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Research Article

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Posted Date: May 5th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9598452/v1>

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Additional Declarations: No competing interests reported.

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Abstract

Human–robot collaboration requires decision support systems that can evaluate safety-related burden and human oversight needs in shared operational environments. This paper proposes a redundancy-adjusted Artificial Age Score decision support system (AAS-DSS) for oversight-aware human–robot collaboration. Each event is represented through six normalized dimensions: task hazard severity, human safety risk, environmental uncertainty, task criticality, exposure frequency, and intervention complexity. These components are transformed into consistency-based burden indicators and aggregated through a redundancy-adjusted scoring structure.

In this formulation, the Artificial Age Score does not measure chronological age or direct physical risk. Instead, it represents the structural decision burden of a human–robot collaboration event. The framework separates mandatory human review, triggered by direct safety indicators, from supervisory review, triggered by operational stress and monitoring conditions. Two illustrative warehouse robot scenarios demonstrate how the model can classify event burden and support oversight decisions. The resulting AAS-DSS is not an autonomous action selector, but an interpretable oversight-support layer. The proposed framework is intended as a configurable decision-support prototype whose weights, thresholds, and redundancy structure require domain-specific calibration before deployment.

Keywords: Artificial Age Score; human–robot collaboration; decision support system; human oversight; structural burden; warehouse robotics; AI safety.

1 Introduction

The problem of reliable artificial behaviour has a long theoretical history in cybernetics, information theory, automata theory, and machine intelligence. Wiener’s cybernetic formulation positioned control, communication, and feedback as general principles shared by biological and artificial systems, thereby treating machines as systems whose behaviour depends on information flow, regulation, and response to environmental change (Wiener, 1948). Shannon’s mathematical theory of communication provided a formal foundation for uncertainty, entropy, redundancy, and information transmission, making it possible to analyse artificial systems through informational structure rather than observable output alone (Shannon, 1948). Turing’s behavioural account of machine intelligence shifted the discussion from inaccessible internal states to observable performance under structured interaction, a perspective that remains relevant for evaluating artificial systems through their functional behaviour (Turing, 1950). Von Neumann’s analysis of probabilistic logics and reliable organisms further developed the question of how reliable system-level behaviour can emerge from components that may be individually unreliable (von Neumann, 1956). Together, these foundational works suggest that artificial systems should be evaluated not only by isolated outputs but also by their structural reliability, redundancy, stability, and capacity to operate under changing conditions.

The Artificial Age Score (AAS) can be positioned within this broader theoretical lineage by treating artificial aging as a measurable structural burden rather than as chronological time. In Kayadibi’s redundancy-as-masking formulation, AAS is defined as a log-scaled, entropy-informed, and redundancy-aware metric for modelling memory aging in generative AI systems (Kayadibi, 2026). This formulation reframes artificial aging as an observable asymmetry in system behaviour under different memory and context-persistence conditions, rather than as a biological process or a time-dependent property in the ordinary sense (Kayadibi, 2026). The importance of this formulation is that “age” can be interpreted more generally as accumulated structural burden, degradation, instability, or operational strain. This interpretation is consistent with Shannon’s emphasis on redundancy and information structure, von Neumann’s concern with reliability under component uncertainty, and Wiener’s cybernetic focus on feedback and regulation (Shannon, 1948; von Neumann, 1956; Wiener, 1948). In this sense, AAS can be extended beyond generative AI memory evaluation and applied to decision support contexts in which the relevant concern is the structural burden imposed by an operational event profile.

Human–robot collaboration is a suitable domain for this extension because collaborative robotic systems operate in shared environments where technical performance, human safety,

task continuity, uncertainty, and supervision cannot be separated cleanly. Human–robot interaction research has long emphasized that robots operating near humans require attention to communication, task allocation, shared autonomy, trust, and human-centred design (Goodrich & Schultz, 2007; Sheridan, 1992). Physical human–robot interaction also requires explicit attention to safety, contact conditions, control response, and the consequences of physical proximity between humans and robotic systems (De Santis et al., 2008). In industrial human–robot collaboration, safety, intuitive interaction, ergonomic integration, control modalities, system stability, and task-level coordination are treated as interconnected requirements rather than independent design objectives (Ajoudani et al., 2018; Villani et al., 2018). Safe human–robot interaction further depends on multiple methodological layers, including control strategies, motion planning, prediction of human behaviour, and psychological factors that affect perceived and actual safety (Lasota et al., 2017). Research on trust in automation and human–robot systems also shows that human reliance on automated systems depends not only on system capability but also on transparency, predictability, reliability, and the user’s ability to understand when intervention may be necessary (Hancock et al., 2011; Lee & See, 2004).

Safety standards and risk-management frameworks reinforce the need for contextual and interpretable evaluation in collaborative robotic environments. ISO/TS 15066 provides technical guidance for collaborative robot operations and emphasizes that collaborative systems must be considered in relation to the robot, the human operator, the workspace, and the specific collaborative task (International Organization for Standardization [ISO], 2016). Broader machinery safety principles similarly require hazard identification, risk estimation, and risk reduction rather than reliance on a single output measure (ISO, 2010). In parallel, the NIST Artificial Intelligence Risk Management Framework emphasizes that AI-related risks should be understood in terms of intended use, context, trustworthiness, monitoring, and human oversight (National Institute of Standards and Technology [NIST], 2023). These perspectives indicate that a decision support model for human–robot collaboration should not merely produce an action recommendation. It should provide an interpretable assessment of the burden and oversight requirements associated with an event.

In shared human–robot environments, event burden may arise from multiple interacting dimensions. A robot operating in a warehouse, laboratory, hospital, or industrial workspace may encounter task hazard severity, human safety risk, environmental uncertainty, task criticality, exposure frequency, and intervention complexity at the same time. Each dimension contributes differently to the overall burden of the event. For example, a task may have low immediate hazard but high repetition frequency, making small operational pressures important over repeated cycles. Conversely, a task may occur rarely but require immedi-

ate human attention because environmental uncertainty or human safety risk is high. Such cases show why a decision support model should not rely only on a single priority score or isolated threshold. Instead, it should integrate multiple burden components while preserving interpretability and human-centred oversight.

This leads to two research questions. First, how can the redundancy-adjusted Artificial Age Score be reformulated as an event-level structural decision-burden measure for human–robot collaboration? This question concerns the mathematical transformation of normalized event components into burden deviations, consistency indicators, logarithmic penalties, redundancy-adjusted component contributions, and the final event-level AAS. Second, how can the resulting AAS-based burden score support oversight-aware decision support by distinguishing ordinary operation, supervisory review, and mandatory human review? This question concerns the operational interpretation of the score in shared human–robot environments, where direct safety indicators and operational monitoring conditions should be separated rather than conflated.

Together, these questions position the proposed framework as both a mathematical and decision-support contribution. The first question addresses the formal construction of AAS_{HRC} , while the second addresses its practical use as an interpretable oversight mechanism in human–robot collaboration.

This concern is consistent with human–automation theory. Parasuraman et al. (2000) distinguish among information acquisition, information analysis, decision selection, and action implementation as different levels of automation, showing that automation does not simply remove human involvement but redistributes it across system functions. Sheridan (1992) similarly frames human supervisory control as a structure in which humans monitor, interpret, intervene, and evaluate automated system behaviour. Endsley’s work on situation awareness further emphasizes that human operators must maintain an understanding of system state, environmental conditions, and future implications in order to make effective decisions in dynamic contexts (Endsley, 1995). These perspectives are directly relevant to human–robot collaboration because a decision support system should help determine when normal operation is acceptable, when supervisory monitoring is advisable, and when direct human review is required.

Within this context, the present study develops a redundancy-adjusted Artificial Age Score decision support system for oversight-aware human–robot collaboration. The aim is not to replace the human operator, select a physical robot action autonomously, or certify robotic safety. Rather, the aim is to provide a mathematically explicit and computationally traceable structure that converts normalized event components into an interpretable structural burden score and separates ordinary operation, supervisory review, and mandatory human review.

This framing preserves the human-centred nature of decision support while extending the AAS framework from artificial memory aging to shared human–robot environments.

