Changing Lanes Toward Open Science: Openness and Transparency in Automotive User Research

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ABSTRACT

We review the state of open science and the perspectives on open data sharing within the automotive user research community. Openness and transparency are critical not only for judging the quality of empirical research, but also for accelerating scientific progress and promoting an inclusive scientific community. However, there is little documentation of these aspects within the automotive user research community. To address this, we report two studies that identify (1) community perspectives on motivators and barriers to data sharing, and (2) how openness and transparency have changed in papers published at AutomotiveUI over the past 5 years. We show that while open science is valued by the community and openness and transparency have improved, overall compliance is low. The most common barriers are legal constraints and confidentiality concerns. Although research published at AutomotiveUI relies more on quantitative methods than research published at CHI, openness and transparency are not as well established. Based on our findings, we provide suggestions for improving openness and transparency, arguing that the motivators for open science must outweigh the barriers. All supporting materials are freely available at: https://osf.io/zdpek/

CCS CONCEPTS

• General and reference → Surveys and overviews; **• Human-centered computing → Empirical studies in HCI**; **• Social and professional topics → Computing / technology policy**.

KEYWORDS

openness, transparency, reproducibility, open science, open data, AutomotiveUI

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1 INTRODUCTION

Automotive user research addresses the challenge of designing and evaluating artifacts and interfaces that improve safety, driver behavior and experience, accessibility, and sustainability [9]. Automotive user research combines principles from Human-Computer Interaction (HCI), human factors, engineering, psychology, and design. The research is published across various conferences (e.g., AutomotiveUI [6], CHI [2], MobileHCI [7], IUI [3], IEEE IV [40] IEEE ITSC [39]) and journals (e.g., AAP [12], Human Factors [62], IJHCS[13]). Of these, the *International ACM Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI)* is the main venue for automotive user research. It takes place annually and has a large community (170-250 annual attendees [67]) with input from both industry and academia.

Since its inception in 2009, and similar to the flagship HCI venue (the SIGCHI Conference on Human Factors in Computing Sciences (CHI)), empirical studies have been the backbone of the research presented at AutomotiveUI (c.f., [28], Table 2). Empirical contributions generate new knowledge [80] using a variety of qualitative, quantitative, and mixed methods (e.g., controlled laboratory experiments, surveys, naturalistic driving studies) [29]. According to Wobbrock and Kientz [80], empirical research contributions are judged primarily on the significance of their findings and the

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soundness of their methods. If empirical findings are considered uninteresting or unimportant, or if the methods used are imprecise, contain errors, or are confounded, then the empirical contributions may be judged unfavorably.

1.1 The Importance of Good Research Practices

The validity of empirical contributions can only be adequately assessed if authors follow good research practices. Good research practices, as introduced by Salehzadeh Niksirat et al. [64], encompass considerations concerning research ethics, openness, and transparency.

Research ethics principles revolve around responsibly conducting scientific research [64]. These principles are reported as universal [51] despite domain-specific adaptations (e.g., see ACM [1], IEEE [41], or Nature [46]). Typical approaches to ethical user research include obtaining ethical approval, anonymizing collected data, obtaining participant consent, and compensating study participants [64].

Openness revolves around open access to publications and materials. In this work and in line with Salehzadeh Niksirat et al. [64], we define openness as *"the availability of research publications and materials"* [64, p. 2]. This includes making the paper and the essential resources (e.g., data, results, and code) needed to understand and validate it available without a paywall. However, sharing is still uncommon in the broader HCI community [75], and while authors often promise the availability of research artifacts upon request, response rates to such requests are low [43]. Availability further decreases with article age [73], and monetary barriers to open access publishing persist, with open access fees of up to €10,290 per paper [45].

Transparency can be defined as *"researchers' actions in disclosing details of methods, data, and other research artifacts"* [64, p. 2]. This is expected to improve reproducibility and replicability. Reproducibility refers to the ability to obtain identical results by performing the same analysis on the same dataset [59]. Guidelines (e.g., [31]) on how to describe datasets can aid reproducibility. Replicability means obtaining comparable results by repeating the study and generating new data that are then analyzed in the same or a different way [59]. Salehzadeh Niksirat et al. [64] further divide transparency into transparency of research methods, transparency of research results, transparency of data, and transparency of research artifacts. However, despite existing guidelines [14], standards [57], and best practices [18], many authors do not transparently report their work, hindering reproducibility and replicability [64].

1.2 Open Science

While openness and transparency are often used in a very similar context [63, 66], the distinction made above illustrates that they are not mutually dependent (i.e., a study and its methods can be described in detail, making it transparent, but the paper can still be behind a paywall, and vice versa). Openness and transparency are two critical elements of the larger umbrella of open science *"that reflects the idea that scientific knowledge of all kinds, where appropriate, should be openly accessible, transparent, rigorous, reproducible, replicable, accumulative and inclusive"* [58, p. 314]. The benefits of open science have been known for some time [50, 68, 81], and open science is recognized as a promising approach to addressing the replication crisis [68]. Accordingly, the open science movement has gained momentum with international organizations such as UNESCO formulating global standards and recommendations [70, 71] and national governments establishing national programs to support open science (e.g., [20, 38, 55]). For example, such standards make recommendations regarding openness, such as publishing data on platforms that follow the FAIR Principles [78], which suggest that materials be findable, accessible, interoperable, and reusable. There are numerous FAIR platforms (e.g., OSF [27], Zenodo [15], Figshare [47]) to share the study material. Publishers such as ACM also offer to share material in the ACM DL [1], which is also considered FAIR. Within the wider HCI community, open science is recognized and has been discussed widely [25, 64, 76]. Furthermore, there is a push among organizations such as ACM towards openness both for sharing materials (see ACM badges [33]) and towards full open access [4].

To summarize, openness and transparency can aid good scientific practice, are useful for judging the quality and validity of empirical contributions, can also promote a more inclusive scientific community [8], and accelerate scientific progress by increasing the availability of knowledge, reducing redundancy, and fostering collaboration [49, 52].

