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Insights from uncrewed air traffic management

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RESEARCH

Towards a unified taxonomy for algorithmic transparency: insights from uncrewed air traffic management

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Abstract

With the rapid advancement of drone technology, their applications have become increasingly widespread. However, the integration of drones into the airspace also poses risks to crewed aircraft, particularly around airports. To address this issue, a highly automated Uncrewed Air Traffic Management (UTM) system is being developed. Since fully safe and reliable automation does not exist yet, UTM still requires human supervision to enhance the overall system safety and reliability. Some form of "seeing-into" transparency may be necessary to help operators better understand the limitations and behavior of the automated UTM system. As UTM is a novel concept, research on transparent UTM is limited. Many efforts have been made in other fields, but there still remains a lack of consensus on what transparency entails, particularly for algorithmic systems. Therefore, this article first presents a unified taxonomy for algorithmic transparency, with operational, domain and engineering transparency introduced as its core concepts. From the taxonomy, twenty UTM transparency elements and their corresponding visual prototypes were then designed, which also showcases how the taxonomy can be applied in practice. A survey-based user study was conducted to collect the opinions of air traffic controllers and drone experts regarding the designed elements and prototypes. Results indicate that transparency is deemed imperative for UTM, especially in scenarios featuring automation failure. It also reveals that operational transparency is generally preferable over engineering transparency in nominal operations. Participants were asked to group the designed elements, and their results closely aligned with the structure of the proposed taxonomy.

Keywords Uncrewed air traffic management · Transparency taxonomy · Operational transparency · Engineering transparency · User study

1 Introduction

In recent years, drone usage has rapidly increased in various domains, such as agriculture, delivery, surveillance and entertainment. In aviation, it is expected that a large number of drones will share the airspace with crewed aircraft in the near future (FAA 2024; SESAR 2016). To safely cope with the increased number of drones, Uncrewed Air Traffic Management (UTM) was proposed and is currently under development (Kopardekar et al. 2016; Mohamed Salleh and Low 2017; FAA 2022, 2023; SESAR 2023). As UTM is a novel concept, a universally recognized standard has not yet been firmly established (Lieb and Sievers 2024). Various solutions for UTM are being actively explored around the world, such as American UTM (FAA 2023), European U-space (SESAR 2023) and Chinese UTMISS (Guan et al. 2024).

Despite the differences among these solutions, there is a consensus that, unlike traditional Air Traffic Management (ATM), UTM will be built from the ground up to rely on high levels of automation. This is because drone traffic often involves much higher flight densities and could be far more complex than existing crewed air traffic. It is nearly impossible for humans to manually control such a large number of drones simultaneously. However, relying heavily on automation may also be problematic, especially in the low-altitude airspace around airports where drones and crewed

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aircraft coexist. Any deficiencies or limitations in automation could increase the risk of collisions between drones and crewed aircraft, posing a threat to human lives. Therefore, although UTM is highly automated, it still requires human supervision, at least in the Controlled Traffic Regions (CTR) around airports, to enhance the overall safety and reliability.

However, a higher level of automation generally makes it more difficult for human supervision (Bainbridge 1983; Endsley 2023). Operators may be unable to understand the automation decisions and their underlying reasoning without any additional support. In this case, they are left no choice but to either blindly follow the actions suggested by automation or manually control everything due to a lack of trust in automation. In UTM, if a drone's behavior is completely unpredictable and uninterpretable, it will pose a huge threat to crewed aircraft and should not be allowed to operate around airports (EASA 2021). To address this issue, some form of "seeing-into" transparency may be needed that presents information and/or explanations about the inputs, outputs and internal processes of automation (Chen et al. 2020; Jamieson et al. 2022; Bhaskara et al. 2020; van de Merwe et al. 2024). UTM operators should be aware of the intents and goals of both drones (e.g., where are their destinations?) and the automated UTM system (e.g., what automated services are provided?). Safety-related metrics, such as Closest Point of Approach (CPA), could also be disclosed to help operators monitor the situation (Papadopoulos et al. 2024).

Since UTM is not fully developed, direct research on transparent UTM is limited (Pongsakornsathien et al. 2021; Janisch et al. 2022, 2023, 2024; Schwoch et al. 2024; Teutsch and Petersen 2024). In other fields, many studies have been conducted to explore the design and impact of transparency (Bhaskara et al. 2020; Arrieta et al. 2020; van de Merwe et al. 2024), such as Chen's Situation Awareness–based Agent Transparency (SAT) model (Chen et al. 2014, 2018), Ecological Interface Design (EID) (Vicente and Rasmussen 1992; Kilgore and Voshell 2014) and Explainable AI (XAI) design frameworks (Wang et al. 2019; Mohseni et al. 2021). Previous research also suggested positive effects of transparency on human performance in one-to-many drone operations (Zhang et al. 2021) and multi-unmanned (air, ground, and sea) vehicle mission planning (Mercado et al. 2016; Stowers et al. 2020; Bhaskara et al. 2021). However, these works generally stem from different perspectives on transparency, and there remains a lack of consensus on what transparency entails, particularly for algorithmic systems. In the UTM context, it is still unclear how to achieve transparency and how transparency could affect the collaborative operations between drones and crewed aircraft. Therefore, this article, an extension of our previous work (Zou and Borst 2023), aims to propose a unified taxonomy for algorithmic transparency to integrate different perspectives. Based on the taxonomy, various information elements and visual prototypes are devised for transparent UTM. According to the designed elements and prototypes, a survey-based user study is conducted to validate the proposed taxonomy and explore operators' needs and preferences for transparency in different UTM scenarios.

The article is structured as follows. In Sect. 2, we review different perspectives and related works on transparency and propose a unified transparency taxonomy. In Sect. 3, based on the taxonomy, we devise twenty transparency elements and fourteen corresponding visual prototypes for UTM. In Sect. 4, we outline the user study methodology, introducing the questionnaire structure and participant background. In Sect. 5, we present the results collected from participants, analyzing their needs and preferences regarding the designed transparency elements and prototypes. In Sect. 6, we discuss the insights gained from the user study and future research directions.

2 Transparency taxonomy

Much research has been conducted to enhance automation transparency (Bhaskara et al. 2020; Gunning and Aha 2019; Arrieta et al. 2020; CORDIS 2022; van de Merwe et al. 2024), but their methods are usually diverse and lack a unified guide or framework. For example, the Single European Sky ATM Research (SESAR) projects ARTIMATION (Hurter et al. 2022), MAHALO (Westin et al. 2022) and TAPAS (Papadopoulos et al. 2024) all explored methods to achieve transparency in tactical ATM operations, yet ended up with different design choices. Some studies (Mercado et al. 2016; Bhaskara et al. 2021; Papadopoulos et al. 2024) emphasized improving operator situation awareness in human-automation collaboration through transparency. They usually followed Endsley's situation awareness theory (Endsley 1995) and Chen's Situation Awareness–based Agent Transparency (SAT) model (Chen et al. 2014, 2018). In contrast, other studies (van Paassen et al. 2018; Westin et al. 2022; Dikmen 2022) focused on revealing the physical and intentional constraints of work domains to establish a common ground for both humans and machines. This approach was mainly based on Ecological Interface Design (EID) (Vicente and Rasmussen 1992) and Cognitive Work Analysis (CWA) (Vicente 1999). Additionally, some other research (Saraf et al. 2020; Hernandez et al. 2021; Hurter et al. 2022) seemed to draw inspiration from the Explainable AI (XAI) community, aiming to design explainable models to elucidate the inner workings of automation.

Although transparency can be approached from different perspectives, the overall goal is to support human supervision of automation and ensure humans remain in the loop. The ecological approach is developed for improving operator situation awareness as well (Mulder et al. 2019), while the XAI methods are implemented to foster the trust and acceptance of human users (Hernandez et al. 2021). Essentially, transparency is about disclosing relevant information to humans, and thus the focus of transparency may shift depending on the needs and background of the user (Langer et al. 2021). Operators may be more concerned with how automation affects operational scenarios and situations, whereas policymakers may need to assess whether an automated system is trustworthy and reliable for real-world application. Different transparency needs may lead to different methods and perspectives on transparency.

However, even for the same type of users, their transparency needs may still be different depending on personal preferences, expertise, and specific contexts (Chen et al. 2018; Miller 2019). In addition to situation-related information, operators may also seek to understand the inner workings of automation, especially when automation behaves unexpectedly (Janisch et al. 2022). To meet user needs across all scenarios, it seems necessary to adopt an overarching approach to disclose as much information as possible. Users can thus access the information they need on demand. Therefore, we attempt to devise a unified *transparency taxonomy* to summarize different perspectives on transparency. The proposed taxonomy could also serve as a guide for transparency design.

As this research focuses on tactical UTM operations within CTR around airports, we primarily investigate the needs and preferences of operational users, such as Air Traffic Controllers (ATCos) and drone experts, rather than those of policymakers or system developers/designers in our survey-based user study.

2.1 Perspectives on transparency

Three main perspectives can be summarized from the literature: *user-centered* (Lyons 2013; Chen et al. 2014; Wang et al. 2019; Springer and Whittaker 2020), *model-centered* (Lundberg and Lee 2017; Juozapaitis et al. 2019; Brandao et al. 2021) and *ecology-centered* (Vicente and Rasmussen 1992; Borst et al. 2015; van Paassen et al. 2018).

From a user-centered perspective, transparency information should be presented in accordance with user demands, limitations, preferences and expertise (Wang et al. 2025). Lyons' human-robot transparency model (Lyons 2013) defines various types of information that need be presented to humans, such as robots' tasks, purposes, decision-making processes and environmental perceptions. To avoid overwhelming users, transparency is generally divided into different levels, enabling a progressive and incremental disclosure of information (Springer and Whittaker 2020). For example, corresponding to the three levels of situation awareness defined by Endsley (1995); Chen et al. (2014) designed three levels of transparency in their SAT model: Basic Information (Level 1), Rationale (Level 2) and Outcomes (Level 3). In practice, these transparency levels are usually combined in visual and/or textual presentations (Stowers et al. 2020). However, information revealed by the SAT model might be insufficient in some cases. When automation fails or behaves unexpectedly, users may seek more information about the agent's internal process (i.e., *how* the agent makes decisions) to understand what happened, why it happened, and how to resolve it Brandao et al. (2021); Liu and Brandão (2024). This type of information is not explicitly reflected in the SAT model.

The model-centered approaches are mostly developed in the XAI community, aiming to construct explainable models that are readily comprehensible to humans. As technology advances, automation becomes increasingly complex and difficult for humans to understand, such as neural networks and reinforcement learning. XAI was thus introduced to enhance the explainability of advanced AI models and algorithms (Gunning and Aha 2019). Many approaches have been developed, including Local Interpretable Model-agnostic Explanations (LIME) (Ribeiro et al. 2016) and Shapley Additive Explanations (SHAP) (Lundberg and Lee 2017). The main focus of the model-centered perspective is to thoroughly dissect the internal processes of models and explain them in human-understandable terms. In recent years, user-centric XAI has gained increasing attention from researchers since explanations should also consider user expertise and needs (Arrieta et al. 2020). For example, a theory-driven user-centric framework for XAI has been proposed (Wang et al. 2019), aiming to support human reasoning and mitigate cognitive biases through tailored explanations.

XAI has also been applied in ATM to improve the operator trust and acceptance of AI-based ATM systems (Saraf et al. 2020; Hernandez et al. 2021; Xie et al. 2021). As the core of UTM is to guide drones to their destinations while avoiding conflicts with crewed aircraft, a centralized conflict-free path-planning algorithm is expected to be implemented to achieve this goal (Janisch et al. 2024). Therefore, in this study, we primarily focus on transparent path planning. Many pathfinding visualizers have been developed to portray the search processes of various path-planning algorithms (Sturtevant 2023; Xu 2023; Toma et al. 2021; Zheng et al. 2024), which could also serve as references for our work.

The ecology-centered approach is derived from EID (Vicente and Rasmussen 1992; Rasmussen and Vicente 1989) and CWA (Vicente 1999). It puts emphasis on visualizing the physical and intentional constraints governing the work domain, revealing its deep structure for achieving *domain* transparency (van Paassen et al. 2018; Borst et al. 2015). This approach can provide a common ground for user-centered and model-centered approaches since both humans and machines should obey the same domain constraints. Technically, the ecological approach seeks to discover the most effective way for presenting domain constraints, fully utilizing the human ability for direct perception (Vicente and Rasmussen 1990; Michaels and Carello 1981). For instance, in drone flight monitoring, drone endurance can be depicted as a virtual battery (Fuchs et al. 2014) or alternatively represented as available maneuvering space (an elliptical space) (Janisch et al. 2022). The latter may be more intuitive for humans in the context of path planning since it builds a direct link between the constraint and the solution: the path should be within the maneuvering space to satisfy the endurance constraint.

The ecology-centered approach could provide users with deeper insights into the *solution space* of a task, fostering a clearer understanding of the feasibility and robustness of solutions as well as serving as input/output feature spaces for human intervention. The ecology-centered approach has yielded many promising results for ATM and aviation (Borst et al. 2017; van Paassen et al. 2018; Mulder et al. 2019; Borst et al. 2019; Velasco et al. 2021). In essence, human and automated agents alike are constrained by the same fundamental laws and causalities that govern the work domain. Contextualizing machine intentions can enhance the comprehension of their underlying motives.

While these three perspectives differ from one another, they are connected when considering a triadic semiotic perspective on socio-technical systems (Flach 2017), as depicted in Fig. 1. The model-centered design identifies what content about machines can be revealed, including implemented algorithms, internal processes, and reasoning mechanisms. The user-centered design determines how the information should be conveyed to humans, taking the goals, skills and preferences of human users into account. The ecology-centered design highlights domain constraints, such as laws of physics, principles and dynamics. The behavior of both humans and machines should be bounded by these constraints. The interface acts as a bridge, facilitating interactions and communications between humans and machines. The transparency information is usually presented on an interface, conveying the state of and constraints within the environment, what the machine does, and what the users may need and/or prefer.

