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Can Artificial Intelligence Help Used-Car Dealers Survive in a Data-driven Used-Car Market?

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Abstract. The used-car market is notoriously untrustworthy and shady. Certified data has been shown to help mitigate the information asymmetry, one of the major factors to an untrustworthy market. In recent times, more and more used-car dealers have had problems surviving in this competitive data-driven market. In this study, we conduct 12 interviews with used-car dealers and several meetings and workshops with employees and executives from the AMAG Group, one of the largest automotive companies in Switzerland. This creates insight into current problems for used-car dealers and how artificial intelligence can help. The problems can be abstracted to the problem of high transaction cost and its subcategories. In reducing transaction costs by utilizing artificial intelligence, new secondary problems arise. People need to trust the certificate, the analytics, and the predictions. Additionally, the data and analytics need to be transparent and understandable, and privacy concerns must be addressed. The implications of this study are manifold. First, we define the problems for used-car dealers on the used-car market and introduce artificial intelligence approaches to the current data-driven used-car market. Afterward, we stress that artificial intelligence needs to follow a human-centered perspective and be designed for trust.

Keywords: Used-Car Market, Transaction Costs, Trust, Artificial Intelligence

1 Introduction

The used-car market has been historically described as untrustworthy. The primary reason for that is the information asymmetry between seller and buyer. The seller has complete information about the car, and the buyer needs to rely on the seller to provide the truth about the car. For example, as estimated by the European Parliament, up to 50% of cars traded across borders within the EU have manipulated odometers [1]. Trading a used car is a challenge for buyers and sellers alike.

When the seller is a professional dealer, ways to mitigate the information asymmetry include, for example, guarantees or online reviews [2]. Furthermore, previous research has shown that certificates, that store data on the blockchain, can mitigate the information asymmetries between seller and buyer by providing trusted and certified data. These certificates help the private individual when buying a car from used-car dealers.

However, it is unclear how these certificates can help used-car dealers survive in the highly competitive and more and more data-driven used-car market. Especially in recent times, fueled by the COVID-19-pandemic and chip shortage, fewer and fewer cars are available on the used car market [3]. Therefore, helping used-car dealers survive and gain a competitive edge in the used-car market is relevant as ever. However, first, the problems used-car dealers face in the used-car market need to be analyzed.

If we utilize existing certificates and blockchain technology, we can ensure our data is trusted and certified, giving it some quality. One can easily think of deploying artificial intelligence (AI) to generate insights and increase the general information on the state of a used car. Nonetheless, AI is known to introduce socio-technical problems, especially in mistrust and intransparency of systems. Therefore, it would be assumed that introducing AI in used-car trading would be without problems. This motivates us to formulate the following research question:

RQ *Can artificial intelligence help used-car dealers survive in a data-driven used-car market?*

To answer this question, we collaborate with the AMAG Group, one of the largest automotive companies in Switzerland. Recently, the AMAG Group has had an ever-increasing problem with the used-car dealers, which have a hard time surviving on the competitive market. Therefore, by analyzing the issues for the AMAG Group and deriving early design objectives and design requirements, we postulate how trusted, and certified data in combination with AI can help the used-car dealers survive in a data-driven used-car market being transformed by certified data.

The study is structured as follows. In the subsequent chapter, the background and related work are introduced. In Chapter 3, we lay down the methodology for this study, and in Chapter 4, we define the problems. The defined solution objectives and design requirements are laid down in Chapter 5. Chapter 6 introduces the new, secondary problems that arise from our design requirements. We end the paper with a discussion in Chapter 7 and an outlook in Chapter 8.

2 Background and Related Work

The trade volume on the used-car market is negatively correlated with the transaction costs [4]. Thus, a dealer's margin decreases with rising transaction costs. Some economists describe the transaction costs as proportional to the sale price [4] or as the difference between retail and wholesale price [5]. These definitions are relatively easy to calculate but cannot catch the complex nature of transaction costs. Another definition of transaction costs describes transaction costs as *"resource losses incurred due to imperfect information"* [6] (based on [7]), which need to be considered on a case-to-case basis. It is also considered for seller and buyer equally.