1.3 Openness and Transparency at AutomotiveUI

We argue that openness and transparency are also particularly important for the automotive user research community, as its findings influence the design of safety-critical interfaces [24] and can inform policy and legislation. It is therefore important that data and findings can be openly and critically evaluated to avoid potential harm. Despite its importance for Automotive User Interface research, and despite the increasing popularity of the open science movement [16, 64, 69], there has been little formal discussion and documentation within the automotive user research community on the topic. Specifically, within 15 years of AutomotiveUI, there has only been one workshop [21], but no course or paper on specifically this topic[1]. However, even this workshop [21] did not provide a definitive overview of the state of the conference or the wider field of automotive user research. Similarly, a review of the first 10 years of the AutomotiveUI conference [9] did also not mention the topic of open science. In contrast, there have been ongoing discussions about open science and good research practices in many other fields [34] such as psychology [35] and the social sciences [36]. In recent years these topics have also been addressed within the larger SIGCHI community (e.g., [25, 64, 75]), some involving members of the automotive user research community [17]. Historically, changes that occur at the larger CHI conference spill over to the other subcommunities, such as the introduction of accessibility and diversity chairs (introduced at CHI'14 and AutomotiveUI'19, respectively) or best practices for document formatting and review. With the increased interest in openness and transparency at SIGCHI and CHI, the question is to what extent this has spread to AutomotiveUI.

[1]We generated this number by searching all AutomotiveUI publications from the start of the conference in 2009 to 2023 for the keywords "Open Data", "Open Science", and "Research Transparency"

1.4 Paper Contribution

It is not known how well openness and transparency criteria are adopted within the automotive user research community. In this paper, we provide a comprehensive picture of the current status quo of openness and transparency in the automotive user research community, specifically at the AutomotiveUI conference. We assess how practices have changed, how automotive user researchers view open data sharing, and where the community needs to improve. To do this, we conducted (1) a survey study to investigate the perspectives of the automotive user research community on open data sharing and (2) a systematic review replicating the work of Salehzadeh Niksirat et al. [64], who operationalized criteria for openness and transparency and evaluated papers published at the CHI conference.

Contribution Statement: The contribution of this paper is twofold: (1) We provide insights into the motivators and barriers that the automotive user research community experiences with regard to open data sharing (Study 1). (2) We systematically report the current state of openness and transparency within the AutomotiveUI conference, quantify how openness and transparency have changed over the last 5 years, and compare this to the CHI conference (Study 2).

Together, these results provide insights into both the subjective experience of AutomotiveUI researchers (Study 1) and the produced output of AutomotiveUI (Study 2), contextualized in how the automotive user research community compares to the broader CHI community. These insights allow us to propose actionable solutions and guidelines specific to the automotive user research community that are applicable to future research and conferences.

While this work addresses the automotive user research community as a whole, we chose AutomotiveUI as a case study for the following reasons: (1) the conference represents an annual meeting ground for numerous researchers working in the area of automotive user research, (2) the community is clearly identifiable due to its annual structure and its relatively stable core, and (3) the AutomotiveUI conference is embedded in a parent organization (ACM SIGCHI) where openness and transparency have been discussed deeply. Therefore, the knowledge is available in the broader research community, and the question is whether the practices of openness and transparency have been widely disseminated or whether there is a need for a domain-specific set of best practices or guidelines.

2 STUDY 1: SURVEY ON OPEN DATA PRACTICES IN AUTOMOTIVEUI RESEARCH

To evaluate AutomotiveUI conference participants' attitudes toward open science practices, we conducted an online survey (largely following the survey of [65]). In particular, we investigated the following research questions (RQs):

RQ1 What are the motivators for AutomotiveUI researchers to share data openly?
RQ2 What are the barriers for AutomotiveUI researchers to share data openly?
RQ3 What features do AutomotiveUI researchers expect from systems that help to share data openly?

We also collected information to assess whether the participants' backgrounds were representative of AutomotiveUI attendees and about the participants' experience with different types of data to test for potential bias.

2.1 Method

2.1.1 Materials. The complete survey can be found in Sup. 1. The questions tackle demographics, experience with the conference, experience with different data types, and questions about open data experience. This is followed by three sections addressing our three RQs, which are mainly taken from Schmidt et al. [65] and that tackle: (RQ1) Motivators (question 12 in [65], adapted from 3-point to 5-point Likert scale), (RQ2) Barriers (question 13 in [65], kept as 3-point Likert scale), and expectations of features (question 10 in [65], adapted from 3-point to 5-point Likert scale).

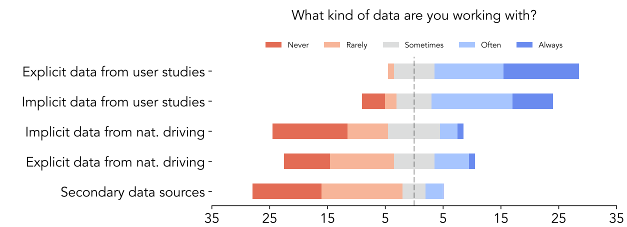
2.1.2 Participants and Procedure. Respondents (N = 33) were recruited through opportunity sampling in three phases surrounding the 2023 AutomotiveUI in Ingolstadt, Germany: (1) Before the conference, in tandem with promotion through social media of a pre-conference workshop on the topic [21], (2) during the conference via advertisements with QR codes, and through personal promotion by workshop attendees, and (3) during a social event at the conference. The survey took between 3:23 and 37:32 minutes to complete (*Median* = 8:04 min; *Mean* = 10:12 min; *SD* = 6:42 min).

2.2 Results

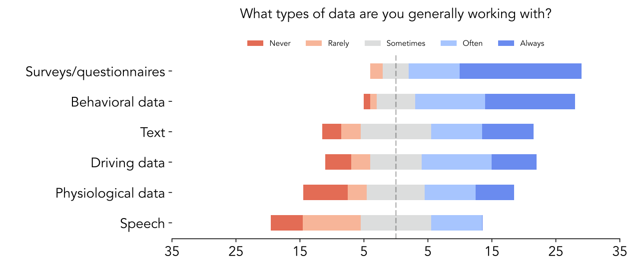
2.2.1 Benchmark: Respondent Characteristics. The participants self-reported that they had attended AutomotiveUI: never (6), once (6), twice (6), three times (5), or between 4 and 13 times (10). 26 participants were from academia and 7 from industry. When asked about their appointment, 10 were graduate students, 5 were post-doctoral researchers, and 17 were either faculty (academia) or scientists or staff (industry). The sample mirrors typical AutomotiveUI attendees [67], considering that the conference typically has a substantial subset of early career researchers (PhD students, post-docs; 15 respondents, 45%) and attendees who are at the conference for the first to third time (17 respondents; 52%).

