International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 07 | Jul 2026 www.irjet.net p-ISSN: 2395-0072

An Ontology-Driven Framework for Explainable Engineering Decision Support, Human-AI Collaboration and Human-in-the-Loop Optimization

Balraj Avinash Waghmare[1], Avinash Vishwanath Waghmare[2]

[1]*Systems Engineer, BALBIRD INDUSTRIES, Pune*
[2]*Associate Professor, AISSMS COE, Pune*

---***---

Abstract-*Engineering decisions are increasingly influenced by interconnected technical, manufacturing, economic, organizational, and stakeholder-related factors. While Artificial Intelligence has expanded the capabilities of engineering decision-support systems, many existing approaches still struggle to capture human expertise, preserve decision rationale, and provide transparent explanations for recommended actions. As a result, engineering knowledge often remains fragmented, and the reasoning behind important decisions can be difficult to understand, validate, or reuse. This study presents the* ***Human-AI Engineering Decision Intelligence (HAEDI)*** *framework, an ontology-driven approach designed to support transparent, traceable, and human-centered engineering decision-making. The framework combines the* ***Engineering Decision Ontology (EDOnt)*** *for structured knowledge representation, the* ***Engineering Reasoning Chain (ERC)*** *for explainable and traceable reasoning, the* ***Engineering Orchestration Model (EOM)*** *for stakeholder participation and Human-AI collaboration, and* ***Human-in-the-Loop Optimization*** *for incorporating expert judgement, preferences, and feedback into decision formation. The proposed framework was evaluated using an industrial electric vehicle chassis manufacturing case study and compared with a conventional Large Language Model-based workflow. The evaluation considered knowledge formalization, reasoning transparency, collaborative decision-making, and optimization support. The findings indicate that the proposed approach provides stronger knowledge organization, improved traceability, clearer decision justification, enhanced stakeholder involvement, and greater transparency throughout the decision process. The research contributes an integrated framework that connects knowledge representation, explainable reasoning, Human-AI collaboration, and optimization within a unified engineering decision-support environment, supporting the creation of reusable and trustworthy Engineering Decision Intelligence.*

Key Words: Engineering Decision Support, Human-AI Collaboration, Engineering Ontology, Explainable AI, Human-in-the-Loop Optimization, Knowledge Representation, Systems Engineering, Large Language Models.

1. INTRODUCTION

Engineering decision-making is becoming progressively more challenging as product development and engineering activities involve a wider range of interconnected technical, economic, operational, and sustainability considerations. Throughout the engineering lifecycle, professionals must balance customer requirements, design choices, manufacturing limitations, available resources, and stakeholder objectives while ensuring that decisions remain reliable, justifiable, and well-documented. The emergence of Artificial Intelligence (AI) has created new opportunities for supporting these activities through advanced data analysis, optimization techniques, and knowledge-based assistance. Nevertheless, successful engineering decision support depends not only on computational performance but also on the ability to provide clear reasoning, incorporate human expertise, and ensure transparency in the decision-making process. Such capabilities are essential for establishing effective, trustworthy, and explainable collaboration between engineers and AI systems [1], [2], [4], [5].

1.1 Background and Motivation

Engineering decision-making is becoming progressively more challenging because of the increasing interaction between technical, economic, operational, and sustainability-related considerations across product development and engineering execution activities. Engineers are expected to assess requirements, alternative design solutions, manufacturing limitations, available resources, and stakeholder needs while ensuring decision accuracy and traceability. Recent developments in Artificial Intelligence (AI) have enhanced engineering decision-support capabilities through machine learning, optimization techniques, knowledge-driven systems, and large language models. Nevertheless, successful engineering support depends not only on computational power but also on the incorporation of human expertise, contextual awareness, and interpretable reasoning. Therefore, there is a growing demand for human-centered and explainable decision-support methods that facilitate reliable Human-AI collaboration within engineering environments [1], [2], [4], [5].

1.2 Problem Statement

Despite considerable progress in AI-assisted engineering, important engineering knowledge often remains dispersed across documents, standards, digital platforms, and individual specialists. In addition, a large portion of engineering expertise exists as tacit knowledge gained through practical experience and contextual understanding, making it difficult to capture, formalize, and reuse within decision-support activities [3]. Consequently, engineering decisions frequently suffer from limited traceability, where the reasoning, assumptions, constraints, and supporting evidence behind a decision are not explicitly recorded. Existing AI-based systems are capable of generating recommendations and analyses; however, they often provide limited insight into how their conclusions are derived. As a result, inadequate integration between human expertise and AI capabilities continues to restrict the effectiveness, reliability, and acceptance of engineering decision-support systems [3]–[5].

1.3 Research Gap

Existing studies have made significant contributions to fields such as knowledge representation, explainable AI, human-in-the-loop systems, optimization-driven decision support, and AI-assisted engineering. Ontology-based methods offer structured representations of engineering knowledge [3], whereas explainable AI techniques enhance the interpretability of algorithmic outcomes [4]. Likewise, optimization approaches assist decision-making under multiple constraints, and Human-AI collaboration frameworks support user involvement during problem-solving activities [5]. However, these approaches are typically developed in isolation and provide limited capability for combining engineering knowledge, human expertise, decision traceability, explainable reasoning, optimization transparency, and feedback-oriented Human-AI collaboration within a unified engineering workflow. Consequently, a gap still exists in enabling transparent, traceable, and human-centered engineering decision-making throughout the entire decision lifecycle [3]– [5].

1.4 Research Questions, Objectives and Contributions

To address the research gaps identified in this study, the investigation focuses on the integration of engineering knowledge, human expertise, explainable reasoning, optimization methods, and Human-AI collaboration within engineering decision-support environments. The associated research questions, objectives, and anticipated contributions are presented in Table 2.

Table -2: Research Questions, Objectives and Contributions Matrix

RQ	Research Question	Objective	Contribution
RQ1	How can engineering knowledge and human expertise be systematically modelled to support engineering decision-making activities?	Formalize engineering knowledge and human expertise.	C1: Engineering Decision Ontology (EDOnt)
RQ2	How can engineering decisions be made traceable and interpretable through a structured reasoning mechanism?	Enable decision traceability and explainability.	C2: Engineering Reasoning Chain (ERC)
RQ3	How can Human-AI collaboration enhance transparency and effectiveness in engineering decision-making processes?	Support Human-AI collaboration, feedback integration, and decision transparency.	C3: Engineering Orchestration Model (EOM)
RQ4	How can knowledge representation, explainable reasoning, optimization, validation, and human feedback be unified within a single decision-support framework?	Develop and evaluate an integrated engineering decision-support framework.	C4: Human-AI Engineering Decision Intelligence (HAEDI)

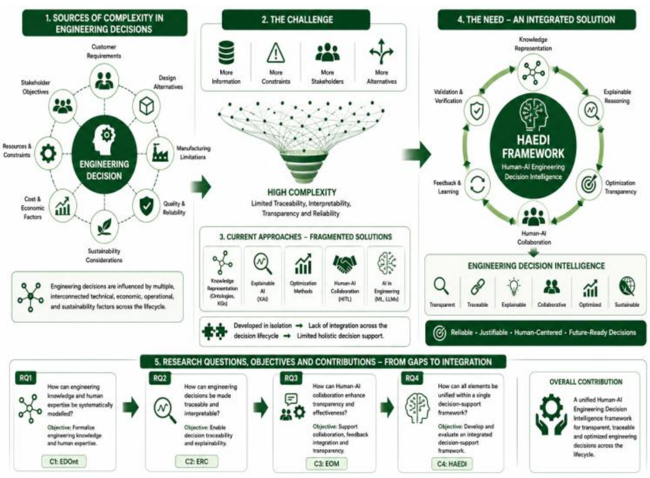

Fig -1: Engineering Decision Complexity Landscape

2. FOUNDATIONS OF HUMAN-AI ENGINEERING DECISION SUPPORT

2.1 AI-Supported Engineering and Product Development

Artificial Intelligence (AI) is being increasingly adopted across engineering and product development activities to assist with requirements analysis, design assessment, manufacturing planning, resource management, and decision-making tasks. Developments in machine learning, optimization approaches, knowledge-based technologies, and large language models have strengthened the capability of engineering systems to handle complex information and deliver valuable decision-support insights. As a result, AI-enabled engineering is progressing from standalone analytical applications toward integrated engineering environments that provide support throughout development activities. Nevertheless, effective implementation requires alignment with engineering methodologies, product goals, organizational priorities, and expert knowledge. Therefore, AI-driven engineering solutions must integrate computational intelligence with structured decision-support approaches to enhance engineering effectiveness, consistency, and decision outcomes [6], [7], [17].