Further, the used-car market is a prime example of a market with asymmetric information [8]. The critical problem of asymmetric information is that buyers and sellers do not have the same information about a good or service, resulting in different quality and price perceptions. Often these trades are disadvantageous for one party. Examples of methods to overcome asymmetric information include guarantees, certificates issued by experts, and third-party assessment [8]. A first indicator for the effect of mitigating information asymmetries are markets that have regulations in place. One example is the housing market, where mandatory energy performance certificates increase transparency and reduce information asymmetry, which directly affects the housing price [9, 10]. Another example is the food market, where it has been shown that nutrition labels can impact consumer behavior and health [11, 12]. However, while buying a car is often associated with significant investment for the private individual, the used-car market finds less attention from the regulatory body. Therefore, the problem of information asymmetry is still prevailing. One recent approach to mitigate the information asymmetry in the used-car market is the inclusion of blockchain to store trusted data. An example of such an approach is the so-called cardossier [13]. The cardossier platform leads to increased data quality [14], new business models [15], and increased market transparency [16]. It ultimately moves more used car business from the garage to online platforms [17]. Used-car dealers may use the certified data of the cardossier platform (1) to apply advanced analytics to evaluate the car state and value, (2) to buy used cars on online platforms, and (3) to offer advanced warranties [18]. With new technology like the cardossier, the used-car market more and more becomes data-driven. But it remains open what precisely the problems of used-car dealers are and how potential solutions can be designed and implemented to help them survive in this market.

In this paper, we utilize the data-richness and look at applying advanced analytics, i.e., AI. In this study, we consider machine learning and deep learning as major approaches to achieve AI, which is in line with [19]. A method on the border of AI is Robotic Process Automation (RPA) [20], where we use technology to automate tasks. RPA can use AI to make decisions; however, it follows a simple logic most of the time. On the other hand, Software Agents [21] are AI as they act autonomously and use machine learning and deep learning methods. In marketplaces, like a used-car marketplace, AI has been shown to help mitigate information asymmetry and make the marketplace more efficient [22]. Further, AI also has the potential to solve additional problems in the used-car market that have not yet been addressed. Price prediction models have successfully been applied in the used-car market [23]. Additionally, the topic of predictive maintenance also impacts the used-car market [24, 25]. However, the advantages of AI come at a cost. Modern AI, especially neural networks, has shown to be an intransparent black box [26] that people have difficulty understanding [27]. However, explainability is one of the major concerns in human-centered AI to achieve trustworthy AI [28, 29]. While a continuous effort is to introduce transparency in the used-car market, we are not aware of explainable and transparent AI applications deployed up to now.

3 Methodology

This study is a part of a larger project and reports on the outcomes of the first steps of the Design Science Research (DSR) cycle, i.e., Problem Definition, Solution Objectives, and Design [30]. In this project, we collaborate with the AMAG Group, one of the largest automotive companies in Switzerland, which has a high two-digit number of associated and independent used-car dealers. In cooperation with its used-car dealers, the AMAG Group aims to solve several problems in the used-car market. Our study aims to analyze the problems the AMAG Group and its used-car dealers have. This analysis helps us derive the objectives and design requirements for a potential AI-based solution for the used-car market.

Fig. 1. Phases in this study and the data source used in each phase.

There are several sources of empirical data in our study. We interviewed several experts in the used-car market and conducted workshops and meetings with employees from the AMAG Group. As shown in Figure 1, first, we define the primary problems using information gathered through workshops, meetings, and interviews. Then, we derive the solution objectives and design requirements. These design requirements entailed new, secondary problems, which also must be considered in the problem identification.

We conducted 12 interviews (abbreviated as I1-I12) with used-car dealers. We included participants that are currently or formerly working as used-car dealers in the AMAG Group and have several years of experience. Further, we excluded former used-car dealers who no longer work in the AMAG Group or are not closely linked to the used-car dealers in their current position. This ensures that all participants have a close relation to the used-car market. On average, the participants have 20.1 years of experience in the automobile industry and 8.6 years in the used-car market. These interviews were transcribed using an intelligent verbatim transcription and analyzed using qualitative coding [31] in MAXQDA software. The interviews were conducted in German and translated into English. Used-car dealers are optimal interview partners for this case, as they can take on a double-role: they buy and sell cars, thus, knowing the requirements for both sides. The workshops and meetings were conducted with several employees from the AMAG Group. The initial goal of these was to derive the current problems the used-car dealers have. After the problems were analyzed, we derived potential solutions for the problems. For the workshops and meetings, we have comprehensive documentation in the form of meeting notes, (digital) whiteboards, and other similar records. With this documentation, we can reconstruct the statement about the current problems and the solution ideas, which motivate the design requirements in this study. This approach provided us with an in-depth view of the problems faced by the AMAG Group and ensured an extensive problem identification.