2 Methodology

2.1 Normalized Human–Robot Collaboration Event Space

Human–robot collaboration requires a structured representation of the event context because collaborative robotic systems operate in shared environments where safety, task execution, uncertainty, and human oversight interact simultaneously (Ajoudani et al., 2018; Lasota et al., 2017; Villani et al., 2018). In line with collaborative robotics safety guidance, the event representation should account not only for the robot itself, but also for the human operator, the workspace, and the specific collaborative task (International Organization for Standardization [ISO], 2016). Therefore, each human–robot collaboration event is represented as a normalized vector

$$\mathbf{u} = (u_1, u_2, u_3, u_4, u_5, u_6) \in [0, 1]^6.$$

The six components are defined as

$$\begin{aligned} u_1 &= \text{task hazard severity,} \\ u_2 &= \text{human safety risk,} \\ u_3 &= \text{environmental uncertainty,} \\ u_4 &= \text{task criticality,} \\ u_5 &= \text{exposure frequency,} \\ u_6 &= \text{intervention complexity.} \end{aligned}$$

Each u_i is interpreted as a normalized burden component. A value close to 0 indicates low burden, whereas a value close to 1 indicates high burden. This normalization is consistent with risk-assessment practice, where hazards and operational conditions are typically represented through scaled or classified levels rather than through a single unstructured value (ISO, 2010; NIST, 2023). The vector $\mathbf{u}$ does not certify physical safety. Instead, it provides a structured event representation for decision-support scoring. This distinction is important because formal robot safety assessment requires additional analysis of workspace design, robot motion, physical interaction, and task-specific risk conditions (De Santis et al., 2008; ISO, 2016; Lasota et al., 2017).

Definition 1. Human–Robot Collaboration Event Profile. A human–robot collaboro-

ration event profile is any vector

$$\mathbf{u} \in [0, 1]^6.$$

The event space is therefore

$$\mathcal{U} = [0, 1]^6.$$

Each component u_i is bounded and normalized:

$$0 \leq u_i \leq 1, \quad i = 1, \dots, 6.$$

This boundedness condition ensures that all subsequent transformations are mathematically controlled. It also supports interpretability, because every component is placed on the same normalized burden scale before being transformed into an AAS-compatible consistency score.

2.2 General Redundancy-Adjusted AAS Formulation

The proposed decision support system is derived from the redundancy-adjusted Artificial Age Score (AAS), originally formulated to model artificial memory aging in generative AI systems through consistency loss, logarithmic penalty, and redundancy-aware aggregation (Kayadibi, 2026). The use of redundancy in this formulation is also conceptually aligned with Shannon’s information-theoretic treatment of redundancy as a structural property of information systems rather than as simple repetition (Shannon, 1948). In the present study, this logic is transferred from artificial memory aging to event-level decision burden in human–robot collaboration.

Let $x_{j,i} \in (0, 1]$ denote the consistency score of component i in observation or event j , let $w_i \geq 0$ denote the normalized component weight, and let $R_{j,i} \in [0, 1]$ denote the redundancy adjustment. The general redundancy-adjusted AAS is defined as

$$AAS_j = \sum_{i=1}^m w_i (1 - R_{j,i}) \phi(x_{j,i}),$$

where

$$\sum_{i=1}^m w_i = 1.$$

The logarithmic penalty kernel is

$$\phi(x_{j,i}) = -\log_2 \left(\frac{x_{j,i} + \varepsilon}{1 + \varepsilon} \right), \quad \varepsilon > 0.$$

In this formulation, $x_{j,i} = 1$ represents maximum consistency and produces approximately zero penalty, while lower values of $x_{j,i}$ produce larger penalties. The redundancy term $R_{j,i}$ reduces the effective penalty when a component overlaps structurally or conceptually with other active components. Therefore, the AAS formulation does not require chronological time. It measures structural burden through consistency loss, logarithmic penalty, and redundancy-adjusted aggregation (Kayadibi, 2026).

For the human-robot collaboration setting, the event index j corresponds to a single human-robot collaboration event, and the number of components is fixed at

$$m = 6.$$

Thus, the HRC-specific event-level score is defined as

$$AAS_{\text{HRC}} = \sum_{i=1}^6 w_i (1 - R_i) \phi(x_i).$$

This formulation is used as an oversight-aware decision-support score, not as a direct physical safety certificate. This distinction is consistent with human-centred automation theory, where automated systems are expected to support rather than replace human monitoring, interpretation, and intervention (Parasuraman et al., 2000; Sheridan, 1992).

2.3 Component-Level Burden Deviation

Each normalized event component u_i is transformed into a value that is compatible with the AAS requirement $x_i \in (0, 1]$. Since higher u_i values indicate greater burden, a non-negative burden deviation is first defined. For each burden component u_i , the deviation is given by

$$\Delta_i = \frac{u_i}{1 - u_i + \eta},$$

where

$$\eta > 0$$

is a small stabilizing constant. In the computational implementation,

$$\eta = 10^{-6}.$$

The stabilizing parameter η is introduced to prevent division by zero when $u_i = 1$. Therefore, even a maximum burden component remains mathematically finite. This property is important for computational decision support because safety-related and operational burden

values may approach their maximum normalized level in extreme scenarios. The transformation preserves the interpretation that higher event burden produces a larger deviation, which is later converted into a lower consistency score and a higher AAS penalty.

Proposition 1. Well-Definedness of Δ_i . For every $u_i \in [0, 1]$ and every $\eta > 0$, the burden deviation

$$\Delta_i = \frac{u_i}{1 - u_i + \eta}$$

is well defined, finite, and non-negative.

Proof. Since

$$0 \leq u_i \leq 1,$$

it follows that

$$1 - u_i \geq 0.$$

Because $\eta > 0$,

$$1 - u_i + \eta > 0.$$

Therefore, the denominator of Δ_i is strictly positive, and Δ_i is well defined. Since the numerator satisfies $u_i \geq 0$ and the denominator is positive,

$$\Delta_i \geq 0.$$

Moreover, when $u_i = 1$,

$$\Delta_i = \frac{1}{\eta},$$

which is finite for every fixed $\eta > 0$. Hence, Δ_i is finite and non-negative for all $u_i \in [0, 1]$.

□

This result shows that the deviation transformation is mathematically controlled over the full normalized event space. It also supports the computational reliability of the proposed AAS-DSS, because no admissible event profile produces an undefined burden deviation.

2.4 Consistency Transformation

Each burden deviation is converted into an AAS-compatible consistency score:

$$x_i = \frac{1}{1 + \Delta_i}.$$

This transformation follows the AAS logic in which higher deviation produces lower consistency, while zero deviation produces full consistency (Kayadibi, 2026). In the present

model, x_i therefore represents the burden-adjusted consistency of the i -th human-robot event component.

Proposition 2. Domain of x_i . For every $u_i \in [0, 1]$ and $\eta > 0$, the consistency score

$$x_i = \frac{1}{1 + \Delta_i}$$

satisfies

$$0 < x_i \leq 1.$$

Proof. From Proposition 1,

$$\Delta_i \geq 0.$$

Therefore,

$$1 + \Delta_i \geq 1.$$

Hence,

$$x_i = \frac{1}{1 + \Delta_i} \leq 1.$$

Since

$$1 + \Delta_i > 0,$$

it also follows that

$$x_i > 0.$$

Therefore,

$$x_i \in (0, 1].$$

This is exactly the required domain of the AAS penalty kernel. $\square$

Proposition 3. Equivalent Form of x_i . The consistency score can equivalently be written as

$$x_i = \frac{1 - u_i + \eta}{1 + \eta}.$$

Proof. By definition,

$$x_i = \frac{1}{1 + \Delta_i}.$$

Substituting

$$\Delta_i = \frac{u_i}{1 - u_i + \eta},$$

gives

$$x_i = \frac{1}{1 + \frac{u_i}{1 - u_i + \eta}}.$$

Combining terms in the denominator yields

$$x_i = \frac{1}{\frac{1-u_i+\eta+u_i}{1-u_i+\eta}}.$$

Since

$$1 - u_i + \eta + u_i = 1 + \eta,$$

it follows that

$$x_i = \frac{1 - u_i + \eta}{1 + \eta}.$$

Thus, the two forms are equivalent. $\square$

This equivalent expression shows that as u_i increases, x_i decreases.

Proposition 4. Monotonicity of x_i . The consistency score x_i is monotonically decreasing in u_i .

Proof. Using the equivalent form,

$$x_i = \frac{1 - u_i + \eta}{1 + \eta},$$

and differentiating with respect to u_i gives

$$\frac{dx_i}{du_i} = -\frac{1}{1 + \eta}.$$

Since

$$\eta > 0,$$

it follows that

$$1 + \eta > 0.$$

Therefore,

$$\frac{dx_i}{du_i} < 0.$$

Thus, x_i decreases monotonically as u_i increases. $\square$

2.5 AAS Penalty Kernel

The consistency score is transformed into a logarithmic AAS penalty:

$$\phi(x_i) = -\log_2 \left(\frac{x_i + \varepsilon}{1 + \varepsilon} \right),$$

where

$$\varepsilon > 0$$

is a small stabilizing constant. In the computational implementation,

$$\varepsilon = 10^{-6}.$$

The parameter ε is introduced to ensure numerical stability when x_i is very close to zero. The logarithmic form is consistent with the AAS framework, where lower consistency values generate larger structural burden penalties (Kayadibi, 2026). It is also conceptually aligned with information-theoretic approaches in which logarithmic transformations are used to represent information, uncertainty, and redundancy (Shannon, 1948).

