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A LIFECYCLE-BASED FRAMEWORK FOR EMBEDDING TRUSTWORTHINESS IN MAINTENANCE PLANNING DECISION-SUPPORT SYSTEMS

Parul Khanna

Luleå University of Technology, Sweden. E-mail: parul.khanna@ltu.se

Ramin Karim

Luleå University of Technology, Sweden. E-mail: ramin.karim@ltu.se

Human centricity is increasingly recognised as essential for the effective adoption of intelligent and digitally enabled maintenance systems, making trustworthiness a critical requirement for maintenance decision support. These systems are intended to support human judgment by providing aggregated information, prioritised recommendations, and scenario exploration capabilities. However, existing research often addresses trust either at the algorithmic level or at the user perception level. This often overlooks the Human-System Interaction (HSI) processes through which trustworthiness is actually established, maintained, and validated. HSI bridges the gap between the technical reliability of a system and the human confidence required for its operation. To address this gap, this paper proposes a lifecycle-based framework for embedding trustworthiness into maintenance planning decision-support systems (DSS) through HSI considerations. The framework conceptualises trustworthiness as a socio-technical system property and systematically links trustworthiness attributes, such as transparency, traceability, predictability, and accountability, to system lifecycle phases, from requirements definition and design to validation and operation. Rather than treating trust as a post-deployment concern, the framework supports proactive integration of trustworthiness during system development. The framework is instantiated using a maintenance planning DSS to illustrate its applicability at the planning level. The proposed approach contributes structured guidance for designing trustworthy, interpretable, and human-centred maintenance planning systems.

Keywords: Maintenance planning, Decision-support systems, Trustworthiness, Human-system interaction, Lifecycle engineering, Human-centric maintenance.

1. Introduction

Maintenance is a combination of all the technical, administrative, and managerial actions required to retain or restore an asset to a state in which it can perform its required function (SS-EN 13306, 2017). Effective and efficient maintenance is crucial for ensuring system safety, availability, and lifecycle cost efficiency in asset-intensive domains, such as railways, aviation, and mining, where maintenance strategies directly impact reliability and risk profiles of assets (Bokrantz et al., 2020). Maintenance strategies, including preventive, corrective, and condition-based approaches, are realized through maintenance activities that define how and when maintenance is carried out in practice (ISO 55001, 2024; SS-EN 13306, 2017). Within this context, maintenance planning plays a central role by determining future maintenance actions, their timing, and the associated resource requirements across the asset lifecycle (da Silva et al., 2023).

In recent years, maintenance planning has increasingly been supported by digital decision-support systems that integrate historical maintenance data, asset condition information, and operational context to assist planners in managing complex systems (Bokrantz et al., 2020; van Oudenhoven et al., 2023). Rather than replacing human expertise, such systems are intended to support human decision-making by providing aggregated views, prioritized recommendations, and exploration capabilities that help planners evaluate trade-offs among risk, cost, and availability (Bokrantz et al., 2020; da Silva et al., 2023). This shift also aligns with broader Industry 5.0 and human-centric maintenance perspectives, which emphasize the role of human judgement, responsibility, and collaboration in technologically advanced systems (Breque et al., 2021; Romero & Stahre, 2021).

However, as maintenance planning decisions remain human-led, the effective use of decision-support systems (DSS) depends not only on their technical capabilities but also on the extent to which their outputs are trusted and correctly interpreted by human decision-makers (Hinrichs et al., 2024; Khanna et al., 2025; Lee & See, 2004). In practice, planners may over-trust system outputs, under-trust them, or misinterpret information, particularly when maintenance decisions are based on long-term planning horizons, aggregated summaries of multiple assets, or assumptions that are not explicitly communicated to the user. Such trust-related issues can lead to unsafe maintenance deferrals, inefficient resource allocation, or reduced system availability, even when the underlying system is technically sound, leading to underutilization of otherwise effective systems (Chen et al., 2021; Gopalakrishnan et al., 2018).

