Using Imperfect AI to Support High-Stakes Decisions

Dissertation

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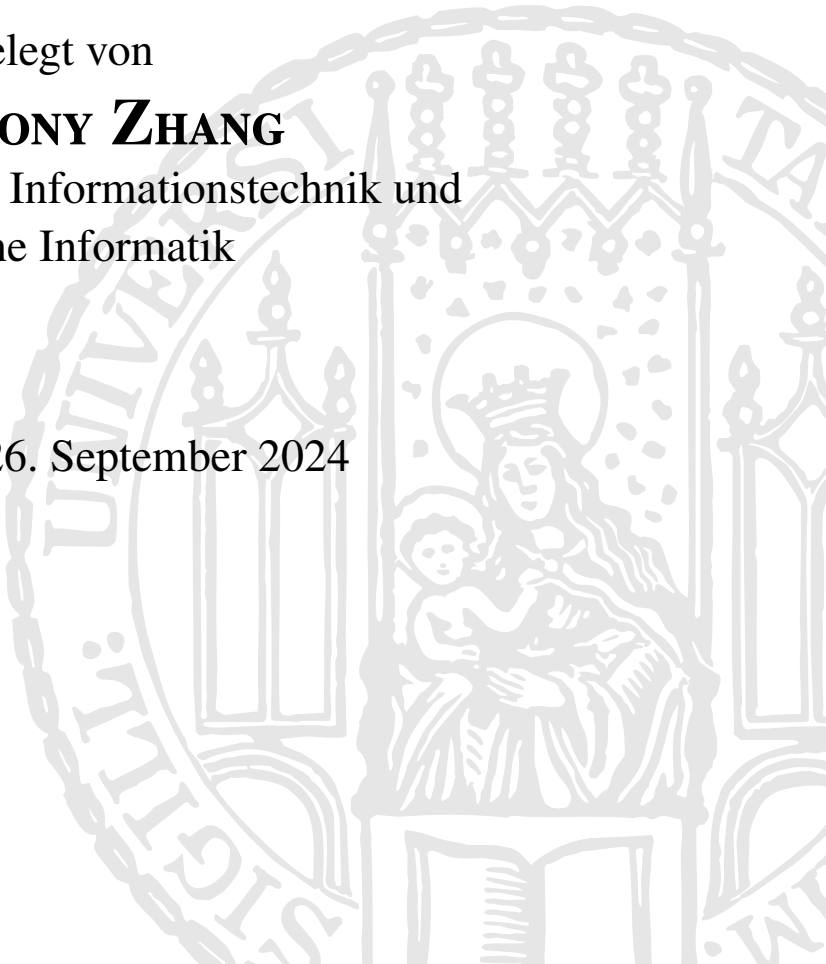

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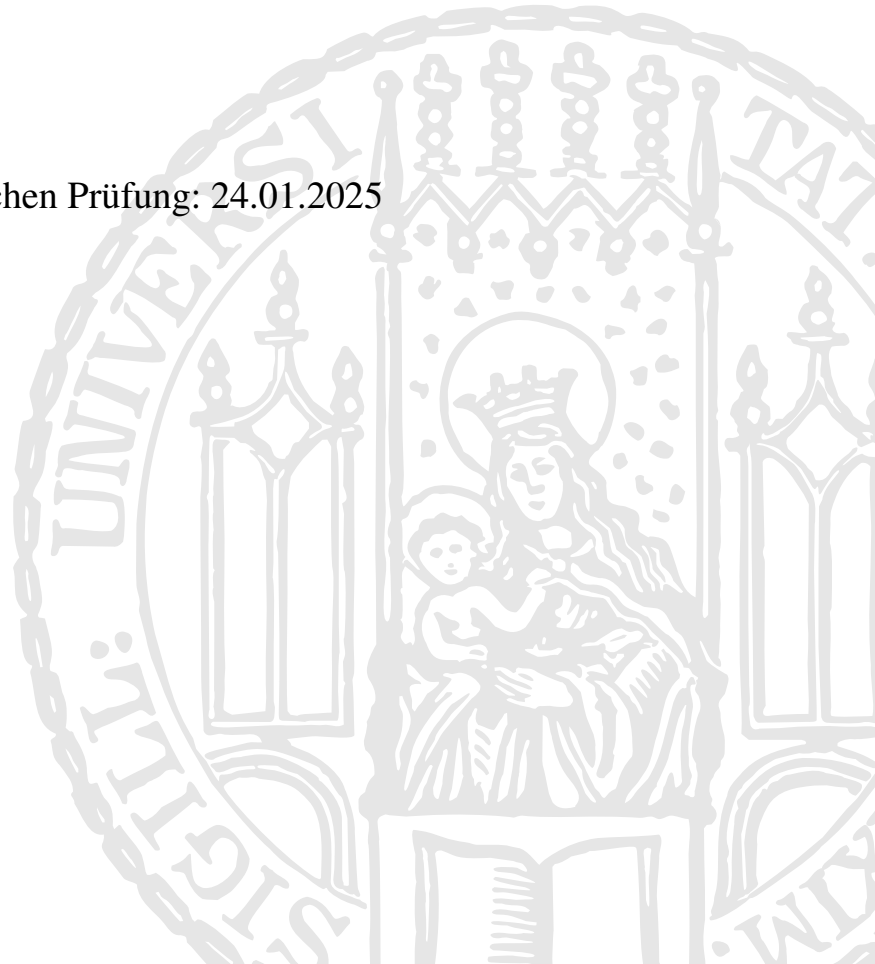

ABSTRACT

Given the impressive technological advances of recent years, artificial intelligence (AI) is anticipated to enhance human decision-making across various fields, including challenging, high-stakes ones like healthcare, finance, or aviation. However, recent research shows that supporting human decision makers with AI is far from straight-forward.

Often, AI decision support is designed to be recommendation-centric, i.e., the AI gives a closed, end-to-end decision recommendation. Since the human is not involved in generating the recommendation, they often cannot work effectively with it, particularly when the AI is wrong. Incorrect recommendations can severely disrupt the human decision maker's workflow or, if unnoticed, lead them to adopt the wrong recommendation (overreliance), which is especially problematic for high-stakes decisions. A common approach to address this is to explain the AI recommendation, but results have been mixed so far. This thesis advances the understanding of how AI—despite its imperfection—can effectively support human decision-making in high-stakes domains, by addressing two major issues:

1) Through experiments on simple, controllable decision tasks with lay users, the thesis contributes a *better understanding of the limitations of recommendation-centric support* for high-stakes decisions. The experiment results reveal that humans are particularly prone to overrely on AI recommendations in challenging decisions and after repeated interactions with the AI. Common feature-based explanations could not effectively mitigate overreliance.

2) Through more qualitative studies with domain experts, the thesis explores *alternative approaches to AI decision support* to overcome the identified limitations. As explored for the use case of diversions in aviation, one promising approach is to design AI to support the process leading up to the final decision, rather than jumping straight to the end of the process with an end-to-end recommendation. The AI support must be granular and flexible enough for the decision maker to use it according to their own momentary intention. Instead of "opening the black box", explanations should help users understand how the AI output fits their intention. Finally, recommendations can be beneficial, but should be introduced toward the end of the decision-making process.

Overall, this thesis contributes to a more holistic view of the design space of AI-driven decision support that goes beyond recommendations and explanations. Discovering these alternative design opportunities requires a thorough understanding of users' decision-making processes and workflows, highlighting that the classic endeavor of human-centered design to start from human needs remains crucial also in the age of advanced AI technology.

ZUSAMMENFASSUNG

Angesichts der beeindruckenden technologischen Fortschritte der letzten Jahre wird davon ausgegangen, dass künstliche Intelligenz (KI) die menschliche Entscheidungsfindung in den unterschiedlichsten Bereichen verbessern wird, darunter auch in anspruchsvollen und riskanten Bereichen wie dem Gesundheitswesen, dem Finanzwesen oder der Luftfahrt. Jüngste Untersuchungen zeigen jedoch, dass die Unterstützung menschlicher Entscheidungsträger durch KI alles andere als einfach ist.

