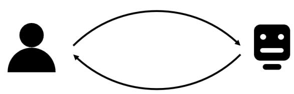
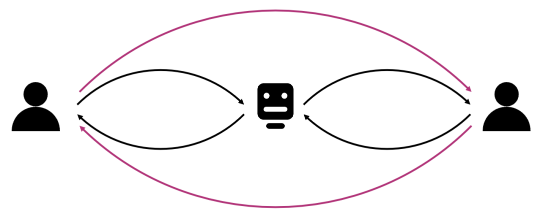
On the Notion of Multi-Party AI Reliance: Learning From AI-Based Price Estimations in the Used-Car Market

SVEN ECKHARDT, University of Zurich, Switzerland
MERLIN KNAEBLE, Karlsruhe Institute of Technology, Germany
MATEUSZ DOLATA, University of Zurich, Switzerland
ALEXANDER MAEDCHE, Karlsruhe Institute of Technology, Germany
GERHARD SCHWABE, University of Zurich, Switzerland



(a) Single-user human-AI interaction.



(b) Multi-party AI setting investigated in this study.

Fig. 1. Comparison between human-AI teams and multi-party AI settings. A multi-party setting has an additional interaction between the parties involved and the AI can serve as an intermediary between the parties.

Current definitions of AI reliance work well to judge appropriateness (or overreliance and underreliance) in single-user human-AI interactions. In practical applications, such as selling or buying used cars, multiple parties are often involved. Against this backdrop, we introduce the notion of multi-party AI reliance (MPAIR). Hereby, we introduce the novel idea of partial reliance, where one user follows the AI's advice, but the other does not. We apply our notion to real-world data from the used car market and discover challenges arising from practical applications. We find that partial reliance is highly relevant in practice, especially for asymmetric scenarios. Furthermore, we discuss the dependence of AI reliance research on the availability of ground truth, which is often not given in practical applications. With this position paper, we provide a starting point for research on multi-party AI reliance.

CCS Concepts: • **Human-centered computing → HCI theory, concepts and models**; • **Computing methodologies → Artificial intelligence**.

Additional Key Words and Phrases: artificial intelligence, reliance, multi-party, used-car market

ACM Reference Format:

Sven Eckhardt, Merlin Knaeble, Mateusz Dolata, Alexander Maedche, and Gerhard Schwabe. 2023. On the Notion of Multi-Party AI Reliance: Learning From AI-Based Price Estimations in the Used-Car Market. In *CHI Conference on Human Factors in Computing Systems (CHI 23), Workshop on Trust and Reliance in AI-Human Teams (trAIt), April 23, 2023, Hamburg, Germany*. ACM, New York, NY, USA, 10 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

AI can augment decision-making processes, e.g., in the form of diagnostic support in health care [3] or as an advice-giver for prices in the real-estate market [8]. When users interact with such AI systems, the issue of trust and reliance becomes critical. Only if users trust and rely on these systems, they will be applied for their intended use. Plenty of research has been conducted to achieve reliance on AI systems [e.g., 4, 11, 17]. A common way to increase reliance is to provide explainable AI [e.g., 6, 9, 30]. However, AI systems are not always correct. Therefore, research is required to not only increase reliance, i.e., understand and follow the AI, but rather target appropriate reliance. Appropriate reliance is when the user to follows the AI according to its ability [26]. Therefore, users should follow the AI, when it is correct, but recognize when the AI is incorrect and deviate from this suggestion [31].

In the CHI trAIt '22 Workshop, Schemmer et al. [25] defined and introduced a metric for appropriate reliance. With this metric, it is possible to measure the *appropriateness of reliance* on AI advice. However this metric and the overall current research on AI reliance rarely goes beyond the single-user human-AI setting, where one user interacts with one AI system. This setting is illustrated in Figure 1a. If the AI gives advice to the user, this is often considered a judge-advisor system [29]. In a judge-advisor system, the AI is the advisor for the human judge and the human judge makes the final decision. However, many practical settings often involve multiple parties, i.e., multiple users that interact with each other. Often these parties are subject to conflicting interests or information asymmetries [13]. Examples include a doctor's appointment [5], a financial advisory service [15], or a used-car sale [12]. For instance, in a used-car sale, the seller can hide certain defects of the car, or a knowledgeable professional dealer can overcharge on used-car prices. These settings can be supported by AI systems, that serve as decision aids for both parties, such as used-car price estimations. In such multi-party settings, the notion of a judge-advisor system does not fit. Rather, AI is to be seen as an intermediary between the two parties. This is illustrated in Figure 1b. In this study, we are concerned with the notion of AI reliance that appears if we move from a single-user to a multi-party setting.