2.2.2 Benchmark: Experience with Different Types/Kinds and Open Data. Figure 1b summarizes answers to questions about data usage. Across all data kinds (e.g., controlled or naturalistic; implicit and explicit) and types (e.g., surveys, physiology, car metrics), there are at least some respondents that have experience with it. Therefore, we interpret our respondent set as constituting data from a wide variety of experiences.

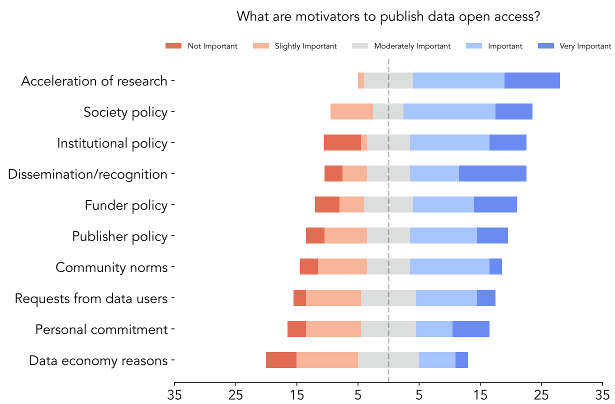
According to our results, the majority of participants have never (39.4%) or rarely (24.2%) shared their research data open access. None of the participants shared "always", but 33.3% shared sometimes, and 1 (3.0%) shared often. A similar pattern is reflected in the use of data shared by others: the majority never (36.4%) or rarely (30.3%) used data shared by others, and a subset sometimes (24.2%) or rarely (30.3%). When the question was asked about the use of experimental data shared by others, the number that never (24.2%) or rarely (45.5%) used them was even higher (21.2% sometimes; 9.1% often; 0 always). In part, the pattern might reflect a lack of



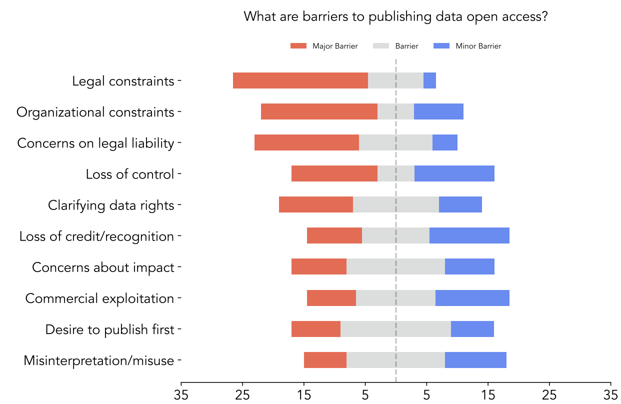
(a) How often have respondents worked with specific kinds of data in the past?



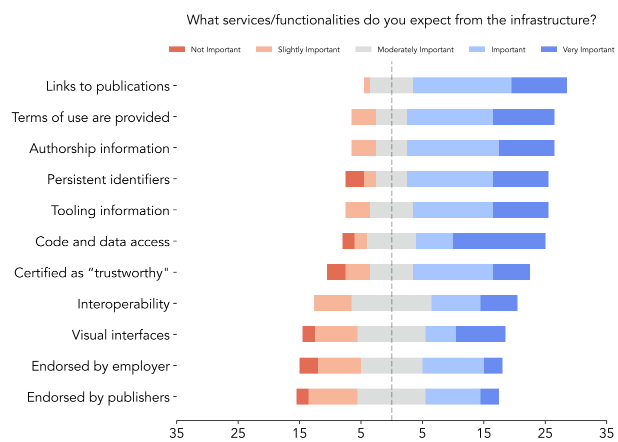
(b) How often have respondents worked with specific types of data in the past?



(c) Importance of various motivators.



(d) Barriers for publishing data as open data.



(e) Services and functionalities participants expect from data sharing platforms.

Figure 1: Survey results.

knowledge: only 15.2% of respondents reported being aware of any guidelines for publishing open data.

2.2.3 RQ1: Motivators for Open Data Sharing. Figure 1c shows how important factors are to the respondents when publishing their data as open data. Respondents are mostly motivated by the potential of open data to accelerate scientific research and applications. The other factors they found important were mostly external factors, such as scientific or organizational policies. Personal factors (e.g., personal success; personal commitment) and data economy (i.e., by publishing the data, third parties can further process it, increasing its value) were considered less important.

2.2.4 RQ2: Barriers for Open Data Sharing. Figure 1d shows how strongly respondents see certain factors as potential barriers to open science, with those seen as most significant at the top. Again, the biggest barriers seem to come from external factors such as legal constraints and concerns about legal liability. An interesting result is the strong divide in the rating of loss of control over Intellectual Property (IP): 39.3% see this as a minor barrier and 42.4% as a major barrier. Interestingly, both groups had respondents from academia and from industry.

2.2.5 RQ3: Expected Features of Open Science Systems/Platforms. As shown in Figure 1e, all services or features are considered important or very important by at least one-third of the respondents. Factors that provide information about the publication and authors score particularly high, as does the feature of having good usability.

3 STUDY 2: SYSTEMATIC REVIEW ON CHANGES IN OPENNESS AND TRANSPARENCY

Study 1 provides insight into the motivators, barriers, and expectations of a subset of the automotive user research community. Because this data is subjective, we investigated how these findings are reflected in the papers published at AutomotiveUI and compared AutomotiveUI to CHI. Our RQs are:

RQ1-1 To what extent do the papers published at AutomotiveUI (2017&2018 and 2022&2023) follow good research practices concerning openness and transparency?