Häufig ist KI-Entscheidungsunterstützung empfehlungsorientiert, d. h., die KI gibt eine geschlossene Entscheidungsempfehlung ab. Da der Mensch nicht an der Erarbeitung der Empfehlung beteiligt ist, kann er oft nicht effektiv damit arbeiten, insbesondere wenn die KI falsch liegt. Fehlerhafte Empfehlungen können die Arbeit des menschlichen Entscheidungsträgers empfindlich stören oder, wenn sie unbemerkt bleiben, dazu führen, dass er die falsche Empfehlung annimmt (Overreliance), was besonders bei risikoreichen Entscheidungen problematisch ist. Ein gängiger Lösungsansatz besteht darin, die KI-Empfehlung zu erklären, doch die Ergebnisse sind bisher durchwachsen. Diese Dissertation erweitert das Verständnis dafür, wie KI trotz ihrer Unvollkommenheit die menschliche Entscheidungsfindung in risikoreichen Domänen effektiv unterstützen kann, indem sie zwei Hauptthemen behandelt:

1) Durch Experimente an simplen, kontrollierbaren Entscheidungsaufgaben mit Laien trägt die Dissertation zu *einem besseren Verständnis der Limitierungen von empfehlungszentrierter Unterstützung* für risikoreiche Entscheidungen bei. Die Ergebnisse zeigen, dass Menschen besonders bei schwierigen Entscheidungen und nach wiederholten Interaktionen mit der KI dazu neigen, sich übermäßig auf KI-Empfehlungen zu verlassen. Übliche merkmalbasierte KI-Erklärungen konnten das übermäßige Verlassen nicht wirksam eindämmen.

2) Durch qualitative Studien mit Domänenexperten werden in der Dissertation *alternative Ansätze zur KI-Entscheidungsunterstützung* untersucht, um die identifizierten Einschränkungen zu überwinden. Wie für den Anwendungsfall der Flugumleitungen in der Luftfahrt untersucht, besteht ein vielversprechender Ansatz darin, mit KI den Prozess bis zur endgültigen Entscheidung zu unterstützen, anstatt direkt ans Ende des Prozesses zu springen und eine abgeschlossene Empfehlung abzugeben. Die KI-Unterstützung muss so granular und flexibel sein, dass der Entscheidungsträger sie je nach seiner momentanen Absicht einsetzen kann. Anstatt die "Blackbox zu öffnen", sollten KI-Erklärungen den Nutzern helfen zu verstehen, wie die KI-Ausgabe zu ihren Absichten passt. Zudem können Empfehlungen zwar nützlich sein, sollten aber erst am Ende des Entscheidungsprozesses eingeführt werden.

Insgesamt trägt diese Dissertation zu einer ganzheitlicheren Sicht auf den Gestaltungsraum für KI-Entscheidungsunterstützung bei, die über KI-Empfehlungen und -Erklärungen hinausgeht. Um diese alternativen Gestaltungsmöglichkeiten zu identifizieren, ist ein gründliches Verständnis der Entscheidungsprozesse und Arbeitsabläufe der Nutzer erforderlich. Dies zeigt, dass das klassische Bestreben der menschenzentrierten Gestaltung, von den menschlichen Bedürfnissen auszugehen, auch im Zeitalter fortschrittlicher KI-Technologie entscheidend bleibt.

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Chapter 1

Introduction

1.1 Thesis Statement

Fueled by the rapid technological advances in recent years, artificial intelligence (AI) has become ubiquitous, permeating more and more aspects of daily life and work. One popular application of AI is to support human decision-making across various domains [50], often in high-stakes ones such as human resources [85], finance [15], or healthcare [103]. Common terms for this field of research include *human-AI decision-making* or *AI-assisted decision-making*. Throughout the thesis, I will use the latter term to emphasize the human-centered perspective that informs all of the work in this thesis: that it is humans who make the decisions and who are responsible for their decisions, with AI only providing assistance, rather than being an equal partner.

A common assumption is that AI will augment human decision-making, given the complementary strengths of humans and machines: While humans are better at understanding context and human values, machines can process far more data [1, 42]. However, AI is imperfect, and some argue that it will always be [93]. The question is therefore how to benefit from AI without AI errors leading to grave consequences in high-stakes applications. A frequently proposed solution is the *human-in-the-loop* [1, 21, 50, 84], i.e., relying on the human to override the AI when necessary. But recent empirical results show that this is far from trivial, since humans frequently override or accept AI recommendations inappropriately, as discussed in more detail in Section 2.1. As a result, the vision of AI augmenting human decision-making, especially in high-stakes applications, has proven difficult to realize.

The aim of this thesis is to contribute toward the realization of this vision through thoughtful human-AI interaction design. The thesis is grounded in three interrelated observations:

1. Systems for AI-assisted decision-making are usually recommendation-centric, i.e., the AI system provides end-to-end decision recommendations, as I will elaborate further in Section 2.2.

2. This recommendation-centric support paradigm may be particularly prone to AI mistakes, as it depends on the ability of the human decision maker to recognize a bad recommendation.

3. AI-assisted decision-making does not have to be recommendation-centric. There are often many more opportunities to support decision-making with AI than end-to-end recommendations.

Motivated by these observations, I pursued two main lines of research: (1) understanding the limitations of recommendation-centric decision support, and (2) how alternative support paradigms might overcome these limitations. The results demonstrate the importance of understanding human decision-making processes and the potential of approaches beyond the common recommendation-centric paradigm.

1.2 Contributing Publications

This thesis is a cumulative dissertation that connects and summarizes the contributing publications listed below and puts them into the context of related work. Throughout the thesis, I reference these publications with a prefixed "P" (e.g., [P1]). An overview of my own contributions to these publications is given in Table 1.1. More details including clarifications of my co-authors' contributions will be given in the respective sections of Chapter 3. This is meant to improve the reading flow, as the context of each publication should help to better understand each author's contribution.

Table 1.1: Overview of own contributions to the publications. *Main contributor* means that these contributions were mostly or entirely mine. *Co-contributor* means that these contributions were shared with my co-authors. Note that a lack of entries under *co-contributor* does not mean a lack of contribution by my co-authors, but only that there was no shared contribution between me and my co-authors. More details about my own as well as my co-authors' contributions are given in the respective sections in Chapter 3.

Publication	Main contributor	Co-contributor
Pilot Attitudes Toward AI in the Cockpit [P1]	study idea, design, and execution; data analysis; writing	
Forward Reasoning Decision Support [P2]	idea for position paper; writing	
Resilience Through Appropriation [P3]	writing	study design and execution; prototype design; data analysis
Is Overreliance on AI Provoked by Study Design? [P4]	study idea; data analysis; writing	study design
You Can Only Verify When You Know the Answer [P5]	study idea; data analysis; writing	study design
Beyond Recommendations [P6]	study idea, design, and execution; system design and implementation; data analysis; writing; framework for process-oriented support	focus group execution
Effect of Mental Workload and Explanations on Appropriate AI Reliance [P7]	study idea; implementation of AI model	study design; data analysis; writing

[P1] Zelun Tony Zhang, Yuanting Liu, and Heinrich Husmann. Pilot attitudes toward AI in the cockpit: implications for design. In *2021 IEEE 2nd International Conference on Human-Machine Systems (ICHMS)*, pp. 33:1–33:6, Magdeburg, Germany, September 2021. IEEE. DOI: 10.1109/ICHMS53169.2021.9582448.

[P2] Zelun Tony Zhang, Yuanting Liu, and Heinrich Hussmann. Forward reasoning decision support: toward a more complete view of the human-AI interaction design space. In *CHItaly 2021: 14th Biannual Conference of the Italian SIGCHI Chapter*, pp. 18:1–18:5, Bolzano, Italy, July 2021. ACM. DOI: 10.1145/3464385.3464696.

[P3] Zelun Tony Zhang, Cara Storath, Yuanting Liu, and Andreas Butz. Resilience through appropriation: Pilots' view on complex decision support. In *Proceedings of the 28th International Conference on Intelligent User Interfaces*, IUI '23, pp. 397–409, Sydney, NSW, Australia, March 2023. ACM. DOI: 10.1145/3581641.3584056.

[P4] Zelun Tony Zhang, Sven Tong, Yuanting Liu, and Andreas Butz. Is overreliance on AI provoked by study design? In José Abdelnour Nocera, Marta Kristín Lárusdóttir, Helen Petrie, Antonio Piccinno, and Marco Winckler, editors, *Human-Computer Interaction – INTERACT 2023*, pp. 49–58, York, UK, August 2023. Springer. DOI: 10.1007/978-3-031-42286-7_3.

[P5] Zelun Tony Zhang, Felicitas Buchner, Yuanting Liu, and Andreas Butz. You can only verify when you know the answer: Feature-based explanations reduce overreliance on AI for easy decisions, but not for hard ones. In *Proceedings of Mensch und Computer 2024*, MuC '24, pp. 156–170, Karlsruhe, Germany, September 2024. ACM. DOI: 10.1145/3670653.3670660.

[P6] Zelun Tony Zhang, Sebastian S. Feger, Lucas Dullenkopf, Rulu Liao, Lou Süsslin, Yuanting Liu, and Andreas Butz. Beyond recommendations: From backward to forward AI support of pilots' decision-making process. *Proceedings of the ACM on Human-Computer Interaction*, 8(CSCW2):485:1–485:32, November 2024. DOI: 10.1145/3687024.