Following the theme of this workshop, we *learn from practice*. By introducing AI-based price estimations in the used car market, we have gained unique insights into reliance AI in a multi-party setting. The used car market is a prime example of a multi-party AI setting (see Figure 1b). We have two people interacting with each other, which are the sellers and the buyers of used cars. Furthermore, these users have an information asymmetry, as the seller has an information advantage about the condition of the car. Also, both users can interact with the AI system to get price estimations about the used car. Overall, each user not only has AI-based price estimations but also receives offers from the other party and has to make a decision. If we consider only the single-user human-AI interaction, two things are missing: (a) the human interacts not only with the AI, but also with the other human, and (b) both humans may be in different states of reliance on the AI's advice, e.g., while one user relies on the AI, the other does not. A successful investigation of practical multi-party settings must take both into account. Hence the need for multi-party AI reliance.

Overall, multi-party settings require a more nuanced approach to AI reliance. In this position paper, we introduce the notion of multi-party AI reliance (MPAIR). MPAIR builds on common definitions of single-user AI reliance. However, because real-world applications often involve multiple users interacting with the AI, we extend AI reliance to these settings. This has several implications for practical use cases, which are discussed in this position paper. In the Section 2, we briefly introduce the literature on reliance and draw on insights from psychology to distinguish between trust and reliance. We also introduce the literature on appropriate reliance on modern AI systems. Section 3 introduces our definition of MPAIR. Section 4 presents a real-world case on AI-based price estimation in the used car market, where we collaborated with a large European automotive company. We use this case to further explain the notion of MPAIR based on real-world data. In Section 5 we discuss the notion of MPAIR and its use in AI research. In Section 6 we end this position paper with a short conclusion and point out the main takeaways.

2 RELATED WORK

As Lee et al. [17] put it in their study, "trust is an attitude and reliance is a behavior". Thus, in the context of AI, reliance is whether or not users follow the advice of the AI. In psychology, trust is often seen as "reliance-plus", where reliance is a necessary but not sufficient condition for trust [14]. Trust can also be seen as "reliance on another's goodwill" [1]. Overall, trust has an additional normative component, i.e., I believe that someone means well for me. In this study, we are concerned with reliance without the notion of trust as the expression of whether a user follows the advice.

In general, reliance on AI can be influenced by the user, the automation system, and the context [18]. Since the advent of automation systems, the question of reliance on these systems has arisen. Much research has been done on underreliance or overreliance on automation system [e.g., 11, 21]. Underreliance is a disuse of the automation system, which means, that the user does not use the system, even when it is well-functioning. Overreliance is a misuse of the system, that is, the user uses the system even when it performs poorly. Consequently, the remaining option for reliance is appropriate reliance, where a user uses the system to its ability [4, 11]. To achieve appropriate reliance, the user needs to be able to distinguish between correct and incorrect recommendations made by the system [26] and not follow incorrect advice [31]. Reliance has been introduced on automation systems [17] and robots [19]. These findings can be directly transferred to machine learning and AI-based systems and advice [16]. To achieve appropriate reliance, explanations have been shown to support this [e.g., 6, 8, 9, 30, 31]. Following the literature on overreliance, underreliance[e.g., 11, 21] and appropriate reliance[4, 17, 26], we introduce a definition of AI reliance in Definition 1. Analogous definitions can be found, for example, found in Schemmer et al. [26, Figure 1], or Yang et al. [31, Figure 2].

Definition 1 (AI Reliance). *Let X, Y, and Z be candidate solutions in the solution space of a problem. We define AI reliance as whether the user follows the AI's advice. The different manifestations of AI reliance are defined in the table below.*

Ground Truth	***AI Advice***	***User Decision***	***AI Reliance***
X	$Y \neq X$	Y	*Overreliance*
X	X	X	*Appropriate Reliance*
X	$Y \neq X$	$Z \neq Y$	
X	X	$Z \neq X$	*Underreliance*