Human-system interaction (HSI) plays a critical role in bridging this gap, as maintenance planning inherently involves interpretation, judgment, and accountability, keeping the human in the loop. Effective use of maintenance planning decision-support systems, therefore, requires planners to understand not only the outputs of the system, but also how and why those outputs are generated (Ucar et al., 2024). Trustworthiness is thus not a function of technical performance alone, but of how system behaviour is made transparent, traceable, and predictable in HSI (Firmino de Souza et al., 2025; Ueno et al., 2022). Since trust-related issues often originate from early requirements and design decisions but only become visible during system operation, a lifecycle perspective is required to address trustworthiness systematically (Morris et al., 2020; Ucar et al., 2024; Ueno et al., 2022). This highlights that trustworthiness should be considered a socio-technical system property, shaped by system design and human decision-making across the system lifecycle. Despite this, trustworthiness in maintenance planning DSS is often treated implicitly or assessed post-deployment, rather than being systematically embedded during system development.

The purpose of this paper is to explore how trustworthiness can be systematically integrated into DSS for maintenance planning, thereby supporting reliable and safe maintenance decisions. To fulfil this paper makes two contributions. First, it proposes a lifecycle-based framework that links trustworthiness attributes, such as transparency, traceability, and reliability, to HSI considerations during system development. Second, it demonstrates the applicability of the framework through system instantiation.

2. Background

2.1. *Decision-Support Systems (DSS) for Maintenance Planning*

DSS have become an integral component of maintenance planning in asset-intensive industries, where planners must manage large volumes of asset information, long planning horizons, and competing objectives related to safety, availability, and cost (Bokrantz et al., 2020; da Silva et al., 2023; Torres-Sainz et al., 2024). Maintenance planning DSS typically integrates historical maintenance records, asset condition or status data, and operational context to support decisions regarding future maintenance actions, prioritization, and resource allocation.

Existing research on decision support in maintenance has largely focused on enhancing optimization performance, prediction accuracy, or computational efficiency (Stipanovic et al., 2021; Tiddens et al., 2023). Trust is often addressed either at the algorithmic level, through model validation and performance metrics, or at the user level, as a matter of perception or acceptance after system deployment (Doshi-Velez & Kim, 2017; Jacovi et al., 2021).

2.2. *Trustworthiness and Human-System Interaction (HSI) in Lifecycle-Oriented Decision Support*

In standard, trust is defined as the degree to which a user or stakeholder has confidence that a system will behave as intended, whereas trustworthiness refers to the ability of a system to meet stakeholders' expectations in a verifiable manner. Trustworthiness is thus conceptualized as a system attribute rather than a purely subjective user perception and encompasses characteristics such as reliability, availability, safety, security, resilience, transparency, and accountability, depending on the application context (IEC TR 24048, 2023).

Despite the growing recognition of trustworthiness as a system attribute, existing research has largely addressed human involvement in maintenance through human-centric maintenance, which has emphasized task execution, operator assistance, and ergonomic support in maintenance and industrial contexts (Bokrantz et al., 2020; Naumann et al., 2013; Romero & Stahre, 2021). While these approaches acknowledge the central role of humans in maintenance systems, they have primarily addressed operational and task-level activities, with limited attention to how trustworthiness can be systematically embedded into maintenance planning decision-support systems during system development, particularly from a lifecycle perspective (Smith et al., 2020; van Oudenhoven et al., 2023).

In the context of maintenance planning DSS, trustworthiness is particularly critical, as planning decisions influence safety, availability, and resource allocation over long time horizons (van Oudenhoven et al., 2023). From an HSI perspective, trustworthiness concerns how such system attributes are made visible, understandable, and actionable for human decision-makers (Doshi-Velez & Kim, 2017; Lee & See, 2004). In DSS, particularly those supporting planning activities, trustworthiness is shaped through interaction mechanisms that allow users to assess system behavior, underlying assumptions, and limitations (Sapienza et al., 2022; Ueno et al., 2022). Accordingly, trustworthiness cannot be treated solely as an outcome of technical performance but must be considered in relation to how systems are designed to support human understanding, judgment, and accountability during use (Firmino de Souza et al., 2025; Ueno et al., 2022).

From a safety and reliability engineering perspective, lifecycle-oriented approaches are well established, where early integration of requirements, verification, and validation is recognized as essential for achieving dependable system behaviour (Estefan, 2008; IEC 60300-3-10, 2025; ISO/IEC/IEEE 15288, 2023). However, there remains limited structured guidance on how trustworthiness can be embedded into maintenance planning decision-support systems across lifecycle phases, from requirements definition and design to validation and operation. Addressing this gap requires moving beyond post-deployment evaluation towards the systematic engineering of trustworthiness throughout system development.