2.2 Human-AI Collaboration

The growing use of AI within engineering has shifted attention from fully automated decision-making toward Human-AI collaboration, where human expertise and computational capabilities work together to solve engineering problems. Human-centered AI promotes the development of systems that complement human objectives, contextual awareness, and decision-making practices rather than replacing engineers. Within engineering domains, experts contribute valuable domain knowledge, practical experience, assumptions, and judgement that are often difficult to represent through purely data-driven methods. Consequently, collaborative decision-support approaches aim to combine AI-generated analysis with human reasoning to achieve decisions that are more transparent, reliable, and effective while preserving human supervision, responsibility, and alignment with engineering goals [8], [9], [18].

2.3 Engineering Methods and Systems Thinking

Engineering decisions seldom occur independently and must be evaluated within a network of interconnected requirements, functions, processes, resources, and stakeholders. Systems engineering offers a structured methodology for addressing such complexity by focusing on the relationships among system elements across the lifecycle [11]. Likewise, engineering methods facilitate consistent decision-making through established procedures, evaluation mechanisms, and validation practices. In product development and engineering execution settings, adherence to defined processes is important for maintaining repeatability, compliance, and decision quality. In addition, engineering traceability enables decisions to be connected to relevant requirements, assumptions, constraints, and supporting evidence. Collectively, systems thinking and engineering methodologies provide a basis for transparent, dependable, and explainable engineering decision-support practices [10], [11].

2.4 Knowledge Representation and Human Mental Models

Successful engineering decision support depends not only on information availability but also on the way knowledge is represented and organized. Knowledge representation techniques offer mechanisms for structuring engineering concepts, relationships, constraints, and decision-relevant information in forms understandable to both humans and computational systems [12], [13]. Beyond explicit technical knowledge, engineering decisions are also shaped by expertise, experience, assumptions, preferences, and contextual awareness. Together, these elements form human mental models that influence problem interpretation and solution assessment. Therefore, the structured representation of engineering knowledge and human mental models is essential for enabling transparent, explainable, and human-oriented engineering decision-making [8], [12], [13].

2.5 Explainable AI and Trust

As AI systems assume a greater role in engineering decision-making, understanding and justifying their outputs has become increasingly important. Explainable Artificial Intelligence (XAI) seeks to improve the interpretability of AI-generated recommendations, predictions, and decisions by providing transparent reasoning and supporting evidence [14], [15]. Transparency allows engineers to understand how conclusions are produced, while trust is influenced by the consistency, reliability, and interpretability of system behavior. Effective Human-AI collaboration also requires appropriate trust calibration, ensuring that users neither depend excessively on AI recommendations nor dismiss them without justification. As a result, explainability and transparency are fundamental to enhancing user acceptance, accountability, and confidence in AI-supported engineering systems [8], [14], [15].

2.6 Human-in-the-Loop Optimization

Optimization methods are extensively applied in engineering to evaluate alternatives and identify solutions that satisfy multiple objectives and constraints. However, engineering decisions frequently involve contextual considerations, expert preferences, and practical factors that cannot be fully represented through mathematical formulations alone. Human-in-the-Loop (HITL) optimization addresses this limitation by allowing experts to contribute domain knowledge, priorities, and constraints both before and during optimization activities [16]. Additionally, feedback mechanisms enable decision-makers to review, refine, and modify optimization outcomes in response to changing requirements and contextual factors. Consequently, HITL optimization promotes greater transparency, improved acceptance of solutions, and a balanced integration of algorithmic recommendations with human judgement [16], [17].

2.7 Conversational Agents and LLMs

Recent progress in conversational agents and Large Language Models (LLMs) has created new possibilities for natural language interaction within engineering environments [19]. Compared with conventional interfaces, conversational systems allow users to communicate requirements, constraints, preferences, and domain knowledge using natural language. This capability supports knowledge elicitation by facilitating the capture of expert insights that are often challenging to formalize using traditional data structures. Furthermore, conversational interfaces provide a practical means for gathering expert feedback, clarifying assumptions, and enabling iterative decision-making. Consequently, conversational agents and LLMs are increasingly being investigated as engineering assistants that improve accessibility, collaboration, and decision support while strengthening communication between human experts and AI technologies [9], [18], [19].

Table -3: Literature Review Matrix

Theme	Key Contribution	Remaining Gap
AI-Supported Engineering	Facilitates engineering analysis and decision-support activities	Limited incorporation of human expertise and traceable reasoning mechanisms
Human-AI Collaboration	Integrates human and AI capabilities within decision-making processes	Limited formalization of engineering knowledge and expertise
Knowledge Representation & Ontologies	Enables structured modeling of domain knowledge	Weak connection with explainability and optimization processes
Explainable AI (XAI)	Enhances transparency and interpretability of AI outputs	Limited capability for supporting engineering decision traceability
Human-in-the-Loop Optimization	Integrates expert knowledge and feedback into optimization activities	Limited linkage with knowledge representation and engineering workflows
Conversational Agents & LLMs	Support natural language interaction and knowledge acquisition	Limited capability for structured engineering decision-support applications

3. ENGINEERING DECISION ONTOLOGY

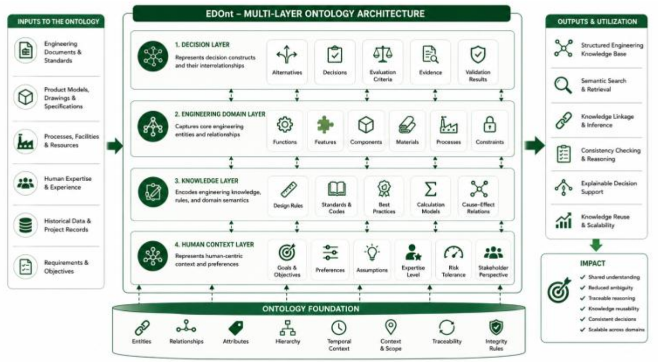

Fig -2: Engineering Decision Ontology (EDOnt): Multi-Layer Ontology Architecture

3.1 Design Principles

The Engineering Decision Ontology (EDOnt) provides a structured framework for representing engineering decision knowledge in a manner that can be understood by both human experts and computational systems. The ontology is developed based on four fundamental design principles:

P1. Formal Representation

Establish a consistent representation of engineering concepts, relationships, constraints, and decision-related elements. Minimize ambiguity in the representation of engineering knowledge [12].

P2. Explainability

Connect decisions with supporting knowledge, assumptions, and evidence. Facilitate clear and understandable decision justification [14].

P3. Traceability

Preserve links between requirements, processes, decisions, and resulting outcomes. Enable decision validation and auditing activities [11].

P4. Human Knowledge Integration

Capture expert knowledge, preferences, assumptions, and contextual insights. Facilitate Human-AI collaboration throughout decision-making activities.

Collectively, these principles provide the basis for transparent, traceable, explainable, and human-oriented engineering decision support.

3.2 Ontology Architecture

The Engineering Decision Ontology (EDOnt) consists of four interconnected layers that collectively capture human expertise, reusable knowledge assets, engineering information, and decision-related outcomes. Table 4 outlines the purpose and primary components associated with each layer. Together, these layers establish a structured framework for knowledge representation, explainability, traceability, and Human-AI collaboration within engineering decision-support environments.

Table -4: Layer Structure

Layer	Purpose	Key Elements
Human Layer	Captures knowledge contributed by experts and stakeholders.	Goals, Preferences, Assumptions, Constraints, Risk Perceptions, Expertise
Knowledge Layer	Represents reusable organizational and domain knowledge.	Standards, Rules, Best Practices, Historical Cases, Organizational Knowledge, Domain Constraints
Engineering Layer	Represents engineering information applied during product development and execution.	Requirements, Functions, Features, Processes, Parameters, Resources, Facilities
Decision Layer	Captures decision-related entities, evaluations, and outcomes.	Alternatives, Evaluation Criteria, Evidence, Recommendations, Decisions, Validation Results

3.3 Human Knowledge Representation

Human expertise shapes engineering decisions through objectives, experience, preferences, and contextual insights that are often challenging to represent using traditional data structures. EDOnt explicitly models these elements to support Human-AI collaboration, decision transparency, and explainability.

Table -5: Human Knowledge Representation Elements

Element	Description	Decision Role
Goals	Intended outcomes or objectives to be accomplished.	Guide decision direction and priorities
Intent	Underlying purpose behind a decision or activity.	Provides contextual meaning
Preferences	Individual priorities among available alternatives.	Facilitate trade-off assessment
Constraints	Technical, organizational, or regulatory limitations.	Define feasible solution boundaries
Assumptions	Accepted conditions in situations with incomplete information.	Affect reasoning and decision outcomes
Expertise	Domain-specific knowledge and practical experience of decision-makers.	Supports informed judgement
Risk Tolerance	Degree of acceptance toward uncertainty or adverse outcomes.	Influences alternative selection

The structured representation of human knowledge allows engineering decision-support systems to incorporate expert reasoning while preserving transparency, traceability, and Human-AI collaboration.