Reliance is a hot topic for human-AI teams. However, there seems to be little research on multi-party settings supported by an AI-based system, where two or more users interact or have access to the system's output. However, many practical settings are such multi-party settings. Examples of that include (1) financial advice in the presence of an advisor, where both the client and the advisor are supported by AI-based systems [15, 27], (2) seeking help from a healthcare professional, where an AI-based system can help detect diseases or make recommendations about treatment [3, 10], or (3) the used car market, where both seller and buyer can be assisted by an AI-based price estimation of the car's value [12, 28]. Given the practical relevance, we see the need to define the notion of multi-party AI reliance. However, several new issues arise in multi-party settings. The notion of appropriate reliance is no longer clear, since the parties may have conflicting interests (the principal-agent problem [13]). With conflicting interests, an alignment between objectives is hard to achieve. Consider a simplified buyer-seller situation with AI-based price estimation. While the seller's goal is a high price, the buyer's goal is a low price. This creates an additional challenge for reliance on AI-based systems.

3 MULTI-PARTY AI RELIANCE (MPAIR): A DEFINITION

In this section, we build on the definition of AI reliance (see Definition 1) by introducing an additional human into the setting. Instead of a human-AI setting (see Figure 1a), we have a setting where two humans interact with an AI system (see Figure 1b). We derive a definition of reliance on AI in this multi-party setting and call it multi-party AI reliance (MPAIR). Definition 2 introduces MPAIR and Example 1 illustrates this definition with some examples. Similar to the metric of appropriate reliance in [25], for the sake of clarity, we base these definitions on classification problems where we have a clear right or wrong. However, these definitions can also be applied directly to regression problems, e.g., by retrospectively classifying the numerical values or by introducing a threshold below which a deviation still counts as reliance on the AI advice. A similar approach is taken, for example, by Petropoulos et al. [22]

Definition 2 (Multi-Party AI Reliance; MPAIR). *Let X, Y, Z_i, and Z_j, with $i, j \in \{1, 2\}$, $i \neq j$ be candidate solutions in the solution space of a problem. We define MPAIR as whether the users follow the AI's advice. The different manifestations of MPAIR are defined in the table below.*

ID	*Ground truth*	*AI advice*	*User i decision*	*User j decision*	*MPAIR*
(I)	X	$Y \neq X$	Y	Y	*Overreliance*
(II)	X	$Y \neq X$	$Z_i \neq Y$	Y	*Partial Overreliance*
(III)	X	$Y \neq X$	$Z_i \neq Y$	$Z_j \neq Y$	*Appropriate Reliance*
(IV)	X	X	X	X	
(V)	X	X	$Z_i \neq X$	X	*Partial Underreliance*
(VI)	X	X	$Z_i \neq X$	$Z_j \neq X$	*Underreliance*

Example 1. *AI applications can be used to estimate the prices of used cars [e.g., 12]. Consider a simplified used car market where cars can be sold for either a low, medium, or high price. In this simplified market, there are two market participants: a private seller wants to sell their car to a professional used-car dealer. Both are assisted by the same AI application to estimate the price of the used car in question. The following examples illustrate the different manifestations of MPAIR.*

(I) *The car's value is medium, but the AI incorrectly suggests a high value. If then both market participants conclude that the car's value is high, we say there is an* ***overreliance****.*

(II) *The car's value is medium, but the AI incorrectly suggests a high value. If one of the market participants finds that the car's value is medium (or low), but the other relies on the AI and concludes that the car's value is high, we say there is a* ***partial overreliance*** *by the latter party.*

(III) *The car's value is medium, but the AI incorrectly suggests a high value. If then both market participants conclude that the car's value is medium (or low), we have* ***appropriate reliance****. Note that in this case, for judging reliance, it does not matter whether the market participants correctly find the car's value, but rather that they did not rely on the faulty AI.*

(IV) *The car's value is medium and the AI correctly suggests this. If then both market participants rely on the AI and conclude that the car's value is medium, we have* ***appropriate reliance****.*

(V) *The car's value is medium and the AI correctly suggests this. If one of the market participants relies on the AI and concludes that the car's value is medium, but the other concludes the car's value is low (or high), we say there is a* ***partial underreliance*** *by the latter party.*

(VI) *The car's value is medium and the AI correctly suggests this. If then both market participants conclude that the car's value is low (or high), we say there is an* ***underreliance****.*

It is important to note that Definition 2 does not take into account dependencies between users. Depending on the social setting (e.g., negotiation or co-decision), decisions may be made in parallel or sequentially, and with or without prior knowledge. If we compare Definition 1 and Definition 2, we see that both concepts consider overreliance, appropriate reliance, and underreliance, while both are defined in an analogous way. However, Definition 2 introduces the notions of *partial overreliance* and *partial underreliance*, where only one user relies on the AI's advice and another does not. This notion of *partial reliance* cannot be observed in the single-user setting but becomes interesting when considering practical settings, as in Section 4. In addition, many practical settings have unknown or non-existent ground truths. For example, some might argue that the value of a good is whatever someone is willing to pay for it. While our definition requires a ground truth, we will discuss MPAIR in settings without an explicit ground truth in Section 5.

