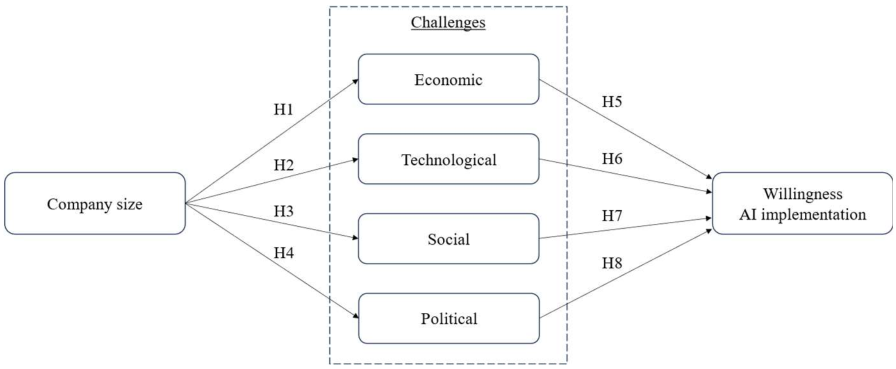

Figure 1. Research model

3 Research Method

According to Gable (1994), our method can be divided into four steps: 1. development of the research model, 2. development of the items, 3. data collection, and 4. data analysis.

Development of the research model: First, we conducted a literature review to identify the perceived challenges in companies regarding the introduction of AI. We searched the scientific databases Scopus, Web of Science, EBSCO, and ProQuest using the search string (“AI” AND “Challenges” AND “Manufacturing”) for journal papers and proceeding articles written in English and published from 2010 onwards. From the selected articles, we derived the major barriers and categorized them into groups using an exploratory factor analysis, followed by Hayton et al. (2004). A screeplot analysis indicated that a four-factor solution would be most appropriate for the collected data. Following the thematic assignment of challenges by the factor analysis, the identified groups could be named into economic, technological, social, and political. The results can be accessed at: https://bit.ly/436Z4z8. For a better overview, coefficients below 0.2 were suppressed. Subsequently, we developed eight hypotheses to explore the interconnection between these groups to enterprise size and willingness for AI implementation, as outlined in section two. Thereby the size of the enterprises is determined based on turnover and the number of employees.

Development of the items: During this step, we selected relevant measurement items for each construct, based on their incidence and importance. These can be called up at https://bit.ly/3TrgYJB. All of these are measured on a five-point Likert scale. The data collection for the structural equation model was conducted through an online survey. To enhance comprehensibility and improve the questionnaire’s quality, two preliminary tests were executed. The feedback received regarding the wording, item assessment, and overall clarity was considered in the revised versions of the questionnaire.

Data collection: As our research focuses on the perceived challenges and their connection to the willingness to implement AI, we specially targeted potential decision-makers for AI implementation when distributing the questionnaire. These are on the one hand the owners or the management in smaller companies and on the other hand the heads of IT departments in larger enterprises. The addresses were identified from both the company’s website and the networking platform (xing.com). The selection of recipients can be characterized as random sampling, where individuals were chosen at random from the total population, following Nassiuma (2001).

The survey was conducted until the beginning of October 2023 and was limited to enterprises in Germany. A total of 168 responses were obtained. We meticulously reviewed these answers for completeness and trustworthiness, employing control questions as a means of verification. Consequently, 110 questionnaires were deemed suitable for inclusion in the statistical analysis. By doing so, we adhered to the common practice of PLS analysis, which suggests that the sample size should be at least ten times the largest number of variables measured for a dependent variable (Chin 1998a). In the chosen data sets, 63 participants identified their roles as the head of the IT department, while only 47 categorized themselves as owner or personnel of the top management. Notably, over 75% of the responders were male. When classifying the companies into industrial and handicraft enterprises, the distribution was approximately 62.7% to 37.3%. The sizes of the participating companies were fairly evenly distributed (available at: https://bit.ly/3VxNTfm), with the lowest willingness to take part among micro companies. Additionally, we checked for nonresponse or common method bias. As no significant abnormalities were found, the mentioned biases can be considered inconsequential in this study.