2.2 Transparency in ATM and UTM

In the fields of ATM and UTM, automation transparency is gaining increasing attention. SESAR 3 Joint Undertaking initiated five projects (SESAR 2022) to address transparency issues of AI in ATM. The most relevant projects for our use case in tactical operations are ARTIMATION (Hurter et al. 2022), MAHALO (Westin et al. 2022) and TAPAS (Papadopoulos et al. 2024).

ARTIMATION proposed three levels of transparency: (1) Black Box, (2) Heat Map and (3) Storytelling. The Black Box showed only the proposed solution along with the instructions for execution. The Heat Map presented what trajectory was explored by the algorithm and whether it was good or bad. The Storytelling provided a step-by-step preview of the proposed solution while also explaining alternative possibilities. A user study of ARTIMATION (Hurter

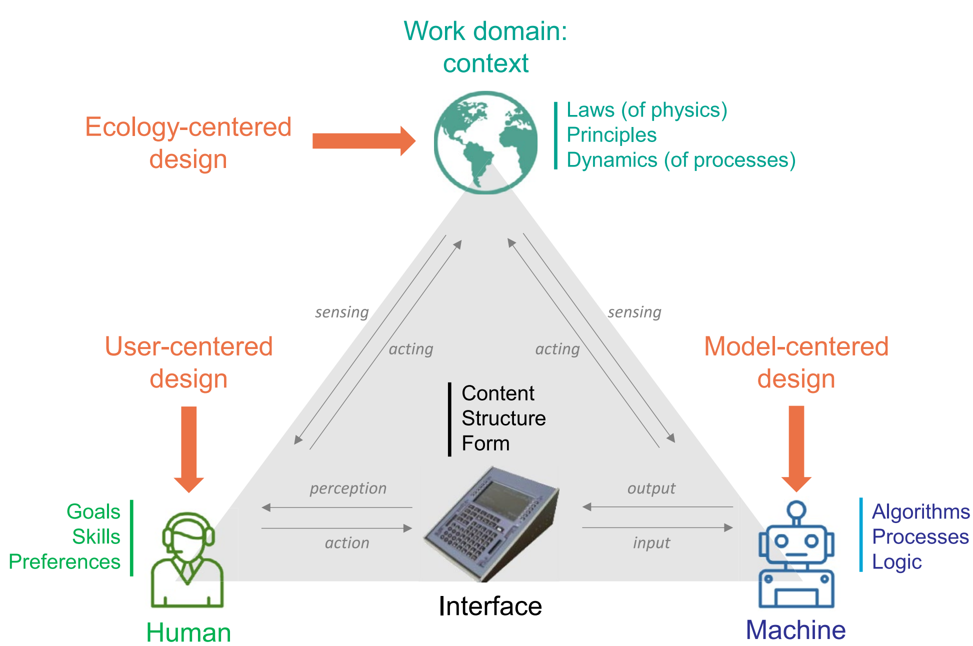


Fig. 1 Triadic perspective on transparency, capturing user-, model-, and ecology-centered perspectives

et al. 2022) showed that ATCos preferred the Black Box because of the time pressure issue. They favored the simplest interface design for Air Traffic Control (ATC). They also thought that transparency would be beneficial for the initial training period to increase the understanding and trust of ATCos. In real operations, transparency should be hidden by default but remain accessible.

MAHALO devised three transparency conditions: (1) Vector Line, (2) Vector Line and Solution Space Diagram (SSD) and (3) Vector Line, SSD and text-based explanation. The Vector Line, indicating flight speed and heading, represented the proposed solution for conflict resolution. The text-based explanation clarified the target Closest Point of Approach (CPA) and the agent's purpose. The core of MAHALO is the SSD, which could *visually* explain whether the proposed solution is feasible and how robust it is. MAHALO also explored the personalization of AI to align its advice more closely with ATCos' preferences. A user study of MAHALO (Westin et al. 2022) indicated that personalized advisories were more easily accepted by ATCos than transparent advisories and that greater personalization may reduce the need for transparency.

TAPAS did not have explicit transparency levels in their Conflict Detection & Resolution (CD&R) use case. Instead, it mainly utilized text-based tables to present detailed information and possible solutions associated with CD&R, such as geometrical features of the CPA detected and suggested actions along with their expected outcomes. Their transparency design is similar to Chen's SAT model, which is also based on Endsley's situation awareness theory (Endsley 1995). A user study of TAPAS (Papadopoulos et al. 2024) suggested that providing information that maintains operators' situation awareness may be sufficient to develop trust in AI, even in high-stakes fields like ATC.

To summarize, these projects all had different perspectives on addressing the same problem (i.e., CD&R in ATC). Each of them developed its unique transparency elements, covering different visual and textual parameters representing the tactical ATM context. Nonetheless, some similarities were found in that they all center transparency information around *solutions*, revealing information about the proposed solution (e.g., planned actions) and the expected outcomes (e.g., predicted minimum separation).

Similar to ATM, although UTM has not been fully established yet, some research has already started to explore how to increase the transparency of UTM based on their envisioned operational concepts and designed simulators (Pongsakornsathien et al. 2021; Janisch et al. 2022). As UTM is expected to rely on high levels of automation, the transparency issue may be more urgent than it is for ATM. Without transparency, operators may struggle to understand the behavior and limitations of automation, leading to a loss of situation awareness (Janisch et al. 2022; Endsley 2023). Transparency research on one-to-many drone operations and multi-unmanned vehicle mission planning indicated positive effects of transparency, such as increased understanding and greater performance (Stowers et al. 2020; Planke et al. 2020; Bhaskara et al. 2021; Zhang et al. 2021, 2024).

2.3 Proposed transparency taxonomy

To integrate the three perspectives on transparency in a pragmatic way in a path-planning context, a unified taxonomy is devised based on Fig. 1, and is shown in Fig. 2. Referring to the European Union Aviation Safety Agency (EASA) AI Roadmap (EASA 2023), two fundamental concepts are proposed: *operational* transparency and *engineering* transparency. Operational transparency reveals

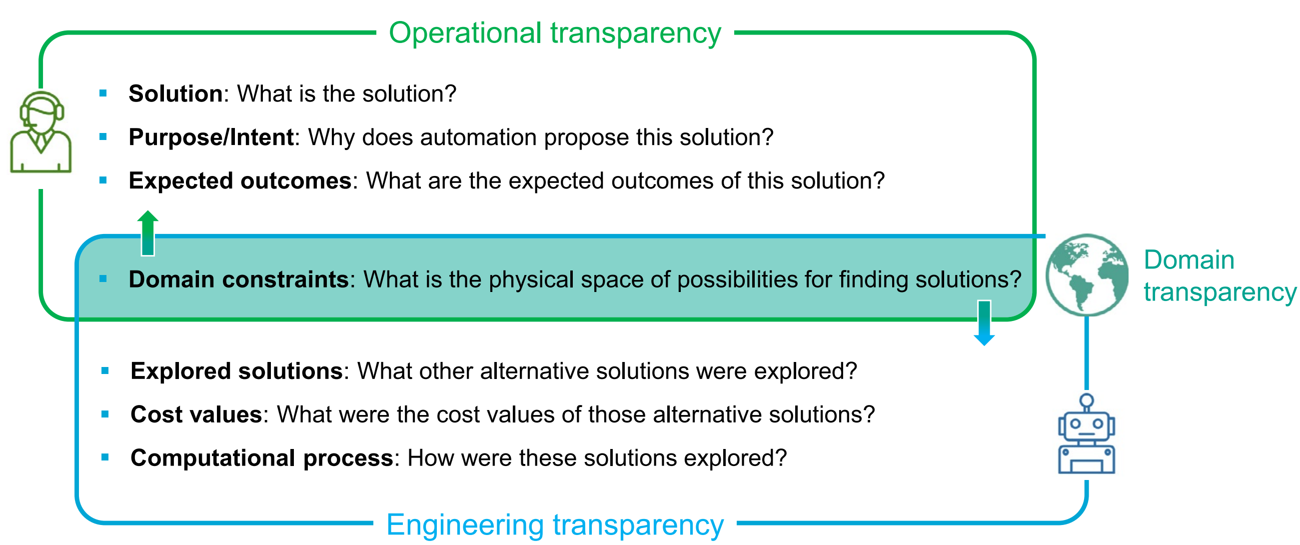


Fig. 2 Proposed unified taxonomy for algorithmic transparency, integrating user-, model-, and ecology-centered perspectives

(real-time) information about system status, goals, activities, and environmental impacts, directly supporting operational users in maintaining situation awareness, making informed decisions, and responding effectively to evolving conditions. Engineering transparency, in contrast, discloses system internal mechanisms, such as reasoning, exploration, evaluation, and decision-making processes, enabling users to develop a deeper understanding of system behavior. When operational transparency is sufficiently provided, operational users may have less need for engineering transparency (Papadopoulos et al. 2024). This is because operational transparency equips users with the information they need to monitor and manage tasks effectively, reducing the necessity to understand the underlying engineering details. However, when unexpected events occur, such as automation failures, engineering transparency may become essential to help users identify the underlying causes and alleviate the stress associated with confusion. Domain transparency, as a shared foundation in the middle, serves to connect the operational and engineering transparency. By clarifying the boundaries of feasible solutions, domain transparency helps users understand why the proposed solution (operational) and the exploration process (engineering) are both constrained within a certain range.

The transparency taxonomy comprises seven categories, ranging from functional purpose and operational impact to operational boundaries and inner physical structure. This type of organization is inspired by Rasmussen's Abstraction Hierarchy (AH) used in CWA and EID (Rasmussen 1985; Rasmussen and Vicente 1989; Vicente and Rasmussen 1992; Vicente 1999). The AH is structured based on typical human top-down, problem-solving strategies, starting at the desired system output (= functional purpose) and progressively descending towards the physical components of a system. As suggested by Springer and Whittaker (Springer and Whittaker 2020), progressive disclosure may be needed for algorithmic transparency. In the proposed taxonomy, the transparency categories are organized hierarchically. From the Solution category to the Computational Process category, deeper algorithmic information is progressively revealed.

The Solution category emphasizes that the algorithm's solutions should be clearly presented to users. For example, a path plan may include a sequence of actions, and users should be informed of when and where each action will take place. The Purpose/Intent category aims to reveal the algorithm's objective. This type of information will be complex if the algorithm has multiple objectives with varying weights. The Expected Outcomes help users assess the quality of the solution and decide whether to accept it or not. This decision depends not only on algorithm optimizations but also on user preferences. The Domain Constraints category lies at the intersection, forming solution spaces to explain the feasibility and robustness of solutions (operational) and also serving as a basis for system computation (engineering). The Explored Solutions indicate the algorithm's exploration results in addition to the final optimal solution. The Cost Values reflect the algorithm's criteria for evaluation and comparison. The Computational Process represents the algorithm's underlying process for finding a solution. In search-based path planning, it mainly refers to the search process. Please note that a transparency category is not entirely equivalent to a transparency level. A level may contain elements from one or more categories.

The proposed operational transparency categories can be regarded as a variant of the SAT model. As indicated by Bhaskara et al. (2021), the projected outcomes (Level 3) in the SAT model may not necessarily represent a higher level, but rather a type of information, which is in line with the concept of our taxonomy. Different from the SAT model (Chen et al. 2014) and Lyons' human-robot transparency model (Lyons 2013), the proposed taxonomy is organized around *solutions*, with each category shedding light on a distinct aspect. This approach strengthens the interconnections between the various transparency categories, highlighting its hierarchical structure. The operational transparency categories also exhibit a correspondence with the engineering transparency categories, such as Solution to Explored Solutions, Purpose/Intent to Cost Function/Values, Expected Outcomes to Computational Process.

3 Transparency design in UTM

As UTM encompasses a wide range of services (FAA 2022; SESAR 2023), this research mainly centers on tactical UTM operations in CTR around airports, in particular Rotterdam The Hague Airport. A web-based simulator DroneCTR[1] has been developed and improved as a test bed (Janisch et al. 2022, 2024). The envisioned operational concept is similar to Dynamic Airspace Reconfiguration (DAR) (Janisch et al. 2023; Teutsch and Petersen 2024). It assumes that CTR is assigned to UTM for navigating drones by default and operators can use geofences to block portions of the UTM airspace as required. As previous studies suggested a dedicated role for UTM supervision (Janisch et al. 2023, 2024), it also assumes that operators can only control drones rather than crewed aircraft. A centralized time-optimal path-planning algorithm is responsible for drone (re)routing to prevent entry into geofences and avoid conflicts with crewed aircraft. Therefore, this research is to reveal information about

[1] Demo: http://dronectr.tudelft.nl/, ID: demo.

the UTM conflict-free routing service and the inner workings of the path-planning algorithm.

3.1 Transparency elements

Following the transparency taxonomy outlined in Fig. 2, a total of 20 transparency elements have been proposed for assisting the supervision of the automated UTM conflict-free routing service, as shown in Table 1. Like the proposed taxonomy, the transparency elements are primarily based on established design practices from previous studies, highlighting that our work complements rather than replaces them.

In terms of operational transparency, the Solution category contains two elements: the old path and the proposed (new) path (Papadopoulos et al. 2024; van Marwijk et al. 2011; Klomp et al. 2019). The old path is the path the drone followed before rerouting, which hints at why the drone needed to reroute in the first place (e.g., due to a conflict).