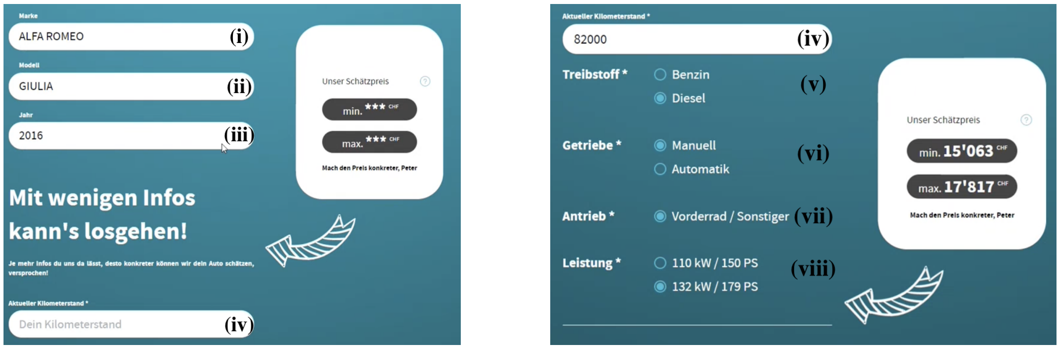
4 MULTI-PARTY AI RELIANCE IN THE USED-CAR MARKET

In this section, we present results from a real-world use case in the used-car market[1]. Rather than having a low, medium, or high value (as in Example 1), we analyze real-world data with numerical prices for used cars. The data was collected as part of a larger research project with a large European automotive company. The goal of the research project is to make the used car market more data-driven and thus more efficient by reducing transaction costs. To this end, the automotive company developed an online platform for private sellers of used cars. These sellers are matched with professional used car dealers who act as potential buyers of the used cars. On the platform, private sellers enter some rudimentary information about their used car, such as brand, model, and mileage. A regression model estimates the value in terms of a price range, i.e., an estimated maximum and minimum value. The model is trained on two separate data sources with separate pipelines - one for internal data and one for external data obtained from external service providers. On the platform, private sellers can contact a potential buyer directly. Subsequent negotiations between the two market participants on the actual sale are conducted in person and off the platform.

In total, we have data from 63 used car negotiations, including the system's estimated prices (*AI advice*), the seller's expected value (*user 1 decision*), the potential buyer's actual bid price (*user 2 decision*), and an expert-based market value. Given the wide variation in used car prices, we standardize all values by dividing by the market value, which results in relative prices[2]. To find our assumed ground truth, we need to subtract the used car dealer's margin from the market price. In our settings, the used car dealer is not able to pay the market price for the car. The margin is highly dependent on several factors, such as the current market situation or the specific car. However, it seems that the typical margin is around 10 - 20% [7, 20, 24], we assume 15%, which is in line with a 2017 Credit Suisse report [2]. This results in a *ground truth* of 0.85.

The results are presented in Figure 3 and the data is grouped into successful negotiations ('Deal'), i.e., negotiations where the seller sold their car to the used car dealer, and unsuccessful negotiations ('No Deal'). Since the use case is a regression problem, while MPAIR is defined as a classification problem in Definition 2, we introduce a threshold

[1]The results are submitted to the *18th International Conference on Design Science Research in Information Systems and Technology (DESRIST 2023)*
[2]The same results hold for the non-standardized prices. However, this standardization allows us to simplify this complicated use case.



(a) Screenshot from the first half of the web page.

(b) Screenshot from the second half of the web page.

Fig. 2. Screenshots from the online platform, where sellers put in the information about their used car and get an estimated price range. The platform focuses on a German-speaking audience. The relevant attributes are (i) brand, (ii) model, (iii) age, (iv) mileage, (v) fuel type, (vi) gearbox type, (vii) drive, and (viii) power.