4 Problem Definition

This section introduces the AMAG Group's primary problems in the emerging data-driven used-car market. The situation for the AMAG Group is that its used-car dealers cannot buy enough cars from private sellers and thus cannot take part in the used-car trade. Further, they cannot generate revenue for the car dealer. Additionally, the automotive company cannot conduct enough cross-selling, like selling new cars or warranties on used cars. Based on the data, we identified the following primary problem areas:

(A) Finding sellers willing to sell their cars: To buy cars, the used-car dealers need to find sellers that are willing to sell their cars. Without that, no used cars can be purchased. The executives in the workshops and meetings stated that the used-car dealers do not get enough cars to participate in the used-car market fully. Additionally, the used-car dealers state, for example, that they *"get many vehicles from the new car departments"* (I5). This statement shows that the used-car dealers rely on the AMAG Group to give them the cars they sell and cannot find enough sellers themselves.

(*B) Quality management and car maintenance*: Used-car dealers need to ensure the quality of the car they buy. But even lengthy inspections cannot always detect malicious fraud (like a manipulated odometer) or hidden defects. Nonetheless, the used-car dealers must ensure the quality of the used cars they buy and then sell again. Further, cars need to be maintained to be sold later. If the car breaks shortly after being bought, the costs will significantly exceed the profit from this trade. As one interviewee stated, the needed steps are as follows: *"you look at the car, make an assessment of the vehicle, the service team makes a test, looks at the car, are there damages, are there defects, document that, make a dossier."* (I10). This process involves several people and a lot of time and effort simply for assessing the car and its future potential.

(C) Market monitoring: Used-car dealers need to constantly monitor the market to get insight into current market prices and subsequently adequate prices for the cars to buy and sell. This is mainly done individually by the used-car dealers and is based on existing tools or websites. When asked about how to monitor the market, one interviewee stated that they are using several tools, they start with *"Eurotax [and] Auto-Data"*, but more importantly, the *"market gives the price [which are] internet-platforms [like] Autolina or Autoscout"* (I4). This highlights how many systems and tools are consulted to monitor the market and set the price of a used car.

(D) Reputation management and providing trust: There are many used-car dealers, and some of them act shady. To participate in the used-car trade, the used-car dealers need to be perceived as trustworthy and of high reputation. This reputation management, while being crucial, is sometimes hard to achieve. Nearly all interviewees stated that having AMAG's brand associated increases their reputation compared to other used-car dealers. Further, the brand, for example, is *"associated with trust"* (I10). However, reputation management is an active and ongoing effort.

The above-introduced problems can be generalized to one abstract problem: the problem of high transaction costs on both sides of the trade. Transaction costs can be categorized into three categories with five different types of transaction costs [6]. This categorization and the concrete transaction costs in the used-car market are shown in Table 1. Table 1 also includes an indicator of whether the transaction cost is relevant for the used-car dealer or the seller in this setting. Several transaction costs need to be considered in our study. Problem *(A)* can directly be mapped on search cost. Used-car dealer needs to spend resources to find potential sellers (e.g., online advertisement), and the seller needs to spend resources finding a used-car dealer willing to buy the car. Additionally, high bargaining and decision costs for the seller decrease the willingness to sell the car. The problem *(B)* can be mapped on information cost for the used-car dealer. The used-car dealer needs to spend resources to figure out the complete information about the quality of the car and possible future issues with the car. The problem *(C)* can be mapped to the bargaining and decision costs of the used-car dealer. The used-car dealer needs to spend resources to figure out an adequate price for the car, communicate the price, and convince the potential seller that the price is adequate. At the same time, these costs also occur for the seller, who, albeit not as thorough as the used-car dealer, needs to conduct similar market monitoring to find the desired price. The problem *(D)* can be mapped on the police/enforcement cost of the seller. The seller must spend resources to determine whether the used-car dealer is trustworthy and will adhere to its part of the trade, i.e., the agreed-on price. All in all, this introduces five problems in the present case: *(1) high search cost for used-car dealer and seller*, *(2) high information cost for the used-car dealer*, *(3) high bargaining cost for used-car dealer and seller*, *(4) high decision cost for used-car dealer and seller*, and *(5) high policing/ enforcement cost for the seller*.