Data analysis: During phase four, data analysis was carried out using structural equation modeling (SEM). We employed the approach of component-based least squares (PLS) due to its advantages in handling complex structures, smaller sample sizes, and avoiding biases (Sarstedt et al. 2016). For the execution, we used the software SmartPLS4 (www.smartpls.com). The subsequent procedure can be divided into two steps: one for assessing the measurement model and the other for assessing the structural model, as outlined by Hair et al. (2011)

Measurement model assessment: In our study, we utilized formative as well as reflective measurements. The evaluation of the formative constructs involved investing the multicollinearity and examining the outer loadings along with their weights and significances. Multicollinearity was assessed using the variance inflation factors (VIF). During our testing, the VIF values consistently ranged from 1.100 to 1.712, therefore remaining below 5, indicating the absence of multicollinearity in this study (Hair et al. 2011). In addition, we conducted significance tests on the outer loadings. Items that satisfied both conditions 'significance' and 'a loading greater than 0.5' remained in our construct (Hair et al. 2017). As a result, we eliminated six items.

Given that the assessment differs between formative and reflective constructs, we scrutinized the following aspects for the reflective measurement: Indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. All loadings of the items within the reflective measurement are significant and have a value greater than 0.85, surpassing the required level of 0.707 (Chin 1998b). Hence, the indicator reliability is given in this study. Moving forward, we assessed the internal consistency reliability using both Cronbach's alpha (CA) and composite reliability (CM). The CA value yields a result of 0.721, while the CM value is 0.876. Consequently, both tests report a satisfactory reliability of over 0.7 (Nunnally & Bernstein 1994). For the convergent validity, the average extracted variance (AVE) must exceed the accepted minimum threshold of 0.5 (Hair et al. 2011). In our study, this condition is met, as the AVE value is 0.780. In the subsequent step, we assessed discriminant validity. Both the criteria according to Fornell & Larcker (1981) and the heterotrait-monotrait ratio (HTMT) are met. As per Henseler et al. (2016) recommendation, the critical value of 0.85 for HTMT was not passed, with a correlation of 0.564. This implies that both reliability and validity are given for the model. The detailed results can be accessed at: https://bit.ly/4abYEtC.

Structural model assessment: In the structural model we determined the significance of the paths and loadings through bootstrapping. This technique involved generating 5,000 resamples to calculate standard errors and t-values (Hair et al. 2017). Figure 2 shows all R^2, path coefficients, p-values, and t-values.

The constructed model elucidates 38.7% of the variance (R^2) in the willingness to introduce an AI solution, considering various challenges. In contrast, 32.6% of the variance is accounted for by perceived economic barriers, 21.0% by technological obstacles, and 17.3% by the variance of the political challenges. According to Chin (1998b), R^2 values should exceed the threshold of 0.19, while other researchers already defined the minimum acceptable level at 0.1 (Falk & Miller 1992). Accordingly, only the variance of the social challenges with an R^2 value of 0.054 does not meet this requirement.