3. Methodological Approach

This study adopts a design-oriented research approach to develop a lifecycle-based framework for embedding trustworthiness into maintenance planning DSS (Fallman, 2003). The framework is developed through a conceptual synthesis of standards, prior research, and practical insights from maintenance planning DSS from industrial practitioners. First, relevant standards and guidelines in safety, reliability, and system lifecycle engineering are reviewed. These standards provide a foundation for lifecycle-oriented system development and the treatment of dependability-related attributes.

Second, literature on maintenance planning DSS, trustworthiness, and HSI is analysed to identify recurring trust-related challenges and interaction needs at the planning level. This synthesis focuses on how trustworthiness-relevant system attributes, such as transparency, traceability, and reliability, are addressed or not addressed in existing approaches. Based on this, a lifecycle-based framework is developed by mapping trustworthiness attributes to HSI considerations across key lifecycle phases, including requirements definition, system design, implementation, validation, and operation. The framework explicitly assumes a human-in-the-loop planning context, where decision authority remains with human planners, and that DSS are used to support, rather than automate, maintenance planning decisions.

To demonstrate applicability, the framework is instantiated using a maintenance planning DSS supporting long-term planning for high-value assets in railways. The instantiation serves as an illustrative application to show how trustworthiness considerations can be operationalised in practice at the planning level, without relying on post-deployment trust assessment or automation of decision-making.

Figure 1 illustrates the methodological approach adopted in this study, showing how standards, literature, and practical insights are synthesised to develop a lifecycle-based framework.

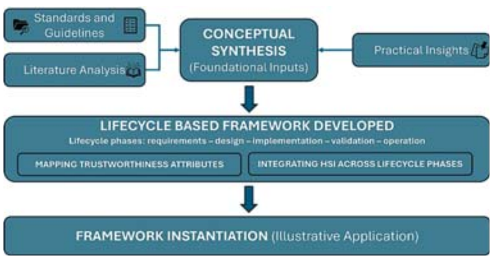

Figure 1: Methodological approach for developing and instantiating a lifecycle-based trustworthiness framework for maintenance planning DSS.

4. Lifecycle-Based Trustworthiness Framework for Maintenance Planning DSS

This section presents a lifecycle-based framework for embedding trustworthiness into maintenance planning DSS through HSI considerations. The framework conceptualises trustworthiness as a socio-technical system property shaped by system design and human decision-making across the lifecycle and provides structured guidance for integrating trustworthiness during system development. It is grounded in lifecycle-oriented principles from safety and reliability engineering and is organised around two dimensions: system lifecycle phases and trustworthiness attributes relevant to planning-level decision-making.

Lifecycle phases are defined in accordance with (ISO/IEC/IEEE 15288, 2023) and include requirements definition, system design, implementation, verification and validation, and operation and evolution. Trustworthiness attributes are derived from standardised definitions and prior research, with a focus on attributes that are particularly relevant in maintenance planning contexts. Figure 2 illustrates the overall structure of the framework, showing how trustworthiness attributes are embedded across lifecycle phases through HSI considerations, with the human planner remaining the final decision authority.

4.1. *Lifecycle Phases and Trustworthiness Integration*

Trustworthiness in maintenance planning DSS is not introduced at a single stage. Instead, it is gradually shaped across the system lifecycle through design and interaction choices that influence how planners understand, use, and rely on system outputs. Each lifecycle phase contributes in a different way to building trust between the system and its users.

Requirements definition establishes the foundations for trustworthiness by clarifying the intended decision scope of the system. At this stage, trustworthiness is supported by clearly stating what kinds of maintenance planning decisions the system is meant to support and what it is not meant to support. This includes defining the relevant planning horizons and making underlying assumptions visible. For example, a system intended for long-term planning should clearly indicate that its outputs are not suitable for detailed short-term scheduling. When these boundaries are clear, planners are less likely to

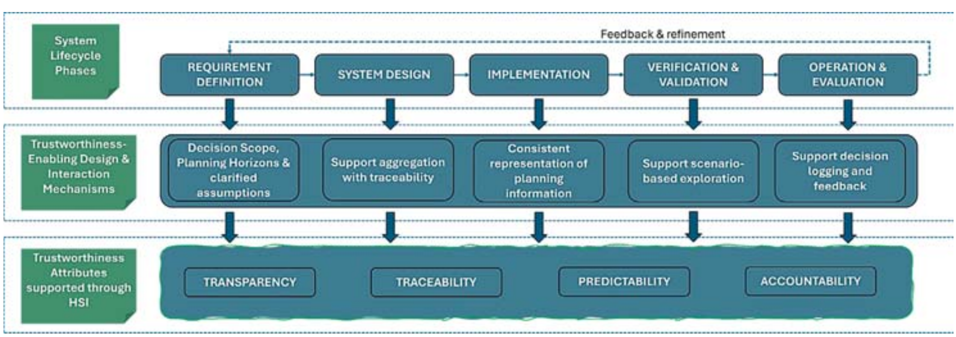

Figure 2: Lifecycle-based trustworthiness framework for maintenance planning decision-support systems.

misunderstand system outputs or rely on them in inappropriate ways.