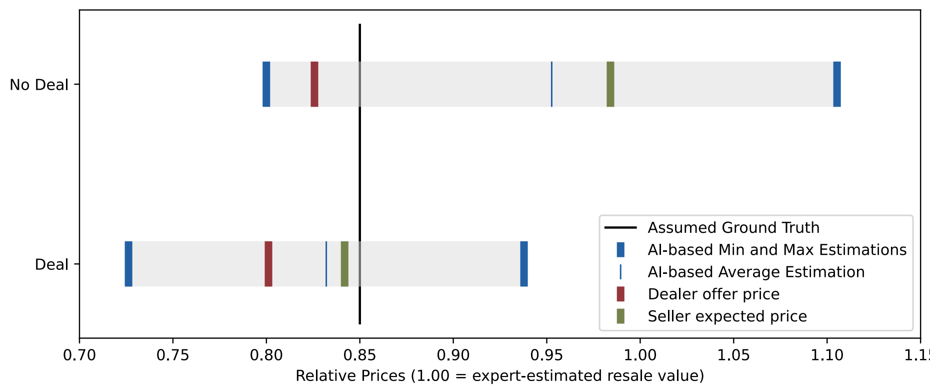


Fig. 3. Results from a real-world application of an AI-based price estimation for used cars. All prices are relative to the actual market price. The *Deal* category indicates that a successful deal happened and the *No Deal* category indicates that no deal happened.

$\theta = 0.05$. A similar approach is taken, for example, by Petropoulos et al. [22]. We say that a market participant follows the AI if their decision is within the AI's advice plus or minus θ. We also say that the AI's advice is correct if it is within the same range of plus or minus θ of the ground truth. In addition, we assume that the average price estimation is the AI's advice.

In the *No Deal* group, we find an average AI-based price of 0.95 ($\notin [0.85 \pm \theta]$), which is far from the assumed ground truth of 0.85. Consequently, the used car dealers are only willing to offer 0.83 ($\notin [0.95 \pm \theta]$). However, the private sellers seem to rely on the price and expect to sell their car for 0.98 ($\in [0.95 \pm \theta]$). Based on our definition, we classify this case as a **partial overreliance** (ID (II) in Definition 2), since the AI gives incorrect advice, the seller relies on this advice, and the buyer does not. This partial overreliance seems to cause market participants not to agree on a price.

In the *Deal* group, we find an average AI-based price of 0.83 ($\in [0.85 \pm \theta]$), which is close to the assumed ground truth of 0.85. While the seller expects to sell their car for 0.84 ($\in [0.83 \pm \theta]$), the buyer offers 0.80 ($\in [0.83 \pm \theta]$), resulting in a successful deal. Overall, given the threshold of θ, the AI's advice is correct and both market participants follow the AI's advice. Therefore, we classify this situation as **appropriate reliance** (ID (III) in Definition 2).

Overall, it seems that private sellers on average always rely on AI, but professional used car dealers only rely on AI when the advice is correct (appropriate reliance). The results emphasize that in multi-party settings, different parties may rely differently on the same AI advice. Therefore, it is important to consider the multi-party setting as a whole, rather than the individual human-AI interactions separately. The goal of this section has been to apply the MPAIR definition and *learn from practice*. To that end, this section omits some results from our submitted paper, such as the design implications of using a price range, to focus on the notion of MPAIR. Also, the threshold is an assumption to highlight the definition of MPAIR. Overall, the results serve well to illustrate MPAIR in a practical setting and help us to guide the following discussion.

5 DISCUSSION

5.1 (MP)AIR in Practice

A practical problem is the definition of the ground truth. In our case, we assumed that the ground truth is the resale value estimated by an expert minus the dealer's margin. This is a reasonable assumption in our case, as it is consistent with the business model of used car dealers. However, even the resale value is simply what a third party is willing to pay, and thus is merely a social construct.

The common definitions of AI reliance [25, 26, 31], as well as our definition of MPAIR, assume a ground truth. Otherwise, the cases of overreliance vs. appropriate reliance and underreliance vs. appropriate reliance could not be distinguished. However, missing ground truth is more common than one might expect, even in single-user settings. While in academia we often study cases and tasks with clear ground truth (e.g., in image classification, the image is either a dog or not, and our data set comes pre-labeled), in practical settings the ground truth is not so clear. In practice, it is often hidden or non-existent. For example, most recommender systems generate advice in settings without clear ground truth, such as Netflix's movie suggestions. While they know that people with similar viewing histories have watched the suggested movies, there is often no way to infer whether the customer actually liked the movie. In other cases, such as stock picks for long-term investments and some diagnostic or treatment suggestions, the ground truth may be so far into the future that a useful evaluation of AI reliance based on that ground truth is largely irrelevant.