[P7] Zelun Tony Zhang, Seniha Ketenci Argın, Mustafa Baha Bilen, Doğan Urgun, Sencer Melih Deniz, Yuanting Liu, and Mariam Hassib. Measuring the effect of mental workload and explanations on appropriate AI reliance using EEG. *Behaviour & Information Technology*, pp. 1–19, November 2024. DOI: 10.1080/0144929X.2024.2431055. Advance online publication.

Publication [P5] received a *Best Paper Award*.

Chapter 2

Background and Definitions

2.1 Appropriate Reliance

This thesis focuses on AI-assisted decision-making in high-stakes applications, where bad decisions can have highly negative consequences. It is therefore crucial that decision makers are not misled into a bad decision by an inevitable AI error. Conversely, it is desirable that the decision maker does not erroneously overrule a good AI recommendation. This notion is captured by the term *appropriate reliance*, which has already been studied for decades in the context of traditional automation [51], and has in recent years also gained much attention in AI-assisted decision-making research [75].

Appropriate reliance is usually defined and measured through decision outcomes on individual decision instances [32]. The setup is typically such that the AI makes a recommendation to the human, who has to make the final decision. If the human accepts a correct AI recommendation or rejects a wrong one, the reliance is said to be appropriate. Conversely, reliance is said to be inappropriate if the human either accepts a wrong AI recommendation (*overreliance*), or rejects a correct recommendation (*underreliance*). This definition of appropriate reliance is straightforward to operationalize by recording participants' decisions conditioned on the correctness of the AI recommendation.

While this outcome-based definition of appropriate reliance is very common (e.g., [11, 38, 56, 72, 75, 88, 92, 97], it has its shortcomings, as highlighted by Fok and Weld [32]. For one, relying on AI can be considered an appropriate strategy even if the AI ends up being wrong, which could be the case for instance when a typically highly reliable AI makes a rare, unexpected mistake. The reverse of this argument also holds. Second, the outcome-based definition does not properly consider non-deterministic elements in decision outcomes. For example, two loan applicants may have the same profiles, resulting in the same AI recommendations, but one may default while the other does not. Fok and Weld therefore propose a "strategy-graded" definition for appropriate reliance [32], where the appropriateness does not depend on the outcome of a decision, but on whether the AI is expected to outperform the

human for a given decision. However, it is often unclear how to operationalize this definition in experiments.

Another limitation of the outcome-based definition is that it does not allow to discriminate different reasons why people do not make optimal use of AI recommendations. To address this limitation, Guo et al. [37] propose a decision-theoretic framework that differentiates between an overall reliance level and the recognition whether the human or the AI is better for a specific decision instance. The framework relies on strong assumptions about people's decision-making process with AI, which are yet to be validated and refined in future work.

In this thesis, I resorted to the established outcome-based definition of appropriate reliance. While I recognize its limitations, work on alternative definitions is still in its infancy and represents an important area for future research. I addressed the limitations of the outcome-based definition through the experiment designs, e.g., by choosing deterministic decision tasks or by carefully selecting the decision instances to include in the experiments. I further focused primarily on overreliance. While underreliance is also undesirable, as it means missed opportunities for potentially critical improvements, overreliance means the AI introduced a change for the worse. Overreliance is arguably also the greater concern both in public debates about AI as well as in research on AI-assisted decision-making [11, 47, 88, 89].

2.2 Recommendation-Centric Decision Support

As previously stated in Section 1.1, the most common approach to AI-assisted decision-making is what I term *recommendation-centric decision support*. By this I refer to systems where the primary functionality is to provide end-to-end decision recommendations, which the human decision maker can either accept or reject. For example, a decision support tool in healthcare could suggest a likely diagnosis to physicians directly from the patient's information. However, numerous studies demonstrate that humans often rely inappropriately on AI recommendations, with both underreliance [17, 19, 22, 69] and—more frequently—overreliance [6, 11, 34, 49, 55, 67, 77] being an issue, which can even be the case for expert decision makers [10, 41].

To help people to rely on AI recommendations appropriately, the recommendations are often accompanied by explanations about how the AI model arrived at its output. The *explainable AI* (XAI) community has contributed numerous approaches to explain the output of an AI model [53], such as by revealing how individual input features contributed to the output (*feature-based explanations*), or by showing examples from the training set that are similar to the current input (*example-based explanations*). The rationale is that by "opening the black box" [36] of AI in this way, humans can judge whether the system is correct or not [74]. However, empirical results have been mixed so far. While explanations are beneficial in some studies [18, 88, 97], it seems more common that explanations have little effect on the appropriateness of reliance [7, 75, 92, 106], or even increase overreliance [6, 10, 41, 49, 77].

Besides explanations, several other approaches have been proposed to improve appropriate reliance on recommendation-centric decision support. One approach is to provide additional information about the AI model to decision makers, such as the model's test set accuracy [38, 71] or descriptions about the model performance [14]. One type of model information that has repeatedly been shown to be effective for calibrating people's reliance is model uncertainty about a given recommendation [6, 58, 68, 106]. The challenge for practical use is that uncertainty is very hard to calibrate, as AI can often be wrong with high confidence [4].

Another approach is the use of cognitive forcing functions [11], which aim to push decision makers to engage more deliberately with AI recommendations, e.g. by displaying recommendations only after the user has entered their own initial decision [11, 31] or by introducing a waiting time before the AI provides a recommendation [11, 65]. While cognitive forcing functions can mitigate overreliance, they are perceived negatively by users [11, 31, 65].

A further line of research is to optimize users' reliance behavior by adapting which of the above strategies to use, or even whether to show recommendations at all. Examples of proposed methods include reinforcement learning based on information such as the user's knowledge of a certain concept [12]; modeling the user's likelihood to make a correct decision in a given task instance [57]; or logically inferring adaptation strategies from simple assumptions about the user's reliance behavior [59]. Initial results on simple decision problems are promising, but the computational inferences introduce additional sources for mistakes. It is thus unclear how well these approaches translate into complex real-world, high-stakes applications.

All of the approaches mentioned above target the problem of inappropriate reliance, but remain focused on supporting human decision-making through end-to-end recommendations. However, besides inducing inappropriate reliance, recommendation-centric support also often proves less helpful to decision makers than expected, as revealed by a growing number of studies on AI-assisted decision-making under real-world conditions [8, 45, 98]. A recurring complaint of users is that recommendation-centric support does not integrate well into their existing work and decision-making processes [13, 46, 98]. Rather than a suggested end result, decision makers often wish for more support of the process leading up to the final decision [101, 105], which is completely ignored by recommendation-centric support. Such findings suggest that for many applications, a paradigm shift away from recommendation-centric support may be necessary for AI-assisted decision-making, although it is often unclear what alternative forms of AI support might look like, as concrete examples are rare.

2.3 Research Questions

While inappropriate reliance is a persistent problem in recommendation-centric support, there are studies showing that it is possible to calibrate human reliance on AI recommendations in some scenarios [97, 106]. For instance, Vasconcelos et al. [88] showed that explana-

tions can reduce overreliance when they lower the cost of verifying the AI recommendation. However, for most constellations, it is not as clear under which conditions people are able to rely appropriately on recommendation-centric support and when not. This motivates the first overarching research question of this thesis:

> ***RQ1:*** *What are the limitations of recommendation-centric support for high-stakes decisions?*

In particular, I focus on the most common form of recommendation-centric support, i.e., recommendations plus explanations. I further concentrate on overreliance, as explained in Section 2.1, and the conditions under which explanations fail to mitigate it.

As outlined in Section 2.2, many researchers attempt to address the issue of inappropriate reliance while holding on to the recommendation-centric paradigm of AI-assisted decision-making. Yet, studies on real-world decision contexts often reveal opportunities for AI support that is not recommendation-centric, even though examples of concrete system designs are rare. It is even less clear how such alternative support paradigms that do not rely on end-to-end decision recommendations would compare to recommendation-centric support. The second research question guiding the work in this thesis is therefore:

> ***RQ2:*** *How can AI support high-stakes decisions without being recommendation-centric to overcome the limitations of recommendation-centric support?*

By studying a use case from commercial aviation, my goal is to identify AI decision support designs that are useful to pilots, but not centered around recommendations, and compare them against the recommendation-centric approach.

Chapter 3

Imperfect AI for High-Stakes Decision Support

This chapter summarizes the contributing publications listed in Section 1.2 and relates them to the two guiding research questions laid out in Section 2.3. As these publications were the result of collaborations with my co-authors, I will use the scientific "*we*" throughout this chapter when describing the individual studies.