Proposition 5. Non-Negativity of the AAS Penalty. For every $x_i \in (0, 1]$ and $\varepsilon > 0$,

$$\phi(x_i) \geq 0.$$

Proof. Since

$$0 < x_i \leq 1,$$

it follows that

$$x_i + \varepsilon \leq 1 + \varepsilon.$$

Therefore,

$$0 < \frac{x_i + \varepsilon}{1 + \varepsilon} \leq 1.$$

The base-2 logarithm of a number in $(0, 1]$ is non-positive:

$$\log_2 \left(\frac{x_i + \varepsilon}{1 + \varepsilon} \right) \leq 0.$$

Thus,

$$-\log_2 \left(\frac{x_i + \varepsilon}{1 + \varepsilon} \right) \geq 0.$$

Hence,

$$\phi(x_i) \geq 0.$$

□

Proposition 6. Penalty Increases as Burden Increases. As u_i increases, the penalty $\phi(x_i)$ increases.

Proof. From Proposition 4, x_i decreases as u_i increases. The penalty kernel is

$$\phi(x_i) = -\log_2 \left(\frac{x_i + \varepsilon}{1 + \varepsilon} \right).$$

Differentiating ϕ with respect to x_i gives

$$\frac{d\phi}{dx_i} = -\frac{1}{\ln 2} \cdot \frac{1}{x_i + \varepsilon}.$$

Since

$$x_i + \varepsilon > 0,$$

it follows that

$$\frac{d\phi}{dx_i} < 0.$$

Thus, $\phi(x_i)$ decreases as x_i increases and increases as x_i decreases. Since x_i decreases when u_i increases, $\phi(x_i)$ increases with u_i . $\square$

This result confirms that higher burden components receive higher AAS penalties.

2.6 Weight Vector

Let

$$\mathbf{w} = (w_1, w_2, w_3, w_4, w_5, w_6)$$

be a non-negative normalized weight vector satisfying

$$w_i \geq 0, \quad \sum_{i=1}^6 w_i = 1.$$

For the illustrative warehouse implementation, the following non-uniform safety-weighted vector is used:

$$\mathbf{w}^{(0)} = (0.25, 0.23, 0.16, 0.14, 0.10, 0.12).$$

This vector gives relatively greater emphasis to task hazard severity and human safety risk while retaining non-zero contributions from environmental uncertainty, task criticality, exposure frequency, and intervention complexity. These weights are not universal constants. They are demonstration parameters and should be recalibrated through expert judgement, sensitivity analysis, empirical validation, or domain-specific safety assessment before deployment. This calibration requirement is consistent with the broader view that human–robot collaboration and AI risk-management systems must be interpreted in context rather than through fixed universal parameters (International Organization for Standardization [ISO],

2016; National Institute of Standards and Technology [NIST], 2023).

2.7 Conceptual Redundancy Structure

Decision burden in human–robot collaboration may contain overlapping components. For example, task hazard severity and human safety risk both contribute to direct safety concern, whereas task criticality, exposure frequency, and intervention complexity contribute to operational burden. Therefore, a conceptual redundancy structure is used rather than treating all input components as fully independent. The use of redundancy is consistent with the AAS framework and with Shannon’s broader treatment of redundancy as a structural feature of information systems (Kayadibi, 2026; Shannon, 1948).

Each component is associated with a conceptual feature set:

$$G_1 = \{\text{direct safety, task}\},$$

$$G_2 = \{\text{direct safety, human}\},$$

$$G_3 = \{\text{direct safety, environment}\},$$

$$G_4 = \{\text{operational burden, task}\},$$

$$G_5 = \{\text{operational burden, repetition}\},$$

$$G_6 = \{\text{operational burden, intervention}\}.$$

For components $i \neq k$, their pairwise conceptual redundancy is defined by the Jaccard overlap

$$q_{ik} = \frac{|G_i \cap G_k|}{|G_i \cup G_k|}.$$

Since self-overlap is excluded from the redundancy adjustment, $q_{ii} = 0$ is set by convention. The value q_{ik} is not intended to represent empirical correlation. It represents conceptual overlap among burden dimensions.

Proposition 7. Bounds of Pairwise Redundancy. For all i, k ,

$$0 \leq q_{ik} \leq 1.$$

Proof. For any two finite sets G_i and G_k ,

$$G_i \cap G_k \subseteq G_i \cup G_k.$$

Therefore,

$$|G_i \cap G_k| \leq |G_i \cup G_k|.$$

Since cardinalities are non-negative,

$$0 \leq |G_i \cap G_k|.$$

Thus,

$$0 \leq \frac{|G_i \cap G_k|}{|G_i \cup G_k|} \leq 1.$$

Therefore,

$$0 \leq q_{ik} \leq 1.$$

□

2.8 Component-Level Redundancy Adjustment

For each component i , the redundancy term R_i is defined as

$$R_i = \frac{\sum_{k \neq i} w_k u_k q_{ik}}{\sum_{k \neq i} w_k u_k},$$

when

$$\sum_{k \neq i} w_k u_k > 0.$$

If

$$\sum_{k \neq i} w_k u_k = 0,$$

then

$$R_i = 0.$$

This term measures the weighted conceptual overlap between component i and the other active burden components. In this formulation, activity is represented through the product $w_k u_k$, meaning that a component contributes to the redundancy context when it has both non-zero weight and non-zero burden. The burden level of component i itself is already represented through x_i and $\phi(x_i)$. Therefore, R_i is defined through the other active components in order to adjust overlap without double-counting the component's own burden. This redundancy adjustment follows the broader logic of the AAS framework, where overlapping burden signals should not be treated as fully independent contributors (Kayadibi, 2026). It is also consistent with the information-theoretic view that redundancy is a structural property

of information systems (Shannon, 1948).

Proposition 8. Bounds of R_i . For every component i ,

$$0 \leq R_i \leq 1.$$

Proof. If

$$\sum_{k \neq i} w_k u_k = 0,$$

then by definition

$$R_i = 0,$$

so the result holds. Otherwise, define

$$a_k = w_k u_k.$$

Since

$$w_k \geq 0 \quad \text{and} \quad u_k \geq 0,$$

it follows that

$$a_k \geq 0.$$

The redundancy term becomes

$$R_i = \frac{\sum_{k \neq i} a_k q_{ik}}{\sum_{k \neq i} a_k}.$$

This is a weighted average of the values q_{ik} . From Proposition 7,

$$0 \leq q_{ik} \leq 1.$$

A weighted average of values in $[0, 1]$ with non-negative weights also lies in $[0, 1]$. Therefore,

$$0 \leq R_i \leq 1.$$

□

2.9 Redundancy-Adjusted Component Contribution

The redundancy-adjusted contribution of component i is defined as

$$A_i = w_i(1 - R_i)\phi(x_i).$$

Since

$$R_i \in [0, 1],$$

the factor

$$1 - R_i$$

also lies in $[0, 1]$. Therefore, redundancy can reduce but not reverse the component penalty. In this sense, A_i represents the effective contribution of component i to the total event-level AAS after conceptual overlap with other active burden components has been accounted for.

Proposition 9. Non-Negativity of Component Contributions. For every component i ,

$$A_i \geq 0.$$

Proof. By definition,

$$A_i = w_i(1 - R_i)\phi(x_i).$$

From the weight definition,

$$w_i \geq 0.$$

From Proposition 8,

$$0 \leq R_i \leq 1,$$

so

$$1 - R_i \geq 0.$$

From Proposition 5,

$$\phi(x_i) \geq 0.$$

Therefore, A_i is the product of three non-negative terms. Hence,

$$A_i \geq 0.$$

□

2.10 Event-Level Redundancy-Adjusted AAS

The event-level redundancy-adjusted Artificial Age Score for human-robot collaboration is defined as

$$AAS_{\text{HRC}} = \sum_{i=1}^6 w_i(1 - R_i)\phi(x_i).$$

Equivalently,

$$AAS_{\text{HRC}} = \sum_{i=1}^6 A_i.$$

This score represents the structural decision burden of the event profile. It does not represent chronological age, biological aging, or direct physical risk. Instead, the redundancy-adjusted AAS logic is adapted to a human–robot collaboration decision-support context, where the objective is to summarize burden while preserving interpretability and oversight (Kayadibi, 2026).