3.4 Engineering Knowledge Representation

Engineering decisions are significantly influenced by technical information generated throughout product development and engineering execution activities. EDOnt models engineering knowledge through six core elements that collectively describe what needs to be achieved, how it can be achieved, and the conditions under which implementation is possible.

Table -6: Engineering Knowledge Representation Elements

Element	Description	Decision Role
Requirements	Functional, technical, quality, and regulatory expectations.	Define objectives and decision constraints
Functions	Intended capabilities or actions of a system or component.	Translate requirements into engineering intent
Features	Physical or logical characteristics of a product.	Link design solutions with functional objectives
Processes	Activities used for	Define

	design, manufacturing, inspection, or operation.	implementation approaches
Parameters	Measurable engineering attributes and performance indicators.	Enable evaluation and comparison of alternatives
Facilities	Available resources, equipment, tools, and operational capabilities.	Determine feasibility and execution constraints

Together, these elements provide a structured representation of engineering knowledge that supports traceability, explainability, process compliance, and engineering decision support.

3.5 Decision Knowledge Representation

Engineering decision-making involves assessing alternatives, examining supporting evidence, balancing multiple objectives, and verifying outcomes against established requirements and constraints. EDOnt explicitly models decision-related knowledge to facilitate transparent, explainable, and traceable decision-making activities.

Table -7: Decision Knowledge Representation Elements

Element	Description	Decision Role
Alternatives	Potential solutions or possible courses of action being evaluated.	Define the decision space
Evidence	Information, data, analyses, or expert justification that supports a decision.	Supports decision reasoning
Optimization Criteria	Measures and metrics used to assess and compare alternatives.	Guide alternative selection
Decisions	Chosen alternatives or final outcomes.	Represent decision results
Validation	Verification of compliance with requirements, constraints, and objectives.	Confirms decision suitability

The explicit representation of decision knowledge allows engineering decisions to be justified, assessed, and traced throughout the entire decision lifecycle.

3.6 Ontology Relationships

The significance of EDOnt extends beyond the representation of individual knowledge elements to the relationships established among them. These relationships create connections between human knowledge, engineering knowledge, and decision outcomes, thereby enhancing explainability, traceability, and Human-AI collaboration.

Table -7: Ontology Relationship Types

Relationship	Description	Example
Supports	Indicates that one element contributes to another.	Expertise supports Decision
Requires	Indicates a dependency relationship between elements.	Process requires Facility
Influences	Indicates an effect on a decision or outcome.	Preference influences Alternative Selection
Explains	Provides justification or reasoning.	Evidence explains Recommendation
Validates	Confirms correctness or compliance.	Requirement validates Decision
Optimizes	Enhances performance according to defined criteria.	Parameter optimizes Process Selection

These relationships enable EDOnt to represent not only engineering knowledge but also the reasoning pathways that connect knowledge, decisions, and outcomes, thereby establishing a foundation for explainable and traceable engineering decision support.

4. ENGINEERING REASONING CHAIN (ERC)

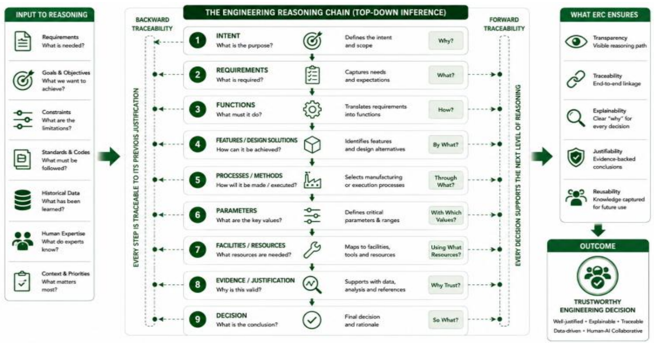

Fig -3: Engineering Reasoning Chain (ERC): Traceable Engineering Decision Mechanism

4.1 Motivation

Engineering decisions are often influenced by multiple technical, operational, economic, and organizational factors. Although modern engineering decision-support systems can generate recommendations and analyses, the reasoning process that leads to a particular decision is frequently difficult to understand and validate. As a result, decision-makers may face challenges in explaining why a decision was made, what information was considered, and how alternative solutions were evaluated.

To address these challenges, engineering decision-support systems must provide traceability, explainability, and transparency throughout the decision-making process. Traceability enables decisions to be linked to the requirements, constraints, assumptions, and evidence that influenced them. Explainability allows engineers and stakeholders to understand the reasoning behind recommendations and outcomes. Transparency further supports validation, accountability, and trust in Human-AI collaboration. Therefore, a structured reasoning mechanism is required to connect engineering knowledge with decision outcomes in a manner that is understandable and auditable.
The Engineering Reasoning Chain (ERC) is proposed to address this need by providing a structured and traceable reasoning pathway that captures how engineering decisions are derived from available knowledge, evidence, and engineering requirements [11], [14].

4.2 ERC Structure

The Engineering Reasoning Chain (ERC) represents engineering decision-making as a sequence of interconnected reasoning elements. Each element contributes information that supports the progression from engineering objectives to final decision outcomes.

The chain begins with **Intent**, which represents the objectives, goals, or purpose underlying a decision. Intent establishes the direction and context for subsequent decision-making activities.

Requirements define the functional, technical, quality, and regulatory needs that must be satisfied. These requirements establish the primary conditions against which alternatives are evaluated.

Based on the identified requirements, **Functions** describe the capabilities that a system, component, or process must perform. Functions translate engineering needs into actionable engineering intent.

Features represent the physical or logical characteristics that enable the required functions. They provide potential solution characteristics that can satisfy engineering requirements.
Processes define the activities, methods, or procedures used to realize the identified features. These may include design, manufacturing, inspection, or operational activities.

Parameters represent measurable engineering attributes used to evaluate and compare alternatives. Examples include cost, weight, efficiency, cycle time, reliability, and performance metrics.

Facilities represent the available resources, equipment, tools, technologies, and organizational capabilities required for implementation.

Evidence consists of data, analyses, simulations, standards, historical cases, expert knowledge, and supporting information used to justify recommendations and decisions.
Finally, the **Decision** represents the selected alternative or outcome derived from the reasoning process.

Together, these elements form a structured pathway that connects engineering objectives to decision outcomes while maintaining transparency and traceability.

4.3 Engineering Decision Traceability

A key capability of ERC is the ability to support engineering decision traceability. Every decision can be linked to the requirements, knowledge sources, constraints, assumptions, and evidence that contributed to its selection.

Requirement-to-decision traceability enables engineers to determine how specific requirements influenced a particular outcome. Knowledge-to-decision traceability links decisions to the engineering knowledge, standards, best practices, and expert inputs used during reasoning. Validation traceability further connects decisions to the verification activities and evaluation results used to confirm decision suitability.

By maintaining these traceability links, ERC supports decision auditing, validation, compliance assessment, and knowledge reuse across engineering projects.

4.4 Explainability Through ERC

ERC improves explainability by exposing the reasoning pathway used to generate engineering decisions. Rather than presenting recommendations as isolated outputs, the framework provides visibility into the intermediate reasoning elements that contributed to the final outcome.

Decision justification is achieved by linking recommendations to relevant requirements, constraints, engineering knowledge, and supporting evidence. Evidence-based reasoning enables engineers to understand why one alternative was preferred over another and which factors influenced the selection process. Transparent recommendations further allow stakeholders to review assumptions, evaluate supporting information, and validate decision logic.

Consequently, ERC enhances confidence in decision-support systems by making engineering reasoning more understandable, interpretable, and trustworthy.

4.5 Integration with EDOnt

The Engineering Reasoning Chain (ERC) operates in conjunction with the Engineering Decision Ontology (EDOnt). While EDOnt provides the structured representation of human knowledge, engineering knowledge, and decision-related information, ERC provides the reasoning pathway that connects these elements during decision-making.

EDOnt defines the entities, concepts, and relationships required for engineering decision support, whereas ERC utilizes these representations to construct traceable and explainable decision pathways. Through this integration, engineering knowledge can be systematically transformed into justified and transparent decisions.
Together, EDOnt and ERC establish the knowledge and reasoning foundation of the Human-AI Engineering Decision Intelligence (HAEDI) framework.