RQ1-2 Did the recent movements on replicability (e.g., articles, workshops, panels) in the broader HCI community help to improve Openness and Transparency in AutomotiveUI?

RQ2 How do papers published at ACM AutomotiveUI compare to papers published at ACM CHI, the premiere venue in HCI research, in terms of Openness and Transparency? What are their main differences?

3.1 Method

This exploratory study was pre-registered[2]. Methodologically, we follow the analysis of CHI papers published in 2017 and 2022 by Salehzadeh Niksirat et al. [64] and apply it to papers published at AutomotiveUI. However, our focus is on the openness and transparency of the automotive user research community and whether recent efforts towards open science in the broader scientific community are reflected in papers published at AutomotiveUI. Therefore, we evaluate only these criteria. We compare papers published in 2017&2018 with those published in 2022&2023 and compare the openness and transparency results with those reported for CHI by Salehzadeh Niksirat et al. [64].

3.1.1 Proceeding Selection and Sampling. We chose the proceedings of 2017&2018 and 2022&2023 for multiple reasons. As one of our goals is to compare the openness and transparency practices of AutomotiveUI and CHI, it is natural to choose similar years. Unlike Salehzadeh Niksirat et al. [64], who were forced to use stratified sampling methods due to the large number of papers published each year at CHI (637 accepted papers in 2022), the size of AutomotiveUI allowed us to consider all papers published in the relevant years. However, as only about 35 full papers are published in AutomotiveUI each year, we merged paper published in 2017 with 2018 and 2022 with 2023. Thus, we can analyze more papers and it allows us to consider the most recent proceedings at the time of writing.

3.1.2 Coding Procedure. We adopt the coding process (with minor adjustments) and the developed criteria of openness and transparency from Salehzadeh Niksirat et al. [64]. In particular, we apply a two-stage process in which each paper is coded independently by two of the eight coders. The coders were two professors (HCI), four postdocs (HCI, Human Factors, AI), and two PhD students (both with more than 4 years of research experience in the field of HCI). For the coding procedure, we used Sysrev [10], a FAIR platform for data curation for systematic reviews. The projects for Stage 1 and Stage 2 are publicly accessible.

Stage 1: Title and Abstract. In the first stage, 135 papers were coded using their title and abstract for the type of *research method* (qualitative, quantitative, mixed-method), their *research questions* (exploratory or confirmatory), *human participants* (yes or no), and their *contribution* type according to Wobbrock and Kientz [80]. Prior to the coding process, an introductory meeting was held to introduce the coding tool and discuss the different codes to create a common understanding. Each article was then coded by two coders. The initial agreement rate across all categories was 76.6%, with *contribution* type being the most disagreed category (51.11%). The discussion in the meetings showed that the *contribution* type is difficult to code because of ambiguities in the category boundaries and the language of the papers. After all papers were coded by two coders, all coders participated in a conflict resolution meeting. During this meeting, all coders discussed representative conflicts to address different perspectives and reach a common understanding of the codes. Any remaining conflicts were then resolved between the two coders involved. In case of disagreement, coding conflicts were brought to the whole group for open discussion. In total, each coder coded between 20 and 42 papers (median = 33.5), resulting in 270 reviews. In accordance with Salehzadeh Niksirat et al. [64], 13 papers with no empirical contribution were excluded, leaving 122 papers (61 each from 2017&2018 and 2022&2023) for the second coding stage. The bibliography files are available in Sup. 3.

Stage 2: Full-Text. In Stage 2, the full texts of the remaining 122 papers were assessed according to the openness and transparency criteria defined in Table 1. We slightly adjusted the procedure of Salehzadeh Niksirat et al. [64] to match the requirements of our coding tool. The complete instructions followed during the coding process and the adjustments we made to the original instructions by Salehzadeh Niksirat et al. [64] are available in Sup. 2. Not all codes that can be assigned in Stage 2 apply to all papers (e.g., QUAN-DATA-RAW is only applicable to quantitative or mixed methods papers). We, therefore, apply a skip logic based on the results of Stage 1. Similar to Stage 1, each paper was coded independently by two coders, resulting in an agreement rate across all criteria of 86.5% after the first round of coding. Exemplary conflicts were then discussed in a review meeting with all coders, and any remaining conflicts were resolved on a coder-to-coder basis.

As the full-text review allowed for a more detailed assessment than the Stage 1 review, some errors in the Stage 1 codes were identified and subsequently corrected. These changes were almost exclusively related to the *research methodology* dimension. Often,

[2] The pre-registered study plan is available here: https://osf.io/c6vtx

Table 1: Summary of openness and transparency criteria adopted from Salehzadeh Niksirat et al. [64]. Full definitions are available here: https://osf.io/qtyab.

Code	Criterion	Sources
Criteria for Openness		
PAYWALL-ACMDL	Is the paper in the ACM Digital Library available as open access?	[4]
FREE-PDF-EXTERN	Is the paper PDF available on external platforms other than ACM DL?	[42]
EXTRA	Are any research artifacts beyond the paper provided anywhere?	[77]
EXTRA-EXIST*	Do all provided research artifacts exist at the location specified in the paper?	[78]
EXTRA-FAIR*	Do any of the locations of provided artifacts satisfy the FAIR principle?	[78]
Criteria for Transparency		
PREREG	Was the study pre-registered?	[18, 54]
SHARE-STIMULI*	Are study stimuli (except survey questionnaires) archived?	[75]
SHARE-SURVEY*	Are questionnaires or surveys archived?	[75]
SHARE-INTERVIEW-GUIDE*	Is interview guide archived?	[75]
SHARE-STUDY-PROTOCOL	Is the study protocol archived?	[60]
JUSTIFY-N-QUAL*	Was the sample size justified (qualitative studies)?	[14]
JUSTIFY-N-QUAN*	Was the sample size justified (quantitative studies)?	[44, 61]
DEMOGRAPHICS*	Was the demographics information of the participants described?	[30]
CONDITION-ASSIGNMENT*	Did the study properly explain study design (e.g., grouping, IDVs)?	[74]
SPECIFY-QUAL-ANALYSIS*	Is qualitative data analysis approach named or explicitly described?	[54, 75]
SHARE-ANALYSIS-CODE*	Is quantitative data analysis code shared?	[54, 75]
QUAL-DATA-RAW*	Is raw qualitative data shared?	[54, 75]
QUAL-DATA-PROCESSED*	Is processed qualitative data shared?	[54, 75]
QUAN-DATA-RAW*	Is raw quantitative data shared?	[54, 75]
QUAN-DATA-PROCESSED*	Is processed quantitative data shared?	[54, 75]
SHARE-SOFTWARE*	Is the source code of the software shared?	[75]
SHARE-HARDWARE*	Is the code of the hardware shared?	[75]
SHARE-SKETCH*	Is any hand-drawn sketch shared?	–