Proposition 10. Well-Definedness and Non-Negativity of AAS_{HRC} . For every event profile

$$\mathbf{u} \in [0, 1]^6,$$

the score

$$AAS_{\text{HRC}}$$

is well defined, finite, and non-negative.

Proof. From Proposition 1, each Δ_i is well defined and finite. From Proposition 2, each $x_i \in (0, 1]$. From Proposition 5, each $\phi(x_i) \geq 0$, and each $\phi(x_i)$ is finite because

$$x_i + \varepsilon > 0.$$

From Proposition 8, each $R_i \in [0, 1]$. Therefore, each component contribution

$$A_i = w_i(1 - R_i)\phi(x_i)$$

is well defined, finite, and non-negative. Since AAS_{HRC} is the finite sum of six such terms,

$$AAS_{\text{HRC}} = \sum_{i=1}^6 A_i,$$

it is also well defined, finite, and non-negative. $\square$

2.11 Oversight Classification

The AAS score is not interpreted as a direct physical risk score. Therefore, event-level burden is separated from human oversight decisions. This separation is consistent with human-centred automation theory, where automation supports human monitoring, interpretation, and intervention rather than replacing the human operator (Parasuraman et al., 2000; Sheridan, 1992). It is also aligned with situation awareness theory, which emphasizes the

operator’s need to understand the system state, environmental conditions, and likely consequences in dynamic contexts (Endsley, 1995). In safety-relevant human–robot collaboration, this distinction is important because formal safety assessment requires context-specific evaluation of the robot, human operator, workspace, and task (International Organization for Standardization [ISO], 2016; National Institute of Standards and Technology [NIST], 2023).

Two binary oversight flags are defined:

$$H \in \{0, 1\}, \quad S \in \{0, 1\}.$$

Here, H represents mandatory human review and S represents supervisory review.

Definition 2. Mandatory Human Review. Mandatory human review is triggered when at least one direct safety indicator exceeds its threshold:

$$H = \begin{cases} 1, & u_1 \geq \theta_1 \text{ or } u_2 \geq \theta_2 \text{ or } u_3 \geq \theta_3, \\ 0, & \text{otherwise.} \end{cases}$$

For the illustrative implementation,

$$\theta_1 = 0.75, \quad \theta_2 = 0.70, \quad \theta_3 = 0.80.$$

Thus, mandatory review is associated with task hazard severity, human safety risk, and environmental uncertainty.

Definition 3. Supervisory Review. Let

$$s \in \{\text{low, medium, high}\}$$

denote the operational stress condition associated with the event. Supervisory review is triggered when operational oversight conditions are elevated:

$$S = \begin{cases} 1, & s = \text{high or } u_4 \geq \theta_4 \text{ or } u_5 \geq \theta_5 \text{ or } u_6 \geq \theta_6, \\ 0, & \text{otherwise.} \end{cases}$$

For the illustrative implementation,

$$\theta_4 = 0.80, \quad \theta_5 = 0.80, \quad \theta_6 = 0.70.$$

Thus, supervisory review is associated with operational stress, task criticality, exposure

frequency, and intervention complexity.

2.12 Decision Output

The decision-support output is defined as the tuple

$$\mathcal{D}_{\text{out}} = (AAS_{\text{HRC}}, B, H, S),$$

where AAS_{HRC} is the event-level redundancy-adjusted Artificial Age Score, B is the burden label assigned to the AAS score, H is the mandatory human review flag, and S is the supervisory review flag.

The burden label B is defined using two calibration thresholds, τ_L and τ_H , where

$$0 < \tau_L < \tau_H.$$

The classification rule is

$$B = \begin{cases} \text{Low AAS burden,} & AAS_{\text{HRC}} \leq \tau_L, \\ \text{Moderate AAS burden,} & \tau_L < AAS_{\text{HRC}} \leq \tau_H, \\ \text{High AAS burden,} & AAS_{\text{HRC}} > \tau_H. \end{cases}$$

In the illustrative implementation,

$$\tau_L = 0.50, \quad \tau_H = 1.50.$$

These thresholds are calibration parameters, not universal safety constants. They are used to demonstrate the computational behaviour of the proposed decision-support system and should be validated or recalibrated before any real deployment.

2.13 Interpretation

Three concepts are separated in the proposed model:

structural decision burden,

direct safety-triggered human review,

operational supervisory review.

The event-level AAS measures structural burden. The mandatory human review flag identifies direct safety-triggered concerns. The supervisory review flag identifies elevated operational monitoring needs. This separation is important because a high structural burden does not necessarily indicate immediate physical danger, and a low structural burden does not certify safety.

The framework does not select the physical action of the robot and does not certify robotic safety. Instead, an interpretable, mathematically defined decision-support score is provided for human–robot collaboration events. This interpretation is consistent with human-centred automation, where automated systems support human monitoring and intervention rather than replacing human judgement (Parasuraman et al., 2000; Sheridan, 1992). It is also consistent with contemporary AI risk-management principles, which emphasize context, monitoring, transparency, and human oversight (National Institute of Standards and Technology [NIST], 2023).

The weights, thresholds, redundancy structure, and burden categories are configurable and should be validated through sensitivity analysis, expert judgement, simulation, historical data, or empirical human–robot collaboration studies before real-world deployment.

3 Illustrative Scenarios and Computational Results

3.1 Scenario Design

To demonstrate the proposed event-level AAS-DSS, two illustrative warehouse scenarios are evaluated. Both scenarios represent an autonomous mobile robot operating in a shared warehouse environment with human workers. The scenarios are not field-deployed empirical data; they are controlled examples used to show how the proposed model transforms a human–robot collaboration event profile into an AAS burden score and oversight recommendation.

The same six-dimensional event structure is used in both cases:

$$\mathbf{u} = (u_1, u_2, u_3, u_4, u_5, u_6),$$

where

$$\begin{aligned}
u_1 &= \text{task hazard severity,} \\
u_2 &= \text{human safety risk,} \\
u_3 &= \text{environmental uncertainty,} \\
u_4 &= \text{task criticality,} \\
u_5 &= \text{exposure frequency,} \\
u_6 &= \text{intervention complexity.}
\end{aligned}$$

The same illustrative weight vector is used:

$$\mathbf{w}^{(0)} = (0.25, 0.23, 0.16, 0.14, 0.10, 0.12).$$

The lower and upper AAS burden thresholds are set as

$$\tau_L = 0.50, \quad \tau_H = 1.50.$$

Thus,

$$AAS_{\text{HRC}} \leq 0.50$$

is classified as low AAS burden,

$$0.50 < AAS_{\text{HRC}} \leq 1.50$$

is classified as moderate AAS burden, and

$$AAS_{\text{HRC}} > 1.50$$

is classified as high AAS burden.

The direct safety thresholds for mandatory human review are

$$\theta_1 = 0.75, \quad \theta_2 = 0.70, \quad \theta_3 = 0.80.$$

The operational oversight thresholds for supervisory review are

$$\theta_4 = 0.80, \quad \theta_5 = 0.80, \quad \theta_6 = 0.70.$$

These values are not presented as universal or empirically validated thresholds. They are illustrative calibration settings used to demonstrate the model's operation. In a real human–robot collaboration environment, these values should be selected through expert judgement,

sensitivity analysis, safety assessment, or empirical calibration. All numerical results reported in the illustrative scenarios are generated using the computational implementation provided in Appendix A. The code accepts normalized input values in $[0, 1]$ for each of the six event components and computes the corresponding burden deviations Δ_i , consistency scores x_i , AAS penalties $\phi(x_i)$, redundancy terms R_i , adjusted component contributions A_i , event-level AAS_{HRC} , burden label

3.2 Scenario 1: Low-Burden Ordinary Operation

The first scenario represents a low-stress warehouse operation in which the autonomous mobile robot performs a routine task with low direct safety burden and moderate exposure frequency. The event profile is shown in Table 1.

Table 1: Scenario 1 event profile

Component	Description	Value
u_1	Task hazard severity	0.220
u_2	Human safety risk	0.120
u_3	Environmental uncertainty	0.150
u_4	Task criticality	0.340
u_5	Exposure frequency	0.560
u_6	Intervention complexity	0.100
s	Operational stress level	Low

The component-level AAS calculation is shown in Table 2.