5. ENGINEERING ORCHESTRATION MODEL (EOM)

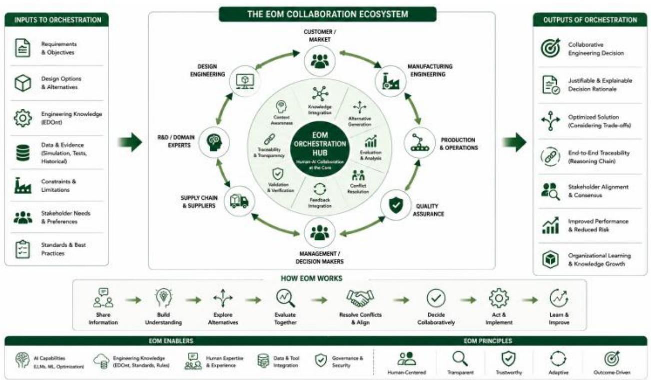

Fig -4: Engineering Orchestration Model (EOM): Human-AI Collaboration Ecosystem

5.1 Human Knowledge Elicitation

Engineering decisions frequently rely on expert knowledge that is not formally documented or readily available within organizational systems. To address this challenge, the Engineering Orchestration Model (EOM) incorporates structured mechanisms for acquiring and interpreting human knowledge through interactive elicitation processes. These mechanisms include conversational interaction, expert knowledge capture, and intent identification. The information gathered during this stage establishes the contextual foundation required for subsequent reasoning, optimization, and decision-support activities.

5.2 Human Mental Model Capture

Engineering professionals assess alternatives based on objectives, assumptions, constraints, and preferences that influence their decision-making behaviour. EOM explicitly captures these elements to facilitate Human-AI collaboration and improve transparency throughout the decision-support process [8], [9].

Table -8: Human Mental Model Elements

Element	Purpose
Goals	Define intended outcomes
Constraints	Limit feasible solution options
Preferences	Enable trade-off assessment
Assumptions	Provide contextual interpretation

5.3 Alternative Generation

Following the acquisition of relevant knowledge, potential alternatives are generated for evaluation and decision support. Alternative generation combines rule-based and AI-assisted approaches to ensure both compliance and exploration. Rule-based alternatives are derived from established engineering knowledge, standards, and constraints, while AI-assisted alternatives support the identification of additional feasible solution possibilities. The integration of these approaches enables a decision-making process that is both systematic and adaptable.

Table -9: Alternative Generation Approaches

Approach	Purpose
Rule-Based Alternatives	Ensure alignment with engineering knowledge, standards, and constraints
AI-Assisted Alternatives	Facilitate exploration of additional feasible solution options

5.4 Optimization Layer

The generated alternatives are subsequently assessed against multiple engineering objectives and constraints. The optimization layer supports trade-off analysis by combining computational evaluation with human judgement and preferences. Evaluation criteria typically include cost, quality, time, risk, sustainability, and manufacturability. By incorporating human input throughout the optimization process, EOM supports Human-in-the-Loop optimization rather than relying solely on algorithmic decision-making [17].

Table -10: Optimization Criteria Matrix

Criterion	Purpose
Cost	Evaluate economic viability
Quality	Assess performance and compliance
Time	Measure delivery and execution effectiveness
Risk	Evaluate uncertainty and potential consequences
Sustainability	Consider environmental and resource impacts
Manufacturability	Assess practical implementation capability

5.5 Learning and Recommendation Layer

To support continuous improvement in decision-making, EOM utilizes historical knowledge and previous decision outcomes. This layer incorporates mechanisms such as case-based reasoning, similarity assessment, and recommendation support. By identifying comparable historical situations and extracting relevant lessons, the system can provide context-aware recommendations that assist decision-makers in addressing current engineering challenges more effectively.

5.6 Explainability and Trust Layer

Effective decision support requires transparency regarding how recommendations are produced and justified. The explainability and trust layer addresses this requirement by providing mechanisms for explanation generation, confidence assessment, evidence evaluation, and human control. Explanation generation clarifies the reasoning behind recommendations, while confidence scores indicate the reliability of suggested outcomes. Evidence strength helps assess the quality of supporting information, and human override mechanisms ensure that final decision authority remains under human control. Together, these capabilities promote transparency, trust calibration, and user acceptance.

Table -11: Explainability and Trust Mechanisms

Mechanism	Purpose
Explanation Generation	Provide justification for recommendations and decisions
Confidence Scores	Indicate the reliability of recommendations
Evidence Strength	Evaluate the quality of supporting information
Human Override	Maintain human authority over final decisions

5.7 Validation and Verification Layer

Prior to implementation, engineering decisions must be evaluated against established requirements, constraints, and organizational objectives. The validation and verification layer performs requirement validation, constraint validation, and decision validation to ensure that selected alternatives are suitable for implementation. This layer supports compliance assessment, consistency checking, feasibility evaluation, and overall decision quality assurance.

5.8 Human Feedback Integration

Engineering decision-making is inherently iterative and benefits from continuous expert involvement. EOM incorporates feedback collection, feedback analysis, and decision refinement mechanisms to support ongoing improvement throughout the decision lifecycle. Human feedback enables the adjustment of assumptions, objectives, preferences, and recommendations as new information becomes available or circumstances change.

5.9 Final Decision Formation

The final decision is established through the integration of engineering knowledge, expert input, optimization outcomes, validation results, supporting evidence, and stakeholder feedback. By combining these elements within a coordinated decision-support process, EOM facilitates transparent, explainable, traceable, and human-centered engineering decision-making while ensuring that responsibility for final decision approval remains with human decision-makers.

6. HUMAN-AI ENGINEERING DECISION INTELLIGENCE (HAEDI)

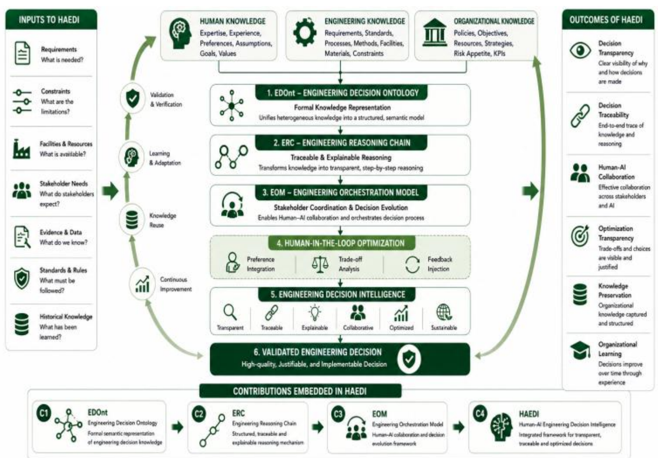

Fig -5: Human-AI Engineering Decision Intelligence (HAEDI): Integrated Decision Intelligence Framework

6.1 Framework Purpose

The Human-AI Engineering Decision Intelligence (HAEDI) framework is proposed to convert dispersed engineering knowledge and tacit human expertise into engineering decision intelligence that is traceable, explainable, validated, and reusable. The framework combines knowledge representation, engineering reasoning, Human-AI collaboration, optimization, explainability, and validation within a single engineering decision-support environment. In doing so, HAEDI seeks to preserve valuable engineering knowledge, enhance decision transparency, facilitate organizational learning, and support more dependable engineering decision-making across diverse application contexts.

6.2 Engineering Decision Intelligence Generation

HAEDI generates Engineering Decision Intelligence through the coordinated integration of the Engineering Decision Ontology (EDOnt), Engineering Reasoning Chain (ERC), and Engineering Orchestration Model (EOM).

Table -12: Decision Intelligence Generation Mechanisms

Component	Function	Outcome
EDOnt	Formalizes human, engineering, and decision-related knowledge	Structured decision context
ERC	Establishes connections between knowledge and reasoning pathways	Explainable decision logic
EOM	Orchestrates Human-AI decision-making activities	Collaborative decision process

Through the interaction of these components, engineering information is transformed from isolated data and knowledge sources into actionable decision intelligence.

6.3 Engineering Decision Intelligence Outcomes

Unlike traditional recommendation systems that primarily generate individual recommendations, HAEDI focuses on creating reusable engineering decision intelligence that can support future decision-making activities.

Table -13: Engineering Decision Intelligence Outcomes

Outcome	Description
Traceable Decisions	Decisions linked to requirements, constraints, assumptions, and supporting evidence
Explainable Decisions	Decisions supported by transparent reasoning pathways
Optimized Decisions	Alternatives assessed using multiple evaluation criteria
Validated Decisions	Decisions verified against engineering objectives and constraints
Reusable Decisions	Decision knowledge preserved for future use and learning
Human-Accepted Decisions	Decisions refined through expert involvement and feedback

Collectively, these outcomes represent the Engineering Decision Intelligence generated by the HAEDI framework.