In cases like the used car dealers we studied, we could use another proxy beyond the expert-estimated resale value minus margin as the assumed ground truth: the fact of whether a deal was made or not. By splitting the data along this decision, we could reveal drastic differences in AI and human behavior, and partially explain why no deal was made. We suggest performing such case-by-case analyses when certain effects may be obscured in the aggregated data. Ideally, one uses a discriminating variable that is closely related to the ground truth. In summary, we believe that future research should provide insights into AI trust and MPAIR in settings without clear ground truth.

5.2 From AI Reliance to MPAIR

The definition of MPAIR is derived directly from the general definition of AI reliance. We see that both notions can manifest as overreliance, underreliance, and appropriate reliance. When users do not follow the AI's advice, they revert to their usual decision-making strategies. In multi-party settings, this would likely lead to negotiation or discussion, depending on the practical settings. In addition, MPAIR also manifests itself as *partial overreliance*. Partial overreliance implies that one user relies on the wrong advice of the AI, while the other user does not rely on (*appropriately relies on*) the advice of the AI. Instead of supporting the multi-party setting, the AI will create disagreement between users and has the potential to serve as a barrier to decision-making. This must be considered when designing systems for these settings.

To solve this problem, AI design must always keep both users in mind. There is a lot of literature on AI reliance and how to achieve appropriate reliance, such as explainable AI [e.g., 6, 30, 31]. However, this literature focuses on one user at a time. In many practical settings, we have users with information asymmetries or conflicting interests [13]. Methods to achieve appropriate reliance, such as explanations, need to achieve appropriate reliance for both users at the same time. This is much more difficult. Continuing with the example of selling used cars, it may not be easy to create the same explanations for a knowledgeable used car dealer and an inexperienced private used car seller. One strategy might be to offer different explanations to the users. However, this might raise some ethical and regulatory issues, as it might only increase information asymmetry. The next extreme option might be to provide different advice to users. We could take advantage of systematic deviations from the AI's advice. For example, if a used car dealer systematically offers 20% less than the AI advice, but the seller always follows the AI advice, we could present this dealer with an inflated price estimate to achieve factually appropriate reliance. However, this manipulation comes with serious ethical and regulatory considerations and probably should not be incorporated into practical systems. This position paper should be seen as a starting point for exploring the design of AI-based systems to achieve reliance on AI in multi-party settings.

Another important note is that many human-AI interactions can be extended to multi-party settings. A common example of explainable AI is house or apartment price estimation. Users should decide on the price of a house with the assistance of an (explainable) AI [e.g., 8, 9, 23]. At first glance, this task looks like a common human-AI team task. However, we argue that when this task is put into practice, it is closer to our use case of used car sales - where buyers and sellers are present. Failure to consider the other party of the system could hinder the reliance and trust of that party and ultimately lead to failure. Therefore, it is important to consider all parties involved in practical settings.

Overall, we emphasize in this position paper that HCI research should consider whether it is investigating a single-user human-AI interaction or, in fact, a multi-party AI setting. Many human-AI interactions can be extended to multi-party settings. Failure to consider the other party in the system could hinder the reliance on AI of that party. This could ultimately lead to the failure of projects and practical applications.

5.3 Limitations and Future Work

The introduced notion of MPAIR is yet to fully mature. With this position paper, we want to emphasize the importance of considering multiple parties in a practical setting. In the future, more learnings from practice can continue to shape the concept of MPAIR. The current definition does not consider dependencies between users and assumes independent decisions. This assumption may not always hold true in practical settings. For future work, there is much potential to explore the social constructions of MPAIR. Research is also needed on how to design for MPAIR in practical settings. In addition, the case of more than two users could be addressed and should be considered in the future.

6 CONCLUSION

In this position paper, we contribute by introducing the definition of multi-party AI reliance (MPAIR). MPAIR is derived by extending the common definition of AI reliance to multi-party settings. We argue that many practical settings are multi-party settings, such as used car transactions. Using a real-world case of used-car negotiations, we evaluate the notion of MPAIR and show that practical settings often do not have a clear or given ground truth, making categorization into overreliance or underreliance challenging. While MPAIR is derived from the common definition of AI reliance, the notion of *partial reliance*, where one user relies on the AI's advice while the other does not, is novel for multi-party settings. Partial reliance leads to problems in decision making in multiparty settings. This increases the challenges of using AI as an intermediary in multi-party settings.