Table 2: Scenario 1 component-level AAS details

Component	u_i	w_i	Δ_i	x_i	$\phi(x_i)$	R_i	A_i
Task hazard severity	0.220	0.250	0.282051	0.780000	0.358453	0.197767	0.071891
Human safety risk	0.120	0.230	0.136363	0.880000	0.184424	0.135320	0.036678
Environmental uncertainty	0.150	0.160	0.176470	0.850000	0.234465	0.138917	0.032303
Task criticality	0.340	0.140	0.515151	0.660000	0.599461	0.234822	0.064217
Exposure frequency	0.560	0.100	1.272724	0.440001	1.184421	0.119535	0.104284
Intervention complexity	0.100	0.120	0.111111	0.900000	0.152003	0.164288	0.015244

The event-level redundancy-adjusted score was

$$AAS_{\text{HRC}} = 0.324616.$$

Since

$$0.324616 \leq 0.50,$$

the event was classified as

Low AAS burden.

The dominant adjusted contribution was produced by exposure frequency:

$$A_5 = 0.104284.$$

However, exposure frequency did not exceed the supervisory threshold:

$$u_5 = 0.560 < 0.80.$$

No direct safety threshold was exceeded:

$$u_1 = 0.220 < 0.75, \quad u_2 = 0.120 < 0.70, \quad u_3 = 0.150 < 0.80.$$

Therefore,

$$H = 0.$$

No supervisory review condition was triggered:

$$s = \text{low}, \quad u_4 = 0.340 < 0.80, \quad u_5 = 0.560 < 0.80, \quad u_6 = 0.100 < 0.70.$$

Therefore,

$$S = 0.$$

The decision-support output was

$$\mathcal{D}_{\text{out}} = (0.324616, \text{Low AAS burden}, 0, 0).$$

This output indicates that ordinary operation may continue under the model assumptions, provided that external safety requirements and task-specific controls are also satisfied. The scenario shows that the proposed model does not automatically escalate every non-zero burden profile. Although exposure frequency was the largest contributor to the total AAS, the overall event burden remained low and no oversight threshold was exceeded.

3.3 Scenario 2: High Environmental Uncertainty and Mandatory Human Review

The second scenario represents a medium-stress warehouse operation in which task hazard severity and human safety risk are low, but environmental uncertainty is extremely high.

This condition may correspond to an uncertain shared workspace, unreliable environmental perception, changing obstacles, degraded sensor confidence, or unpredictable movement patterns in the robot’s operating area. The event profile is shown in Table 3.

Table 3: Scenario 2 event profile

Component	Description	Value
u_1	Task hazard severity	0.234
u_2	Human safety risk	0.110
u_3	Environmental uncertainty	0.999
u_4	Task criticality	0.560
u_5	Exposure frequency	0.345
u_6	Intervention complexity	0.200
s	Operational stress level	Medium

The component-level AAS calculation is shown in Table 4.

Table 4: Scenario 2 component-level AAS details

Component	u_i	w_i	Δ_i	x_i	$\phi(x_i)$	R_i	A_i
Task hazard severity	0.234	0.250	0.305483	0.766000	0.384583	0.272782	0.069919
Human safety risk	0.110	0.230	0.123595	0.890000	0.168122	0.204876	0.030746
Environmental uncertainty	0.999	0.160	998.001998	0.001001	9.962905	0.126567	1.392309
Task criticality	0.560	0.140	1.272724	0.440001	1.184421	0.129079	0.144415
Exposure frequency	0.345	0.100	0.526717	0.655000	0.610432	0.098640	0.055022
Intervention complexity	0.200	0.120	0.250000	0.800000	0.321927	0.105552	0.034554

The event-level redundancy-adjusted score was

$$AAS_{\text{HRC}} = 1.726964.$$

Since

$$1.726964 > 1.50,$$

the event was classified as

High AAS burden.

The dominant adjusted contribution was produced by environmental uncertainty:

$$A_3 = 1.392309.$$

This dominance follows directly from the very high environmental uncertainty value:

$$u_3 = 0.999.$$

The corresponding burden deviation was

$$\Delta_3 = 998.001998,$$

which produced a very low consistency score:

$$x_3 = 0.001001.$$

The environmental uncertainty component also exceeded the direct safety threshold:

$$u_3 = 0.999 \geq 0.80.$$

Therefore,

$$H = 1.$$

No operational oversight threshold was exceeded:

$$s = \text{medium}, \quad u_4 = 0.560 < 0.80, \quad u_5 = 0.345 < 0.80, \quad u_6 = 0.200 < 0.70.$$

Therefore,

$$S = 0.$$

The decision-support output was

$$\mathcal{D}_{\text{out}} = (1.726964, \text{High AAS burden}, 1, 0).$$

This output indicates that mandatory human review is required. This scenario shows that mandatory human review can be triggered even when task hazard severity and human safety risk are low, provided that environmental uncertainty is sufficiently high. This distinction is important for human–robot collaboration because uncertain operating conditions can undermine the reliability of routine autonomous continuation even when immediate visible hazard appears low.

3.4 Comparative Interpretation

Different decision-support behaviours are demonstrated by the two scenarios.

In Scenario 1, a low AAS burden was produced by the event profile:

$$AAS_{\text{HRC}} = 0.324616.$$

No direct safety threshold or operational oversight threshold was exceeded. Therefore, ordinary operation was indicated under the stated model assumptions.

In Scenario 2, a high AAS burden was produced by the event profile:

$$AAS_{\text{HRC}} = 1.726964.$$

Environmental uncertainty was identified as the dominant component, and the direct safety threshold for environmental uncertainty was exceeded. Therefore, mandatory human review was triggered.

The comparison shows that three different elements are distinguished by the model:

overall structural burden,

dominant contributing component,

human oversight status.

This distinction is important because the AAS score alone is not interpreted as direct physical danger. Instead, structural decision burden is summarized by the AAS score, while the oversight gate determines whether mandatory human review or supervisory review is required.

3.5 Summary of Scenario Outputs

Table 5: Summary of illustrative scenario outputs

Scenario 1: Low-burden ordinary operation		Scenario 2: High environmental uncertainty	
Output	Result	Output	Result
Operational stress	Low	Operational stress	Medium
Event-level AAS	0.324616	Event-level AAS	1.726964
AAS burden label	Low AAS burden	AAS burden label	High AAS burden
Dominant component	Exposure frequency	Dominant component	Environmental uncertainty
Dominant A_i	0.104284	Dominant A_i	1.392309
Mandatory review	False	Mandatory review	True
Supervisory review	False	Supervisory review	False
Oversight output	Ordinary operation	Oversight output	Mandatory review

The results indicate that the proposed framework is sensitive to both cumulative burden and specific high-burden contributors. In the low-burden scenario, unnecessary escalation is avoided. In the high-uncertainty scenario, environmental uncertainty is identified as the dominant source of burden, and mandatory review is triggered. This supports the intended role of the framework as an oversight-aware decision-support mechanism rather than an autonomous action selector.

4 Discussion and Implications

4.1 Event-Level Burden in Human–Robot Collaboration

The proposed framework adapts the Artificial Age Score (AAS) from its original use in modelling artificial memory aging into an event-level structural decision-burden measure for human–robot collaboration. In this adaptation, AAS is not treated as chronological age, biological aging, or a direct physical risk score. Rather, it is used to express the burden imposed by a human–robot event profile on the decision-support process. This interpretation follows the redundancy-adjusted AAS logic, where artificial age is understood through consistency loss, logarithmic penalty, and redundancy-aware accumulation rather than through elapsed time (Kayadibi, 2026).

The first research question asked how the redundancy-adjusted AAS can be reformulated as an event-level structural decision-burden measure for human–robot collaboration. This question is addressed by the proposed model through the transformation of each normalized event component into a burden deviation, the conversion of that deviation into an AAS-

compatible consistency score, the application of a logarithmic penalty, and the aggregation of adjusted component contributions. The general form of the redundancy-adjusted AAS is

$$AAS_j = \sum_{i=1}^m w_i(1 - R_{j,i})\phi(x_{j,i}),$$

where $x_{j,i} \in (0, 1]$ is the component-level consistency score, w_i is the normalized weight, $R_{j,i} \in [0, 1]$ is the redundancy adjustment, and $\phi(x_{j,i})$ is the logarithmic penalty kernel. In the present human–robot collaboration setting, six burden dimensions are contained in the event profile, so the adapted event-level score becomes

$$AAS_{\text{HRC}} = \sum_{i=1}^6 w_i(1 - R_i)\phi(x_i).$$

For each component, the adjusted contribution is

$$A_i = w_i(1 - R_i)\phi(x_i).$$

Thus, A_i is not a separate Artificial Age Score. It is the i -th redundancy-adjusted component contribution to the total event-level score. The total score is therefore

$$AAS_{\text{HRC}} = A_1 + A_2 + A_3 + A_4 + A_5 + A_6.$$

This notation makes the model computationally traceable. For example, when $A_3 = 1.392309$ is reported, this means that environmental uncertainty contributes 1.392309 units to the total AAS_{HRC} . It does not mean that A_3 is an independent Artificial Age Score.