6.4 Human-AI Decision Lifecycle

HAEDI operates as a continuous Human-AI engineering decision lifecycle. Human expertise and engineering knowledge are initially structured through EDOnt, transformed into reasoning pathways through ERC, and coordinated through EOM. The resulting decision process is subsequently enhanced through optimization, explanation, validation, and feedback integration before a final decision is established.

This lifecycle ensures that engineering knowledge, human expertise, decision reasoning, optimization outcomes, and validation results remain interconnected throughout the decision-making process. Furthermore, continuous feedback allows knowledge and decisions to be refined over time, supporting learning and improvement across future engineering applications.

6.5 Framework Characteristics

HAEDI is developed around a set of core characteristics that define its approach to engineering decision support:

- Knowledge-Driven
- Human-Centered
- Explainable
- Traceable
- Optimization-Aware
- Validation-Oriented
- Reusable
- Continuously Adaptive

Together, these characteristics enable a decision-support capability that extends beyond recommendation generation toward the creation and preservation of reusable organizational decision knowledge.

Table -14: Scientific Basis Matrix

Framework Element	Scientific Basis
EDOnt	Ontology Engineering
ERC	Systems Engineering and Traceability Theory
EOM	Human-AI Collaboration and Workflow Orchestration
Optimization	Multi-Criteria Decision Analysis (MCDA)
Recommendation	Case-Based Reasoning (CBR)
Explainability	Explainable Artificial Intelligence (XAI)
Validation	Verification and Validation (V&V) Theory

HAEDI extends beyond the generation of engineering decisions by transforming fragmented engineering knowledge and tacit human expertise into Engineering Decision Intelligence that is traceable, explainable, validated, and reusable. This enables organizations to preserve decision knowledge, improve transparency, strengthen Human-AI collaboration, and support more informed engineering decision-making over time.

7. Knowledge Acquisition and Formalization Validation

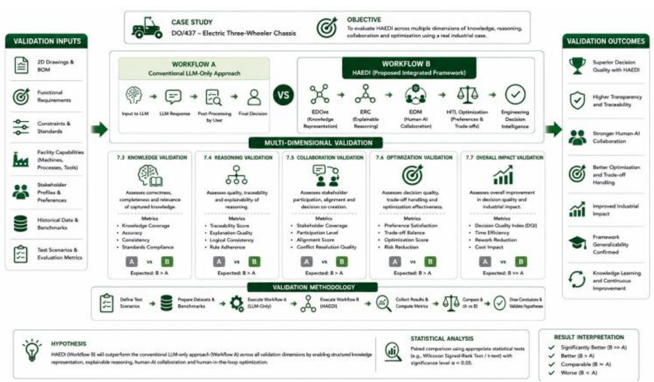

Fig -6: Experimental Validation Framework for HAEDI Evaluation

7.1 Objective

This evaluation examines whether the proposed Engineering Decision Acquisition Template (EDAT) can provide a more systematic representation of engineering knowledge compared with conventional LLM-based extraction. The assessment focuses on the identification, preservation, and formalization of engineering knowledge derived from engineering drawings, stakeholder inputs, manufacturing resources, requirements, constraints, and production-related information.

7.2 Experimental Setup

The evaluation was performed using the DO/437 EV chassis case study. Both workflows were supplied with an identical engineering information package comprising engineering drawings, facility information, project requirements, project constraints, production details, and stakeholder notes. Workflow A employed a conventional engineering knowledge extraction approach, whereas Workflow B utilized the proposed EDAT-based formalization approach.

7.3 Evaluation Criteria

Five evaluation dimensions were defined for comparison: Knowledge Coverage (KC), Knowledge Formalization (KF), Human Knowledge Capture (HKC), Traceability Readiness (TR), and Decision Readiness (DR). Collectively, these dimensions assess the completeness, organization, traceability potential, and applicability of the extracted knowledge for future engineering activities.

7.4 Results

Both workflows successfully identified engineering information from the selected case study. Workflow A generated a traditional engineering information inventory, while Workflow B represented comparable information using EDAT categories, including Intent, Goals, Requirements, Constraints, Preferences, Assumptions, Facilities and Resources, Risks and Concerns, and Supporting Evidence. This resulted in a more organized and reusable knowledge structure.

Table -15: Knowledge Representation Comparison

Capability	Workflow A	Workflow B
Product Purpose Representation	Yes	Yes
Functional Information Representation	Yes	Yes
Requirement Representation	Yes	Yes
Constraint Representation	Yes	Yes
Facility Representation	Partial	Yes
Stakeholder Knowledge Representation	Partial	Yes
Goal Representation	Partial	Yes
Preference Representation	No	Yes
Assumption Representation	Partial	Yes
Supporting Evidence Representation	No	Yes
Traceability-Oriented Structure	Partial	Yes
Decision-Oriented Knowledge Structure	Partial	Yes

7.5 Comparative Assessment

A five-point evaluation scale was adopted, where 1 indicates Very Low performance and 5 indicates Very High performance. Although both workflows demonstrated similar levels of information coverage, Workflow B showed stronger performance in knowledge structuring, representation of human-related knowledge, traceability preparedness, and support for subsequent decision-making activities.

Table -16: Comparative Evaluation Matrix

Evaluation Dimension	Workflow A	Workflow B
Knowledge Coverage (KC)	5	5
Knowledge Formalization (KF)	3	5
Human Knowledge Capture (HKC)	2	5
Traceability Readiness (TR)	3	5
Decision Readiness (DR)	3	5

$$KRI = \frac{KC + KF + HKC + TR + DR}{5}$$

$$KRI_A = \frac{5 + 3 + 2 + 3 + 3}{5} = 3.2$$

$$KRI_B = \frac{5 + 5 + 5 + 5 + 5}{5} = 5.0$$

$$Improvement = \frac{KRI_B - KRI_A}{KRI_A} \times 100$$

$$Improvement = \frac{5.0 - 3.2}{3.2} \times 100 = 56.25\%$$

7.6 Discussion

The findings suggest that the principal benefit of EDAT lies in the way knowledge is structured rather than in the amount of information extracted. Workflow B converted engineering information into explicit knowledge entities representing both technical and human-related aspects. Such a representation enhances transparency, improves traceability, and provides a stronger foundation for future reasoning, validation, and engineering decision-support activities.

7.7 Validation of Research Objectives and Contributions

The results indicate that engineering knowledge and human expertise can be acquired and represented in a structured manner using EDAT. Accordingly, the evaluation provides evidence in support of **RQ1**, **O1**, and **O2**, while offering initial validation of **C1 – Engineering Decision Ontology (EDOnt)** as the foundational knowledge layer of the proposed HAEDI framework.

8. Engineering Reasoning Chain (ERC) Validation

8.1 Objective

This evaluation examines whether the proposed Engineering Reasoning Chain (ERC) can enhance the traceability and interpretability of engineering decisions when compared with conventional LLM-supported reasoning. The assessment focuses on establishing clear connections between stakeholder objectives, engineering requirements, functional needs, manufacturing considerations, supporting evidence, and the resulting engineering decision.

8.2 Experimental Setup

The DO/437 EV chassis case study was selected for this evaluation. The same engineering information package used in the previous experiment was retained to ensure consistency between studies. Workflow A employed a conventional LLM-based reasoning approach, whereas Workflow B applied the proposed ERC methodology. Both workflows were tasked with identifying an appropriate manufacturing strategy using identical engineering inputs.

8.3 Evaluation Criteria

Four evaluation dimensions were used to assess the reasoning process:

- Reasoning Completeness (RC)
- Traceability Coverage (TC)
- Evidence Support (ES)
- Explainability (EX)

These dimensions were selected to evaluate how effectively each workflow reveals the reasoning process, connects supporting information to conclusions, and justifies engineering decisions.

8.4 Results

Both workflows produced technically feasible manufacturing recommendations for the EV chassis. Workflow A generated a conventional engineering assessment consisting of product analysis, manufacturing evaluation, risk identification, and a final recommendation. Workflow B produced a complete Engineering Reasoning Chain linking Intent, Requirements, Functions, Features, Processes, Parameters, Facilities, Evidence, and Decisions. In addition, explicit traceability and explanation structures were generated for all major decision elements.

Table-17: Engineering Reasoning Capability Comparison

Capability	Workflow A	Workflow B
Intent Visibility	No	Yes
Requirement Traceability	Partial	Yes
Function Traceability	No	Yes
Feature Traceability	No	Yes
Process Traceability	Partial	Yes
Parameter Traceability	No	Yes
Facility Traceability	Partial	Yes
Evidence Traceability	No	Yes
Decision Traceability	Partial	Yes
Explainability Support	Partial	Yes

8.5 Comparative Assessment

A five-point evaluation scale was adopted, where 1 indicates Very Low performance and 5 indicates Very High performance. While Workflow A generated a reasonable engineering recommendation, much of the reasoning remained implicit. Workflow B provided a more transparent reasoning structure by exposing intermediate reasoning stages and explicitly linking supporting information to the final decision.