3.1 Limitations of Recommendation-Centric Support

> ***RQ1:*** *What are the limitations of recommendation-centric support for high-stakes decisions?*

I primarily investigated RQ1 through experiments on simple decision tasks (Sections 3.1.1 and 3.1.2), which is the most common way to empirically study AI-assisted decision-making [50]. While somewhat artificial, such simple decision tasks allow for controlled investigations of the human factors involved in AI-assisted decision-making. However, they also tend to conceal challenges that only become apparent in complex real-world use cases. I therefore also studied commercial aviation as a high-stakes domain to understand limitations arising in actual use (Section 3.1.3).

3.1.1 Increasing Overreliance Over Time

This section is based on the publication

***"Is overreliance on AI provoked by study design?"** [P4].*

The established outcome-based definition of appropriate reliance (Section 2.1) requires a study design where participants have to solve a series of decision tasks. In order to collect enough data, these task series are often quite long (see Table 3.1), long enough to suspect that many participants may become complacent and less engaged toward the end of the task series. At the same time, prior work has shown that overreliance in AI-assisted decision-making may be caused by a lack of cognitive engagement [11, 33]. We therefore asked whether observations of overreliance in empirical studies are provoked by the long task series used in many studies, which may not reflect how decisions are made in many real-world use cases.

Table 3.1: Examples of research finding overreliance in AI-assisted decision-making, including the decision tasks and the lengths of the task series participants had to complete in the respective studies. Adapted from [P4].

Publication	Study task	# Tasks
Bansal et al. [6]	Sentiment classification	50
	Law School Admission Test	20
Buçinca et al. [11]	Nutrition assessment	26
Green and Chen [34]	Recidivism risk assessment	40
	Loan risk assessment	40
Lai and Tan [49]	Deception detection	20
Liu et al. [55]	Recidivism prediction	20
	Profession classification	20
Schmidt and Biessmann [77]	Sentiment classification	50
Wang and Yin [92]	Recidivism prediction	32
	Forest cover prediction	32

To answer this question, we designed an online experiment with 47 participants based on a profession classification task that had been used in several other studies on AI-assisted decision-making [18, 55, 66, 78]. Participants had to read a short biography and decide with the help of recommendation-centric AI assistance which profession the described person has. The core idea was to design a study condition in which the 50 decision tasks were split into ten short sessions of five tasks each, which were sent to participants with a minimum break of one hour between two sessions. Participants were free to choose when they would complete the new session once they received the link to it. This condition (*multiple session*

group—MSG) was meant to induce less complacency among participants than the typical setup where all 50 tasks had to be completed in a single session (*single session group*—SSG).

The results showed that for both MSG and SSG, participants' agreement with the AI and their overreliance increased significantly as they progressed through the task series, while the decision time decreased significantly, indicating decreasing effort with ongoing time. This implies that typical study designs with long task series indeed favor the occurrence of overreliance. However, overreliance may increase over time even in settings like the MSG condition where people do not have to solve a large amount of decision tasks in a short time period. One reason could be that our MSG condition was not effective enough at reducing complacency. On the other hand, we ensured that participants could conveniently solve the tasks at their own schedule. Therefore, our findings potentially suggest a more fundamental limitation of recommendation-centric support, i.e., as people become more familiar with such a system, they become more likely to overrely on it, irrespective of whether they interact with it in long, tiring sessions, or in shorter sessions embedded into their daily context.

Author contributions: This publication is the result of the master thesis of my student Sven Tong. I provided the study idea, conducted the statistical analysis in the form found in the publication, and wrote the paper. Sven designed the study under my guidance, implemented the machine learning model, the explanations, and the study interface, and conducted the study. Yuanting Liu and Andreas Butz provided guidance and feedback and edited the final version of the submission.

3.1.2 Inappropriate Reliance in Difficult Decisions

This section is based on the following publications:

> *"**You can only verify when you know the answer: Feature-based explanations reduce overreliance on AI for easy decisions, but not for hard ones**" [P5],*
>
> *"**Measuring the effect of mental workload and explanations on appropriate AI reliance using EEG**" [P7].*

As shown by an increasing number of empirical studies, countless factors can influence whether people can rely appropriately on recommendation-centric decision support, such as users' personality traits [11, 77], their domain expertise [39, 92], model performance [61, 64, 102], or the type [89, 92] and design [97] of explanations. We were interested in the effect of task characteristics, in particular decision difficulty, as AI-assisted decision-making is often aimed at difficult decisions in high-stakes domains like healthcare [79] or finance [15], where overreliance is especially undesirable. At the same time, given their high stakes, the call for explainability is particularly prominent in these domains [2, 5]. We therefore conducted two experiments to investigate how decision difficulty affects the appropriateness of human reliance on AI, and how the effectiveness of explanations to mitigate overreliance depends on decision difficulty.

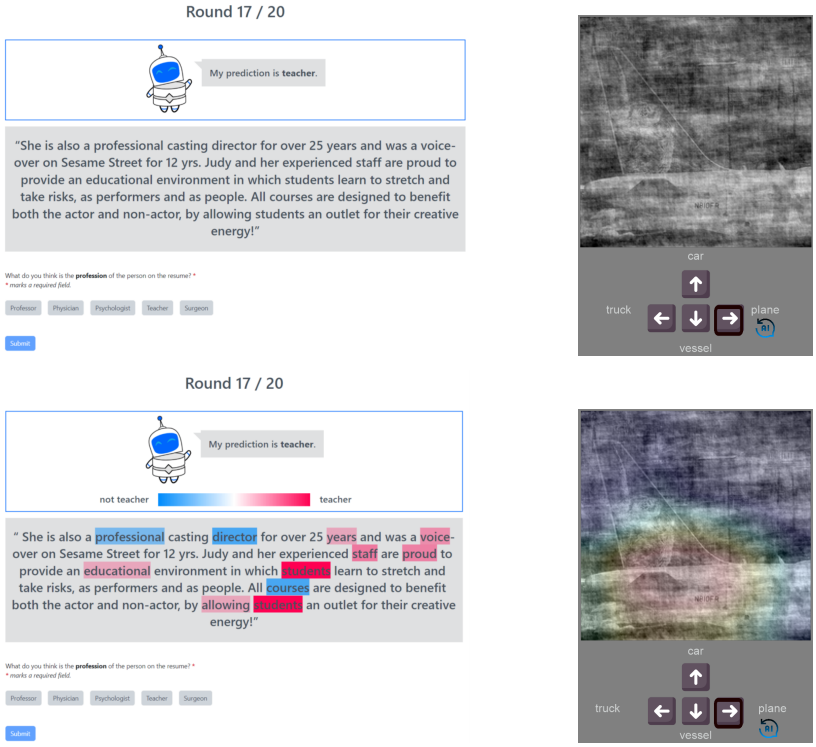

Figure 3.1: Task interfaces used in the decision difficulty experiments. Left: profession classification task used in [P5]. Right: image recognition task used in [P7]. Top: AI support without explanations. Bottom: AI support with explanations.

The two experiments covered two different types of tasks (see Figure 3.1): the text-based profession classification task [P5] which we also used in [P4], as described in Section 3.1.1, and an image recognition task [P7]. Both experiments had one condition where the AI only gave a recommendation, and one condition where it in addition gave feature-based explanations that are typical for the respective task. In [P5], we conducted an online experiment with 200 participants. We measured decision difficulty through the agreement among participants, where lower agreement indicated higher decision difficulty. In [P7], we used electroencephalography (EEG) with 34 participants to measure mental workload as an indicator for decision difficulty. Both approaches had complementary strengths and weaknesses, as shown in Table 3.2.

We found in both studies that participants' reliance on AI was significantly less appropriate in more difficult decisions. In [P5], explanations helped to mitigate overreliance for easy decisions, but became less effective with increasing decision difficulty, with a tendency to even increase overreliance in the most difficult decisions. In [P7], the explanations had no significant effect, but we found indications that in principle, they could be helpful for easy decisions, but not for difficult ones.

We conclude that recommendation-centric support is helpful for easy decisions, where humans often know the answer themselves or at least have an intuition about the decision.

Table 3.2: Advantages and disadvantages of the two approaches used in this thesis for measuring decision difficulty.

	Advantages	**Disadvantages**
Agreement-based measure [P5]	Assesses decision difficulty on a continuous scale.	Does not account for subject dependency of decision difficulty.
EEG-based measure [P7]	Measures decision difficulty as subjectively experienced by each participant.	Only allows for binary distinction between easy and difficult decisions.

Here, recommendations and explanations can occasionally provide a useful second opinion. However, for difficult decisions where humans are highly uncertain about the correct answer, recommendation-centric support may be inappropriate, since the end-to-end recommendations and the technical explanations mostly do not help with forming a better intuition about the task. Consequently, decision makers have few other clues to work with than the recommendation and are likely to overrely on the AI.