*Evaluated on an applicable subset of empirical papers as defined by Salehzadeh Niksirat et al. [64] here: https://osf.io/qtyab

short interviews are conducted as part of studies that appear to be quantitative based on the title and abstract. Accordingly, 15 studies were re-classified as mixed methods. In addition to the manual checks, we used an automated evaluation script to check for skip logic compliance and made corrections accordingly. The analysis code and all raw and processed data are available in Sup. 4.

3.1.3 Data Analysis. In contrast to the original work [64], we analyzed all papers published at AutomotiveUI in 2017&2018 and 2022&2023. As we do not sample from a population but directly describe the population of papers in the respective years, we can compare the counts for each code without having to apply statistical hypothesis testing to account for sampling error [26]. If a criterion was met, it was coded as "yes"; otherwise, it was coded as "no". The proportions for each criterion were calculated based on the applicable denominator subset [3]. For the criterion SHARE-SURVEY coders could use the label "Partially", if for example they share one out of two surveys that they used. In line with Salehzadeh Niksirat et al. [64] we treated "partially" as "yes". Furthermore, as described in Sup 2., to assess the EXTRA-FAIR two co-authors independently studied the EXTRA criterion. All in all we evaluated 122 papers for 23 criteria.

3.2 Results

Table 2 summarizes the characteristics of AutomotiveUI papers in 2017&2018 and 2022&2023. Most papers published are purely quantitative (54.9%), followed by mixed-method papers (37.7%) and a few qualitative papers (7.4%). Overall, there is a slight trend toward more mixed-method research from 2017&2018 to 2022&2023. About half of the papers present results from confirmatory or exploratory research, with a trend toward more exploratory research in 2022&2023 compared to 2017&2018 (52.5% vs. 42.6%). In accordance with our inclusion criteria, all papers in the analysis make an empirical contribution. 43.5% of the papers also make other contributions, with artifact contributions being the most prominent (36.1%), followed by methodological (4.1%) and theoretical contributions (2.5%). Nearly all studies in both time periods involve human participants (> 96%).

The comparison to CHI [64] shows that AutomotiveUI papers rely more on quantitative research methods (92.6% vs. 64.8%) and confirmatory research (52.5% vs. 20.8%), indicating that the automotive user research community is much more focused on classical empirical research.

3.2.1 RQ1: Changes in Openness Practices. Figure 2 shows a comparison of the openness criteria, as introduced in Table 1, between AutomotiveUI papers published in 2017&2018 and 2022&2023. Overall, we observe an improvement in 4 out of 5 criteria. While only 8% of the 61 papers published in 2017&2018 are open or public access and will eventually be available in the ACM DL without a paywall (PAYWALL-ACMDL), 45% of the papers published in 2022&2023 are open or public access. However, the number of papers that are available on platforms other than the ACM DL (FREE-PDF-EXTERN) is higher with 65% in 2017&2018 and 60% in 2022&2023. The slight

[3] See tables 2-4 here: https://osf.io/qtyab

Table 2: Characteristics of the papers published at AutomotiveUI 2017&2018 and AutomotiveUI 2022&2023.

		2017&2018	2022&2023	Total
Method	Quantitative	35 (57.4%)	32 (52.5.2%)	67 (54.9%)
	Mixed-Method	21 (34.4%)	25 (41.0%)	46 (37.7%)
	Qualitative	5 (8.2%)	4 (6.6%)	9 (7.4%)
Hypothesis Testing	Confirmatory	35 (57.4%)	29 (47.5%)	64 (52.5%)
	Exploratory	26 (42.6%)	32 (52.5%)	58 (47.5%)
Contribution	Empirical	61 (100.0%)	61 (100.0%)	122 (100.0%)
	Artifact	26 (42.6%)	18 (29.5%)	44 (36.1%)
	Methodological	2 (3.3%)	3 (4.9%)	5 (4.1%)
	Theoretical	1 (1.6%)	2 (3.3%)	3 (2.5%)
	Survey	1 (1.6%)	0 (0.0%)	1 (0.8%)
	Dataset	0 (0.0%)	0 (0.0%)	0 (0.0%)
	Opinion	0 (0.0%)	0 (0.0%)	0 (0.0%)
Participants	With Participants	60 (98.4%)	59 (96.7%)	119 (97.5%)
	Without Participants	1 (1.6%)	2 (3.3%)	3 (2.5%)
	Total	61	61	122

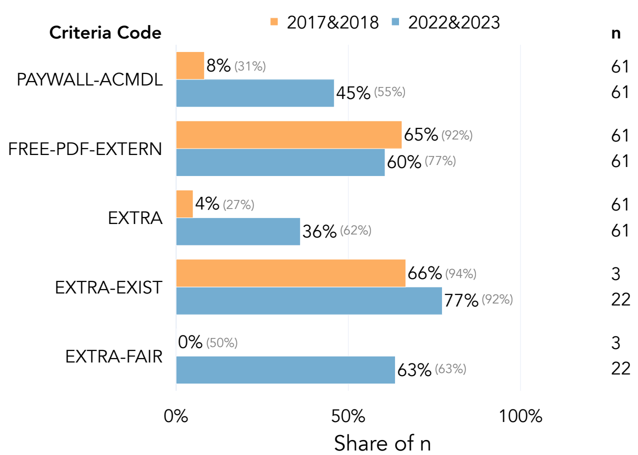


Figure 2: Comparison of openness criteria. CHI numbers of 2017 and 2022 in parentheses.