Table 1. Transaction costs and indication if they occur for the used-car dealer or the seller

Transaction cost	Definition (based on [6])	Used-car dealer	Seller
search cost	Imperfect information about the existence and location of trading opportunities.	✓	✓
information cost	Imperfect information about the quality or other characteristics of items available.	✓	
bargaining cost	Resources spent in finding out the desire of economic agents to participate in trading at certain prices and condition.	✓	✓
decision cost	Resources spent in determining whether the terms of the trade are mutually agreed	✓	✓
policing/ enforcement cost	Lack of knowledge as to whether one (or both) of the parties involved in the agreement will violate his part of the bargain		✓

5 Solution Objectives and Design Requirements

Based on the five problems introduced in the previous chapter, we defined solution objectives and proposed design requirements based on the meetings, workshops, and interviews. The solution objectives are introduced and summarized in Table 2, together with the design requirements. To solve problem *(1)*, we need to increase the information about possible trading opportunities. This leads us to the solution objective of (*i) Provide better access to potential market partners for used-car dealer and seller*, which will help reduce the search cost. Next, to solve problem *(2)*, we need to focus on the used-car dealer and increase the information about the quality of the car. Thus, we introduce solution objective *(ii) give the used-car dealer faster access to the full information about the car,* including predictions about the future life cycle. Additionally, to address problem *(3)*, we need to reduce the resources spent in the actual bargaining. This is mainly the time needed for bargaining for the used-car dealer. For the seller, this is the time and the cognitive effort for the bargaining. Private individuals do not like to bargain, which is also cost for the seller. Therefore, we introduce solution objective *(iii) reduce the need for bargaining for both market participants*. Furthermore, to solve problem *(4)*, we need to reduce the effort to decide if the bargaining outcome is desirable for both parties. This again increases the cognitive effort of the seller. At the same time, it is also important for the used-car dealer to be sure if the outcome is desirable. Therefore, we introduce solution objective *(iv) simplify the final decision for both market participants.* Finally, to solve problem *(5)*, we need to increase the seller's knowledge that the used-car dealer will hold up to its end of the trade, i.e., will hand over the agreed-on amount of money. Therefore, we introduce solution objective *(v) ensure the compliance of the used-car dealer for the trade.* The solution objectives are also summarized in Table 2, together with the design requirements introduced in the subsequent chapter.

Table 2. Problems, solution objectives, design requirements in the present setting.

Problem	**Solution Objective**	**Design Requirement**
(1) high search cost for dealer and seller	(i) Provide better access to potential market partners.	(a) Provide an application where sellers directly get allocated a potential buyer.
"We don't find enough seller of used cars" (paraphrased, internal workshop with executives)		
(2) high information cost for dealer	(ii) Give the used-car dealer faster access to the full information about the car.	(b) Provide trusted and certified car data and prediction about the car's life cycle.
"The added value (of the certificate) is, I can trade in faster or better because I have the confidence in the car, I can offer the customer more for the car than the others" (I12) *"If you can prove the service history well, that also creates trust. That would certainly be good." (I5)* *"[If] a seller has a certificate [...] that would take away great fears or create great security." (I2)* *"Because the driving data alone don't mean anything to me, an analysis of this data would be useful" (I2)*		
(3) high bargaining cost for dealer and seller	(iii) Reduce the need for bargaining for both market participants.	(c) Suggest an adequate automatically calculated price for the specific car at hand based on the data.
"If everything is defined [it leaves no room for the] bargain leeway of the used-car dealer" (I1) *"Analyses [...] is of course an advantage, because we don't know all the markets either" (I7)*		
(4) high decision cost for used-car dealer and seller	(iv) Simplify the final decision for both market participants.	(d) Show the market price to simplify the decision process.
"[For deciding prices] I am mainly oriented to the market; I am interested in the market" (I9) *"I orient myself very strongly, also in pricing [at the car market] (I8)*		
(5) high policing/ enforcement cost for seller	(v) Ensure the compliance of the used-car dealer for the trade.	(e) Incorporate independent organizations and components into the system.
"[A car] is the second highest investment you make [...] I think that's where trust is very important." (I12) *"If [the customer] has confidence [they even] pay a few francs more for the vehicle." (I11)* *"[the car dealer's brand is] associated with trust" (I10)*		