If we as a research community strive to learn from practice, as proposed by this workshop[3], we must acknowledge cases where ground truth is unavailable or limited. At the workshop, we hope to discuss the next steps for measuring reliance without such ground truth, and to extend our definition. As suggested above, one option might be to use proxy data that is more readily available. In our context, the fact that a deal was struck could be used as a proxy for the alignment of price expectations. In turn, to inform practical applications as researchers, we highlight the problem of partial reliance, especially in asymmetric settings. With the other workshop participants, we discuss how to design for shaping appropriate reliance in multi-party settings. We show that asymmetric roles, e.g., private seller vs. professional used car dealer, may require individualized designs to achieve such a state. On this basis, future research should focus on AI reliance in multi-party settings.

REFERENCES

[1] Annette Baier. 1986. Trust and antitrust. *ethics* 96, 2 (1986), 231–260.

[2] Joseph Barnet-Lamb, Sophie Bell, Matthew Walker, and Stephanie MacAulay. 2017. Autotrader: Cycle set to bite – shifting down a gear. (2017).

[3] Emma Beede, Elizabeth Baylor, Fred Hersch, Anna Iurchenko, Lauren Wilcox, Paisan Ruamviboonsuk, and Laura M. Vardoulakis. 2020. A Human-Centered Evaluation of a Deep Learning System Deployed in Clinics for the Detection of Diabetic Retinopathy *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3313831.3376718

[4] Natalie C Benda, Laurie L Novak, Carrie Reale, and Jessica S Ancker. 2022. Trust in AI: why we should be designing for APPROPRIATE reliance. *Journal of the American Medical Informatics Association* 29, 1 (2022), 207–212.

[5] Åke Blomqvist. 1991. The doctor as double agent: Information asymmetry, health insurance, and medical care. *Journal of Health Economics* 10, 4 (1991), 411–432.

[6] Adrian Bussone, Simone Stumpf, and Dympna O'Sullivan. 2015. The role of explanations on trust and reliance in clinical decision support systems. In *2015 international conference on healthcare informatics*. IEEE, 160–169.

[7] Mercer Capital. 2021. Used Vehicle Margins in 2021. https://mercercapital.com/auto-dealer-valuation-insights/used-vehicle-margins-in-2021/

[8] Chun-Wei Chiang and Ming Yin. 2021. You'd Better Stop! Understanding Human Reliance on Machine Learning Models under Covariate Shift. In *13th ACM Web Science Conference 2021* (Virtual Event, United Kingdom) *(WebSci '21)*. Association for Computing Machinery, New York, NY, USA, 120–129. https://doi.org/10.1145/3447535.3462487

[9] Chun-Wei Chiang and Ming Yin. 2022. Exploring the Effects of Machine Learning Literacy Interventions on Laypeople's Reliance on Machine Learning Models. In *27th International Conference on Intelligent User Interfaces* (Helsinki, Finland) *(IUI '22)*. Association for Computing Machinery, New York, NY, USA, 148–161. https://doi.org/10.1145/3490099.3511121

[10] Alex Dennis and William Newman. 1996. Supporting Doctor-Patient Interaction: Using a Surrogate Application as a Basis for Evaluation. In *Conference Companion on Human Factors in Computing Systems* (Vancouver, British Columbia, Canada) *(CHI '96)*. Association for Computing Machinery, New York, NY, USA, 223–224. https://doi.org/10.1145/257089.257292

[11] Mary T Dzindolet, Linda G Pierce, Hall P Beck, and Lloyd A Dawe. 1999. Misuse and disuse of automated aids. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 43. SAGE Publications Sage CA: Los Angeles, CA, 339–339.

[12] Sven Eckhardt, Kilian Sprenkamp, Liudmila Zavolokina, Ingrid Bauer, and Gerhard Schwabe. 2022. Can Artificial Intelligence Help Used-Car Dealers Survive in a Data-Driven Used-Car Market?. In *The Transdisciplinary Reach of Design Science Research: 17th International Conference on Design Science Research in Information Systems and Technology, DESRIST 2022, St Petersburg, FL, USA, June 1–3, 2022, Proceedings*. Springer, 115–127.