decrease from 2017&2018 to 2022&2023 may be due to the shorter time available to authors of 2022&2023 papers to make their work available on other platforms, to embargo periods that have not yet passed at the time of the data collection, or to lower motivation as more papers published in 2022&2023 are openly available in the ACM DL anyway. To share papers externally, most of the authors use ResearchGate [32], followed by arXiv [72], university repositories, and personal websites. Regarding the publication of research artifacts beyond the paper itself (EXTRA), we observe an increase from 4% in 2017&2018 to 36% in 2022&2023. This means that 9 times more papers share additional research artifacts either in the ACM DL, in the appendix of the paper, or on other platforms like OSF or Zenodo. However, the research artifacts do not always (34% in 2017&2018 and 27% in 2022&2023) exist at the location specified in the paper (EXTRA-EXIST). Looking more closely at the platforms on which the additional material is published, none of the papers published in 2017&2018 used a FAIR-compatible platform, while 63% of the papers in 2022&2023 used a FAIR-compatible platform.

Overall, we see a trend that automotive user research has become more open (RQ1-2). Nonetheless, it should be noted that in 2017&2018, only three out of 61 papers published additional research artifacts, and in 2022&2023, still two-thirds of the papers come without them. Thus, the general level is still low (RQ1-1).

3.2.2 RQ1: Changes in Transparency Practices. Figure 3 shows the comparison of the transparency practices between AutomotiveUI papers published in 2017&2018 and 2022&2023. Despite an overall low level of transparency, we observe an improvement in 11/18 (61.11%) criteria. However, except for the archiving of questionnaires or surveys (SHARE-SURVEY, 62% in 2017&2018 vs. 85% in 2022&2023) and the specification of qualitative research methods (SPECIFY-QUAL-ANALYSIS, 35% in 2017&2018 vs. 44% in 2022&2023), all changes are in the range of 1% - 7%. The relatively high number of shared surveys is also partly because many papers use at least one standard survey (e.g., NASA-TLX [37], SUS [11], etc.) and were therefore coded as partially shared. In contrast, demographic surveys, which are often conducted at the beginning of a study, are often not shared. The same applies to the sharing of interview guides (SHARE-INTERVIEW-GUIDE), where we observe a decrease from 20% (2017&2018) to 13% (2022&2023). Similarly, none of the papers shared a study protocol (SHARE-STUDY-PROTOCOL, 0% in 2017&2018, 3% in 2022&2023). Furthermore, none of the papers published in 2017&2018 or 2022&2023 were pre-registered (PREREG), showing that this practice has not yet been adopted automotive user research community. Also, only 1% (2017&2018) and 5% (2022&2023) of the papers share the stimuli presented to the participants (SHARE-STIMULI).

When justifying sample sizes (JUSTIFY-N-QUAL and JUSTIFY-N-QUAN), we do not see any changes for qualitative studies (3% in both periods). However, for quantitative studies, the proportion of papers justifying their sample size (e.g., using a power analysis), improved from 3% to 10%. The percentage of papers that share any kind of source code or data is very low, with slight improvements from 2017&2018 to 2022&2023. 1% of papers in 2017&2018 and 5% of papers in 2022&2023 with a quantitative study share the

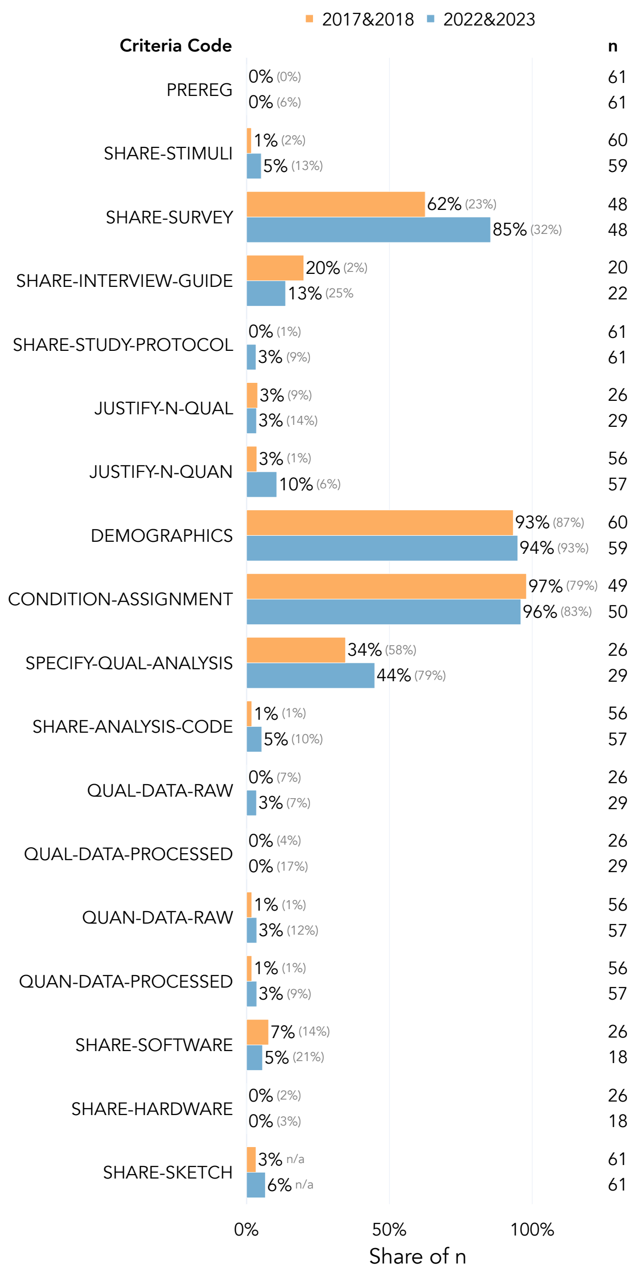


Figure 3: Comparison of transparency criteria. CHI numbers of 2017 and 2022 in parentheses.

code used for data analysis (SHARE-ANALYSIS-CODE). While 7% of papers published in 2017&2018 also share code of software artifacts (SHARE-SOFTWARE), this number decreased in 2022&2023 to 5%. The situation is similar for sharing raw quantitative data (QUAN-DATA-RAW) and processed quantitative data. Only 1% of authors shared their data in 2017&2018 and 3% in 2022&2023. Regarding qualitative data, neither raw (QUAL-DATA-RAW) nor processed (QUAL-DATA-PROCESSED) data is shared in papers published in 2017&2018. In 2022&2023, 3% of the papers share their raw qualitative data, but no papers share their processed qualitative data. Overall, we observe a slight trend towards more transparency in automotive user research, suggesting that the recent movements towards replicability also have an effect on this community (RQ1-2). However, similar to openness, the overall level of transparency is still low (RQ1-1).