Author contributions for [P5]: This publication is the result of the master thesis of my student Felicitas Buchner. I provided the study idea, conducted the statistical analysis in the form found in the publication, and wrote the paper. Felicitas designed the study under my guidance, implemented the machine learning model, the explanations, and study interface, and conducted the study. Andreas Butz contributed to the statistical analysis. Yuanting Liu and Andreas provided guidance and feedback and edited the final version of the submission.

Author contributions for [P7]: I contributed the study idea for this publication and led the collaboration. The experiment design was a joint effort, with Mariam Hassib and I focusing on the requirements from the perspective of AI-assisted decision-making, while the colleagues from TUBITAK—Seniha Ketenci Argın, Mustafa Baha Bilen, Doğan Urgun, and Sencer Melih Deniz—ensured that the experiment was compatible with the constraints of EEG data acquisition. I trained the neural network and implemented the explanations. The study interface and EEG data acquisition pipeline were implemented by the colleagues from TUBITAK, who also conducted the experiment and derived mental workload measures from the EEG data. Mariam and I performed the statistical analysis. Writing was a joint effort by Mariam, Doğan, Sencer, and me. Yuanting Liu provided guidance and feedback and edited the final submission.

3.1.3 Helpful When Correct, but a Burden When Wrong

This section is based on the following publications:

> *"**Pilot attitudes toward AI in the cockpit: implications for design**" [P1],*
>
> *"**Resilience through appropriation: Pilots' view on complex decision support**" [P3].*

To understand what hinders the adoption of AI-assisted decision-making in high-stakes domains, it is important to study real-world use cases in addition to experiments like those in Sections 3.1.1 and 3.1.2. We considered a use case from commercial aviation, which will be explained in more detail in Section 3.2.2. We conducted an initial exploratory interview study with four professional pilots [P1] to understand their perspective on the introduction of AI in the cockpit. We found that pilots' primary concern is not the black box nature of AI systems, as is often assumed when explanations are added to AI recommendations. Our participants were more concerned that AI may not be able to properly handle complex situations. A recurring example was that aviation relies on well-defined procedures that cover the majority of events; but in extraordinary situations, pilots may need to flexibly deviate from usual procedures. Our interviewees feared that an AI system may lack this flexibility and judgment, and become a burden rather than a help in such situations.

These findings highlight an important requirement for AI systems in high-stakes applications that is often not sufficiently addressed: Imperfect AI outputs, which are unavoidable in a complex domain such as aviation, should have minimal negative impact on users, a property Gu et al. [35] call *AI-resilient*. Recommendation-centric support tends to violate this requirement especially for complex decisions, as discussed by participants in a second study [P3], which will be explained in more detail in Section 3.2.2. While pilots stated that they would not blindly trust AI, they rejected the notion that they have to question case-by-case whether the AI recommendation is correct or not. Yet, this is the assumption driving most research on appropriate reliance in AI-assisted decision-making. Pilots emphasized that such a system would burden them more than it would help.

The seeming contradiction of not blindly trusting AI, but also not wanting to question it on a case-by-case basis, points to what makes recommendation-centric support difficult to work with: It diverts users' cognitive resources away from their own decision-making process and toward the review of a recommendation in which they have not been involved. Instead of augmenting users' decision-making process, reviewing the recommendation creates extra effort, especially when the decision is a complex one.

Author contributions for [P1]: The study idea was mine, and I also conducted the interviews, analyzed the data, and wrote the paper. Yuanting Liu and Heinrich Hußmann provided guidance and feedback and edited the final version of the submission.

Author contributions for [P3]: Given in Section 3.2.2, where the publication is described in more detail.

3.2 Exploration of Alternatives to Recommendation-Centric Support

> ***RQ2:*** *How can AI support high-stakes decisions without being recommendation-centric to overcome the limitations of recommendation-centric support?*

Similar to Section 3.1.3, studies of AI-assisted decision-making in real-world applications, such as in healthcare [9, 40, 98], social work [46], or sales [8], frequently find how recommendation-centric support does not fit well into users' decision-making process. However, concrete examples for alternative, *not* recommendation-centric ways to support human decision-making are rare; the few existing examples are mostly found in healthcare [54, 99, 105]. It is even less clear how such alternative designs compare to recommendation-centric support.

For RQ2, my objective was therefore to identify concrete ways for AI decision support that are not focused on recommendations, and compare them against typical recommendation-centric support. To this end, I studied a use case from commercial aviation.

3.2.1 Backward and Forward Reasoning

This section is based on the publication

> *"**Forward reasoning decision support: toward a more complete view of the human-AI interaction design space**" [P2].*

In this position paper, we laid out the conceptual groundwork for the following studies described in Sections 3.2.2 and 3.2.3. We argued that recommendation-centric support introduces a secondary task on top of users' primary decision-making task, namely the review of the AI's recommendation. This review task requires users to reason *backward* from the AI-recommended end result, which is error-prone and leads to inappropriate reliance [91]. In addition, for complex decisions, reasoning backward to validate an AI recommendation can be an effortful "research task", as Burgess et al. [9] put it. Users are unlikely to accept this extra effort on top of their demanding primary task [9, 40] [P3].

As an alternative, we proposed that rather than trying to solve the task for users end-to-end via a decision recommendation, AI could provide more incremental support. The goal is to avoid introducing a secondary task, and instead to support users to reason *forward* through their primary decision-making task.

On the surface, this incremental support seems less ambitious than recommendation-centric support because it appears to do less for users. Our key insight was that in reality, recommendation-centric support does not necessarily lead to less effort than more incremental support. Rather, the difference is that recommendation-centric support induces backward reasoning, while incremental support encourages forward reasoning, which can potentially

address the limitations of recommendation-centric support as identified in Section 3.1. This insight guided the studies in the following sections, where we aimed to identify ways to support pilots' reasoning in a forward direction (Section 3.2.2) and to compare this approach to recommendation-centric support (Section 3.2.3).

Author contributions: The idea for this position paper was mine, and I also wrote the paper. Yuanting Liu and Heinrich Hußmann provided guidance and feedback and edited the final version of the submission.

3.2.2 Continuous Support

This section is based on the publication

> *"**Resilience through appropriation: Pilots' view on complex decision support**" [P3].*

For the studies in this and the following section, we considered *diversions* in commercial aviation as a real-world use case for AI-assisted decision-making. Diversions are when a flight cannot reach its planned destination and has to divert to another airport, e.g. due to a medical emergency on board, a technical failure, or adverse weather conditions at the destination. Diversion decisions are in the responsibility of the pilots and are one of the primary use cases where pilots can imagine AI support [94].

To understand how AI can assist with diversion decisions, we designed two click-dummy prototypes and discussed them with eight professional pilots. The *Global Suggestions* prototype represents a typical recommendation-centric concept, where the system ranks the surrounding airports and recommends up to three of them. To make the recommendations transparent, the underlying decision criteria speaking for and against a particular airport are provided with a color coding in a table view. The idea behind the *Local Hints* prototype (Figure 3.2) on the other hand is to give hints about potential constraints at the surrounding airports, without explicitly recommending an airport. Crucially, the system is meant to be permanently displayed to pilots, even in normal flight when no diversion is imminent. This is supposed to improve pilots' situation awareness and to support their reasoning in a forward direction. During an emergency, pilots can enter an emergency mode to get hints that are tailored to the specific situation.

We found that diversion decisions involve much more than merely the point at which pilots choose the diversion airport. Before this point, during normal flight, pilots constantly aim to maintain situation awareness to be prepared for a possible diversion. They also ensure that there is always a valid plan B to avoid running out of options. After the decision point, pilots continue to check that their current plan is valid. Recommendation-centric support disregards this process nature of diversion decisions and only addresses the point where the actual decision is made. Our findings reveal the importance of continuously supporting the entire decision-making process, as exemplified by our Local Hints concept.