During system design and implementation, trustworthiness depends on how planning information is presented and how users can interact with it. Maintenance planning often relies on aggregated indicators to reduce complexity, such as urgency levels, criticality categories, or overall resource demand. For these indicators to be trusted, planners need to understand what they are based on. This requires consistent terminology, clear visual structure, and interaction options that allow users to trace aggregated results back to their underlying factors. When system behaviour is consistent, and changes in inputs lead to understandable changes in outputs, planners can easily make sense of the results.

During verification and validation, trustworthiness can be examined by looking at how the system behaves in typical planning situations. Rather than focusing only on whether calculations are technically correct, this phase considers whether the system's outputs make sense from a planning perspective. Scenario-based walkthroughs, where assumptions or planning conditions are varied, help assess whether the system responds in a predictable and understandable way and whether users can correctly interpret the consequences for their planning decisions.

Finally, during operation and evolution, trustworthiness is strengthened through support for accountability and learning over time. In real planning situations, users may choose not to follow system-supported recommendations due to contextual factors that are not captured by the system. Recording system outputs, user decisions, and outcomes makes it possible to review how decisions were made and to identify recurring patterns. Over time, this feedback supports calibrated trust, where users understand both the value and the limitations of the decision-support system and know when to rely on it and when to apply their own judgement.

4.2. *Trustworthiness Attributes and HSI Considerations*

Within the proposed framework, trustworthiness is operationalised through a set of attributes that directly influence maintenance planning decision-making. While trustworthiness can include many characteristics depending on context, the framework focuses on attributes that are particularly relevant at the planning level, where decisions are advisory, forward-looking, and often made under uncertainty. Transparency supports understanding of how planning outputs are produced. This includes making data sources, modelling assumptions, planning horizons, and aggregation logic visible to users. When planners can see what information underlies a recommendation and what assumptions are applied, they are better able to judge its relevance and limitations. Traceability enables planners to relate aggregated planning indicators to their underlying elements, such as individual assets, maintenance actions, or contributing data. Traceability supports sense-making by allowing users to move between high-level planning views and more detailed information when needed, rather than relying solely on summary indicators. Predictability refers to the consistency of system behaviour. At the planning level, predictability means that planners can anticipate how system outputs will change when inputs or assumptions are modified. Consistent categorisation, stable terminology, and repeatable responses to similar scenarios support planners in forming accurate mental models of system behaviour. Accountability ensures that responsibility for maintenance planning decisions remains clearly with human planners. The role of the system is to support, not replace, human judgment. Accountability is supported by mechanisms that allow decisions, overrides, and justifications to be recorded and reviewed, making it possible to understand how and why planning decisions were made.

These trustworthiness attributes are embedded through HSI considerations that support interpretation, exploration, and reflective decision-making, rather than through automated decision enforcement. The framework, therefore, emphasises interaction mechanisms that help planners understand and reason about system outputs, rather than prescribing actions. Table 1 summarises how trustworthiness attributes are mapped to lifecycle phases and corresponding HSI considerations within the framework.

Table 1: Mapping trustworthiness attributes to lifecycle phases and HSI considerations.

Lifecycle Phase	Trustworthiness Attribute	HSI Consideration
Requirements	Transparency	Explicit definition of planning horizons, scope, and decision assumptions
Design	Traceability	Ability to drill down from aggregated planning views to component-level data
Design	Predictability	Consistent categorization and presentation of maintenance urgency
Validation	Predictability / Calibrated trust	Scenario-based walkthroughs of representative planning situations
Operation	Accountability	Logging of planning decisions, overrides, and underlying rationale

5. Framework Instantiation: Maintenance Planning DSS

The proposed framework is instantiated using an illustrative maintenance planning DSS for high-value railway components. The purpose of this instantiation is to provide representative examples, rather than to evaluate system performance, of how trustworthiness attributes can be supported through HSI. The illustrative interaction views shown in Figure 3, and an example of traceability provided in Table 2 are therefore intended to show some illustrations of framework concepts. The illustrative system combines preventive maintenance records, turnaround time data, and component status information with configurable planning parameters to generate aggregated planning-level indicators intended to support, rather than prescribe, maintenance planning decisions.