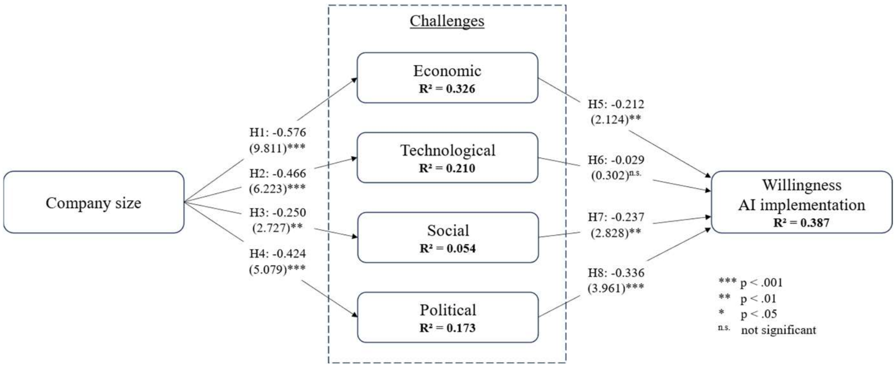

Figure 2. Evaluation of the research model

Moreover, it is essential to consider, on the one hand, the critical p-values (*$p < 0.05$), and on the other hand, the path coefficients, which are anticipated to surpass the critical value of 0.2 (Chin 1998b). The only path failing to satisfy these criteria is the relationship between technological barriers to the willingness to AI implementation, therefore H6 is rejected. The remaining significant path coefficients vary between −0.212 and −0.576 and the t-values between 2.124 and 9.811. Thereby the relationship between company size and the perceived economic barriers exhibits the strongest correlation (−0.576, t-value: 9.811). Furthermore, the paths from size to technological challenges (−0.466, t-value: 6.223) and to political challenges (−0.424, t-value: 5.079) also display significant and substantial influences. However, the path from enterprise size to the social obstacles is significant, the coefficient is notably less pronounced (−0.250, t-value: 2.727), in addition to the previously mentioned low R^2 of this variable.

When analyzing the path from challenges to willingness, it is evident that all these coefficients display a less meaningful significance when compared to the relationships with the company's size. However, except for the technological barriers, all these paths meet the critical value threshold. The path from political challenges to willingness (−0.366, t-value: 3.961) has the greatest correlation, while the paths from economic (−0.212, t-value: 2.124) and social (−0.237, t-value: 2.828) to willingness are close to each other. Table 1 provides a summary of the results and the subsequent determination of supported and rejected hypotheses.

Table 1. Evaluation of the test criteria of the structural model

Hypo-thesis	Path coefficient	t-value	p-value	Effect strength f^2	Decision
H1	−0.576	9.811	0.000	0.497	Supported
H2	−0.466	6.223	0.000	0.277	Supported
H3	−0.250	2.727	0.006	0.067	Supported
H4	−0.424	5.079	0.000	0.220	Supported
H5	−0.212	2.124	0.034	0.043	Supported
H6	−0.029	0.302	0.763	0.001	Rejected
H7	−0.237	2.828	0.005	0.070	Supported
H8	−0.336	3.961	0.000	0.133	Supported

4 Discussion and Implications

Our study found evidence regarding our two research questions of whether company size has a significant influence on the perceived challenges during an AI implementation (RQ1), and which barriers have a particularly substantial impact on the willingness to implement AI in companies (RQ2).

Grouping challenges: The open and alternative approach to grouping the various challenges using a factor analysis enabled us to structure the various challenges into the four categories of economic, technological, social, and political, based on the data. This classification can be used as a starting point for future analyses and discussions of AI challenges to present them in a summarized and clear manner.

4.1 Relation of Company Size and Challenges of AI Implementation

Concerning our first research question, the analysis reveals a significant correlation, especially in economic and technological challenges, as well as the political challenges. Compared to previous research (Bauer et al. 2020; Iftikhar & Nordbjerg 2021; Szedlak et al. 2021), our findings not only show the variations in the perceived challenges of AI implementation across different company sizes but also afford the possibility to quantify the extent of this influence.

Economic challenges: Our findings indicate that the company size exerts the most significant influence on the economic challenges when compared with the other three categories (technological, social, and political challenges). This category predominantly encompasses the costs, profitability, and solutions on the market associated with an AI implementation. We see various reasons for the different perceptions of the economic barriers. On the one hand, along with the results of Lu et al. (2022), we consider the often limited financial capacity of smaller companies and the associated effects of a potential failure of the project as one of the main reasons. On the other hand, however, we see the calculation or estimation of the cost-benefit ratio as another important factor, which differs between smaller and larger enterprises. Bunte et al. (2021) showed in a survey that only 5% of SMEs that implement AI were also able to determine the economic benefit. The limited expertise in calculating the return on investment (ROI) often compels smaller firms to rely on intuition rather than concrete financial metrics. Therefore, we recommend raising awareness among SMEs about the possibilities of simple and cost-effective AI applications. In addition to free software such as ChatGPT (openai.com), Kim et al. (2019) presented that partially individual AI solutions are already possible for less than $500. This stands in contrast to the findings of our survey, in which SMEs, on average, indicated that the expected implementation cost of at least 43,236€ (median: 27,500€) for a basic AI application. It is reasonable to assume that many SMEs may be overestimating the cost barrier on these assumptions, leading them to overlook the potential benefits of adopting AI in their businesses.