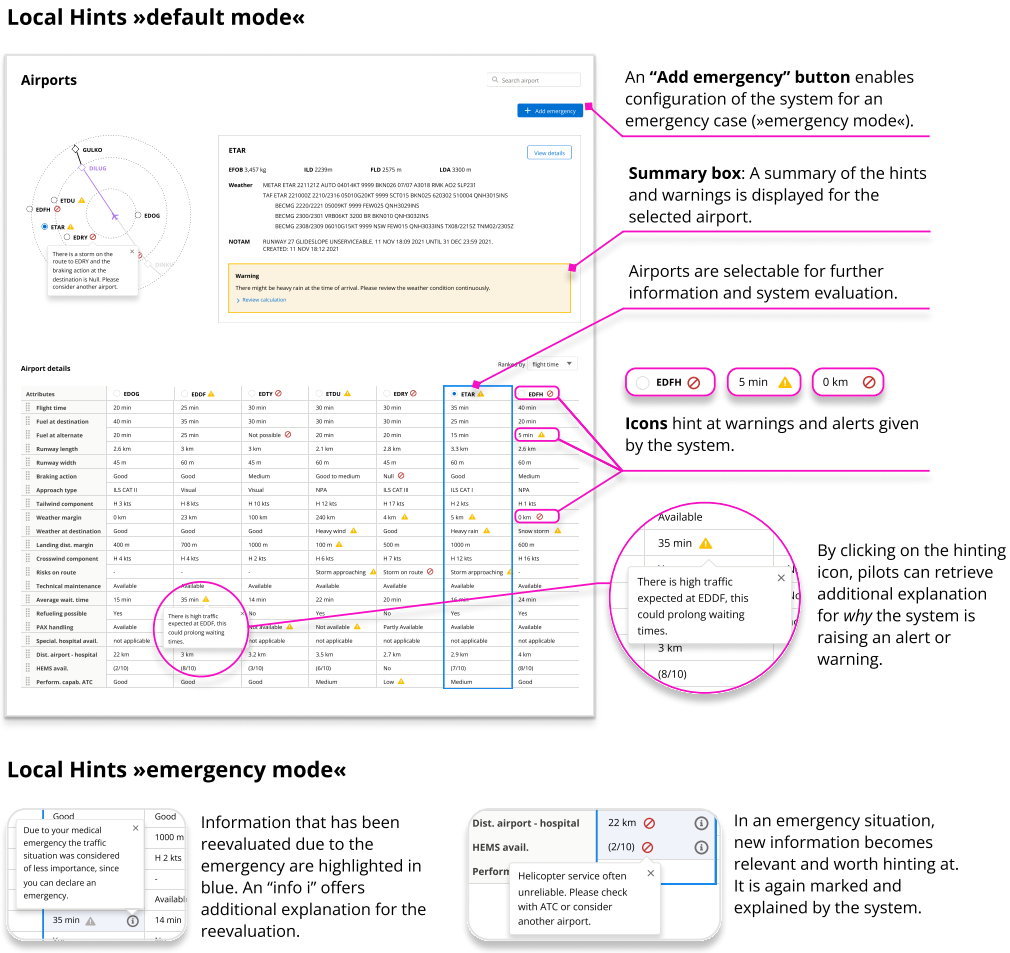

Figure 3.2: Overview of the Local Hints concept. Source: [P3].

We further found that pilots would not blindly trust an AI decision support tool, but they also do not want to be burdened with constantly questioning the correctness of the AI, as mentioned in Section 3.1.3. We found *appropriation* [23] to be a useful lens to make sense of this seeming contradiction. Pilots want to appropriate the AI support according to their current intention, such that the AI complements their reasoning, instead of creating a review task that is not integrated into pilots' decision-making. A more open form of support like the continuous provision of local hints might be easier to appropriate than closed, end-to-end recommendations.

Author contributions: Cara Storath and I contributed equally to this publication. Cara provided the study idea, and I contributed the writing of the paper. The study design and execution, prototype design, and data analysis were joint efforts by the two of us. Yuanting Liu and Andreas Butz provided guidance and feedback and edited the final version of the submission.

3.2.3 Comparison With Recommendation-Centric Support

This section is based on the publication

> ***"Beyond recommendations: From backward to forward AI support of pilots' decision-making process"*** *[P6].*

The results described in Section 3.2.2 showed that continuous support through local hints is a promising approach to support diversion decisions that is viewed favorably by pilots. However, it remained unclear how this approach compares to recommendation-centric support. Clarifying this question by conducting an empirical comparison was the aim of the work described in this section. We designed four versions of an AI-based diversion assistance tool for this mixed-methods study (see Figure 3.3): a recommendation-centric version (*Rec*), similar to the Global Suggestions concept described in Section 3.2.2; a continuous support version (*Cont*), similar to the Local Hints concept described in Section 3.2.2; a combined version that continuously provides local hints during normal flight and recommendations during emergency (*Rec+Cont*); and a baseline version that only presents surrounding airports and their data without AI elements.

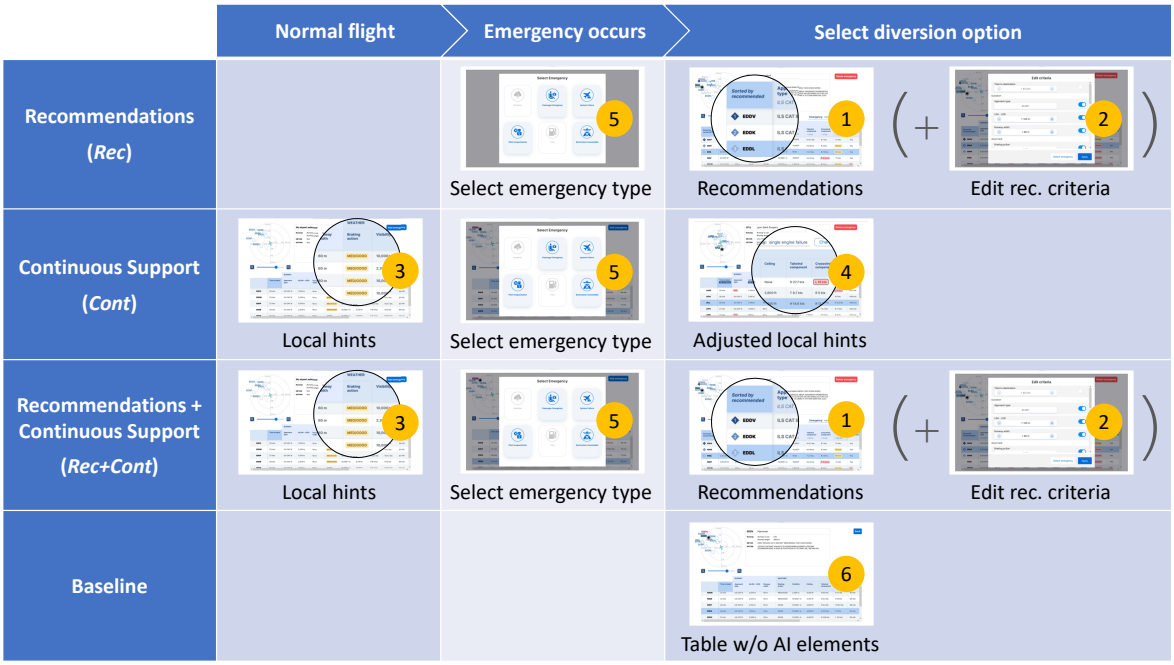

Figure 3.3: Study conditions for empirical comparison between recommendation-centric and continuous support. Source: [P6].

The study was based on three flight simulator scenarios that we validated and refined through a focus group with four professional pilots. Of particular interest was the third scenario, in which one airport—Hanover—would appear to be the best diversion option based on the AI evaluation. However, due to heavy traffic at that airport, which the AI does not consider in

its evaluation, Hanover would not be an optimal choice. We recruited 32 professional pilots for the study, with the diversion assistance version as between-subjects variable. Each pilot had to complete all three scenarios.

We found that the *Rec* version pushed pilots to reason backward, resulting in strong overreliance, as significantly more pilots chose Hanover in the third scenario than with the baseline version. In contrast, continuous support helped pilots to reason more in a forward direction, even when combined with recommendations. Consequently, pilots using the *Cont* and *Rec+Cont* versions where more likely than with the *Rec* version to think beyond the limits of the system in the third scenario and avoid Hanover. However, pilots were prone to fall back into backward reasoning in case of disruptions between normal flight and emergency, which also showed in that *Cont* and *Rec+Cont* participants were still more likely to choose Hanover than those using the baseline version.

Surprisingly, the *Rec* version did not lead to faster decisions than the *Cont* version, as the efficiency gain of directly receiving a recommendation was negated by the need to review the recommendation (backward reasoning). Yet, recommendations did lead to faster decisions in the second scenario with the *Rec+Cont* version, as the continuous support during normal flight allowed pilots to prepare a plan, which was then confirmed by the recommendation. As the recommendation fitted into pilots' reasoning (forward reasoning), there was no need to spend extra effort and time to review it.

Participants' statements in the exit interviews further revealed that pilots' biggest challenge during diversions is not to choose a suitable airport once they have the necessary information. Rather, the challenge is to gather and to integrate the information from multiple sources. Hence, even the baseline version was praised by participants since it conveniently displays the information at a glance. But due to the overwhelming amount of information, participants welcomed AI elements like recommendations or local hints to help them focus on what is relevant. However, recommendations were controversial among participants since some felt that recommendations would disengage them from the decision-making process. Continuous provision of local hints on the other hand was unanimously seen as positive.