3.2.3 RQ2: Comparison to CHI. Comparing the results to CHI in [64], we see that although the automotive user research community improved its openness practices, it is still at a relatively low level. At CHI'22, an estimated 62% of the papers shared additional research artifacts (EXTRA), and 92% of these artifacts were available at the specified location (EXTRA-EXIST). Comparing the proportion of papers that are openly available (PAYWALL-ACMDL) and the use of FAIR-compatible platforms (EXTRA-FAIR), AutomotiveUI 2022&2023 and CHI'22 do not differ much (c.f., Salehzadeh Niksirat et al. [64]).

Our analysis of the transparency criteria shows a trend towards improved transparency practices at AutomotiveUI, mirroring the observations at CHI. However, across both time periods, the level of transparency in AutomotiveUI papers is lower than in papers published at CHI.

We also observe that over the last 5 years, CHI has improved more than AutomotiveUI in terms of transparency. Investigating the two time periods, we see that papers published at CHI in 2017 achieve a higher score only in 7 out of 17 transparency criteria (SHARE-STIMULI, SHARE-STUDY-PROTOCOL, JUSTIFY-N-QUAL, SPECIFY-QUAL-ANALYSIS, QUAL-DATA-PROCESSED, SHARE-SOFTWARE, SHARE-HARDWARE) compared to AutomotiveUI papers published in 2017&2018. We do not consider the SHARE-SKETCH criterion in this comparison as it was not evaluated by Salehzadeh Niksirat et al. [64]. However, comparing CHI papers published in 2022 to AutomotiveUI papers published in 2022&2023, CHI papers achieve a higher score in 13/17 criteria. AutomotiveUI papers show more transparent practices in 4 categories (SHARE-SURVEY, JUSTIFY-N-QUAN, DEMOGRAPHICS, CONDITION-ASSIGNMENT). AutomotiveUI papers might be more transparent in these categories due to AutomotiveUI 's focus on quantitative and confirmatory research (see Table 2). This highlights the importance of being transparent about the criteria that are important to reviewers of a community. This finding can be underlined by considering the criteria that show the biggest differences between the two communities: SPECIFY-QUAL-ANALYSIS (much higher share at CHI) and SHARE-SURVEY (much higher share at AutomotiveUI).

4 DISCUSSION, LIMITATIONS, AND RECOMMENDATIONS

Taken together, the online survey and systematic review provide a snapshot of the perception and status quo of transparency and openness in the automotive user research community. We discuss the most common issues, methodological limitations, and provide actionable recommendations for the future.

4.1 Open Science is Valued by the Community

Foremost, the automotive user research community is quite positive about open science principles. According to our survey study (Study 1), open science principles are seen as a valid way to accelerate scientific research and applications, determine societal and institutional policy, and foster dissemination and recognition. Similarly positive, the number of papers published open access has strongly increased over the last couple of years. Still, it is unclear if this is an effect of changing research practices or stems from other reasons, such as the increasing tendency of funding agencies to request their project results to be made open access [19, 56]. The consideration of other parameters addressed in our literature review (i.e., such as pre-registrations or sharing of research artifacts) does not suggest this change stems from the individual researchers' attitudes towards open science practices. This mirrors the results from our survey, where external factors are among the biggest motivators and barriers (such as social and institutional policies or legal constraints). Thus, interventions at a higher level could balance motivations and barriers and may have a comparably high impact.

4.2 The Empiristic Paradox in Automotive User Research

Study 2 shows that the majority of publications at AutomotiveUI use quantitative methods and are confirmatory (i.e., aimed at validating hypotheses). The percentage of quantitative studies at AutomotiveUI is also higher than at CHI. Given this, it is perhaps surprising that the percentage of openly shared and transparent papers is lower at AutomotiveUI than at CHI. After all, quantitative and confirmatory research lends itself particularly well to open data practices, such as the pre-registration of hypotheses or the publication of artifacts, datasets, and algorithms for evaluation (following arguments from other domains with similar issues [53]). Why then might there be less data sharing in AutomotiveUI?

The data from our studies does not directly answer this question. However, we have some speculations. Data from AutomotiveUI studies is often tailored to specific infrastructure(s). The infrastructure, composed of professional (c.f. [22, 23]) or self-developed (c.f. [79]) driving simulators or hard- and software to gather data, is often unique [29]. Some data might not be easily interpretable without the hardware, or authors might want to protect the IP of their infrastructure (see Figure 1d). Also, datasets might be very large (e.g., real-time logging of driving characteristics and physiology, videos, etc.). This creates an *Empiristic Paradox* in automotive user research: Although the community collects largely quantitative data, the data is not widely shared. As a result, others can't fully build on the knowledge and expertise previously gained, limiting the ability to move forward as a field.

4.3 Legal Barriers and Confidentiality

Our survey results (Study 1) suggest that the biggest concerns regarding data sharing stem from legal matters (see Figure 1d). These barriers can arise at the institutional level or the legal framework of institutions' national regulations (i.e., IPs of cooperation partners, limited online storage, etc.). On a higher level, legislation such as the General Data Protection Regulation (GDPR) sometimes conflicts with open data practices despite both being fostered by the European Commission [48]. Researchers expressed concerns about their legal liability. Even with considerable effort, it is difficult to completely anonymize datasets to protect privacy, leaving the risk of re-identification and potential complaints. Guidelines for anonymization and examples of best practices for different types of data (see Figure 1) could help researchers overcome their uncertainty. However, opaque requirements and regulatory differences among research institutions also exist in other areas, such as whether a study needs to get approved by an Institutional Review Board. For this issue, SIGCHI has defined general legal and ethical principles, but still recognizes that local policies vary from country to country and institution to institution. A similar approach could be used to address legal issues in open science practices.