Table 1 Proposed transparency elements

Transparency category	Transparency element
Solution	The proposed (new) path and old path Estimated state and planned action (e.g., heading change) at each waypoint
Purpose/Intent	The underlying goals and intentions of the system (e.g., minimizing flown track miles)
Expected outcomes	*If the drone follows the old path* Predicted location of separation loss Predicted start time of separation loss Predicted minimum separation Predicted probability of separation loss *If the drone follows the proposed (new) path* Predicted location of CPA Predicted time to CPA Predicted minimum separation Predicted probability of separation loss
Domain constraints	Safe separation standards between aircraft *Maneuvering space*: the flight range governed by battery power and environmental conditions *Flight mission boundary*: certain drones can only fly within a pre-approved area *Wind field*: wind speed and direction
Explored solutions	*Search graph*: a search graph is how automation discretizes a continuous space, and the generated path can only follow the edges of the graph *Explored nodes*: explored potential waypoints *Search trees*: explored potential paths
Cost function/values	The cost values of the explored potential paths given the system's goals and intentions
Computational process	*Search process*: a dynamic process that indicates how to generate the path

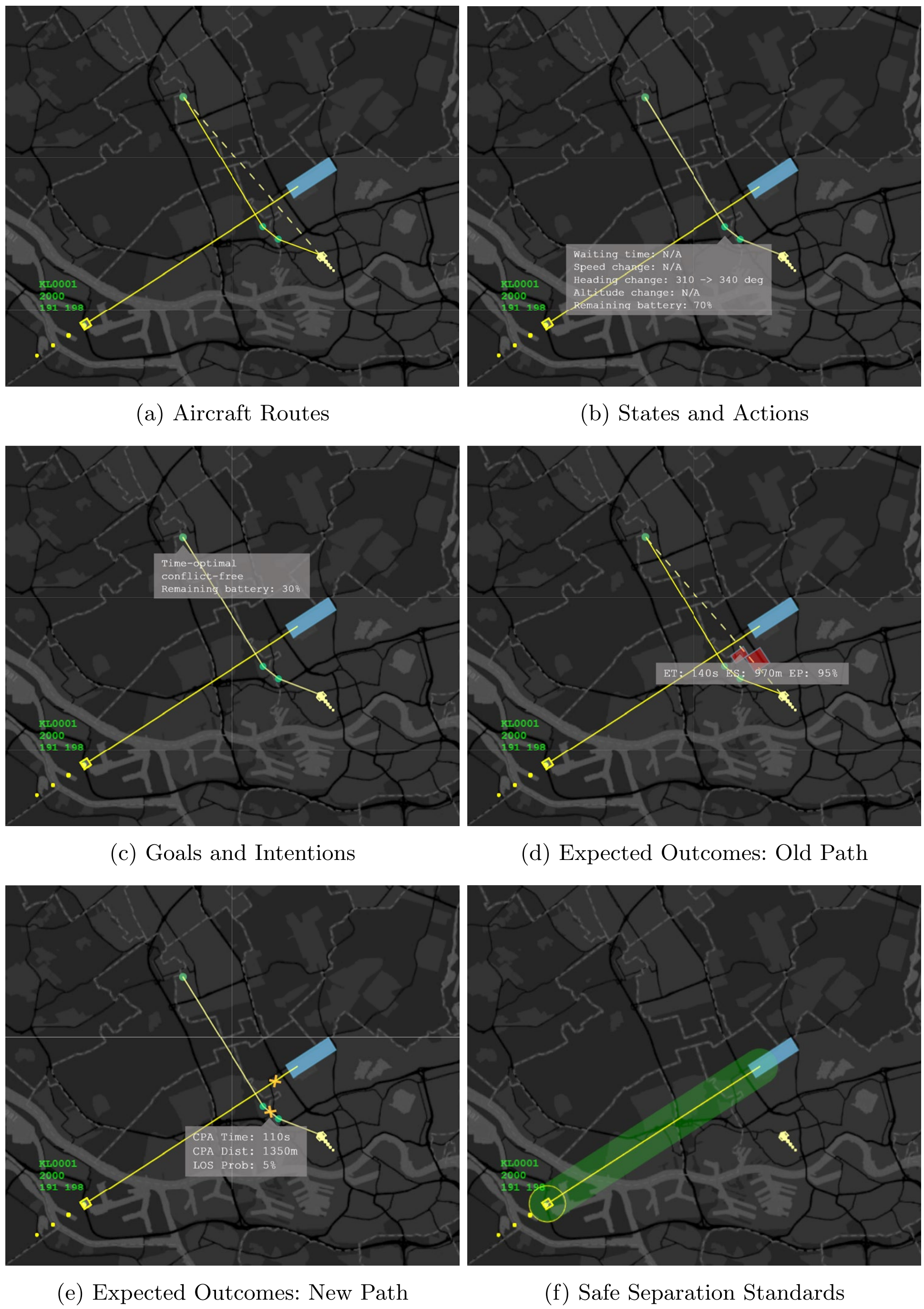
A path is essentially built from a sequence of states and actions. To gain a deeper understanding of the proposed path (solution), the estimated states and planned actions should be clearly revealed (e.g., where certain heading/altitude changes will take place). The Purpose/Intent category can be presented by text-based explanations (Cha et al. 2019; Westin et al. 2022). In this case, the path generated by the UTM system aims to be time-optimal and conflict-free. For the Expected Outcomes category, two different "what-if" situations are considered: what if the drone continues following the old path, and what if it flies along the proposed (new) path. To observe the outcomes of the paths, four metrics were proposed referring to other research (Hurter et al. 2022; Papadopoulos et al. 2024): predicted location of separation loss (and predicted location of CPA), predicted start time of separation loss (and predicted time to CPA), predicted minimum separation and predicted probability of separation loss. Regarding the Domain Constraints, a range of restrictions linked to drone endurance and no-fly zones, such as drone maneuvering space and flight mission boundary, were presented (Janisch et al. 2022; van Paassen et al. 2018). The wind field was also incorporated since drones are susceptible to wind (Alharbi et al. 2022).

In terms of engineering transparency, the domain constraints, such as the maneuvering space, limit the search space of path planning, explaining why the system only searches within a certain range (Koerkamp et al. 2019). For the Explored Solutions category, three elements were proposed with reference to existing pathfinding visualizers (Sturtevant 2023; Xu 2023; Toma et al. 2021; Zheng et al. 2024): search graphs, explored nodes and search trees. These three elements can also be simultaneously showcased to convey information that is more meaningful and integrated. The cost function/value is somewhat similar to the expected outcomes, with both utilizing specific metrics for computation. However, the cost function represents the goals of the system, while the outcomes are future projections of the solution. The cost function in this study optimizes only a subset of factors, such as flight efficiency (time-optimal), without considering environmental uncertainty (e.g., optimizing for robustness). The Computational Process category reveals the algorithm's dynamic search process (can be achieved through animation (Tversky et al. 2002; Urquiza-Fuentes and Velázquez-Iturbide 2009; Aysolmaz and Reijers 2021)), providing more details about the algorithm's expansion of search nodes and search trees.

3.2 Visual prototypes

The corresponding visual prototypes for the proposed transparency elements have also been developed, as shown in Figs. 3, 4 and 5. The proposed (new) path is a solid yellow line that the drone will follow, while the old path is drawn as a dashed yellow line that can be hidden if desired. The waypoints of the proposed path are presented as green dots and more details regarding the waypoints can be accessed, such as waiting (loitering) time, speed/heading/altitude change and remaining battery. The destination of the drone is also represented as a dot, containing information about the goals and intentions of the drone (path-planning algorithm).

For the Expected Outcome category, the proposed metrics can be collectively showcased, allowing us to depict the expected outcomes with only two images. One is for the conflict situation (old path): the red area indicates the predicted location of separation loss. More information about the conflict can be displayed, including estimated start time of separation loss (ET), estimated minimum separation distance (ES) and estimated probability of separation loss (EP). The other one is for the normal situation (new path): the amber crosses indicate the predicted locations of CPA. The predicted time to CPA (CPA Time), predicted distance at CPA (CPA Dist) and predicted probability of separation loss (LOS Prob) can also be accessed via the crosses.



(a) Aircraft Routes

(b) States and Actions

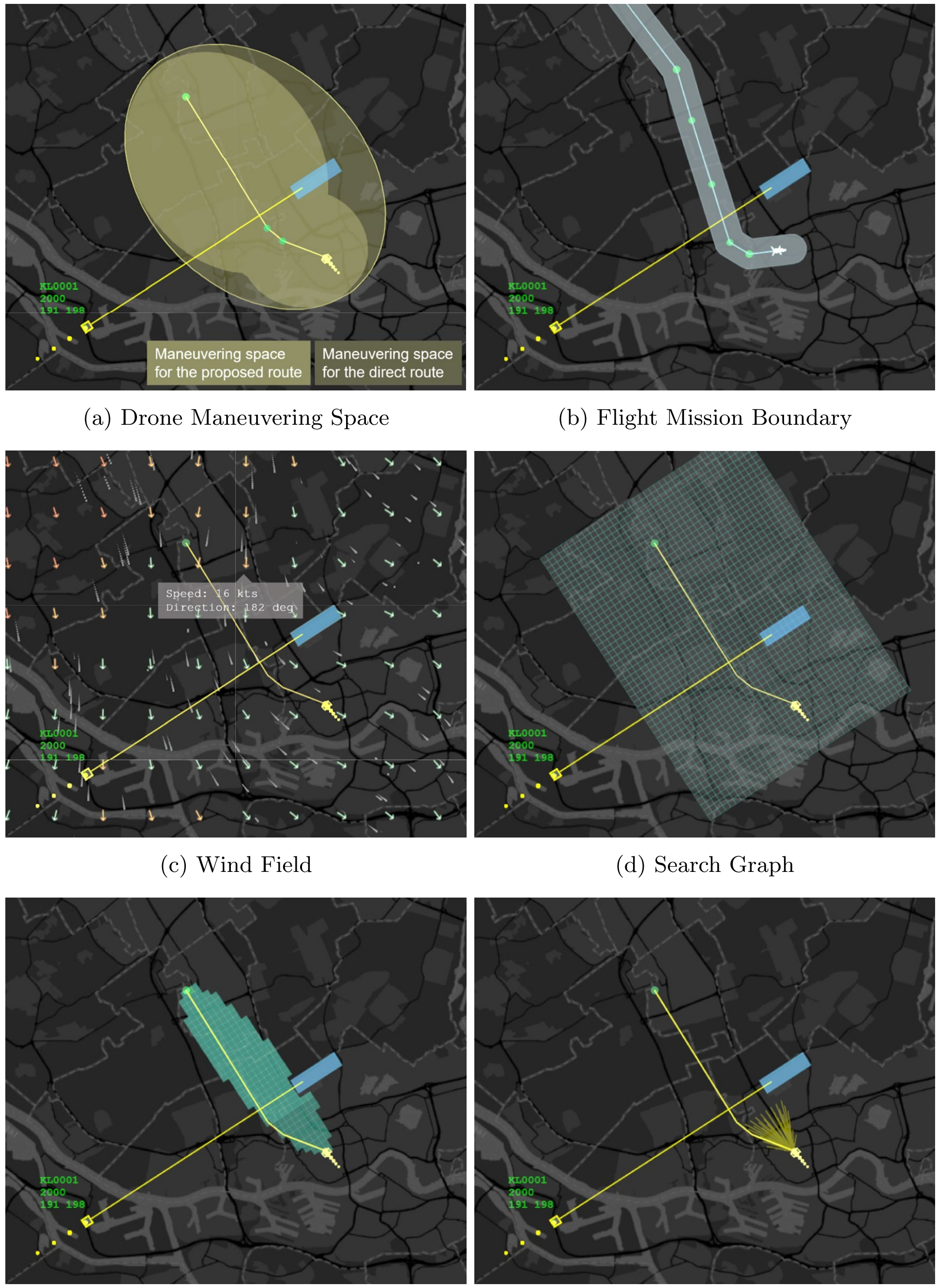
(c) Goals and Intentions

(d) Expected Outcomes: Old Path

(e) Expected Outcomes: New Path

(f) Safe Separation Standards

Fig. 3 Prototypes showcasing the proposed transparency elements (Part 1)



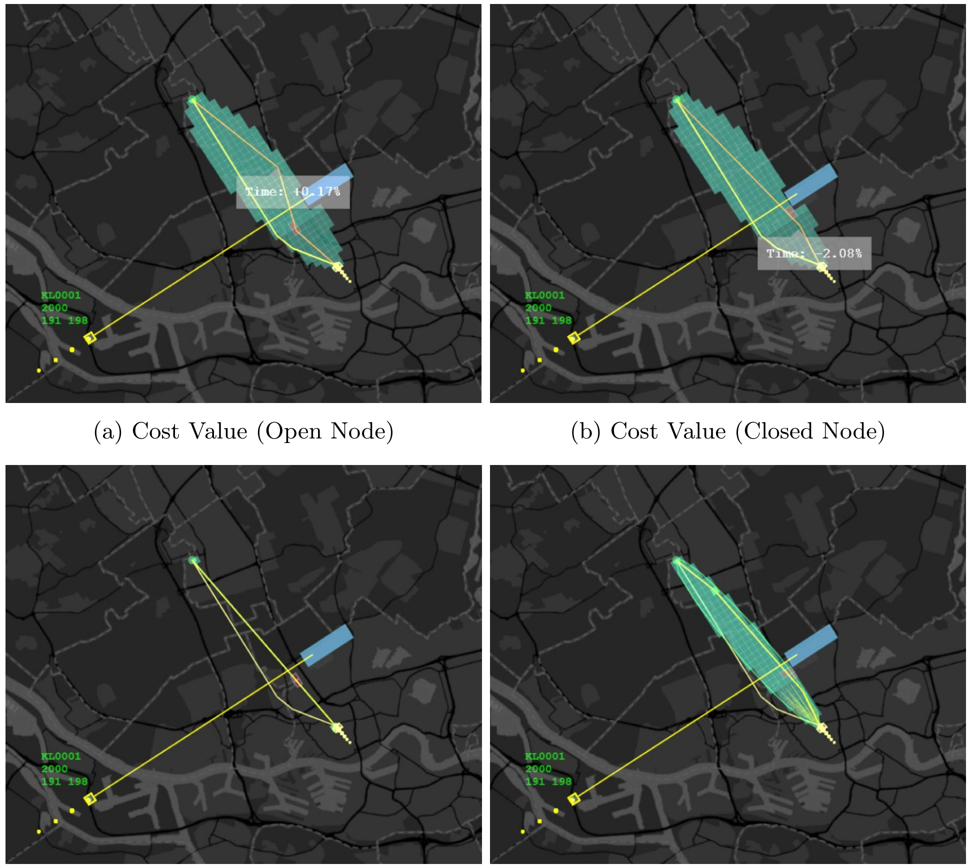
(a) Drone Maneuvering Space (b) Flight Mission Boundary

(c) Wind Field (d) Search Graph

(e) Explored Nodes (f) Search Tree

Fig. 4 Prototypes showcasing the proposed transparency elements (Part 2)

For the domain constraints, the safe separation is represented by a yellow circle around crewed aircraft. It means that if a drone flies into this circle, there will be a loss of separation. Combined with the route, a green air corridor for crewed aircraft can be presented. The drone maneuvering space is a visual representation of the drone's range governed by battery power and environmental conditions such as wind. Generally, a narrow maneuvering space corresponds to low excess battery power and/or increased headwind conditions. Two different types of maneuvering space are presented in the figure: the dark yellow indicates the proposed route and the bright yellow denotes the direct route. The mission boundary is designed as an air corridor in this case and the drone can only fly within this area. Wind field information can not only be shown by speed and directional values, but also in the form of animated particles and/or colored arrows. Different colors indicate different wind speeds: green denotes winds that have relatively little impact on drones while red represents strong winds that could cause drones to drift.