Taken together, the results show that continuous support has advantages over the recommendation-centric support paradigm in terms of appropriate reliance, efficiency, and user acceptance. Recommendations can be beneficial, but rather than being the primary functionality of the AI system, recommendations should be embedded such that users engage with them while reasoning forward.

Author contributions: I provided the study idea and designed and conducted the main study. Sebastian Feger had the idea of the focus group and we conducted it together. Lucas Dullenkopf supported me with the design and implementation of the flight simulator scenarios. I designed and implemented most of the diversion assistance system, with support from my students Rulu Liao (interface design) and Lou Süsslin (implementation). I performed the data analysis, with Sebastian supporting as a second coder for the qualitative analysis. I also contributed the writing of the paper and the *process-oriented support* framework described

in Section 3.2.4. Sebastian, Yuanting Liu and Andreas Butz provided guidance and feedback and edited the final version of the submission.

3.2.4 Piecing It All Together: Process-Oriented Support

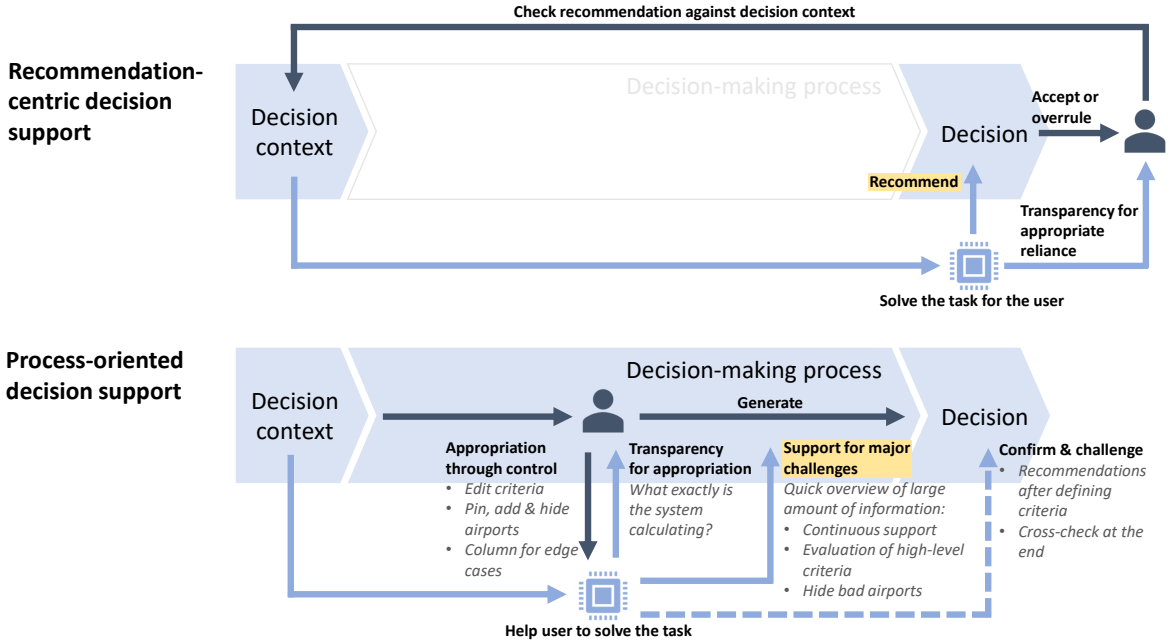

Figure 3.4: Comparison between recommendation-centric and process-oriented decision support. The yellow highlights signify the primary role of the AI in both paradigms. The dashed arrow indicates that recommendations are optional in process-oriented support. The italicised text describes examples for concrete implementations of process-oriented support for the diversion use case. Source: [P6].

Based on the results of Sections 3.2.1–3.2.3, we propose *process-oriented support* as a framework for designing AI decision support that is not recommendation-centric (see Figure 3.4). The framework is not limited to diversions or aviation, but meant to be widely applicable for AI-assisted decision-making in high-stakes applications, where it is crucial that humans remain fully in control. Continuous support can be seen as a concrete implementation of process-oriented support for the diversion use case. Figure 3.4 shows additional possibilities to implement process-oriented support, based on participants' suggestions in [P6].

Core to process-oriented support is to keep users engaged in the decision-making process in a forward direction. The primary functionality of the AI system is not to recommend a finished solution, but to provide support for the major challenges in users' decision-making process, which depend on the concrete application. In the diversion use case for instance, pilots' major challenge is to obtain a quick overview of a large amount of information. The goal is to help users make the decision, rather than making the decision for users.

To make the system resilient against imperfect AI inferences, a key component of the framework is to enable users to appropriate the system according to their momentary intentions. Appropriation can be facilitated through both transparency and control. Transparency is required to help users understand how well the system actions are aligned with their current intentions. As we discuss in more detail in [P6], this differs from the common notion of transparency for reliance calibration. Control is needed to steer the system when its actions do not fully align with users' intentions. This prevents a situation where the system is useful when it is correct, but useless when not. Note that this notion of control differs from interactive machine learning [3, 25], where users provide feedback that the system can learn from. Control for appropriation on the other hand is about users' momentary intentions that are heavily context-dependent and not necessarily learnable.

Process-oriented support might be able to address all of the limitations of recommendation-centric support identified in Section 3.1. In Section 3.1.1, we found that with recommendation-centric support, overreliance tends to increase over time, likely because users become less engaged as they familiarize with the AI system. This might be less of a problem with process-oriented support. Since the AI does not make the decision for users, users necessarily have to remain engaged in the decision-making process.

The results in Section 3.1.2 showed that users are able to rely appropriately on recommendation-centric support in easy decisions, but not in hard decisions where they are highly uncertain about the correct answer. The problem is that recommendation-centric support often does not help users to reduce their uncertainty and to develop a better intuition for the decision at hand. With process-oriented support, the decision-making is led by users' intuition and intentions. Ideally, any AI inference should build upon and help users develop their intuition about the decision task. In turn, this might help users to make better sense of how the AI's outputs fit into the decision context, leading to more appropriate reliance, as with the *Cont* and *Rec+Cont* variants in Section 3.2.3.

Lastly, in Section 3.1.3, we found that recommendation-centric support can be a burden for users due to the need to review the recommendations, which is especially effortful when the decision is complex. The problem is that users are not involved in the generation of end-to-end recommendations, meaning they have to reconstruct the recommendation from an external perspective. With process-oriented support, the aim is to integrate AI inferences into users' own decision-making process, which minimizes the extra effort of reviewing AI outputs. We observed this in Section 3.2.3 with the *Rec+Cont* version, where the recommendation served as a confirmation of users' own reasoning and led to a faster decision, while in the *Rec* version, pilots had to first review the recommendation, which slowed them down.

Chapter 4

Discussion

4.1 Related Concepts and Ideas

While the majority of research in AI-assisted decision-making takes a recommendation-centric approach, there is also a small, but growing body of work that explores alternative approaches. For instance, Lindvall et al. [54] designed a system for cancer assessment which, instead of marking images as containing cancer or not, helps pathologists to quickly identify and navigate to potentially interesting areas of an image to review. Zhang et al. [105] redesigned an existing tool for sepsis diagnosis to make actionable recommendations such as specific laboratory tests that can reduce the uncertainty of the diagnosis, instead of classifying whether a patient is septic or not. Studies like these give concrete examples for how AI can support human decision-making by other means than end-to-end recommendations and demonstrate the viability of these solutions. However, they represent point designs that can be hard to apply to other settings, and it is unclear how their effectiveness compares to recommendation-centric support.

In an attempt to move beyond point designs, Miller [60] proposed the concept of *Evaluative AI*, where the goal is to help users generate and evaluate different hypotheses, while leaving the choice between the candidate hypotheses to users. Evaluative AI can be considered a special case of process-oriented support, specifically for decision tasks where the main challenge is to compare several hypotheses, such as making medical diagnoses. So far, the concept has only been proposed as a position paper, without implemented systems and empirical studies to back it up.

Lately, another stream of work that aims to overcome the limitations of recommendation-centric support emerged under the term *human-centered explainable AI* (HCXAI) [27]. The goal with HCXAI is to shift away from explaining how the AI model technically generated its recommendation, toward providing explanations that are meaningful to the decision task itself. For example, Yang et al. [100] supplemented AI recommendations with references to evidence in the medical literature that supports or contradicts the recommendation. Ehsan

et al. [26] explored including socio-organizational factors into explanations in a sales use case. These approaches give users more context for their decision and help them to better reconcile the AI recommendation with the decision context. The recommendations become one part of a more holistic support instead of the primary functionality of the system. I consider HCXAI and approaches like process-oriented support that aim to identify alternative roles for AI support to be complementary on the path toward AI decision support that truly complements and augments human reasoning.