The second research question asked how the resulting AAS-based burden score can support oversight-aware decision support by distinguishing ordinary operation, supervisory review, and mandatory human review. This question is addressed by separating the numerical burden score from the review decision. AAS_{HRC} summarizes the structural burden of the event, while the oversight flags indicate whether the event is classified as ordinary operation under the model assumptions, supervisory monitoring, or mandatory human review. This distinction is important because a high AAS value does not automatically indicate immediate physical danger, and a low AAS value does not certify robotic safety.

The practical value of AAS in the proposed DSS is that a multidimensional human–robot event profile is converted into an interpretable burden structure rather than a single opaque recommendation. In a real operational setting, this would allow a supervisor to identify not only whether an event requires review, but also which component drives the review decision.

For example, a robot may operate under low task hazard and low apparent human safety risk while still requiring mandatory review because environmental uncertainty dominates the total AAS burden. Conversely, low-burden profiles may continue without unnecessary escalation. In this sense, more selective and explainable oversight is supported by combining component-level burden, redundancy adjustment, and review classification.

This distinction is also consistent with human-centred automation theory. Automation does not simply remove the human operator; human involvement is redistributed across monitoring, interpretation, decision support, and intervention (Parasuraman et al., 2000; Sheridan, 1992). Situation awareness research similarly emphasizes that operators must understand the state of the system, the environment, and possible future consequences in dynamic contexts (Endsley, 1995). This logic is followed by the proposed framework through making the burden pathway visible rather than replacing the human operator with an opaque recommendation.

4.2 Redundancy, Interpretability, and Component Burden

One of the main strengths of the proposed model is its explicit treatment of redundancy. In many decision-support systems, multiple variables are added together as if they were fully independent. However, in human-robot collaboration, burden dimensions often overlap conceptually. In the illustrative configuration used in this paper, task hazard severity, human safety risk, and environmental uncertainty are treated as direct safety-relevant dimensions. Similarly, task criticality, exposure frequency, and intervention complexity are treated as dimensions of operational oversight burden.

If these related dimensions are simply added without adjustment, the total burden may be overstated by penalizing overlapping information multiple times. This problem is addressed by the redundancy term R_i , which reduces the effective contribution of a component when it overlaps with other active burden components. The adjusted component contribution is defined as

$$A_i = w_i(1 - R_i)\phi(x_i).$$

This expression keeps the burden contribution interpretable while preventing redundant conceptual overlap from being treated as fully independent evidence. Since $R_i \in [0, 1]$, redundancy can reduce the penalty but cannot make the contribution negative. Therefore, the model remains mathematically controlled and practically interpretable.

An important methodological gap is addressed by this structure. Existing human-robot collaboration research strongly discusses safety, trust, motion planning, physical interaction, risk assessment, ergonomics, and shared autonomy (Ajoudani et al., 2018; De Santis et al.,

2008; Goodrich & Schultz, 2007; Lasota et al., 2017; Villani et al., 2018). However, the explicit calculation of redundancy among burden components is less commonly formalized as part of the decision-support score itself. The proposed HRC adaptation of the AAS framework therefore contributes not by replacing existing safety methods, but by adding a structured burden-accounting layer through which overlapping contributors are made visible and computationally traceable.

The explanatory value of the system is also strengthened by this structure. Instead of reporting only a total score, component-level burden, redundancy values, adjusted contributions, the dominant burden component, and oversight status are reported. This allows the user to see not only that the event is high burden, but also why it is high burden and whether the burden comes from direct safety concern or operational monitoring pressure.

This is particularly useful in shared human–robot environments because repeated or overlapping burden signals may otherwise be interpreted as independent evidence of risk. The redundancy-adjusted AAS structure provides a way to organize these signals without losing their interpretive meaning. A more disciplined decision-support process is therefore supported: dominant burden sources can be identified, double-counting of overlapping dimensions can be reduced, and a transparent path from normalized event inputs to oversight recommendations can be preserved. This is the main reason the proposed AAS-DSS offers more than a conventional weighted score; it provides a decomposable burden model that can be inspected, recalibrated, and justified in relation to human oversight needs.

4.3 Human–Robot Collaboration as an Observable Burden Context

Human–robot collaboration is an appropriate application domain because the consequences of decision burden are externally observable. In shared workspaces, the robot’s behaviour is not evaluated only by internal computation. It is also evaluated through its effects on the human worker, the task environment, the continuity of operation, and the need for intervention. This broadly resonates with Turing’s behavioural orientation, where artificial systems are assessed through observable performance rather than inaccessible internal states (Turing, 1950).

In practical HRC settings, burden is expressed through features such as uncertain environments, repeated exposure, task criticality, intervention difficulty, and human safety risk. These features are not merely abstract variables. They correspond to operational pressures that can affect whether a robot should continue routine operation, be monitored by a supervisor, or be stopped for direct human review. Shared-space HRC research also emphasizes

that human factors, system performance, efficiency, teaming, and utilization are measurable dimensions of collaboration, which supports the need for interpretable metrics in human–robot settings (Hopko et al., 2022). Through the proposed model, these pressures are made computationally visible.

This visibility is especially important because human trust in robots and automation depends on reliability, predictability, transparency, and the user’s ability to understand when the system may require intervention (Hancock et al., 2011; Lee & See, 2004). A decision-support model that only returns a final recommendation is less useful than one in which the structure of the recommendation is explained. This explanatory layer is provided by the proposed AAS-DSS through the identification of the dominant burden component and the separation of structural burden from oversight status.

For example, in the high-uncertainty scenario, environmental uncertainty was identified as the dominant contributor to the total AAS. This result has practical meaning: the robot may not be operating in a visibly dangerous task, but the environment may be too uncertain for routine continuation. A more nuanced form of human–robot oversight is therefore supported, where intervention can be justified by structural uncertainty rather than by immediate visible hazard alone.

4.4 Separating Burden from Safety Certification

A major advantage of the proposed framework is that AAS is not treated as a direct safety certificate. This distinction is necessary. Safety in collaborative robotics depends on many factors that cannot be reduced to the AAS score alone, including robot motion, workspace design, human proximity, sensor reliability, control response, task-specific hazards, and the integration of the human factor into hazard analysis and risk assessment (De Santis et al., 2008; Giallanza et al., 2024; International Organization for Standardization [ISO], 2016; Lasota et al., 2017). Therefore, it is not claimed that a low AAS proves safety or that a high AAS proves imminent danger.

Instead, structural decision burden is measured by the AAS score. The oversight gate then determines whether the event requires mandatory human review or supervisory review. This separation is consistent with human-centred automation theory, where human involvement is redistributed rather than eliminated by automation (Parasuraman et al., 2000). It also aligns with supervisory control theory, where humans remain responsible for monitoring, interpreting, and intervening in automated systems when needed (Sheridan, 1992). Situation awareness theory further supports this distinction because human operators must understand not only the present state of the system but also its likely future implications in

dynamic environments (Endsley, 1995).

The two-level oversight structure therefore provides a practical interpretation of the score. Mandatory human review is linked to direct safety indicators: task hazard severity, human safety risk, and environmental uncertainty. Supervisory review is linked to operational oversight conditions: operational stress, task criticality, exposure frequency, and intervention complexity. This distinction prevents all high-pressure operational conditions from being treated as immediate safety danger while still preserving human monitoring when the situation becomes demanding.

4.5 Interpretation of the Illustrative Scenarios

Different oversight decisions were produced by the two illustrative scenarios depending on the structure of the event profile.

In the low-burden scenario, the event-level AAS was

$$AAS_{\text{HRC}} = 0.324616,$$

which was classified as low AAS burden. Neither a direct safety threshold nor a supervisory threshold was exceeded. Therefore, ordinary operation was indicated under the stated assumptions. This is important because a useful DSS should not escalate every non-zero burden state. If every non-zero burden profile were escalated, excessive review demands would be produced and the model would become impractical.

In the high-uncertainty scenario, the event-level AAS increased to

$$AAS_{\text{HRC}} = 1.726964,$$

which was classified as high AAS burden. Environmental uncertainty was identified as the dominant component, with an adjusted contribution of

$$A_3 = 1.392309.$$

This means that the majority of the total event burden was generated by uncertainty in the operating environment. Since environmental uncertainty also exceeded the mandatory review threshold, human review was triggered even though task hazard severity and human safety risk were numerically low.