[13] Kathleen M Eisenhardt. 1989. Agency theory: An assessment and review. *Academy of management review* 14, 1 (1989), 57–74.

[14] Katherine Hawley. 2014. Trust, distrust and commitment. *Noûs* 48, 1 (2014), 1–20.

[15] Mehmet Kilic, Peter Heinrich, and Gerhard Schwabe. 2015. Coercing into completeness in financial advisory service encounters. In *proceedings of the 18th ACM conference on Computer supported cooperative work & social computing*. 1324–1335.

[16] Vivian Lai, Chacha Chen, Q Vera Liao, Alison Smith-Renner, and Chenhao Tan. 2021. Towards a science of human-ai decision making: a survey of empirical studies. *arXiv preprint arXiv:2112.11471* (2021).

[17] John D Lee and Katrina A See. 2004. Trust in automation: Designing for appropriate reliance. *Human factors* 46, 1 (2004), 50–80.

[18] Zhuoran Lu and Ming Yin. 2021. Human reliance on machine learning models when performance feedback is limited: Heuristics and risks. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–16.

[3] https://chi-trait.github.io/ (last accessed 2023-02-20)

[19] Scott Ososky, Tracy Sanders, Florian Jentsch, Peter Hancock, and Jessie YC Chen. 2014. Determinants of system transparency and its influence on trust in and reliance on unmanned robotic systems. In *Unmanned systems technology XVI*, Vol. 9084. SPIE, 112–123.

[20] Charlie Paolino. 2021. 2021 Dealership Facts and Figures – Used Vehicle Sales. http://www.downeycocpa.com/2021-dealership-facts-and-figures-used-vehicle-sales/

[21] Raja Parasuraman and Victor Riley. 1997. Humans and automation: Use, misuse, disuse, abuse. *Human factors* 39, 2 (1997), 230–253.

[22] Fotios Petropoulos, Robert Fildes, and Paul Goodwin. 2016. Do 'big losses' in judgmental adjustments to statistical forecasts affect experts' behaviour? *European Journal of Operational Research* 249, 3 (2016), 842–852.

[23] Forough Poursabzi-Sangdeh, Daniel G Goldstein, Jake M Hofman, Jennifer Wortman Wortman Vaughan, and Hanna Wallach. 2021. Manipulating and measuring model interpretability. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. 1–52.

[24] ProfitableVenture. 2021. Average Gross Margin for an Independent Used Car Dealership. https://www.profitableventure.com/gross-margin-used-car-dealership/

[25] Max Schemmer, Patrick Hemmer, Niklas Kühl, Carina Benz, and Gerhard Satzger. 2022. Should I Follow AI-based Advice? Measuring Appropriate Reliance in Human-AI Decision-Making. https://doi.org/10.48550/ARXIV.2204.06916

[26] Max Schemmer, Niklas Kühl, Carina Benz, Andrea Bartos, and Gerhard Satzger. 2023. Appropriate Reliance on AI Advice: Conceptualization and the Effect of Explanations. https://doi.org/10.48550/ARXIV.2302.02187

[27] Damaris Schmid, Dario Staehelin, Andreas Bucher, Mateusz Dolata, and Gerhard Schwabe. 2022. Does Social Presence Increase Perceived Competence? Evaluating Conversational Agents in Advice Giving Through a Video-Based Survey. *Proceedings of the ACM on Human-Computer Interaction* 6, GROUP (2022), 1–22.

[28] Naser Shanti, Akram Assi, Hamza Shakhshir, and Adnan Salman. 2021. Machine Learning-Powered Mobile App for Predicting Used Car Prices. In *2021 3rd International Conference on Big-data Service and Intelligent Computation*. 52–60.

[29] Janet A Sniezek and Lyn M Van Swol. 2001. Trust, confidence, and expertise in a judge-advisor system. *Organizational behavior and human decision processes* 84, 2 (2001), 288–307.

[30] Xinru Wang and Ming Yin. 2021. Are explanations helpful? a comparative study of the effects of explanations in ai-assisted decision-making. In *26th International Conference on Intelligent User Interfaces*. 318–328.

[31] Fumeng Yang, Zhuanyi Huang, Jean Scholtz, and Dustin L Arendt. 2020. How do visual explanations foster end users' appropriate trust in machine learning?. In *Proceedings of the 25th International Conference on Intelligent User Interfaces*. 189–201.

Received 23 February 2023