4.2 Positioning Within the Broader Human-Centered AI Landscape

Beyond AI-assisted decision-making, this thesis can be situated within the more general research field of *human-centered AI* (HCAI) [81]. Calls for developing AI that is human-centered have become commonplace [48, 52, 63, 76, 95, 96], but the understanding of what human-centeredness means in AI systems can diverge considerably [16]. For some, "human-centered" may primarily mean interacting with humans and seeking technical solutions to address human needs, while others emphasize the importance of human-centered design of AI applications. With the work in this thesis, I strongly subscribe to the latter understanding of HCAI, mostly informed by my study of a complex, high-stakes domain like aviation, where tolerance for mistakes is low, but potential for mistakes is high. In such a domain, addressing shortcomings of AI systems with more AI inferences (e.g., detection of user states, or interpretation of user context) is likely to introduce even more sources of error, especially given that today's machine learning-based AI systems are essentially pattern recognizers without real understanding of our world [30].

It appears more promising to me, at least in the short term, but likely also in the long term [93], to address the imperfections of AI through careful design informed by a deep understanding of human needs. The high-level ideas underlying the work in this thesis have been well articulated by Shneiderman [81]. First, when designing AI applications, it is helpful to break away from the urge to replicate human capabilities with AI. In successful applications, AI frequently assumes a well-defined, clearly scoped functionality that can differ significantly from human work [80]. Second, the widespread call for human-in-the-loop solutions reflects a thinking where AI systems are designed with as much autonomy as possible as a starting point; the human is then placed back into the loop to act as a fallback for the AI's limitations [29]. This often results in AI-centered systems, despite claims of pursuing human-centered AI, as Woods eloquently put it: "*The road to technology-centered systems is paved with user-centered intentions.*" [73]. As Shneiderman argues, it may be more useful to think of *AI-in-the-loop*, where the starting point is the human work and how AI can fit in there [81]. Both ideas—AI functionality beyond replicating human capabilities, and AI-in-the-loop—are reflected in the continuous support concept in Sections 3.2.2 and 3.2.3. Rather than mimicking a human co-pilot, the system continuously displays helpful information in a way that fits into pilots' decision-making process.

4.3 On Trust and Reliance

The attentive reader might have noticed that I did not address trust in this thesis; instead, I focused on reliance. As trust is one of the most prominent constructs in AI-assisted decision-making [90] and HCAI in general [20, 82], a dedicated section about my reasons for this decision seems appropriate. The first reason, as argued by Dorsch and Deroy [24], is that in high-stakes applications, trustworthiness may be a misguided objective for the development of AI systems, since AI does not posses moral agency and accountability. Instead, reliability is what is required. The second reason is that a central aspect of common definitions of trust is a situation of vulnerability as precondition for trust to exist [90]. Yet, I argue that for high-stakes applications, one should strive to minimize users' vulnerability to imperfections of AI, which implies that essentially trust should not be required.

To elaborate on the second reason, I suggest that rather than asking users to trust AI, high-stakes AI applications should be resilient against AI mistakes (see Section 3.1.3). Ideally, the cost to the user should be minimal when AI makes mistakes. If that is not possible, users should be able to judge when they want to rely on AI to perform certain tasks, based on an understanding of whether the cost of imperfect AI performance is acceptable in a specific situation. For instance, if an imperfect result is good enough or easily correctable for the user, the user may still want to rely and iterate on the imperfect AI output. Conversely, if the cost of an AI mistake is too high, the user should be able to easily recognize this and dismiss the AI. This puts users in control and never leaves them vulnerable to the possibility of AI mistakes. To put it a little provocatively: trust is good, control is better.

4.4 Limitations and Future Work

When exploring alternatives to recommendation-centric support (Section 3.2), I mostly focused on the *roles* AI could assume in AI-assisted decision-making. While the diversion assistance system provided transparency and control mechanisms, they were not the focus of my work. Yet, the results emphasized the importance of enabling appropriation of AI tools through transparency and control. Future work should investigate further how to facilitate appropriation in AI-assisted decision-making.

Another obvious direction for future work is to study how process-oriented support applies to other use cases and domains than diversions in aviation. Related studies, especially in the healthcare domain, point to very similar concerns to those expressed by pilots around recommendation-centric support [9, 40], as well as users' desire for AI to support more intermediary stages of their decision-making process [101, 105]. Therefore, and given that the process-oriented support framework is kept fairly general, I argue that the framework also applies to other high-stakes decision tasks. While I am confident that the framework can already be useful in its general form presented in Section 3.2.4 by emphasizing appropriation and supporting the decision-making process, future work can explore how it can be con-

cretized for specific use cases. In addition, there is a wealth of other helpful AI support roles that future work can explore, as other decision tasks may offer different opportunities for AI support. Future work should further aim to better understand when either recommendation-centric or process-oriented support is preferable. For example, the results in Section 3.1.2 suggest that for easy decisions, recommendation-centric support may very well be an effective form of support.

As a third line of future work, it is important to recognize that in this thesis, I take a highly positive view of human expertise. However, as evidenced by the rich body of work on human cognitive heuristics and biases [43, 87], human decision-making can be flawed, which can also manifest when humans take the lead in interactions with AI [62, 70]. An interesting research question, therefore, is how AI can help mitigate human decision errors. For instance, AI can be used to detect and understand sources of human error [104]. Research on human decision-making has also uncovered conditions delineating when humans are likely to make mistakes or to display true expertise [44]. Building on these results is crucial to understand how AI can mitigate human errors while promoting human expertise in AI-assisted decision-making.

Finally, the work in this thesis remains relevant with the current surge in large language models and generative AI. On the one hand, the recent breakthroughs in generative AI could enable powerful novel capabilities for AI-assisted decision-making [28]. On the other hand, generative AI could aggravate the problems identified in this thesis, for example through end-to-end recommendations for even more complex problems [83], or through even more complex failure modes [86]. It remains to be seen how the potential of generative AI can be effectively leveraged for AI-assisted decision-making, but I expect that appropriation and aiming to help users solve their task, rather than solving the task for them, will remain important strategies.

Chapter 5

Conclusion

In this thesis, I investigated the limitations of recommendation-centric support in minimizing the impact of imperfect AI performance in AI-assisted decision-making. I further explored how reconsidering the role of AI from solving the task for users, to helping users to solve the task, is a promising path to benefit from imperfect AI in high-stakes decisions. Rather than sophisticated algorithms, this approach, which I captured in my framework for process-oriented support, first and foremost requires a deep understanding of users' decision-making processes and challenges.

My research contributes to the growing, but still small, body of work that challenges the assumption that AI-assisted decision-making should be recommendation-centric. In contrast to related work, which is mostly concerned with the healthcare domain, I studied a use case from aviation, a domain that is rarely studied in HCI. By finding that pilots share many of the same concerns as clinicians, I contribute to the generalizability of recent results beyond the healthcare domain. Related work is also often formative, in that studies uncover problems with recommendation-centric support and identify opportunities for alternative forms of support at an abstract level, but concrete solutions that exploit these opportunities are rare. I contribute such a concrete solution for the diversion use case in the form of continuous support, and captured the generalizable elements of it in the process-oriented support framework. Most importantly, I conducted an empirical comparison between continuous and recommendation-centric support, contributing some of the first evidence that alternative forms of support may be more effective at supporting human decision-making than recommendation-centric support in certain use cases.

I argue that my results are also relevant for the broader field of human-centered AI. Despite its impressive capabilities, AI is always imperfect. We cannot ignore this and design AI-driven systems as if AI was perfect. Yet, this seemingly trivial statement is often not given enough attention, which usually shows in that an AI system is designed to solve users' tasks for them. Solving tasks for users is desirable if you can always solve them perfectly, but that is rarely the case. Due to the focus on the expected gains when AI performs well, the potential for imperfect AI performance becomes an afterthought, addressed by assigning

users the difficult role of a fallback for AI. In AI-assisted decision-making, this approach is embodied by the predominant recommendation-centric support paradigm, and the goal of calibrating users' reliance on end-to-end decision recommendations. A similar tendency can be observed for other human-centered AI applications. Based on my research, I suspect that for other AI applications as well, it might be helpful to explore more carefully designed incremental AI support that keeps users engaged in their tasks, rather than using AI to solve tasks end-to-end by default.

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Eidesstattliche Versicherung

(Siehe Promotionsordnung vom 12.07.11, § 8, Abs. 2 Pkt. 5)

Hiermit erkläre ich an Eidesstatt, dass die Dissertation von mir selbstständig und ohne unerlaubte Beihilfe angefertigt wurde.

München, den 26.09.2024

Zelun Tony Zhang