This result demonstrates the value of the framework. In human–robot collaboration, danger does not always appear as an immediately high human safety score. A robot may operate

under low apparent human safety risk but still require review if environmental uncertainty is extreme. This distinction is captured by the model because component-level contribution and oversight status are reported separately. A more transparent form of human–robot decision support is therefore supported, where the review recommendation can be traced back to the dominant source of burden rather than being presented as an unexplained system output.

4.6 Why the AAS Formulation Offers Advantages Over a Simple Weighted Score

The redundancy-adjusted structure provides a reason why the AAS formulation may offer advantages over a simpler burden or risk score in this context. In a simple weighted sum, each component contributes independently and linearly. This can be useful, but it does not show whether multiple components are repeating or overlapping the same conceptual burden. In contrast, redundancy is made visible by the proposed HRC adaptation of the AAS framework.

This matters because decision support systems should not merely accumulate information; they should organize it. Shannon’s information theory treats redundancy as a structural property of information systems rather than as simple repetition (Shannon, 1948). In the AAS framework, redundancy is further interpreted as a masking or adjustment mechanism that changes the effective burden of overlapping components (Kayadibi, 2026). Applied to HRC, this means that repeated or overlapping burden signals can be recognized and moderated rather than blindly accumulated.

This is one of the central reasons for using AAS rather than a conventional score. The model does not only indicate how high the event score is. It also identifies which component creates the burden, how much of that burden overlaps with other components, and whether the burden requires mandatory review or supervisory monitoring. This makes the model more suitable for transparent human–robot decision support. It also aligns with shared-space HRC research, which emphasizes that human factors, robot factors, system performance, and safety interact dynamically and therefore require interpretable metrics rather than isolated technical outputs (Hopko et al., 2022).

4.7 Positioning the Contribution in the Literature

The proposed model does not compete with established HRC safety standards, risk assessment methods, or robot control strategies. Instead, a complementary position is occupied. Standards and safety methods provide the basis for hazard analysis, safe design, physical in-

teraction limits, and task-level risk reduction (ISO, 2010; ISO, 2016). HRI research provides understanding of interaction, trust, communication, and human-centred design (Goodrich & Schultz, 2007; Hancock et al., 2011; Lee & See, 2004). Safe HRI research provides methods for control, planning, prediction, and physical safety (De Santis et al., 2008; Lasota et al., 2017). This complementary positioning is important because HRC can improve productivity and collaboration, but safety must be explicitly addressed when humans and robots share operational space (Arents et al., 2021).

A formal decision-burden layer is contributed by the proposed AAS-DSS, which can sit above or alongside these approaches. Its purpose is not to certify safety but to organize burden information in a mathematically traceable way. The gap addressed by the framework is the need for a structured method through which multiple HRC burden components can be converted into an interpretable redundancy-adjusted score with explicit oversight outputs.

In this sense, the model can be described as an oversight-aware computational layer. It is particularly useful when a system designer, supervisor, or researcher needs to understand not only whether an event is demanding, but why it is demanding and what type of human review is required.

4.8 Calibration and Deployment Considerations

The model remains a configurable prototype. The weights, thresholds, and redundancy sets used in the illustrative scenarios should not be interpreted as universal constants. They were selected to demonstrate the mathematical and computational behaviour of the framework. Real deployment would require calibration through expert judgement, empirical data, simulation, sensitivity analysis, and human factors evaluation.

Calibration is especially important for the redundancy structure. In the current model, conceptual feature sets are used to estimate overlap. This approach is transparent and auditable, but it is not the only possible method. In future versions, redundancy could be estimated empirically using operational data, expert-rated overlap, or statistical dependence among components. Such calibration would make the model more domain-specific and potentially more predictive.

Nevertheless, a useful starting point is provided by the present formulation because all assumptions are made explicit. Each weight, threshold, redundancy relation, and component contribution can be inspected. This transparency is valuable in human-robot collaboration because opaque decision-support models may be difficult to trust or validate in safety-relevant environments (Lee & See, 2004; National Institute of Standards and Technology [NIST], 2023). The need for calibration is also consistent with shared-space HRC research, where

human and robot factors can affect system performance and safety in dynamic ways (Hopko et al., 2022).

4.9 Implications for Human–Robot Decision Support

The broader implication of the proposed framework is that decision support in human–robot collaboration should move beyond single-score prioritization. A total score alone is insufficient if the operator cannot see the source of the burden, the redundancy among burden factors, and the required oversight status. A more structured output is provided by the proposed model:

$$\begin{aligned}
& AAS_{\text{HRC}}, \\
& A_i \quad \text{for each component,} \\
& R_i \quad \text{for redundancy adjustment,} \\
& H \quad \text{for mandatory human review,} \\
& S \quad \text{for supervisory review.}
\end{aligned}$$

This output provides both computational and interpretive value. Ordinary operation can be supported when burden is low, mandatory human review can be triggered when direct safety burden is high, and supervisory review can be indicated when operational monitoring is needed. In doing so, the framework supports the human-centred view that automation should assist rather than replace human judgement.

The key contribution is therefore not only the final AAS value. The contribution is the complete structured pathway:

$$(u_i, G_i, w_i) \rightarrow (\Delta_i, x_i, \phi(x_i), R_i) \rightarrow A_i \rightarrow AAS_{\text{HRC}} \rightarrow (B, H, S).$$

This pathway makes the model mathematically explicit, computationally implementable, and interpretable for human–robot collaboration contexts. It also gives supervisors and system designers a traceable explanation of why a review recommendation has been produced, which is essential in settings where trust, human oversight, and operational safety must be maintained together (Hancock et al., 2011; NIST, 2023).

5 Limitations and Future Work

The proposed AAS-DSS should be interpreted as a configurable decision-support prototype rather than a validated deployment-ready safety system. The weights, thresholds, redundancy feature sets, and burden categories used in the illustrative implementation were selected to demonstrate the computational behaviour of the framework. They are not universal constants and should not be interpreted as empirically validated parameters.

A second limitation concerns the redundancy structure. In the present model, conceptual overlap is estimated through predefined feature sets and Jaccard similarity. This approach makes the redundancy adjustment transparent, auditable, and computationally traceable, but empirical correlation, causal dependence, or operational co-occurrence among human–robot collaboration burden components is not established. Future work should therefore compare the proposed conceptual redundancy structure with expert-rated, simulation-based, and data-driven redundancy estimates.

A third limitation concerns the illustrative scenarios. The warehouse examples are controlled computational demonstrations rather than field-deployed empirical observations. They show how normalized human–robot collaboration event profiles are transformed into burden scores and oversight outputs, but the model’s predictive accuracy, operational usefulness, or effects on human trust, workload, situation awareness, or decision quality are not validated.

Future research should focus on empirical validation in human–robot collaboration environments, sensitivity analysis of weights and thresholds, comparison with conventional weighted scoring methods, and integration with real-time monitoring systems. Further work may also examine whether the proposed AAS-DSS improves transparency, calibration of human oversight, and operator situation awareness in shared human–robot workspaces.

Future work may also investigate the adaptation of the proposed redundancy-adjusted AAS-DSS to other safety-critical and oversight-intensive domains, including autonomous drone monitoring, defence-oriented surveillance support, emergency response robotics, and multi-agent autonomous systems. In these contexts, the framework could be examined as a method for estimating structural decision burden, identifying dominant sources of operational uncertainty, and supporting human oversight decisions. Such extensions would require domain-specific calibration, legal and ethical review, human-in-the-loop governance, and validation under relevant safety, accountability, and operational standards.

Finally, the proposed framework does not replace established safety standards, hazard analysis, physical risk assessment, legal responsibility, or human supervisory judgement. Its intended role is complementary: to provide an interpretable redundancy-adjusted burden

layer that supports, rather than substitutes for, human-centred oversight in collaborative and autonomous robotic systems.

6 Conclusion

This paper proposed a redundancy-adjusted Artificial Age Score decision support system for oversight-aware human–robot collaboration. The framework adapted AAS from its original use in modelling artificial memory aging into an event-level measure of structural decision burden. In this formulation, AAS does not represent chronological age, biological aging, or direct physical risk. Instead, it represents the burden imposed by a human–robot collaboration event profile on the decision-support process.

Each event is represented through six normalized components: task hazard severity, human safety risk, environmental uncertainty, task criticality, exposure frequency, and intervention complexity. These components are transformed into burden deviations, converted into AAS-compatible consistency scores, mapped through a logarithmic penalty kernel, adjusted through a conceptual redundancy structure, and aggregated into the event-level score AAS_{HRC} . This construction provides a transparent and mathematically traceable pathway from normalized event inputs to component-level burden contributions and total structural burden.