Table-18: ERC Evaluation Matrix

Evaluation Dimension	Workflow A	Workflow B
Reasoning Completeness (RC)	2	5
Traceability Coverage (TC)	2	5
Evidence Support (ES)	1	5
Explainability (EX)	3	5

The overall Engineering Reasoning Index (ERI) is defined as:

$$ERI = \frac{RC + TC + ES + EX}{4}$$

For Workflow A:

$$ERI_A = \frac{2+2+1+3}{4} = 2.0$$

For Workflow B:

$$ERI_B = \frac{5+5+5+5}{4} = 5.0$$

The relative improvement achieved by Workflow B is calculated as:

$$Improvement = \frac{ERI_B - ERI_A}{ERI_A} \times 100$$

$$Improvement = \frac{5.0 - 2.0}{2.0} \times 100 = 150\%$$

8.6 Discussion

The findings suggest that the primary contribution of ERC lies in improving visibility into the reasoning process rather than altering the final engineering outcome. Although Workflow A produced a technically acceptable recommendation, the logic connecting information, assumptions, and conclusions remained largely hidden. Workflow B, however, explicitly connected stakeholder intentions, engineering requirements, functional objectives, product features, manufacturing processes, facility capabilities, supporting evidence, and final decisions. This structured representation enhances transparency, facilitates auditing, and improves the ability to understand how engineering decisions are formed.

8.7 Validation of Research Objectives and Contributions

The evaluation demonstrates that engineering decisions can be systematically explained and traced using the proposed Engineering Reasoning Chain. The results provide evidence supporting **RQ2**, which investigates how engineering decisions can be made traceable and explainable through structured reasoning. Furthermore, the findings support **O4** by enabling transparent engineering decision-making and provide validation for **C2 – Engineering Reasoning Chain (ERC)** as the reasoning mechanism within the HAEDI framework. The explicit linkage between engineering knowledge, supporting evidence, reasoning activities, and final decisions establishes a foundation for transparent and accountable engineering decision support.

9. Human–AI Collaboration Validation (EOM)

9.1 Objective

This evaluation examines the capability of the proposed Engineering Orchestration Model (EOM) to support collaborative engineering decision-making between human stakeholders and AI systems. Particular attention is given to stakeholder participation, knowledge contribution, conflict management, feedback incorporation, and the progressive development of engineering decisions within a Human–AI environment.

9.2 Experimental Setup

The evaluation was performed using the DO/437 EV chassis case study. To maintain consistency across experiments, the same engineering information package used in Sections 7.3 and 7.4 was adopted. Workflow A followed a conventional LLM-assisted decision-making approach, whereas Workflow B implemented the proposed EOM-based collaboration process. Both workflows considered inputs from Design, Manufacturing, Quality, Production, Management, and Customer stakeholders during the decision-making exercise.

9.3 Evaluation Criteria

Five evaluation dimensions were established:

- Stakeholder Knowledge Capture (SKC)
- Mental Model Representation (MMR)
- Feedback Integration (FI)
- Collaboration Transparency (CT)
- Human Control and Override (HCO)

These dimensions were selected to evaluate how effectively each workflow incorporates human knowledge, represents stakeholder perspectives, supports collaboration, and preserves human involvement during decision formation.

9.4 Results

Both workflows incorporated stakeholder perspectives during the evaluation process. Workflow A identified stakeholder concerns and recognized several conflicting interests before arriving at a manufacturing recommendation. Workflow B extended this process by explicitly documenting stakeholder goals, preferences, assumptions, constraints, concerns, mental models, feedback, decision revisions, and override actions. Furthermore, Workflow B recorded how the decision evolved as stakeholder input was progressively incorporated.

Table-19: Human–AI Collaboration Capability Comparison

Capability	Workflow A	Workflow B
Stakeholder Identification	Yes	Yes
Goal Capture	Partial	Yes
Preference Capture	No	Yes
Assumption Capture	No	Yes
Mental Model Representation	No	Yes
Conflict Identification	Yes	Yes
Conflict Severity Assessment	No	Yes
Alternative Generation	Partial	Yes
Feedback Integration	No	Yes
Decision Evolution Tracking	No	Yes
Human Override Support	No	Yes
Collaboration Transparency	Partial	Yes

9.5 Comparative Assessment

A five-point assessment scale was used, where 1 represents Very Low capability and 5 represents Very High capability. While Workflow A demonstrated basic consideration of stakeholder viewpoints, the collaboration process remained largely implicit. In contrast, Workflow B provided a structured collaboration mechanism in which stakeholder knowledge, feedback, and decision modifications were explicitly represented and preserved.

Table-20: Human Collaboration Evaluation Matrix

Evaluation Dimension	Workflow A	Workflow B
Stakeholder Knowledge Capture (SKC)	3	5
Mental Model Representation (MMR)	1	5
Feedback Integration (FI)	1	5
Collaboration Transparency (CT)	2	5
Human Control and Override (HCO)	1	5

The overall Human Collaboration Index (HCI) is defined as:

$$HCI = \frac{SKC + MMR + FI + CT + HCO}{5}$$

For Workflow A:

$$HCI_A = \frac{3 + 1 + 1 + 2 + 1}{5} = 1.6$$

For Workflow B:

$$HCI_B = \frac{5+5+5+5+5}{5} = 5.0$$

The relative improvement achieved by Workflow B is calculated as:

$$Improvement = \frac{HCI_B - HCI_A}{HCI_A} \times 100$$

$$Improvement = \frac{5.0 - 1.6}{1.6} \times 100 = 212.5\%$$

9.6 Discussion

The findings suggest that the primary contribution of EOM lies in structuring and managing the collaborative decision-making process rather than changing the final engineering recommendation itself. Workflow A considered stakeholder viewpoints; however, the interactions remained largely static once a recommendation was generated. Workflow B explicitly represented stakeholder objectives, assumptions, preferences, concerns, feedback, and subsequent decision revisions. The framework also supported alternative generation, conflict analysis, feedback-driven refinement, and documented situations where human judgement influenced or modified AI-generated outputs. Consequently, the decision process became more transparent, participative, and easier to review.

9.7 Validation of Research Objectives and Contributions

The evaluation demonstrates that Human–AI collaboration can be systematically incorporated into engineering decision-making through the proposed Engineering Orchestration Model. The results provide evidence supporting **RQ3**, which investigates how Human–AI collaboration can contribute to more transparent and effective engineering decision processes. The findings also support **O3** by enabling structured stakeholder participation and collaborative decision development. Furthermore, the evaluation provides validation for **C3 – Engineering Orchestration Model (EOM)** as the collaboration layer of the HAEDI framework. By capturing stakeholder knowledge, integrating feedback, documenting decision evolution, and preserving human oversight, EOM establishes a structured foundation for collaborative engineering decision support.

10. Human-in-the-Loop Optimization Validation

10.1 Objective

This evaluation explores the ability of the proposed framework to incorporate stakeholder preferences, engineering objectives, operational constraints, and expert judgement into the decision-making process through Human-in-the-Loop (HITL) optimization. The purpose is to examine whether engineering decisions can be refined by balancing technical performance with stakeholder expectations and practical implementation requirements.

10.2 Experimental Setup

The evaluation was conducted using the DO/437 EV chassis case study. Three manufacturing alternatives were developed and assessed using the same engineering information package applied throughout the previous validation studies. Workflow A followed a conventional LLM-based alternative selection approach, whereas Workflow B utilized the proposed HITL optimization mechanism. Both workflows were evaluated using identical technical, manufacturing, quality, production, business, and stakeholder inputs.

10.3 Evaluation Criteria

Five evaluation dimensions were considered:

- Preference Capture (PC)
- Trade-Off Transparency (TT)
- Optimization Support (OS)
- Human Acceptance Analysis (HA)
- Human Intervention Capability (HI)

These criteria were selected to assess how effectively stakeholder preferences are represented, how transparently trade-offs are managed, and how human participation influences optimization outcomes.

10.4 Results

Both workflows assessed the available manufacturing alternatives and identified a preferred solution. Workflow A relied primarily on qualitative engineering assessment to compare and select alternatives. Workflow B expanded this process by formally capturing stakeholder preferences, establishing weighted evaluation criteria, performing trade-off analysis, calculating optimization scores, conducting stakeholder reviews, and incorporating human intervention before final decision selection.