Social challenges: A further noticeable aspect of our analysis is the relationship between the size of a company and the perceived social barriers. Contrary to previous publications that mainly associate social challenges in the context of an AI implementation, such as knowledge gaps, management issues, and ethical concerns, with smaller companies (Kim et al. 2019; Kumar & Kalse 2021), our model shows only a very weak correlation with an exceptionally weak coefficient of determination. One explanation is the diverse interpretation of these barriers. For instance, smaller firms may be more inclined to refer to general AI-related knowledge gaps (e.g., understanding of the technology, use cases, and implementation processes). In contrast, larger companies might perceive knowledge as a challenge in more specific and detailed areas such as the selection of the right AI method or algorithm. This highlights the necessity for precise definitions and underscores the importance of recognizing that different aspects can be addressed even when mentoring the same challenge. The result further implies that certain social challenges, such as employee acceptance, remain consistent across different company sizes. This aligns with prior research findings that have identified acceptance as a common barrier to AI realization, both in SMEs and large businesses (Barton et al. 2022).

Technological and political challenges: Furthermore, our study shows similarly strong correlations between the technological and the political challenges with regard to the different company sizes (H2, H4). This is unexpected, as existing research on AI implementation mainly only differentiated between company sizes in terms of the technological starting conditions and challenges, such the different data availability, data quality, and the existing IT infrastructure (Bettoni et al. 2021; Barton et al. 2022). Conversely, the political challenges are typically portrayed in an undifferentiated manner in previous publications (Sharma et al. 2022a). This stands in contrast to our findings, which indicate that the perception of political challenges varies between the company sizes to a similar degree as technological challenges. Consequently, we contend the political challenges must be more strongly distinguished according to the diverse business sizes. So, governments should leverage these insights to tailor their support and proposal more effectively. A potential approach could be to trailer access to these resources to the needs of the respective size of firms and to make them only available to a specific target group, akin to other supportive initiatives. Furthermore, we propose a greater distinction in the realm of research between the different company sizes or at least, a more detailed exposition of the group under consideration in the study. This is predicated on the understanding that frameworks and use cases, developed based on large businesses, can only be transferred to other sizes of enterprises to a limited extent due to the varying initial conditions.

Smaller companies perceive more challenges: The negative correlation that can be observed between the size of the company and the economic, technological, social, and political challenges, confirm the assumption that smaller businesses perceive more barriers to AI implementation, making them more cautious and slower to initiate the new technology. These findings align with earlier studies on the relationship between enterprise size and the realization of other new technologies (Mittal et al. 2018). Our study has now also empirically confirmed this correlation for AI technology. We, therefore, recommend differentiating more strongly between the various company sizes when considering aspects of an AI implementation.

4.2 Relation of Challenges and Willingness to Implement AI

Political challenges: This finding is also related to the second research question (RQ2), which examined the effects of perceived challenges on the willingness to implement AI, regardless of the size. Our structural equation model elucidates that the connection between obstacles arising from the political challenges and the willingness to implement AI exhibits the most substantial correlation. In comparison to previous studies, our findings not only identify a connection but also indicate that it surpasses the economic, technological, and social challenges of an AI implementation. Following Huang et al. (2024) and Lu et al. (2022), the existing deficiency in regulations and statutory frameworks regarding AI is an important factor in shaping this assessment. The establishment of comprehensive regulatory and ethical directives, along with well-defined constraints for AI, ideally coordinated globally, is essential. However, our findings extend beyond this, highlighting that apart from the missing regulation, the lack of financial support or advisory services within the political challenges also exerts another important influence on the willingness to implement. We therefore encourage more governmental support elements in this field. Despite the previous fact that these requirements pose a notably greater obstacle for SMEs, it is important to acknowledge that these aspects nevertheless have an impact on the willingness to implement AI across all company sizes.