Based on the problems and the solution objectives, five design requirements were derived in internal workshops. First, a digital app (implemented as a web app) should be provided where a seller can automatically get assigned to a potential buyer. This platform can be supported by AI by providing a suitable buyer-seller pairing and solving the resource allocation problem. Second, as stated by an executive of the car dealer, an *"awesome"* certificate should be defined based on certified and trusted data, containing the essential data about the cars, including predictions about the car life cycle. These predictions should utilize AI to predict the car's future life cycle. The most common use case for that is predictive maintenance. Third, an adequate price for the specific car at hand should automatically be calculated and shown to the seller and used-car dealer. AI approaches have successfully been applied for price prediction models, e.g., regression models based on historical data. If the market participants rely on this predicted price, this greatly reduces the bargaining cost. Another option that would at least reduce the bargaining cost for one side is software agents that take over the bargaining. Fourth, the car's market price should be shown, making the profit margin of the used-car dealer more transparent. Currently, used-car dealers can scrape the internet for the current market price by searching on marketplaces like Autolina or AutoScout. However, this task takes up time, which increases the decision cost. By directly showing the price, the decision cost is reduced. This task can be optimized, for example, by Robotic Process Automation. This can also be solved more sophisticatedly by AI that can learn the importance of different online marketplaces based on various factors to filter the actual market price. Finally, independent organizations or components should be integrated to generate more trustworthiness and reputation. This could be done by other AI solutions, like machine learning-based ratings of car dealerships or simple solutions like manual ratings of said dealerships.

6 Secondary Problems

During the interviews, it became apparent that the proposed design requirements lead to new problems. These problems arise from solving the initial problems. Therefore, it is also inevitable to consider these problems. These secondary problems are summarized in Table 3 and explained in the following. Overall, we derived four secondary problems from the interviews. First, there is the problem of *trust in self-issued certificate.* Since the certificate is issued by the AMAG Group itself and supports their used-car dealers, this might come across as untrustworthy. The AMAG Group could have the incentive to manipulate the certificate to generate more profit. Here an independent instance needs to be introduced to create more trust in the certificate. The quote underlines this: *"The certificate needs to be independent and […] created by an independent institution"* (I12). Second, there is the problem of *trust in analytics.* Many participants still do not trust analytics. Some have problems with analyzing the driver behavior (I1). Some other interviewee states that price predictions could be daunting for the seller (I5). This is especially the case as stating exactly that factors that decrease the price might lead the seller to think that the price is too low—but it is just the regular price. Finally, one problem with the trust in analytics is that some interviewees do not trust the performance of the predictions (I9). That means that price predictions need to be very accurate to outperform the expert user and thus gain trust. As the used-car dealers are experts in their field, they rely on their knowledge rather than analytics and predictions. Third, there is the problem of *interpretability of data and analytics.* Interviewee (I11) stated that data is hard to interpret, leading to intransparency. This is especially true if too much data is present (I1)—too much detail might lose the user (I8). Further, the uninformed user might have additional questions that arise through analyses and predictions, which might confuse them more than help (I6). Fourth, there is the problem of *data privacy concerns*. Many of our participants have privacy concerns (I1, I3, I5, I7, I8, I12). They are unsure which kind of data should be stored and how they should be allowed to have access to the data. They especially do not like the idea of tracking granular data or including personal information.

Table 3. Secondary problems identified with the interviews

Problems	Description
Trust in self-issued certificate	People tend to have a lower trust in the certificate if it is self-issued and would prefer a certificate of an independent vendor (I12)
Trust in analytics	Some have problems, if the driving behavior is analyzed (I1) and think that price predictions and analyses could be daunting (I5). Further, some do not rely on analytics, since they are unsure of its quality and rather rely on their own assessment (I9)
Interpretability of data & analytics	The analytics is described as intransparent and the data as hard to interpret (I11) and additional question may arise because of these analyses and predictions (I6). Further, there is too much information (I1), and too much detail that may lose the customer (I8)
Data privacy concerns	Many people have data privacy concerns and are unsure what data should be included in the first place (I1, I3, I5, I7, I8, I12)

7 Discussion

This paper addressed the following research question: *Can Artificial Intelligence help used-car dealers survive in a data-driven used-car market?* To answer it, we first analyzed the primary problems of used-car dealers, derived the solution objectives, and design requirements for an AI-based solution. By introducing AI in the data-driven used-car market that builds on trusted and certified data, new, secondary problems arise that need to be considered. The overall contribution of this paper can broadly be divided into two parts: (1) the problem analysis and design requirements for AI to increase the value and performance in the used-car market, contributing to the discourse on data-driven used-car markets; (2) the discussion on human-centered AI, contributing to its practical usage and challenges when using AI.