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 07 | Jul 2026 www.irjet.net p-ISSN: 2395-0072

Table-21: Human-in-the-Loop Optimization Capability Comparison

Capability	Workflow A	Workflow B
Alternative Evaluation	Yes	Yes
Stakeholder Preference Capture	Partial	Yes
Preference Weighting	No	Yes
Organizational Weight Aggregation	No	Yes
Trade-Off Analysis	Partial	Yes
Optimization Calculations	No	Yes
Alternative Ranking	Partial	Yes
Human Review	No	Yes
Human Intervention	No	Yes
Acceptance Analysis	No	Yes
Human-in-the-Loop Optimization	No	Yes

10.5 Comparative Assessment

A five-point assessment scale was adopted, where a score of 1 represents Very Low capability and a score of 5 represents Very High capability. Although Workflow A provided a reasonable comparison of alternatives, stakeholder influence and optimization logic remained largely implicit. Workflow B introduced a structured optimization process by integrating stakeholder preferences, weighted decision criteria, trade-off evaluation, acceptance analysis, and human review activities.

Table-22: Optimization Evaluation Matrix

Evaluation Dimension	Workflow A	Workflow B
Preference Capture (PC)	2	5
Trade-Off Transparency (TT)	2	5
Optimization Support (OS)	1	5
Human Acceptance Analysis (HA)	1	5
Human Intervention Capability (HI)	1	5

The overall Optimization Quality Index (OQI) is defined as:

$$OQI = \frac{PC + TT + OS + HA + HI}{5}$$

For Workflow A:

$$OQI_A = \frac{2+2+1+1+1}{5} = 1.4$$

For Workflow B:

$$OQI_B = \frac{5+5+5+5+5}{5} = 5.0$$

The relative improvement achieved by Workflow B is calculated as:

$$Improvement = \frac{OQI_B - OQI_A}{OQI_A} \times 100$$

$$Improvement = \frac{5.0 - 1.4}{1.4} \times 100 = 257.1\%$$

10.6 Discussion

The results suggest that the primary value of the proposed approach lies in making optimization activities visible, participative, and explainable. While Workflow A identified a preferred manufacturing alternative through engineering judgement, the role of stakeholder priorities remained largely embedded within the final recommendation. In contrast, Workflow B transformed stakeholder objectives into explicit evaluation criteria, quantified their influence through weighting mechanisms, examined trade-offs systematically, and incorporated stakeholder review before confirming the final decision. Consequently, the selected solution reflected not only technical suitability but also stakeholder acceptance and organizational feasibility.

10.7 Validation of Research Objectives and Contributions

The evaluation demonstrates that Human-in-the-Loop optimization can be integrated into engineering decision-making using the proposed framework. The findings provide evidence supporting **O5**, which focuses on incorporating stakeholder knowledge and human expertise into optimization activities. The results further show that engineering decisions can be refined through a combination of optimization, trade-off evaluation, stakeholder review, and expert intervention. By bringing these activities together within a single process, the framework provides a transparent and structured approach for preference-aware engineering decision support.

11. Integrated HAEDI Validation and Research Validation

11.1 Objective

The preceding evaluations focused on individual elements of the proposed framework, namely the Engineering Decision Ontology (EDOnt), Engineering Reasoning Chain (ERC), Engineering Orchestration Model (EOM), and Human-in-the-Loop Optimization. This section assesses the framework as a unified system and examines its capability to support engineering knowledge formalization, reasoning, stakeholder participation, optimization, and decision-making within a single Human–AI decision-support environment.

11.2 Integrated Framework Assessment

The evaluation results indicate that the proposed framework functions as an interconnected system in which each component contributes to the overall decision process. Rather than operating independently, the framework components work together to transform engineering information into transparent and traceable engineering decisions.

The overall decision flow can be represented as:
Engineering Information
↓
EDOnt
(Knowledge Representation)
↓
ERC
(Reasoning and Traceability)
↓
EOM
(Collaboration and Stakeholder Integration)
↓
Human-in-the-Loop Optimization
↓
Engineering Decision

This workflow enables engineering information, stakeholder contributions, reasoning activities, optimization processes, and final decisions to remain connected throughout the decision lifecycle.

11.3 Overall Comparative Assessment

Table 22 presents a consolidated summary of the results obtained from all validation studies.

Table-23: Consolidated Framework Evaluation Results

Section	Metric	Workflow A	Workflow B
7.3 Knowledge Formalization	KRI	3.2	5.0
7.4 Engineering Reasoning	ERI	2.0	5.0
7.5 Human–AI Collaboration	HCI	1.6	5.0
7.6 HITL Optimization	OQI	1.4	5.0

To obtain an overall assessment of framework performance, the Human–AI Decision Intelligence Index (HDII) is defined as:

$$HDII = \frac{KRI + ERI + HCI + OQI}{4}$$

For Workflow A:

$$HDII_A = \frac{3.2 + 2.0 + 1.6 + 1.4}{4}$$

$$HDII_A = 2.05$$

For Workflow B:

$$HDII_B = \frac{5.0 + 5.0 + 5.0 + 5.0}{4}$$

$$HDII_B = 5.0$$

The relative improvement achieved by Workflow B is calculated as:

$$Improvement = \frac{HDII_B - HDII_A}{HDII_A} \times 100$$

$$Improvement = \frac{5.0 - 2.05}{2.05} \times 100$$

$$Improvement = 143.9\%$$

The results indicate a substantial improvement in overall decision-support capability when the proposed framework is applied.

11.4 Research Question Validation

Table-24: Validation of Research Questions

Research Question	Validation Evidence
RQ1: How can engineering knowledge and human expertise be represented to support engineering decisions?	Validated through Section 7.3
RQ2: How can engineering decisions be made traceable and explainable through structured reasoning?	Validated through Section 7.4
RQ3: How can Human–AI collaboration contribute to engineering decision-making?	Validated through Section 7.5
RQ4: How can the integration of knowledge representation, reasoning, collaboration, and optimization improve engineering decision support?	Validated through the combined results of Sections 7.3–7.6

The experimental findings collectively provide evidence that the proposed research questions have been satisfactorily addressed.

11.5 Research Objective Validation

Table-25: Validation of Research Objectives

Objective	Validation Section
O1 – Formalize engineering knowledge	7.3
O2 – Formalize human knowledge, assumptions, and constraints	7.3
O3 – Support Human–AI collaboration	7.5
O4 – Enable transparent engineering reasoning	7.4
O5 – Support Human-in-the-Loop optimization	7.6
O6 – Integrate knowledge, reasoning, collaboration, and optimization	7.7
O7 – Establish an Engineering Decision Intelligence framework	7.7

The validation results demonstrate that each research objective has been addressed through the proposed framework and its associated evaluations.

11.6 Research Contribution Validation

Table-26: Validation of Research Contributions

Contribution	Validation Section
C1 – Engineering Decision Ontology (EDOnt)	7.3
C2 – Engineering Reasoning Chain (ERC)	7.4
C3 – Engineering Orchestration Model (EOM)	7.5
C4 – Human–AI Engineering Decision Intelligence (HAEDI) Framework	7.7

The evaluation confirms that each contribution fulfils its intended role and collectively forms the foundation of the proposed Engineering Decision Intelligence approach.

11.7 Chapter Summary

This chapter presented a structured evaluation of the proposed Human–AI Engineering Decision Intelligence (HAEDI) framework using the DO/437 EV chassis case study. A series of validation studies were carried out to examine knowledge representation, engineering reasoning, Human–AI collaboration, and Human-in-the-Loop optimization. The outcomes demonstrate that the proposed framework improves the organization, transparency, traceability, collaboration, and decision-support capabilities of AI-assisted engineering workflows when compared with conventional LLM-based approaches.

The integrated assessment further shows that engineering knowledge, stakeholder inputs, reasoning activities, optimization procedures, and final decisions can be connected within a coherent Human–AI decision-support process. The overall findings provide evidence supporting the research questions, objectives, and contributions presented in this work and establish the HAEDI framework as a structured approach for Engineering Decision Intelligence in AI-enabled engineering environments.

12. DISCUSSION

12.1 Implications for AI-Supported Engineering

AI has increasingly been adopted to support individual engineering activities such as design generation, simulation assistance, and information retrieval. However, engineering decisions involve significantly more than isolated technical tasks. The findings of this study indicate that AI can also support the broader decision-making process by integrating engineering knowledge, reasoning, stakeholder perspectives, and optimization activities. In this sense, the proposed framework extends AI support from task execution toward structured engineering decision support [6], [7].