(a) Cost Value (Open Node) (b) Cost Value (Closed Node)

(c) Search Process (Animation 1) (d) Search Process (Animation N)

Fig. 5 Prototypes showcasing the proposed transparency elements (Part 3)

A grid-based time-optimal path-planning algorithm (Zou and Borst 2024) is implemented for the UTM conflict-free routing service. Therefore, the search graph in this case is a grid bounded by the search space, which is determined by the drone maneuvering space and, if applicable, the mission boundary. The explored nodes are the green cells that are potential waypoints explored by the algorithm while the search tree represents all potential paths that have been explored. The "heuristic" (direct) lines between the branch ends and the destination node have been hidden to avoid visual clutter. Please note that the potential paths explored by the algorithm are just promising to be time-optimal and conflict-free (the purpose of the algorithm). During the search process, the algorithm produces (many) intermediate results that failed to be the final solution, because they are not optimal and/or are unsafe. The cost value of a node, representing the cost of an explored path passing through it, can be retrieved. The search process is a dynamic process that indicates how the search tree is composed and how the final path was found. Similar to Sturtevant (2023); Xu (2023); Toma et al. (2021), the dynamic search process can be demonstrated through (fast-time) animation.

4 User study methodology

4.1 Overview

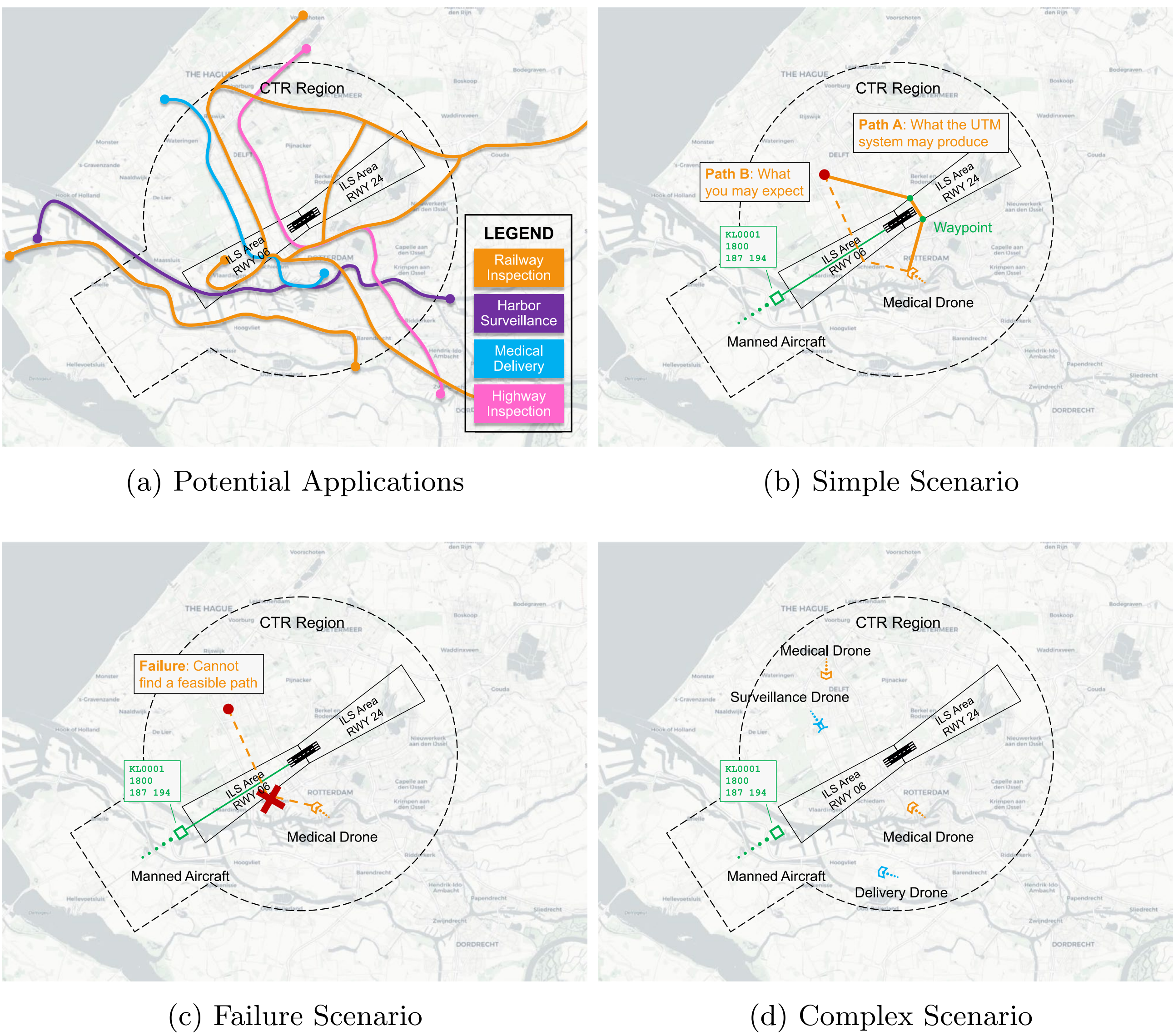
Based on the proposed transparency elements and visual prototypes, a questionnaire was designed to investigate the transparency needs of operators for supervising the UTM system. The overall goal of this survey study is to validate the content and structure of the proposed transparency taxonomy in the tactical UTM context. If all the devised elements are deemed valuable for UTM supervision, then every category in the taxonomy is indispensable. The survey study also examines how operators categorize these transparency elements, exploring whether three distinct types of transparency emerge from operators' viewpoints.

At the start of the questionnaire, participants were given a detailed explanation of the background and a hypothetical operational concept, recognizing that they may have different visions of future UTM operations. Some personal information was then collected to aid data analysis. This study was approved by the Human Research Ethics Committee (HREC) under number 3374.

Given the primary focus of this study on UTM in CTR, Rotterdam-The Hague Airport was selected as a use case.

The potential drone applications in the airport's vicinity, such as railway and highway inspection and medical delivery, are illustrated in Fig. 6a. Three distinct hypothetical scenarios, as depicted in Fig. 6b–d, were presented to stimulate participants' thoughts: a simple scenario encompassing only a single drone, a failure scenario entailing an automation failure case and a complex scenario involving multiple drones with diverse missions and types. For the simple and failure scenarios, a trajectory-contrastive question and a failure question (Miller 2019; Brandao et al. 2021) were provided for further inspiration: (1) why path A rather than path B, and (2) why the system fails. For the complex scenario, time pressure issues may be more salient (Hurter et al. 2022) and the usefulness of transparency information for supervision might be different.

To enhance the authenticity of the scenarios, descriptive text for the three operational scenarios was also provided before the rating began. For the simple and failure scenarios, "*a medical drone needs to pass through an area near the runway to deliver emergency supplies between two hospitals (from Rotterdam to Delft) as quickly and as safe as possible, but a crewed aircraft is about to land. The automated UTM conflict detection service has detected a potential separation problem (= conflict) between these two aircraft*". For the complex scenario, "*when more drones need to cross the area covering the extended runway centerline, the conflict scenario may become more complex. Such increased complexity may have an impact on your transparency needs in the light of 'information overload'. Note that the UTM system in this investigation only deals with separation conflicts between crewed and uncrewed aircraft. The*



(a) Potential Applications

(b) Simple Scenario

(c) Failure Scenario

(d) Complex Scenario

Fig. 6 Schematic diagrams for operational scenarios *collision avoidance among drones is assumed to be achieved by 'sense and avoid' systems onboard drones. Therefore, the automated conflict detection & resolution services for drones only regard crewed aircraft as dynamic obstacles*".

4.2 Questionnaire structure

There were two main phases in the questionnaire, as shown in Fig. 7. In the first phase, the proposed 20 candidate transparency elements derived from the unified taxonomy were presented as response options, with their order being randomized. Participants were asked to rate the elements using a 5-point Likert scale according to their perceived usefulness for understanding and supervising the automated UTM conflict-free routing service. Open-ended questions were also present to inquire the reasoning behind their ratings. To obtain the original opinions of participants and prevent any potential bias in their results, the visual prototypes were deliberately withheld from participants in the first phase.

Then, the questionnaire investigates how participants proposed to group transparency elements that belonged together in their opinions. This could offer valuable insights into what transparency categories or elements should be connected and/or presented together in practice. The groups identified by operators could also help validate whether the proposed unified taxonomy is reasonable from the operators' perspective, specifically whether there are indeed three distinct types of transparency. Considering that each participant may have their own groups of transparency elements, we employ a weighted adjacency matrix to summarize their preferences. The weight here refers to the number of times two elements are divided into the same group. Then, based on this adjacency matrix, a weighted graph can be constructed to visually depict the interconnections among various transparency elements. Finally, to group these elements (i.e., the vertices of the weighted graph), the Walktrap community detection algorithm (Pons and Latapy 2005) will be applied, as illustrated in Fig. 8.

In the second phase, the visual prototypes for the proposed transparency elements were presented and then 5-point Likert scale questions were provided to inquire the usefulness of the prototypes for understanding and supervision in the simple and complex scenarios again. To restrict the questionnaire length, we presented participants only with examples that successfully generate paths, as shown in Figs. 3, 4 and 5, and thus the failure scenario was omitted in the second phase. Previous studies indicated that user preferences on transparency may change after actual experience with it Springer and Whittaker (2020); Hurter et al. (2022). This phase allows us to assess whether participants altered their perspectives after viewing our prototypes.

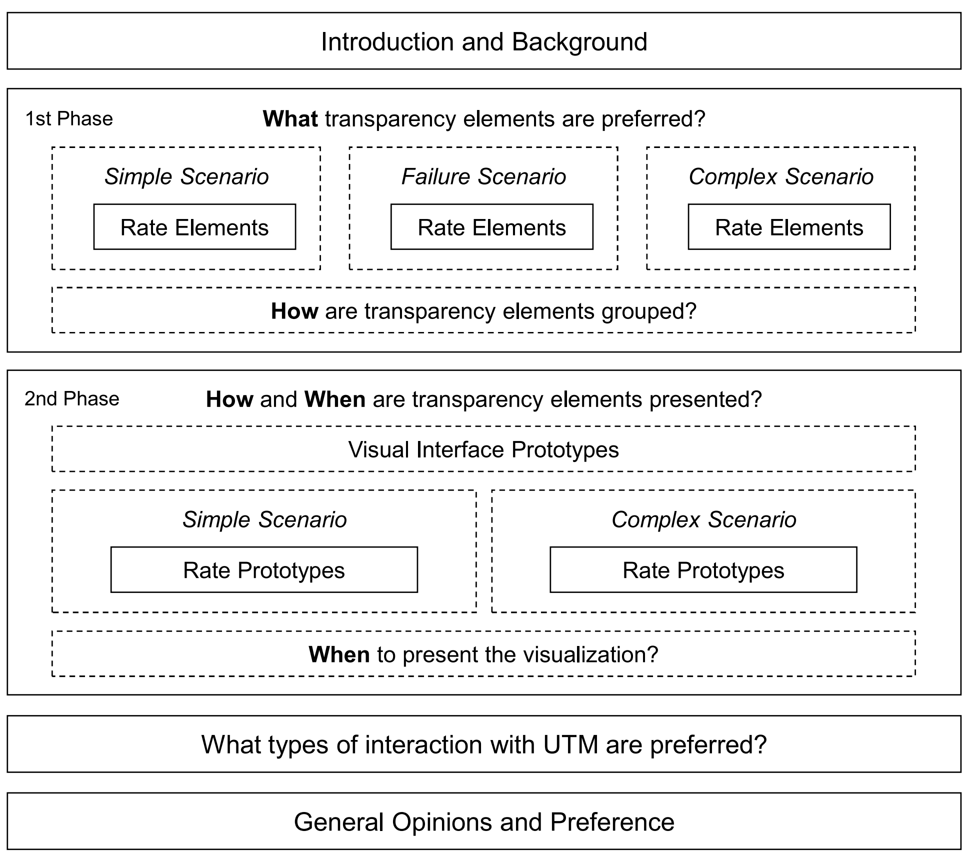


Fig. 7 The structure of the questionnaire

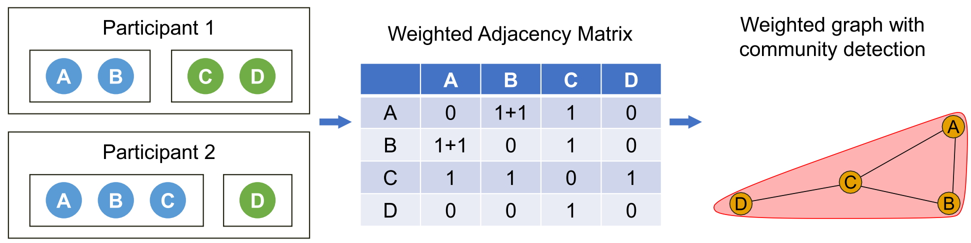


Fig. 8 Data processing of the grouped transparency elements

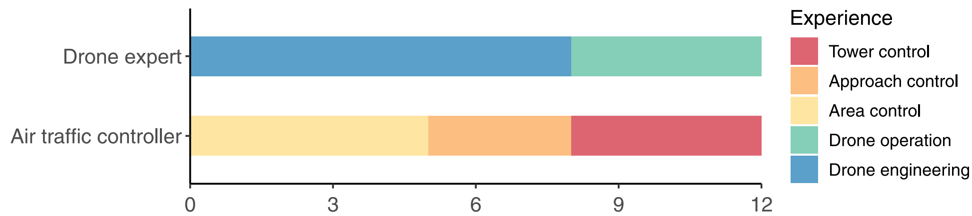


Fig. 9 Participants' experience in air traffic control and drone operations

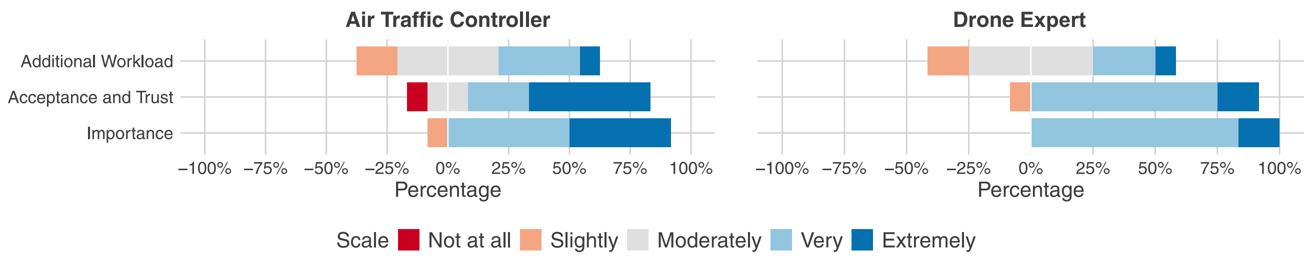


Fig. 10 General opinions on transparency

When to present each prototype was also investigated after then. For example, operators could enable the UTM system to automatically determine the timing of information presentation (adaptive). Alternatively, operators could manually show or hide the elements by clicking on relevant buttons (adaptable). After rating the transparency elements and prototypes, participants were asked to select and rank their preferred types of interactions with the UTM system. Finally, the questionnaire ended with some general questions on transparent UTM systems in terms of importance, additional workload and acceptance concerns.