First, our design requirements leverage AI to simplify tasks, like the active comparing of market price as needed for *(C) Market Monitoring*, and with this, reduce transaction costs. However, the final trade still must be done by the used-car dealer, i.e., AI does not replace the used-car dealer but instead supports them. Nonetheless, many design requirements have the potential to reduce the tasks of used-car dealers to a minimum. Additionally, our design requirements can mitigate information asymmetry, e.g., by transparently showing the market price, or utilizing price prediction models, like

[23], to give both parties the same information. At the same time, a reduced information asymmetry further reduces the transaction costs since, for example, the need for bargaining and the cost to gather information about the car is reduced. By reducing the transaction costs, the used-car dealers can be helped to survive in the market. More so, the potential to increase sales in the new car market is increased. Therefore, not only used-car dealers but also new-car dealers will be interested in the presented design requirements. We point out potential solutions to reduce the high transaction costs. These solutions build on concepts like a cardossier [13]. We propose solutions that leverage AI (e.g., prediction models [23], or predictive maintenance [24]). This can further accelerate the current shift of responsibilities in maintenance from service workers to data-driven approaches, as introduced in [25]. However, such approaches depend on good data quality. A cardossier has been shown to increase the data quality [14] and, thus, is a good foundation for well-built AI models. This AI then can be used to extend the online platforms introduced in [17] with the new functionalities.

Second, even though, in theory, AI solutions seem to reduce transaction costs instantly, we still need to consider the secondary problems that come with an AI solution. In this specific case, the problems that come with the introduction of AI are the trust and the interpretability of the system, trust in the certificate, and data privacy concerns. Thus, our results confirm the current developments in AI research that focuses on explainable AI [27, 29]. However, our results achieve more. We also point out the need for trust in AI. Trust is the central topic in the secondary problems. That means for the context we studied, i.e., the used-car market, more design for trust is needed. Given our results, explainable AI and FATE AI are good candidates to design for trust; however, that alone is not enough. This is also in line with the concept of human-centered AI. With this, we also contribute to the general discussion of AI. We highlight that while AI methods, like price prediction models [23] or predictive maintenance [24], in theory, are capable of reducing information asymmetries and transaction costs. However, in practice, new problems arise that prevent the direct implementation of these methods. Solutions to the secondary problems must be human-centered. They could include strategies like validating the quality and completeness of the certificate and data by an independent authority or instance, creating transparency by deploying state-of-the-art explainable AI and ensuring data privacy. This also raises the question of if AI is always necessary. Some tasks do not need to incorporate sophisticated AI solutions, but the simpler logic-based rule could work equally well. RPA [20] could be used to solve tedious tasks without the need for AI. In software development, a common rule is to keep things as simple as possible. This should also hold for AI development. Additionally, several technological implementation and economic challenges will occur. We do not have any indication if people are willing to pay for such a system, and thus, the question of pricing remains unanswered. Additionally, practical problems arise when such a system is implemented. We need to ensure data sources with high data quality for AI models to perform well.

All in all, to answer the RQ on whether *Artificial Intelligence can help used-car dealers survive in a data-driven used-car market*, the answer to that is yes, potentially. Our design requirements are a substantial step towards a holistic solution. However, all solutions entail additional problems that need to be considered for the development.

8 Conclusion

To conclude, we showed how AI could be used to potentially solve the major problems of used-car dealers in the used-car market. However, new, secondary problems arise with these potential solutions that need to be addressed. These secondary problems are not easy to solve as they require unique properties to remain human-centered, like transparent and explainable AI. AI can only bring added value to the used-car dealers and *help used-car dealers survive in a data-driven used-car market.*

This study comes with some limitations. One limitation is the focus on used-car dealers as interview partners. While we argue that used-car dealers can take on both roles, sellers, and buyers, there still is a difference in experience between dealers and private individuals. This might lead to different requirements. Further, the design was evaluated with project partners on the level of the design requirements. The next step would be to design the solution based on these requirements and test it in experimental settings and the field. Additionally, we only follow one automotive company, the AMAG Group, with several used-car dealers. While still trying to be as general as possible, we cannot rule out that other automotive companies might have different or additional problems. The findings can also be different for other cultural or business contexts. Overall, it will be interesting to investigate the secondary problems and find further solutions for them for future research. Lastly, the system can be developed for practical use. Nonetheless, this study is a fitting starting point for future research.

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