12.2 Implications for Human–AI Engineering Collaboration

The results suggest that engineering decisions are rarely determined by technical factors alone. Instead, they emerge through interactions between stakeholder expectations, engineering requirements, business objectives, and expert judgement. The proposed framework demonstrates how human knowledge and AI-generated insights can be combined within a structured workflow. Rather than replacing engineers, AI acts as a supporting participant that contributes reasoning, analysis, and decision support while preserving human control [8], [9], [18].

12.3 Implications for Engineering Knowledge Representation

Engineering knowledge is often dispersed across drawings, specifications, standards, stakeholder inputs, and organizational practices. Such information is frequently difficult to capture in a form that supports computational reasoning. The proposed Engineering Decision Ontology provides a structured mechanism for organizing these diverse knowledge sources. The results indicate that formal knowledge representation can improve consistency, support traceable decision-making, and provide a foundation for future intelligent engineering systems [12], [13].

12.4 Implications for Explainable Engineering AI

Transparency remains an important requirement for AI adoption in engineering environments. Engineers must often justify decisions, verify recommendations, and demonstrate compliance with requirements and constraints. The Engineering Reasoning Chain addresses this need by exposing the relationships between engineering objectives, requirements, processes, evidence, and final decisions. As a result, engineering recommendations become easier to understand, validate, and communicate, thereby improving confidence in AI-supported decision-making [14], [15].

12.5 Implications for Human-in-the-Loop Optimization

The evaluation highlights the importance of incorporating human judgement into optimization activities. Engineering decisions frequently involve trade-offs that cannot be fully represented using mathematical objectives alone. Stakeholder preferences, organizational priorities, and practical constraints often influence the final decision. The proposed approach demonstrates how optimization outcomes can be refined through human participation, resulting in solutions that are both technically suitable and practically acceptable [16], [17].

12.6 Implications for Systems Engineering and Product Development

The study reinforces the view that engineering decisions should be considered from a systems perspective. Requirements, functions, manufacturing processes, resources, quality considerations, and business objectives are closely interconnected. The proposed framework captures these relationships within a unified decision environment, allowing engineers to evaluate decisions in terms of their wider impact across the product development lifecycle rather than focusing on isolated technical aspects.

12.7 Industrial Applicability

The framework has potential relevance for manufacturing SMEs, engineering organizations, and future engineering decision-support systems. Possible applications include manufacturability assessment, process planning, engineering reviews, facility-aware decision-making, and collaborative problem solving. By preserving decision rationale, stakeholder knowledge, and supporting evidence, the framework may contribute to improved decision consistency and knowledge retention within industrial settings.

12.8 Educational Applicability

Beyond industrial use, the framework may also support engineering education and training. The explicit representation of engineering knowledge, reasoning activities, stakeholder perspectives, and optimization processes provides learners with greater visibility into how engineering decisions are formed. Consequently, the framework can support both engineering instruction and the development of decision-making skills among students and early-career engineers.

12.9 Limitations

Several limitations should be considered when interpreting the results. The validation was primarily based on a single industrial case study and utilized LLM-supported evaluation workflows rather than full-scale industrial deployment. In addition, stakeholder participation was represented through structured scenarios. Future studies involving multiple case studies, industrial practitioners, and long-term implementations would provide a broader assessment of the framework's applicability and effectiveness.

13. CONCLUSION AND FUTURE WORK

13.1 Summary of Contributions

This research proposed the Human–AI Engineering Decision Intelligence (HAEDI) framework as a structured approach for supporting engineering decision-making. The framework combines knowledge representation, reasoning, collaboration, and Human-in-the-Loop optimization within a single decision-support environment. The evaluation results demonstrated improvements in knowledge formalization, decision traceability, stakeholder participation, and optimization transparency when compared with conventional LLM-based approaches.

13.2 Future Research in Engineering Knowledge Intelligence

Future research may explore automated methods for constructing engineering knowledge models from design documents, specifications, standards, and historical project information. Additional opportunities include the development of engineering knowledge graphs and intelligent retrieval mechanisms capable of supporting more advanced reasoning and decision-support activities across different engineering domains.

13.3 Future Research in Human–AI Decision Behaviour

Further investigation is required to better understand how engineers interact with AI-supported decision environments. Areas of interest include trust development, explanation effectiveness, intervention behaviour, mental model alignment, and decision acceptance. Such studies would provide valuable insights into the factors that influence collaboration between engineers and AI systems during decision-making activities.

13.4 Future Research in Human-in-the-Loop Optimization

Future work may focus on adaptive preference modelling, dynamic stakeholder weighting, uncertainty-aware optimization, and iterative optimization processes that continuously incorporate expert feedback. Additional research is also needed to examine how explanations influence optimization outcomes and how human intervention affects solution quality under different engineering conditions.

13.5 Future Industrial Deployment

A natural progression of this work is the deployment of the framework within industrial engineering environments. Future implementations may involve integration with CAD, PLM, ERP, MES, and Digital Twin platforms. Validation across multiple organizations and engineering sectors would provide stronger evidence regarding scalability, robustness, and long-term industrial value of the proposed Human–AI Engineering Decision Intelligence framework.

14. REFERENCES

[1] G. Pahl, W. Beitz, J. Feldhusen, and K.-H. Grote, Engineering Design: A Systematic Approach, 3rd ed. London, U.K.: Springer, 2007.

[2] INCOSE, Systems Engineering Handbook: A Guide for System Life Cycle Processes and Activities, 5th ed. Hoboken, NJ, USA: Wiley, 2023.

[3] T. R. Gruber, "A Translation Approach to Portable Ontology Specifications," Knowledge Acquisition, vol. 5, no. 2, pp. 199–220, 1993.

[4] A. Adadi and M. Berrada, "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)," IEEE Access, vol. 6, pp. 52138–52160, 2018.

[5] S. Amershi et al., "Guidelines for Human-AI Interaction," Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1–13, 2019.

[6] S. Russell and P. Norvig, Artificial Intelligence: A Modern Approach, 4th ed. Hoboken, NJ, USA: Pearson, 2021.

[7] T. H. Davenport and R. Ronanki, "Artificial Intelligence for the Real World," Harvard Business Review, vol. 96, no. 1, pp. 108–116, 2018.

[8] T. Miller, "Explanation in Artificial Intelligence: Insights from the Social Sciences," Artificial Intelligence, vol. 267, pp. 1–38, 2019.

[9] A. Jacovi, A. Marasović, T. Miller, and Y. Goldberg, "Formalizing Trust in Artificial Intelligence: Prerequisites, Causes and Goals of Human Trust in AI," Proceedings of the ACM Conference on Fairness, Accountability, and Transparency (FAccT), 2021.

[10] N. F. Noy and D. L. McGuinness, "Ontology Development 101: A Guide to Creating Your First Ontology," Stanford Knowledge Systems Laboratory, Technical Report KSL-01-05, 2001.

[11] B. W. Boehm, "A View of 20th and 21st Century Software Engineering," Proceedings of the 28th International Conference on Software Engineering (ICSE), pp. 12–29, 2006.

[12] T. R. Gruber, "Toward Principles for the Design of Ontologies Used for Knowledge Sharing," International Journal of Human-Computer Studies, vol. 43, no. 5–6, pp. 907–928, 1995.

[13] J. Euzenat and P. Shvaiko, Ontology Matching, 2nd ed. Berlin, Germany: Springer, 2013.

[14] F. Doshi-Velez and B. Kim, "Towards a Rigorous Science of Interpretable Machine Learning," arXiv:1702.08608, 2017.

[15] D. Gunning and D. W. Aha, "DARPA's Explainable Artificial Intelligence (XAI) Program," AI Magazine, vol. 40, no. 2, pp. 44–58, 2019.

[16] A. Holzinger, "Interactive Machine Learning for Health Informatics: When Do We Need the Human-in-the-Loop?", Brain Informatics, vol. 3, no. 2, pp. 119–131, 2016.

[17] J. R. R. A. Martins and A. B. Lambe, "Multidisciplinary Design Optimization: A Survey of Architectures," AIAA Journal, vol. 51, no. 9, pp. 2049–2075, 2013.

[18] M. H. Jarrahi, "Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision

Making," Business Horizons, vol. 61, no. 4, pp. 577–586, 2018.

[19] OpenAI, "GPT-4 Technical Report," arXiv:2303.08774, 2023.

[20] A. Aamodt and E. Plaza, "Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches," AI Communications, vol. 7, no. 1, pp. 39–59, 1994.

[21] R. L. Keeney and H. Raiffa, Decisions with Multiple Objectives: Preferences and Value Trade-Offs, Cambridge, U.K.: Cambridge University Press, 1993.

[22] IEEE, IEEE Standard for System, Software, and Hardware Verification and Validation, IEEE Std 1012-2016, Piscataway, NJ, USA: IEEE, 2017.