4.3 Participants

Previous research indicated that UTM supervision may not be appropriate for ATCos to perform besides their regular ATC tasks and a dedicated UTM supervisor may be required (Janisch et al. 2023, 2024). As the role of UTM supervisors differs from ATC such as tower control, they are not required to undergo the same training and licensing as ATCos. Instead, they could be someone more familiar with drone operations, like drone pilots or drone engineers. Therefore, we invited both ATCos and drone experts to participate in our user study. The results could offer a more comprehensive insight into the transparency needs of operational users. Additionally, given the diverse professional backgrounds of ATCos and drone experts, their transparency needs may also be different (Westin et al. 2022; Arrieta et al. 2020; Langer et al. 2021).

Twenty four operators from Europe and China volunteered to participate in this survey of which twelve were licensed ATCos (e.g., Rotterdam and Shanghai controllers) and twelve were drone experts (e.g., drone engineers from TU Delft and drone pilots from companies). Their experience in ATC and drone operations is summarized in Fig. 9. One participant who serves as both an ATCo and a drone expert was classified as an ATCo in this survey.

5 User study results

5.1 General opinions on transparency

Figure 10 presents the general opinions of participants on transparency after filling out the questionnaire. Most participants believed that transparency plays an important role in supervising the UTM system and will significantly influence their level of acceptance and trust. One ATCo held the view that transparency would not affect acceptance at all, because his/her main concern was about the number of aircraft in flight. One drone expert believed that transparency would have a slight impact on trust, because he/she would trust the UTM system overall once it is fully operational. The additional workload that transparency could bring is considered to be relatively manageable. Over half of the participants thought that the additional workload would not be very high. This result should be interpreted with care, because this study did not feature a real-time, interactive human-in-the-loop simulation with dynamic traffic situations. As such, conclusions about transparency-induced workload warrants further research.

5.2 Preferred transparency information

5.2.1 Data analysis and statistics

By converting the Likert scale ratings into numerical values, we could perform statistical analysis to assess the impact of different factors on operators' transparency needs. Wilcoxon Signed-Rank tests were conducted for an overall comparison of operational and engineering transparency. The matched-pairs rank biserial correlation coefficient *rc* (King et al. 2018) was then calculated to measure the effect size for Wilcoxon Signed-Rank tests (small ≥ 0.1, medium ≥ 0.3, large ≥ 0.5). Friedman tests were performed to further analyze the differences in operational and engineering transparency among various scenarios, followed by Exact tests (Eisinga et al. 2017) with the Bonferroni correction for pairwise comparisons. Kendall's coefficient of concordance w was used to measure the effect size for Friedman tests (small ≥ 0.1, medium ≥ 0.3, large ≥ 0.5). To compare the differences between ATCos and drone experts, Mann-Whitney U tests were conducted. The effect size r was calculated for Mann–Whitney U tests (small ≥ 0.1, medium ≥ 0.3, large ≥ 0.5), which is defined by the standardized test statistic z from the tests divided by the square root of the total number of observations. The significance level was set to 0.05. As the effect size reflects the magnitude of the difference between groups (Sullivan and Feinn 2012), it is ideal to have both a statistically significant result ($p < 0.05$) and a large effect size to claim a clear and meaningful difference. A low effect size suggests that the statistical significance should be interpreted with caution.

5.2.2 Comparison of operational and engineering transparency

The Likert scale ratings for the proposed transparency elements and the visual prototypes are shown in Figs. 11 and 12. The failure scenario was not included in the second rating phase with the visual prototypes and the reason has already been mentioned in the previous section. Generally, all proposed elements were considered valuable for supervising the UTM system, although some of them may have limited utility in some scenarios.

Compared to operational transparency, engineering transparency is considered less useful in the tactical UTM operations, as expressed by an ATCo: "*I need it to tell me why it gives this route and the disadvantage of this route. I don't think how it finds this route is useful*". Drone experts had similar views: "*I would be most interested in knowing when, where and how the conflict might occur from the system's point of view ... I need to access objective metrics from which I can verify the soundness of the proposals. I do not want to be bothered by the inner workings of the system (e.g. how the search is conducted) since I feel it may lead to an information overload.*" These arguments are consistent with the SESAR projects reviewed in this paper, which focuses on the goals and intentions of systems and the expected outcomes of solutions. Additionally, a drone expert remarked: "*It has to be simple during actual operations ... the operational environment might be over-engineered - these items should be more of things to revisit in hindsight*". Interestingly, we did not mention the concepts of operational and engineering transparency in the questionnaire, but judging from the results, participants seemed to distinguish between them very well.

The operational transparency encompasses two distinct categories of expected outcomes: one pertaining to the proposed (new) path and the other to the old path. A drone expert suggested that "*a really simple table was needed to compare the main elements of two paths*". This comment shares similarities with the TAPAS project which also utilizes tables to present various metrics. The expected outcomes of the old path are also considered relatively less useful. One expressed it as follows: "*I think the old path is not necessary for avoidance. The current states of both manned and unmanned aircraft and their predicted paths are more important*". Another drone expert also remarked: "*The predicted states based on the proposed path matters more than the old path*". This is probably because the proposed path is more relevant to the current situation.

As for the domain constraints, although a drone expert pointed out that "*Large wind or stormy weather will create critical situations for aircraft, especially drones*", the wind field is generally considered least useless compared to other constraints. A possible reason is that the wind field only presents basic environmental information, which is not directly associated with the goals of operators. It might be more effective to introduce no-fly zones determined by wind conditions, taking into account both wind speed and drone performance. In other words, presenting wind information in terms of how it impacts drones is considered more useful than simply presenting the wind condition itself.

For a clearer comparison, average ratings for operational and engineering transparency in different scenarios are computed, as shown in Fig. 13. Based on the average ratings of

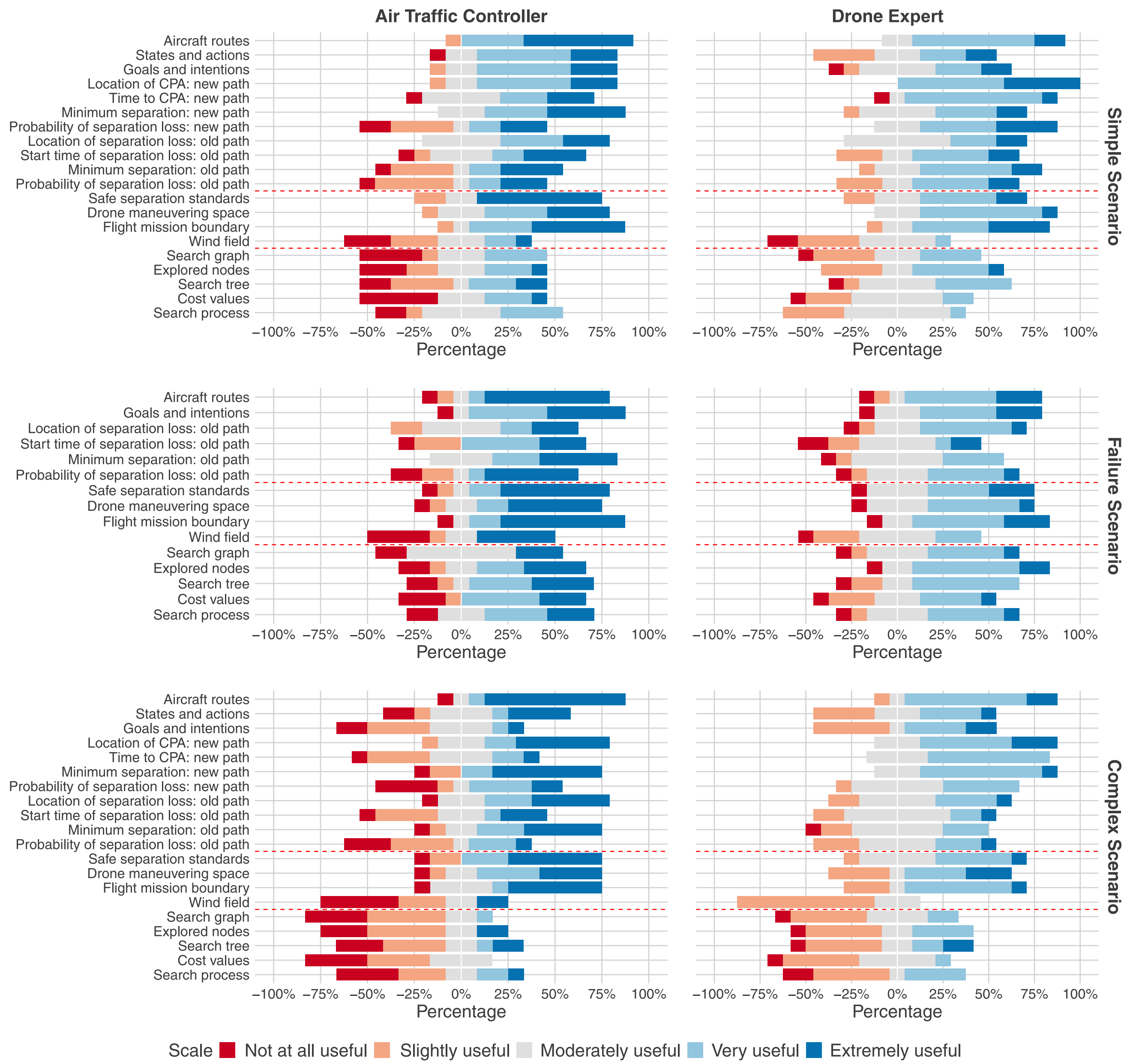


Fig. 11 Likert scale ratings for the proposed transparency elements. The red dashed lines denote the operational, domain and engineering transparency categories. The transparency elements from the "Solution" category are absent in the failure scenario because there is no solution in this case

the two phases, Wilcoxon Signed-Rank tests revealed significant differences between operational and engineering transparency in both ATCo ($V = 74$, $p < 0.01$, $rc = 0.897$) and drone expert ($V = 63$, $p < 0.01$, $rc = 0.909$) groups.

5.2.3 Preferences in different scenarios

Figures 11, 12 and 13 also indicate that differences exist not only between the types of transparency but also among the scenarios. In the failure scenario, engineering transparency is deemed more useful compared to other scenarios. This is probably because operators need more information about the system's internal process to figure out what happened inside the system. The information concerning constraints could be particularly helpful: "*If there's no good solution, this should come from some limitations from the dynamics of drones*". "*The waypoints, maneuvering space, and boundaries are the key to finding the desired path*". Actually, some participants indicated, "*that everything allowing to understand why the system fails is useful*". However, it is worth noting that the occurrence of failure scenarios should be minimized as much as possible. *Robustness* was repeatedly mentioned as one of the crucial factors influencing their acceptance of a highly automated UTM system.