4.4 Outperforming the Barriers by Generating Benefits

One way to look at open data practices is through a cost-benefit lens: the motivators should outweigh the barriers. If the legal framework is unclear and complying with it is resource-intensive, while the benefit of data sharing is low, many researchers might refrain from it. Our systematic review indicates low percentages for criteria related to the paper contents and supplementary materials (i.e., sample size justifications, sharing of used surveys, etc.) but also for sharing code and raw/processed data (c.f., Figure 3). Given that policies are also considered motivators (see section 2), conferences could instruct reviewers to consider these in their evaluation so that including such information becomes a prerequisite for acceptance. Shared data could be attributed with persistent identifiers and could count as contributions in tenure evaluations or hiring processes. Conferences can dedicate individual tracks to the topic so that researchers do not feel that a lack of novelty (i.e., confirming existing results, describing and publishing data sets of already published works) hinders the acceptance of data- or artifact/toolkit-oriented papers. Finally, conferences could provide additional motivators, such as conference badges and awards. However, our data suggests that personal motivators are not among the strongest motivators. Therefore, such measures can only serve as a supplement. In addition to raising the benefits, it is also important to reduce the costs. Researchers could benefit from dedicated policies, guidelines, or dedicated repositories with sufficient space to upload data. Guidelines should explicitly address best practices and provide examples with regard to questions of liability and legal constraints.

Finally, we want to emphasize that open science practices need not be seen as an "all or nothing" effort, and the community should also support incrementalist perspectives. For example, barriers such as those mentioned above (i.e., legal and organizational constraints, data rights, or loss of control) may prevent researchers from sharing their datasets, but they could still pre-register their hypotheses, publish appendices where surveys and interview guides are shared, and the like. By actively promoting and valuing such practices (rather than simply asking "why are the data missing?"), we can contribute to iteratively improving the quality of research in our field - which should be the ultimate goal and key message of open science practices!

4.5 Limitations

The survey study (Study 1) suffers from two main limitations - the sample of participants is limited, and it may be biased towards researchers with generally positive attitudes towards open science. Nevertheless, as we have argued, the sample is representative of

AutomotiveUI attendees in many characteristics (e.g., the proportion of academia vs. industry, seniority, or the number of times they attended the conference). Even if the sample was slightly biased, the group still reported various barriers that limit open science practices beyond intrinsic motivations. Thus, we believe that the survey provides an accurate picture of conference attendees' perceptions.

The literature review (Study 2) is limited because we only included and compared two sets of papers from 2017&2018 and 2022&2023. Choosing different conference years could lead to slightly different results. We justify our selection by the 5-year interval also used by Salehzadeh Niksirat et al. [64], which makes it possible to compare our results, at least from a descriptive perspective. Another limitation is the subjectivity of the coding process. We closely followed the process developed by Salehzadeh Niksirat et al. [64], coding each paper by at least two researchers independently and resolving any conflicts in direct interaction. However, there is still a risk that we may have missed some information. We did our best to limit such potential inconsistencies and believe that our evaluation is representative of the papers presented at AutomotiveUI. An additional limitation of Study 2 is the exclusive comparison with CHI, although openness and transparency have been discussed for some time in other research communities [35, 36]. However, we focus on the comparison with CHI because the timeliness and reproducible methodology of the work by Salehzadeh Niksirat et al. [64] allows for a valid comparison and provide insights on how good research practices spread to sub-communities.

A more overarching limitation is that both the published work (Study 2) and the participants' reflections (Study 1) focused on quantitative studies. Openness and transparency for qualitative (and mixed) studies may present additional unique problems. For example, if a finding is highly dependent on the study context, revealing more of that context through data sharing could de-anonymize participants. Promoting openness and transparency should not result in qualitative work failing to meet the criteria or standards of the field. Therefore, more attention must be paid to the challenges facing qualitative work.

4.6 Recommendations for Improving Open Sciences Practices at AutomotiveUI

We conclude with recommendations emerging from our analyses for future AutomotiveUI conferences:

(1) **Publication of an Open Science Policy:** Explicit conference-dependent guidelines for open data practices should be published in a working document. Authors are motivated by external factors (see Study 1 and Figure 1). Therefore, developing a policy on this front can guide authors. An open science policy document could, for example, contain standards, best practices, and examples from the community.

(2) **Support for Overcoming Legal Barriers:** Legal concerns are among the strongest concerns preventing researchers from applying open science practices (see Study 1 and Figure 1). The community should consider how it can accommodate legal technicalities – for example, by clearly defining under which conditions data can be shared, by providing a decision tree that can be followed by paper authors, and best practices with positive and negative examples for different types of data.

(3) **Providing a Central Platform:** The conference could accommodate research transparency by providing one platform (e.g., a website or an already established platform such as OSF) to share links to their materials. Study 2 shows that authors use different platforms to share their data. Although ACM provides its own platform, it lacks functionality and is therefore not used by all. If the conference has a central place to share open science data, it will be easier to find. To encourage such practices and increase the visibility of work that follows open science practices, we have created a website with guidelines and practical tips, and offer authors the opportunity to submit their work for public display: https://autoui-open-data-initiative.github.io.

(4) **Recognition and Acknowledgment of Open Science Practices:** The conference could provide benefits to authors who share their research artifacts openly and transparently. For example, by linking datasets to authors and publications, providing unique identifiers, having a special call for papers and datasets, or giving "soft" benefits in the form of awards and badges, as was done for the first time in 2024 [5]. Although most authors are not so much driven by personal factors (see Study 1 and Figure 1), some are. In addition, by making some benefits more explicit, an explicit discussion of norms at the conference may become salient. This may influence discussions at the institutional level, which motivates individuals. Thereby, also small steps (i.e., hypothesis preregistration, sharing experimental protocols and surveys, etc.) should be valued.

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