Figure 3, illustrates key interaction mechanisms aligned with the framework, with markers 1-5 in highlighted circles. A user-adjustable planning assumption (1) supports transparency by making input assumptions explicit. The baseline planning output (2) and the corresponding system response to changed assumptions (3) support predictability and interpretability by revealing how outputs change in response to input variations. Trustworthiness during operation is further illustrated through data freshness indicators (4) and data quality status flags (5), which make data recency and limitations visible and support calibrated trust. Traceability is illustrated through filter-based drill-down mechanisms that link aggregated planning indicators to subsets of component-level data. Table 2 provides an illustrative example of how such mechanisms support accountability and informed human oversight.

Traceability in the instantiated system is supported through filter-based drill-down mechanisms that link aggregated planning indicators to relevant subsets of individual components. Filters such as component type, fleet, depot, urgency, and criticality enable targeted exploration of planning results by relating planning-level assessments to their underlying component data. Table 2 illustrates how such traceability mechanisms operate under different planning scenarios.

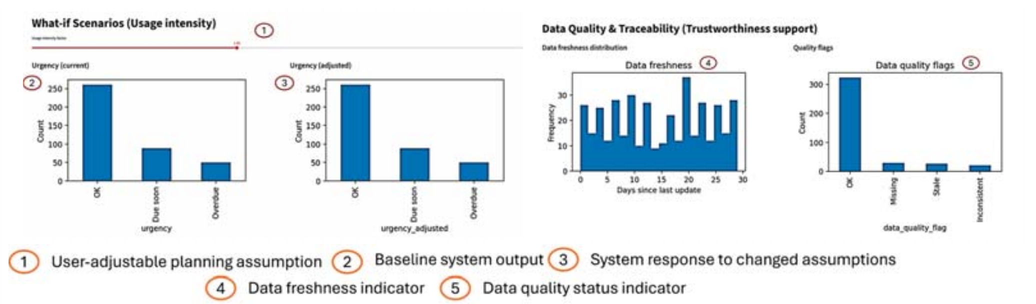

Figure 3: Illustrative views from the maintenance planning DSS used to instantiate the proposed framework.

6. Conclusions and Future Work

Table 2: Traceability is realised by linking planning-level indicators to component-level information through filter-based drill-down.

Traceability Scenario	Planning-Level Indicator	Traceability Path	Component-Level Information Exposed	Decision Support Purpose
Scenario 1: Urgency-driven traceability	High maintenance demand within planning horizon	Planning indicator → Urgency category → Component list	Component ID, component type, fleet, depot, days to maintenance due, urgency, criticality	Enables planners to identify which individual components contribute to high planning urgency and assess their operational status
Scenario 2: Data-quality-aware traceability	Medium maintenance demand with data uncertainty	Planning indicator → Data quality flag → Component list	Component ID, data freshness, data quality flag, last maintenance date, turnaround characteristics	Enables planners to assess whether planning indicators are influenced by outdated or uncertain data and adjust confidence in system outputs

This paper presented a lifecycle-based framework for embedding trustworthiness into maintenance planning DSS through HSI considerations. The framework addresses a key need in maintenance planning by ensuring that DSS are not only technically capable but also used appropriately and reliably by human planners. By treating trustworthiness as a property that must be engineered throughout the system lifecycle, the framework provides structured guidance for addressing trust-related risks during system development rather than after deployment. The framework is particularly relevant for designers, developers, and organisations deploying maintenance planning DSS in asset-intensive domains, where planning decisions have long-term safety, availability, and cost implications and where planners must balance system-supported insights with professional judgement to avoid over-trust or misinterpretation of planning outputs. Through illustrative examples, the paper showed how trustworthiness attributes can be operationalised at the planning level while preserving human decision authority and supporting appropriate reliance on system outputs.

The framework is conceptual in nature and illustrated through representative examples rather than empirical validation. Future work will focus on empirical evaluation through user studies and real planning environments, as well as extensions to address uncertainty, additional trustworthiness attributes, and broader application domains.

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