Technological challenges: Equally important is the rejection of hypothesis six. Even though the recurrent emphasis on different technological obstacles in previous research (Barton et al. 2022; Kinkel et al. 2022), our model contrasts this by revealing that the technological barriers do not exert a significant influence on the willingness to realize. We attribute this to two reasons. Firstly, our survey exclusively targets German enterprises, distinguishing it from the other studies. By specifically examining companies within an industrial location, they tend to be more advanced technologically on average. For example, more enterprises have modern machines that automatically collect large amounts of data. This contributes to the observation that technological challenges in Germany are less decisive regarding the willingness to implement AI.

Secondly, we see a risk that businesses do not recognize or underestimate the technological challenges, such as access to data. The current media attention often fosters the impression that AI applications can optimize any area of a company merely through the acquisition or development of a corresponding solution. Despite decision-makers recognizing the importance of the data, there is still the hazard that the associated technological barriers are perceived as an inherent part of the implementation process, rather than being appraised as criteria for determining the ability of their own company with AI requisites. Therefore, we advocate for enterprises to place specific emphasis on the assessment of technological challenges, including aspects like data availability, data quality, and data security, before embarking on an AI implementation, to avoid underestimating potential risks. This proposition is substantiated by numerous studies, which highlighted that a company's data serves as a primary contributing factor to the failure of AI projects (Barton et al. 2022).

Triad of economic, social, and political challenges: Moreover, our findings indicate that the willingness to implement AI is significantly influenced by a triad of economic, social, and political barriers. Consequently, we propose a holistic approach to addressing the perceived challenges faced by companies. Both from a political and scientific standpoint, therefore, it is insufficient to put the focus solely on one of these dimensions.

5 Limitations and Conclusions

There are some limitations to our research. First, our research refers to AI in general, although the different characteristics and subfields of AI can lead to different results. But the general approach enabled us to achieve greater acceptance in our survey of smaller companies or companies that had previously only dealt with AI in a rudimentary way than if AI had been specified in greater detail. Further research should therefore refine our analysis with regard to individual subfields of AI and identify the challenges that differ significantly from our general approach. The factor analysis consolidates various challenges into a single group. The classification of the groups in economic, technological, social, and political represents a method-specific limitation due to different possibilities for naming the clusters and interpreting the chosen terms.

Our study contributes to a better understanding of the challenges associated with AI implementation in manufacturing companies and its impact on willingness to implement AI. Thereby, we differentiate between the enterprise sizes to investigate how this factor influences the perception of the barriers. This research was conducted using data collected from an online survey of German manufacturing companies, which was subsequently analyzed through a factor analysis and a structural equation model.

The findings regarding the first research question could empirically prove that the influence of company size on the perceived economic challenges is greatest in comparison to the technological, social, and political challenges. This can be attributed primarily to variations in the perception of financial risks and the complexity involved in assessing the cost-benefit impact. The very weak correlation with an extremely weak coefficient of determination between company size and the perceived social challenges is also noteworthy. Despite the very different starting conditions in the various company sizes with regard to social challenges, such as existing knowledge, there are no substantial differences in the assessment of these obstacles across different company sizes. We attribute this to different interpretations of the evaluation of the challenges and therefore call for awareness to be raised in studies and politics.

According to our second research question, our findings reveal that the political challenges have the most substantial correlation to the willingness to implement AI and therefore have a greater influence than the economic, technological, and social challenges. We attribute this to the absence of comprehensive regulations but also to the inadequate government support services, including subsidies and independent advisory services. Additionally noteworthy is the rejection of hypothesis six and, consequently, the absence of a significant correlation in terms of perceived technological barriers, such as data, concerning the willingness to implement AI. There is a risk that companies may perceive technological obstacles as part of the normal implementation process rather than as hurdles that need to be addressed before AI implementation.

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