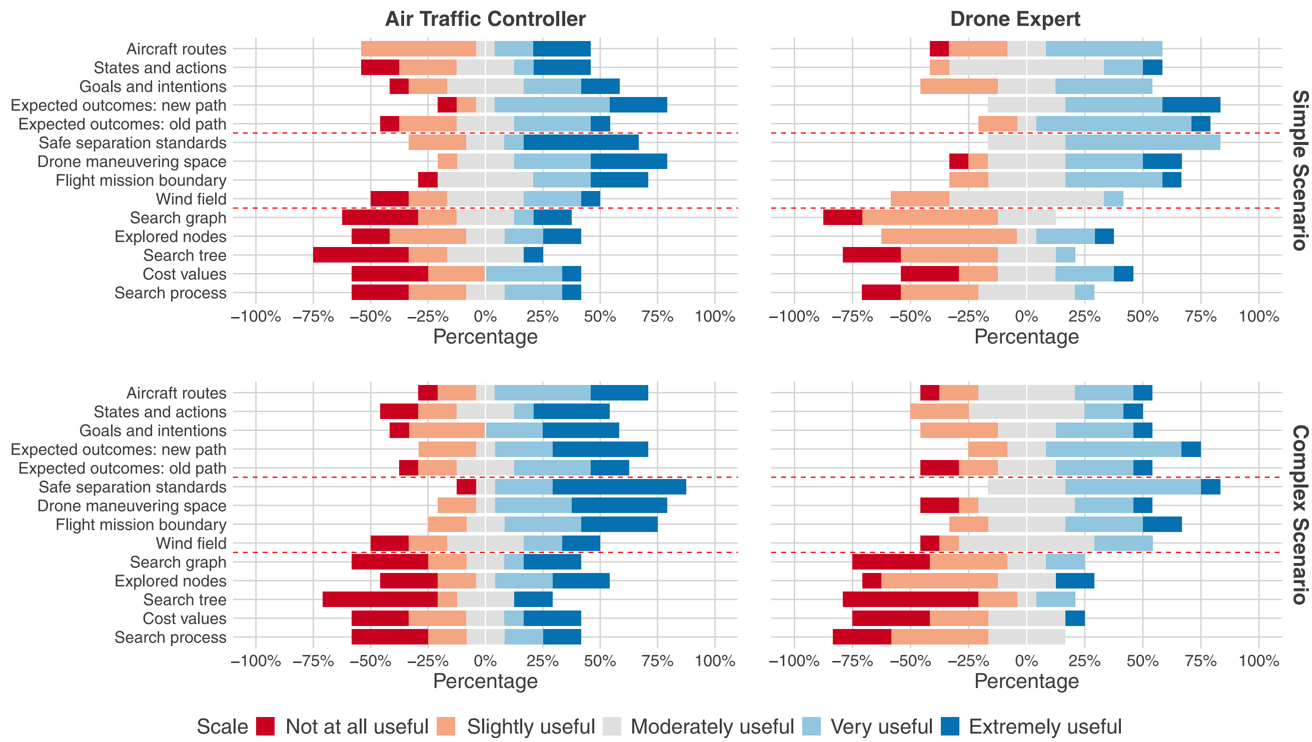


Fig. 12 Likert scale ratings for the visual prototypes

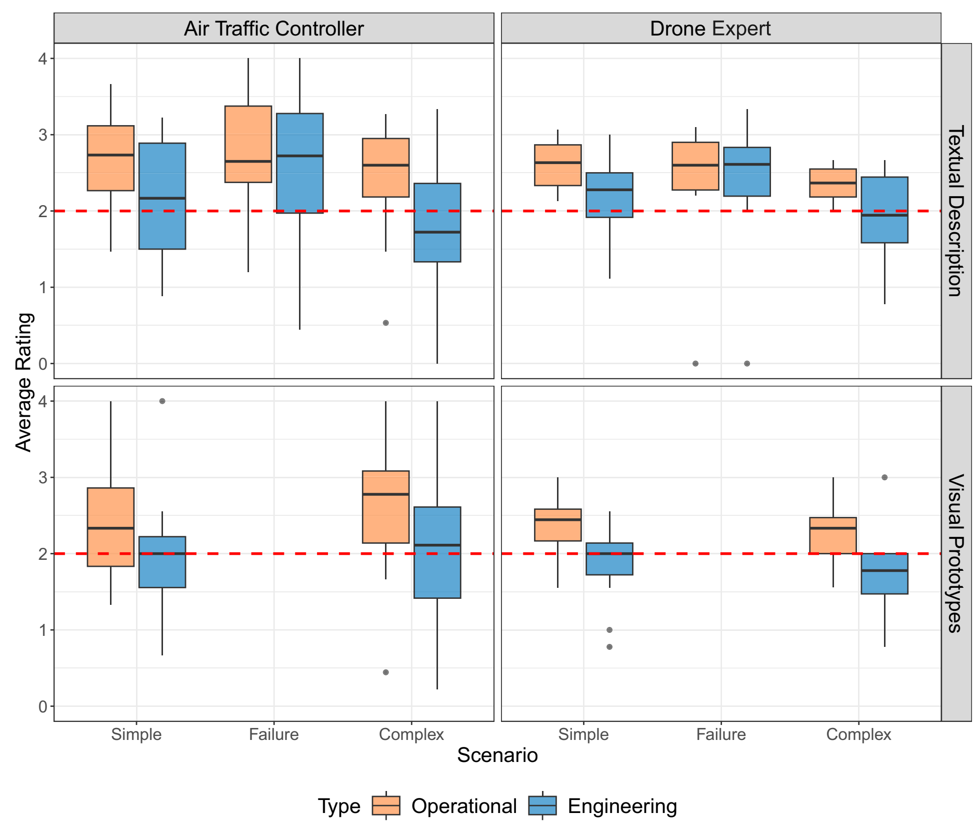


Fig. 13 Average ratings for operational and engineering transparency based on "Not at all useful = 0" to "Extremely useful = 4". Domain transparency is included in both operational and engineering transparency

One participant stated, "*If there is no feasible path, it should never cross a route with manned traffic*". In the complex scenario, engineering transparency is considered even less useful, because "*too much information could overwhelm operators*." One respondent suggested that "*it is more important to only look at the conclusive information*". The transparency information indirectly related to safety and situations should probably be hidden in the first place.

To further confirm these differences, a statistical analysis was performed based on Fig. 13. For the ratings with only textual description, Friedman tests revealed significant differences among conditions (Three Scenarios $\times$ Two Transparency Types) in the ATCo group ($\chi^2(5) = 23.002$, $p < 0.01$, $w = 0.383$), but no such differences were observed in the drone expert group. For the ATCo group, pairwise comparisons with the Bonferroni correction further revealed that the "Complex-Engineering" condition was significantly different from the "Simple-Operational" ($D = 33.5$, $p < 0.01$), "Failure-Operational" ($D = 35.0$, $p < 0.01$) and "Failure-Engineering" ($D = 30.5$, $p < 0.01$) conditions. For the ratings with visual prototypes, Friedman tests revealed significant differences among conditions in both ATCo ($\chi^2(3) = 9.083$, $p = 0.028$, $w = 0.252$) and drone expert ($\chi^2(3) = 19.817$, $p < 0.01, w = 0.550$) groups. However, pairwise comparisons did not confirm significant differences in the ATCo group between conditions. It can also be observed in Fig. 13 that the data spread in the ATCo group is relatively large. For the drone expert group, pairwise comparisons with the Bonferroni correction further revealed that the "Complex-Engineering" condition was significantly different from the "Simple-Operational" ($D = 24$, $p < 0.01$) and "Complex-Operational" ($D = 18$, $p = 0.027$) conditions.

5.2.4 Preferences with visual prototypes

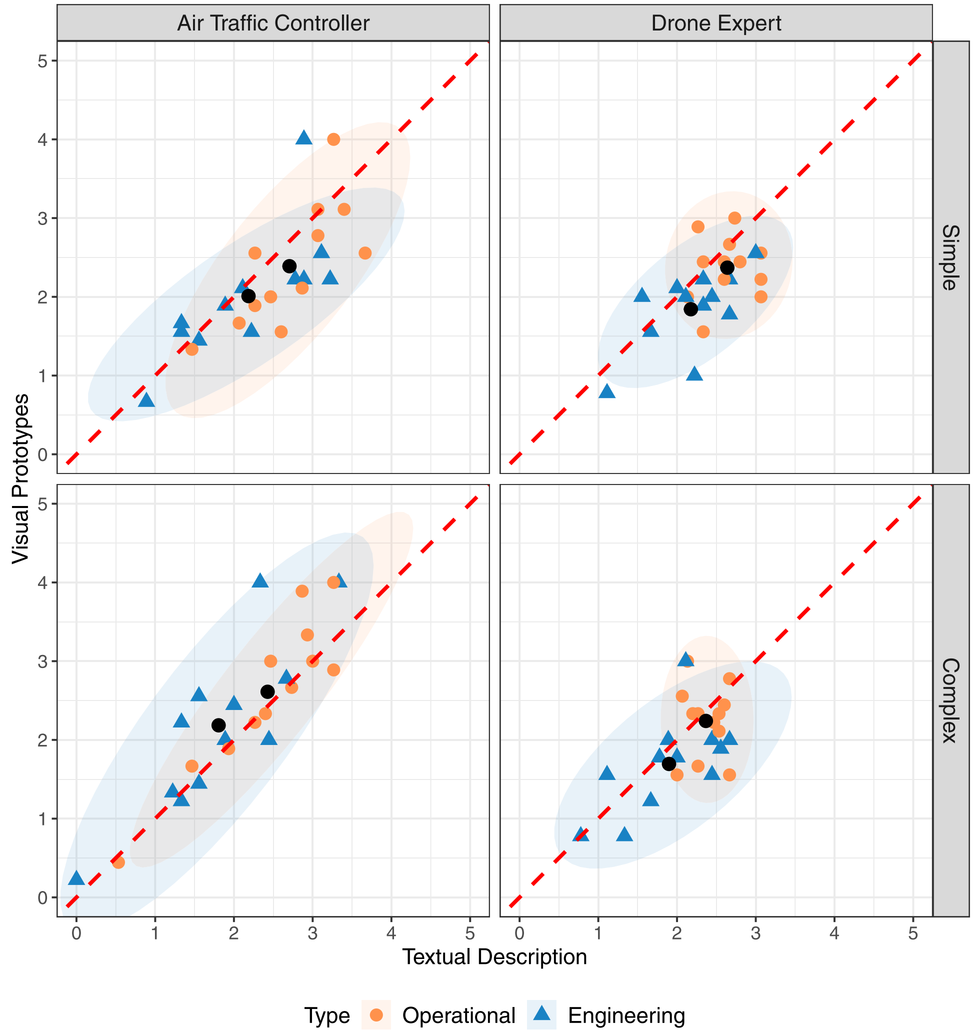
To further explore whether participants' preferences changed after viewing the visual prototypes, Fig. 14 presents the relationships between the average ratings for the two rating phases. Overall, participants' preferences remained relatively consistent, suggesting that the visual prototypes in the second phase aligned with their expectations formed through the textual descriptions in the first phase. However, there are still some notable changes. After viewing the visual prototypes, ATCos found the transparency information less beneficial in simple scenarios than previously thought (negative change), but more beneficial in complex scenarios (positive change). In contrast, drone experts regarded the transparency information as less useful in both simple and complex scenarios than initially expected (negative changes). The negative changes for participants are likely driven by concerns about visual clutter and a preference for maintaining a clean interface. The positive change for ATCos may stem from their experience with ATC interfaces. They may believe that more supportive information is required in complex scenarios and that the visual prototypes can be integrated into a single interface for support without excessive visual overlap.

5.2.5 Comparison of ATCos and drone experts

Generally, the needs for different types of transparency were found to be similar between ATCos and drone experts. Mann–Whitney U tests did not reveal any significant difference between the two operator groups. However, as evident from Figs. 11 and 12, some minor distinctions still exist on specific elements. Among the four metrics indicating the expected outcomes, the probability of separation loss is found to be favorable by drone experts: "*I may pay more attention to ... the predicted probability of separation loss*." The probability would indicate the uncertainties of the system. If the system's confidence in resolving the conflict is not high enough, operators may be required to intervene in the system. However, as one ATCo stated, "*ATC does not control considering probability*". Also, another ATCo expressed: "*To some extent, probability may not represent its level of danger very well. If I realized the separation was not enough, I thought my priority was to increase the separation to prevent it, not just to compare the probability*". In fact, the automated UTM conflict-free routing service should be robust enough to reduce the probability of separation loss to "zero" in most cases. When the probability is not zero, the system should provide some additional explanations to indicate its limitations. For example, changes in wind conditions could lead to variations in flight duration, thereby increasing the probability of separation loss and triggering new conflicts. Furthermore, ATCos also emphasize the transparency information regarding predicted locations of separation loss and CPA and predicted minimum separation. As mentioned by an ATCo, "*Two elements are of utmost importance: which location will the separation loss be and to which location does it shift when a new route is proposed*." This preference can be clearly observed in the complex scenario (see Fig. 11).

As shown in Figs 13 and 14, there is a notable discrepancy in the variance of ratings between ATCos and drone experts. It appears that ATCos tend to be more forthright and confident, often expressing their views at either end of Likert scales. There also seems to be a disagreement among ATCos, resulting in the increased variance. This phenomenon mainly exists within the tower and area controller groups. In contrast, drone experts tend to hold more conservative views, leaning toward the neutral side. There appears to be more consensus among drone experts. Since

Fig. 14 The relationships between the average ratings for the two phases: one with only textual descriptions and the other with visual prototypes. Confidence ellipses (95%) are presented per transparency type, with black dots indicating their centers



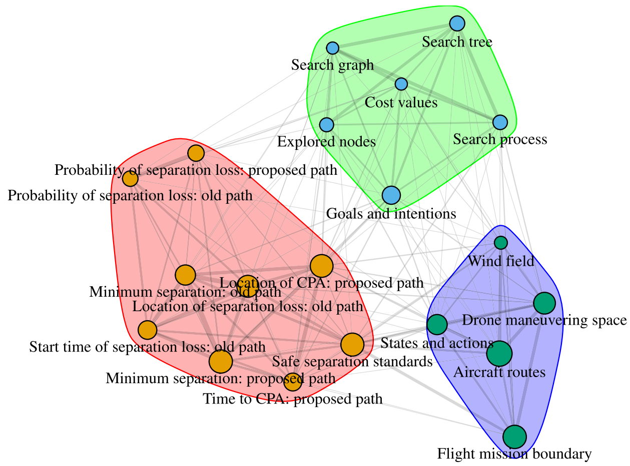
the sample size is not large, more data would be needed to substantiate this observation.

Additionally, ATCos expressed a greater preference for engineering transparency elements than drone experts in complex scenarios after viewing the visual prototypes (see Figs. 12 and 13). One possible reason is that ATCos generally take a more critical view of automation (Westin et al. 2015) and thus may seek as much information as possible to audit it. In comparison, drone experts, being more familiar with automation, may be more biased to accept and trust UTM (as noted by one drone expert shown in Sect. 5.1), and thus may require less engineering transparency information.

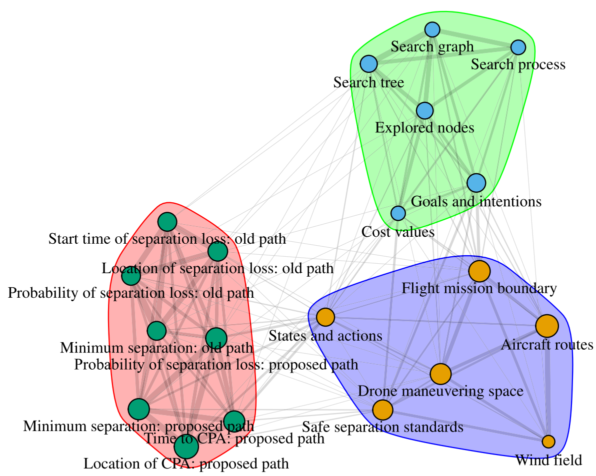
5.3 Transparency element grouping

Based on the weighted adjacency matrix and the Walktrap community detection algorithm, the correlations between the proposed transparency elements are computed, as shown in Fig. 15. Both ATCos and drone experts categorize these elements into three groups, with their results being nearly identical. The sole distinction lies in how the safe separation standard is allocated: for ATCos, it is associated with the expected outcomes (red group) whereas for drone experts, it is linked to domain constraints and solutions (purple group). This is possibly because the goal of ATCos is to ensure that the outcomes meet the established separation standards. The safe separation can be regarded as a baseline or minimum requirement for the outcomes, which is very often presented in ATC decision-support tools.

In summary, the groups classified by operators can be labeled as follows: Expected Outcomes (red), Solution & Solution Space (purple) and Internal Process (green). This can be viewed as a more condensed variant of our proposed taxonomy. In the green group, the goals and intentions are closely connected to the cost values since cost functions should typically be designed in accordance with goals. The correlations among the proposed transparency elements can provide guidance and reference for further devising transparency levels and models, as they illustrate which elements



(a) Air Traffic Controller



(b) Drone Expert

Fig. 15 The correlations between the proposed transparency elements. The vertex size corresponds to the average rating

operators prefer to see concurrently for understanding and supervision.

5.4 Interaction and intervention

Figure 16 depicts the trigger conditions preferred by operators for the transparency elements. Overall, there is no universally agreed-upon trigger condition for each transparency element. The operators have their individual preferences for determining when to present the transparency information. It seems that ATCos generally prefer to click on (or hover over) aircraft, while drone experts tend to favor global or automatic activation on demand. This is probably due to their different experiences with ATC and drone operations. For ATCos, they are more accustomed to interacting with radar screens where information and actions are typically associated with each aircraft, including radar labels, speed vector lines and history dots. In contrast, for drone experts, they may rely more on automation to assist in planning trajectories and avoiding obstacles. More than 25% of the ATCos opted to never present the inner workings of the algorithm, likely to maintain a clean interface, which is in line with their ratings on the transparency elements (See Figs. 11 and 12). Conversely, drone experts prefer retaining the option to access more additional information.

With transparency information, operators may be able to understand the current system state and maintain situation awareness. However, they also need to know what actions they can take if something goes wrong; otherwise, human supervision of the system would be pointless. Sometimes, the generated path may not align with operators' expectations or preferences on how to resolve conflicts. The UTM system should incorporate interaction methods that allow operators to intervene when required or desired. Therefore, during the user study, in addition to rating the elements, we also asked participants to select and rank different interaction methods with UTM. The results are presented in Fig. 17. Interestingly, according to the Rank 1, more than 50% of the ATCos and drone experts prefer active control over drones instead of passive control (geofence activation) or mixed control (waypoint constraints on algorithms). This observation is in line with previous human-in-the-loop experiments in dynamic UTM scenarios (Janisch et al. 2022, 2023, 2024). As the scenario becomes more complex, ATCos tend to prefer passive control to protect crewed aircraft from drones whereas drone experts favor active control to navigate drones manually. This is probably because of their different professional backgrounds and experiences with drone operations. Drone experts may be more confident in taking control of drones to address issues, whereas ATCos prioritize maintaining the safety of crewed aircraft by clearing their paths of any obstacles.

6 Discussion

6.1 Trade-off between operational and engineering transparency

The results of the user study revealed that operational transparency is more useful than engineering transparency for tactical UTM operations, as recognized by both ATCo and drone expert groups. This finding aligns with the previous transparency research in ATM (Hurter et al. 2022; Westin et al. 2022; Papadopoulos et al. 2024). For example, TAPAS (Papadopoulos et al. 2024) also introduced the concept of operational transparency in their research, defining it as the provision of operational information driving decisions with

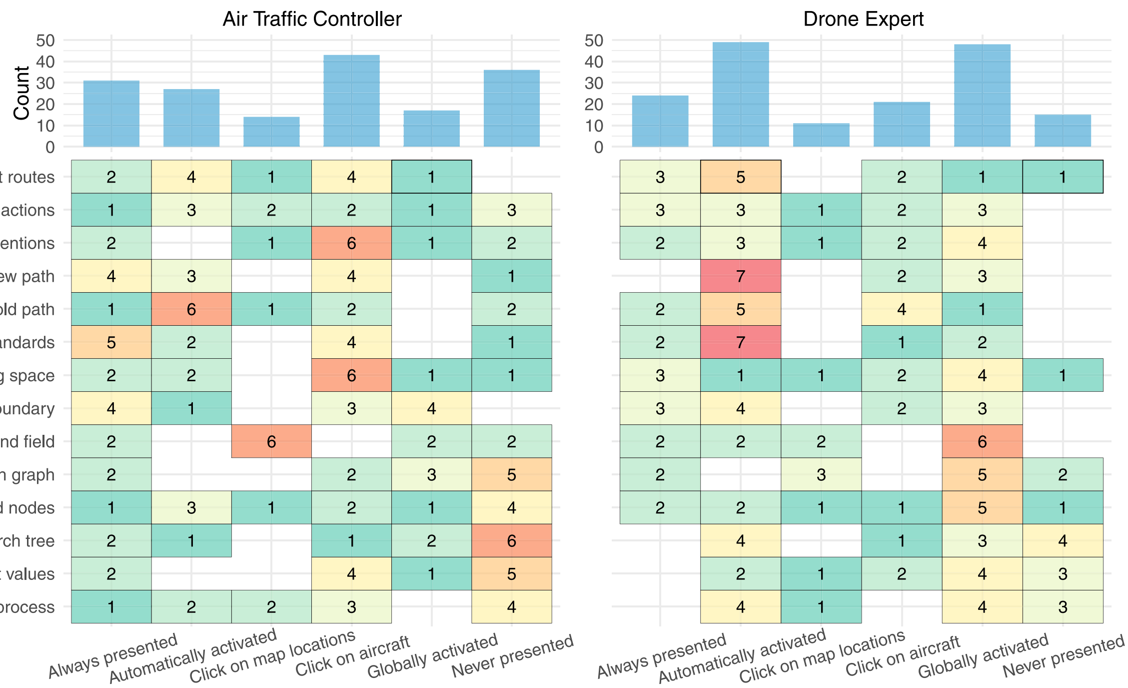


Fig. 16 Trigger conditions of the visual prototypes

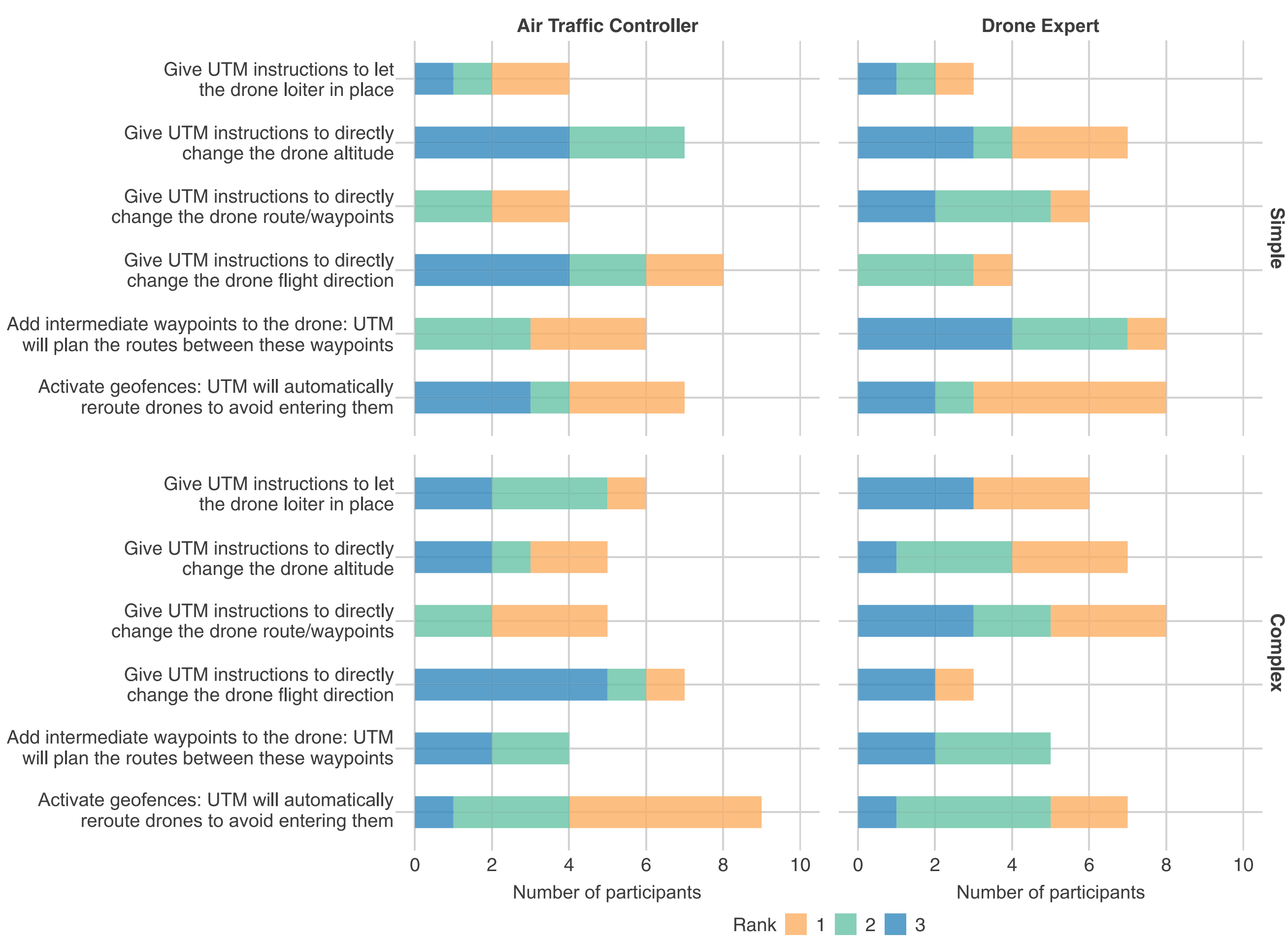


Fig. 17 Ranks of interaction methods with the UTM system

respect to operators' pragmatics constraints. They believed that providing information that maintains operators' situation awareness is sufficient to develop trust in AI, even in high-stakes fields like ATC.

This conclusion appears to contradict the prevailing perspective in XAI research that aims to open "black boxes" (engineering transparency) to increase human understanding, trust and acceptance of AI-based systems (Gunning and Aha 2019; Arrieta et al. 2020). However, actually, there is no contradiction between them. As indicated by Springer and Whittaker (2020) and Kizilcec (2016), trust is affected by *expectation violation*. For ATM and UTM, operators' expectations are to ensure safe and efficient operations. As long as the system's proposed solution can meet this goal, operators will probably accept and trust it. In this case, operational transparency is to help operators evaluate the proposed solution within a specific context (Simon et al. 2024) and thereby maintain their situation awareness. There is almost no need for operators to access engineering transparency in normal scenarios, especially when operators have extensive operational experience like ATCos (Papadopoulos et al. 2024). Operators' transparency needs may diminish over time as they become increasingly familiar with the automated system.

However, as our study suggests, in the case of automation failure, operators tend to want more engineering transparency to understand what happened deeper inside the system. This is precisely because of expectation violation. The automated system did not work as expected, resulting in a reduced trust and an increased demand for explanations and engineering transparency (Sreedharan et al. 2021). Therefore, to effectively address all possible situations, both operational and engineering transparency is important. Certainly, it does not mean that we need to present all information simultaneously. To avoid overwhelming operators, transparency should be provided on demand (Springer and Whittaker 2020).

6.2 Potential improvements to transparency design in UTM

In Sect. 3, we devised twenty transparency elements and fourteen corresponding visual prototypes. Based on the results of the user study, we could further improve the transparency design in UTM.

In operational transparency, some operators considered the old path relatively less important, possibly because drones may frequently adjust their paths in dynamic environments, causing the old path to change often as well. Focusing on the old path may provide limited value for monitoring the current situation and system state. Therefore, it may be better to present the drone's original plan as the "old path", allowing operators to understand how the new path deviates from the original plan. For a point-to-point flying drone, its original plan represents a direct path from its current location to its destination. Highlighting the expected outcomes of this direct path not only explains why the drone had to reroute but also indicates when it can resume direct, point-to-point flight. Thus, this information element could more effectively reflect the current situation. Additionally, for consistency, using a cross symbol similar to those marking the expected outcomes of the new path may be better than red grid cells for indicating the expected outcomes of the direct path or original plan. The red grid cells rely on the shape of geofences, making them applicable only within the concept of Dynamic Airspace Reconfiguration (DAR). In contrast, the cross symbol is independent of geofences and can be applied to a broader range of operational concepts.

Since most engineering transparency elements were deemed relatively less useful in nominal scenarios, we could simplify or condense them further to enhance their usability. For example, the search graph can be omitted for grid-based path-planning algorithms to reduce visual clutter. The explored nodes and search trees can be combined to indicate the space explored by the algorithm. As shown in Fig. 5, the cost values have already been embedded within the explored nodes. In this way, we only need two transparency elements to reveal the inner workings of a path-planning algorithm: Explored Space and Search Process. The explored space represents the final results of the algorithm's exploration, while the search process illustrates the step-by-step details of how the exploration unfolds. They represent two distinct presentation styles for opening the "black box": a static image and a dynamic animation.

6.3 Integration of transparency into UTM systems

This research aligns with the U-space Concept of Operations (ConOps) (SESAR 2023), which mandates a collaborative interface with ATC to support human operators in managing drone traffic within controlled airspace. Several corresponding interface prototypes have been developed in previous studies (Janisch et al. 2022, 2023, 2024; Teutsch and Petersen 2024), with one of them created by our team (Janisch et al. 2022, 2024) shown in Fig. 18. On the left side of the display is a selection panel where users can activate various options to display different information layers on the main radar screen. Our proposed transparency elements can be integrated as additional options within this selection panel. As discussed in Sect. 6.2, the transparency elements can be further condensed, thereby limiting the number of options. Otherwise, presenting too many options may overwhelm users. The operational transparency elements can also be considered as contributing to the provision of

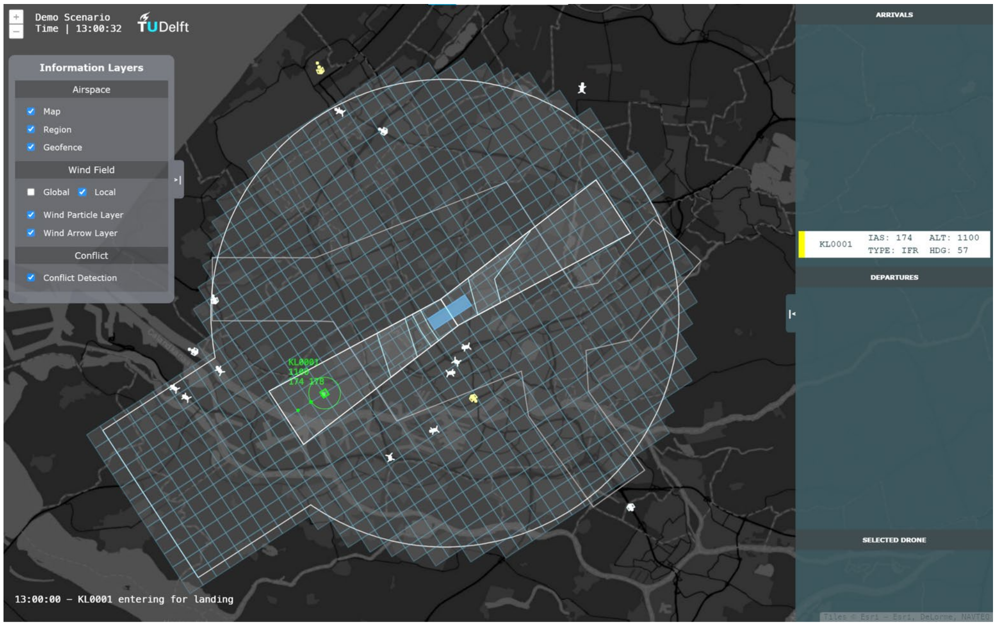


Fig. 18 UTM interface prototype DroneCTR[1] developed by Janisch et al. (2024)

certain UTM services, such as intent sharing, conflict alerts and weather information. All services can be integrated into a single interface, enabling UTM supervisors to share information seamlessly with drone operators.

In such a UTM system, a centralized (conflict-free path-planning) algorithm is expected to control all drones during tactical operations, meaning that flight plans are generated by the UTM system rather than by individual drones. This centralized approach allows both operational and engineering transparency elements to be computed directly within the UTM system, thereby reducing the volume of data that needs to be transferred between drones and UTM. If the UTM system is decentralized, the role of UTM supervisors may become unnecessary, and drone operators should be responsible for the safety of their own flights. An interface similar to Fig. 18, integrated with the transparency elements, can be adapted to help drone operators monitor whether their drones are maintaining safe separation from other aircraft during operations. As long as humans remain involved, transparency is essential for effective human-automation collaboration.

From a technical feasibility standpoint, integrating transparency elements into the UTM interface requires a robust backend architecture capable of real-time data processing and integration. The centralized conflict-free path-planning algorithm operates on a server-side platform, generating safe and efficient flight plans under dynamic airspace conditions. These flight plans should then be transmitted to the drones securely and reliably. To ensure accurate drone positioning, the system needs to continuously aggregate data from diverse sources, including Global Positioning System (GPS), onboard sensors, and external surveillance systems. It is also imperative to maintain low latency and support timely updates to the user interface.

6.4 Training needs for UTM supervision

As noted by both ATCos and drone experts, when scenarios become more complex (e.g., increased number of drones), they are concerned about the risk of information overload, thereby preferring less information. However, such traffic complexity also heightens the risk of conflicts between drones and crewed aircraft. Operators may in fact need greater transparency to support their supervision in complex scenarios. Moreover, when automation fails, which is often an urgent situation, ATCos and drone experts express a preference for access to nearly all available information. In such cases, the risk of information overload may be even more pronounced. Therefore, future UTM supervisors should be able to quickly identify the most relevant information in various situations. Appropriate training is required to ensure that they are familiar with how to effectively utilize transparency information to learn more about the nature of the supervisory control task and the system that needs to be monitored.

Our proposed transparency taxonomy could serve as a reference for training practices that rely on providing information "scaffolds" to guide the learning process in a phased manner, such as the Four-Component Instructional Design (4C/ID) model (Van Merriënboer and Kester 2005; Van Merriënboer 2019). The hierarchical structure of the proposed transparency taxonomy seems inline with progressively providing deeper (algorithmic) information, ranging from easily-interpretable operational parameters to more complex engineering parameters. For example, due to the large speed difference between drones and crewed aircraft, it may be difficult for inexperienced people to predict their Closest Point of Approach (CPA). In this case, the CPA-related transparency elements can offer valuable support. On the one hand, they can help operators learn how to predict CPA more accurately. On the other hand, they reassure operators that this information can be relied upon when they feel uncertain about their own predictions. Engineering transparency further helps operators understand an algorithm's capabilities and limitations, fostering well-calibrated trust, preventing over-reliance, and promoting learning—potentially reducing the need for transparency over time.

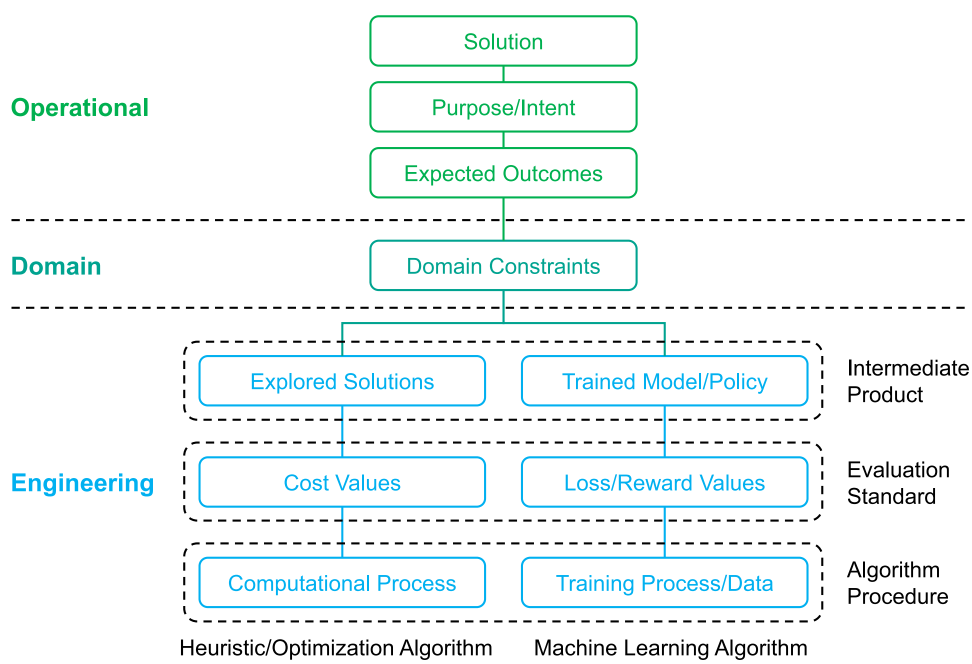
The hierarchical structure of the proposed taxonomy may also serve as procedural information to some extent, guiding operators through a step-by-step process for diagnosing issues such as automation failures. For instance, when UTM rerouting fails, the expected outcomes of the old path may help operators understand the initial cause, such as to avoid a conflict with a newly incoming crewed aircraft (a new constraint appears). Then, operators could further inspect the domain constraints, since the failure may have been caused by some other factors such as limited remaining battery or a strong headwind. Finally, they could examine the algorithm's inner workings to gain deeper insights. The grid size may be too large to find a feasible path, or the search tree may be overly constrained, preventing the drone from flying around certain obstacles. After repeated execution of this step-by-step process, operators could acquire sufficient understanding (of the algorithm and context) to reduce their reliance on transparency mechanisms.

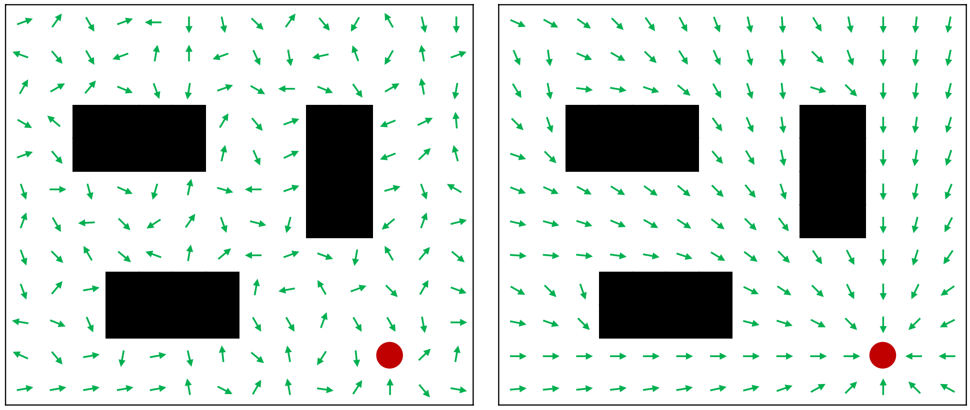
6.5 Extensions to machine learning methods

The engineering transparency categories in the unified taxonomy were largely derived from both literature and our experience with "traditional" planning algorithms such as graph-based and sampling-based algorithms. We chose traditional path planning, rather than machine learning-based path planning, for UTM routing because the operational UTM environment within controlled airspace is assumed to be fully known (similar to current ATC), and the future trajectories of all flights are generally predictable, making the traditional approach particularly suitable in this case. Traditional path planning can be a feasible and practical solution to UTM in the near future due to its solid mathematical foundations and theoretical guarantees. This "traditional" field also continues to evolve, with algorithms becoming increasingly faster and optimal (Shen et al. 2022; Zou and Borst 2024).

However, owing to the substantial potential offered by machine learning, future research could further explore how to extend this taxonomy to include machine learning methods as well, addressing transparency for training data, training algorithms and trained models (Arrieta et al. 2020). Figure 19 presents a possible extension of the proposed transparency taxonomy to incorporate machine learning algorithms. Since operational transparency primarily concerns the proposed solution and its interaction with the external environment, the distinction between heuristic/optimization algorithms and machine learning algorithms lies in

Fig. 19 Extended transparency taxonomy including machine learning algorithms





(a) Random initialization

(b) Final policy

Fig. 20 Vector field-based visualization for reinforcement learning policies

(internal) engineering transparency. Each type of engineering transparency in machine learning algorithms has a direct counterpart in heuristic/optimization algorithms. Explanations for trained models or policies in machine learning are also associated with XAI. Further research is required to validate and refine this extended transparency taxonomy.

The extended taxonomy can also inform the design of transparency elements for machine learning methods. For instance, visualizing the policy in reinforcement learning can offer deeper insights into the AI decision-making strategy (Groot et al. 2023). Revealing the training process/data can assist policymakers in identifying bias in learning-based AI models (Obermeyer et al. 2019). Figure 20 illustrates an example of visualizing the initial and final policies in reinforcement learning based on vector fields (Ren et al. 2022). The training process can be interpreted as a convergence of the policy from an initial random state to a final optimized state.

6.6 Limitations and future research

In this research, we conducted the user study only via a questionnaire. Participants did not experience the actual functioning of transparency in (simulated) UTM operations, and thus their ratings were mainly based on their prior experience and expectations. The responses to the questionnaire can only provide subjective measurements that may be biased due to the small sample size. To address these limitations, our future research will involve human-in-the-loop experiments in dynamic scenarios to further explore the practical usage of different transparency elements. During the second rating phase, participants were only required to rate elements in normal scenarios and the failure scenario may warrant further exploration.

As shown in Fig. 16, some operators preferred certain transparency elements to be activated automatically based on situations. This preference reflects the concept of *adaptive transparency*, which involves dynamically tailoring transparency information based on automation-driven assessments of users' context, workload, and task demands (Lim et al. 2021). Adaptive transparency is particularly useful in urgent situations, such as conflicts or emergencies, where it helps ensure that critical information is delivered promptly without overwhelming users. Future research could explore how to achieve adaptive transparency in UTM.

7 Conclusion

This research introduces a unified taxonomy for algorithmic transparency, integrating established user-, ecology-, and model-centered perspectives to achieve operational, domain, and engineering transparency. Based on the taxonomy, twenty transparency elements and fourteen corresponding visual prototypes were designed to support the supervision of tactical UTM operations within CTR around airports. A survey-based user study was then conducted to investigate the needs and preferences of ATCos and drone experts on these elements in different scenarios. The results suggest that transparency is a dynamic construct that depends on situational demands and operator background. In nominal UTM scenarios, operational transparency is deemed more useful than engineering transparency. In the case of automation failure, operators tend to seek more engineering transparency to understand what happened deeper inside the system. Our proposed unified transparency taxonomy offers the flexibility to accommodate these varying transparency needs across various scenarios. As scenarios become more complex, the issue of information overload may intensify. To mitigate this issue, appropriate training may be necessary for UTM supervisors to effectively access and interpret transparency information in different situations. The grouping results of the transparency elements validated the structure of the proposed taxonomy. As demonstrated in this article, the taxonomy could serve as a guide for system developers in designing transparency.

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Author contributions Y. Zou conducted the main research under the supervision of Dr. C. Borst. Both authors reviewed the manuscript.

Data availability All data generated or analyzed during this study are included in this published article.

Declarations

Conflict of interest The authors declare no conflict of interest.

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