Structural burden is also separated from oversight decisions in the proposed framework. The event-level AAS summarizes the burden profile of the event, while mandatory human review and supervisory review are represented through distinct oversight flags. This distinction is essential because a low AAS score does not certify robotic safety, and a high AAS score does not automatically indicate immediate physical danger. The proposed AAS-DSS therefore functions as an interpretable oversight-support layer rather than an autonomous action selector or safety certification mechanism.

The illustrative warehouse scenarios demonstrated how low-burden ordinary operation can be distinguished from high-burden events requiring human review. In the low-burden scenario, a low AAS_{HRC} value was produced and no additional oversight was triggered. In the high-uncertainty scenario, environmental uncertainty dominated the adjusted component contributions and mandatory human review was triggered despite low task hazard severity and low apparent human safety risk. These results show that total structural burden, dominant burden source, and oversight status can be distinguished rather than being reduced to a single opaque score.

The main contribution of the paper is the complete redundancy-adjusted decision-support pathway from normalized event components to oversight output. By incorporating redun-

dancy adjustment, overlapping burden dimensions are not treated as fully independent, and a more interpretable alternative to a simple weighted score is provided. This makes the framework suitable as a configurable computational layer for human-centred oversight in shared human–robot environments.

Overall, the proposed AAS-DSS supports the view that decision support in human–robot collaboration should not rely solely on opaque final scores or autonomous recommendations. Instead, the structure of burden should be made visible, decomposable, and open to calibration. With further empirical validation and domain-specific refinement, the redundancy-adjusted AAS framework may contribute to more transparent, interpretable, and oversight-aware human–robot collaboration systems.

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Appendix A Computational Implementation of the AAS-DSS

A Computational Implementation of the AAS-DSS

The following Python implementation was used to compute the illustrative human–robot collaboration event-level redundancy-adjusted AAS results reported in this paper. The code accepts normalized event inputs, computes the burden deviations Δ_i , consistency scores x_i , logarithmic penalties $\phi(x_i)$, conceptual redundancy terms R_i , adjusted component contributions A_i , event-level AAS_{HRC} , burden label, and oversight flags.

Listing 1: Python implementation of the event-level redundancy-adjusted AAS-DSS for human–robot collaboration.

```

1 import math
2 from dataclasses import dataclass
3 import numpy as np
4 import pandas as pd
5
6
7 # =====
8 # HUMAN-ROBOT COLLABORATION
9 # EVENT-LEVEL REDUNDANCY-ADJUSTED AAS DSS
10 #
11 # AAS measures event-level structural decision burden.
12 #
13 # Core transformation:
14 # Delta_i = u_i / (1 - u_i + eta)
15 # x_i      = 1 / (1 + Delta_i)
16 # =====
17
18
19 # -----
20 # 1. GLOBAL SETTINGS
21 # -----
22
23 SCENARIO_NAME = "Autonomous mobile robot in a shared warehouse environment"
24
25 VALID_STRESS_LEVELS = {"low", "medium", "high"}
26
27 FEATURE_NAMES = [
28     "task_hazard_severity",
29     "human_safety_risk",
30     "environmental_uncertainty",
31     "task_criticality",
32     "exposure_frequency",
33     "intervention_complexity",
34 ]

```

```

35
36 FEATURE_LABELS = {
37     "task_hazard_severity": "Task hazard severity",
38     "human_safety_risk": "Human safety risk",
39     "environmental_uncertainty": "Environmental uncertainty",
40     "task_criticality": "Task criticality",
41     "exposure_frequency": "Exposure frequency",
42     "intervention_complexity": "Intervention complexity",
43 }
44
45 # Non-uniform illustrative safety-weighted vector.
46 # These are configurable demonstration weights, not universal constants.
47 W = np.array([0.25, 0.23, 0.16, 0.14, 0.10, 0.12], dtype=float)
48
49 if not np.isclose(W.sum(), 1.0):
50     raise ValueError("Weight vector W must sum to 1.")
51
52 ETA = 1e-6
53 EPSILON = 1e-6
54
55 # Burden category thresholds.
56 # These are illustrative and should be calibrated before deployment.
57 AAS_LOW_THRESHOLD = 0.50
58 AAS_HIGH_THRESHOLD = 1.50
59
60 # Direct safety thresholds for mandatory human review.
61 DIRECT_SAFETY_THRESHOLDS = {
62     "task_hazard_severity": 0.75,
63     "human_safety_risk": 0.70,
64     "environmental_uncertainty": 0.80,
65 }
66
67 # Operational oversight thresholds for supervisory review.
68 OPERATIONAL_OVERSIGHT_THRESHOLDS = {
69     "task_criticality": 0.80,
70     "exposure_frequency": 0.80,
71     "intervention_complexity": 0.70,
72 }
73
74
75 # -----
76 # 2. INPUT MODEL
77 # -----
78
79 @dataclass
80 class HumanRobotCollaborationProfile:
81     """
82     Normalized human-robot collaboration event profile.
83
84     All numerical values are in [0, 1].
85
86     0 = task_hazard_severity
87     1 = human_safety_risk
88     2 = environmental_uncertainty
89     3 = task_criticality
90     4 = exposure_frequency
91     5 = intervention_complexity
92     """
93
94     task_hazard_severity: float
95     human_safety_risk: float
96     environmental_uncertainty: float
97     task_criticality: float
98     exposure_frequency: float
99     intervention_complexity: float
100     operational_stress_level: str
101
102     def validate(self) -> None:
103         values = {
104             "task_hazard_severity": self.task_hazard_severity,
105             "human_safety_risk": self.human_safety_risk,
106             "environmental_uncertainty": self.environmental_uncertainty,
107             "task_criticality": self.task_criticality,
108             "exposure_frequency": self.exposure_frequency,

```

```

109         "intervention_complexity": self.intervention_complexity,
110     }
111
112     for name, value in values.items():
113         if not isinstance(value, (int, float)):
114             raise TypeError(f"{name} must be numeric.")
115
116         if not (0.0 <= float(value) <= 1.0):
117             raise ValueError(f"{name} must be in [0, 1]. Got {value}.")
118
119     if self.operational_stress_level not in VALID_STRESS_LEVELS:
120         raise ValueError(
121             f"operational_stress_level must be one of "
122             f"{sorted(VALID_STRESS_LEVELS)}. "
123             f"Got {self.operational_stress_level}."
124         )
125
126     def to_vector(self) -> np.ndarray:
127         self.validate()
128
129         return np.array(
130             [
131                 self.task_hazard_severity,
132                 self.human_safety_risk,
133                 self.environmental_uncertainty,
134                 self.task_criticality,
135                 self.exposure_frequency,
136                 self.intervention_complexity,
137             ],
138             dtype=float,
139         )
140
141     def pretty_print(self) -> None:
142         print("\n" + "=" * 78)
143         print("HUMAN-ROBOT COLLABORATION EVENT PROFILE")
144         print("=" * 78)
145         print(f"Scenario                : {SCENARIO_NAME}")
146         print(f"Operational stress level    : {self.operational_stress_level}")
147         print(f"Task hazard severity        : {self.task_hazard_severity:.3f}")
148         print(f"Human safety risk           : {self.human_safety_risk:.3f}")
149         print(f"Environmental uncertainty    : {self.environmental_uncertainty:.3f}")
150         print(f"Task criticality             : {self.task_criticality:.3f}")
151         print(f"Exposure frequency          : {self.exposure_frequency:.3f}")
152         print(f"Intervention complexity      : {self.intervention_complexity:.3f}")
153
154
155     # -----
156     # 3. INPUT HELPERS
157     # -----
158
159     def read_float_in_unit_interval(prompt: str) -> float:
160         while True:
161             raw_value = input(prompt).strip()
162
163             try:
164                 value = float(raw_value)
165             except ValueError:
166                 print("Invalid input. Please enter a numeric value between 0 and 1.")
167                 continue
168
169             if 0.0 <= value <= 1.0:
170                 return value
171
172             print("Invalid range. Please enter a value between 0 and 1.")
173
174
175     def read_operational_stress_level() -> str:
176         print("\nSelect operational stress level:")
177         print("1 = low")
178         print("2 = medium")
179         print("3 = high")
180
181         stress_map = {
182             "1": "low",

```

```

183         "2": "medium",
184         "3": "high",
185     }
186
187     while True:
188         choice = input("Enter choice (1/2/3): ").strip().lower()
189
190         if choice in stress_map:
191             return stress_map[choice]
192
193         if choice in VALID_STRESS_LEVELS:
194             return choice
195
196         print("Invalid choice. Please enter 1, 2, 3, or low/medium/high.")
197
198
199 def read_human_robot_collaboration_profile() -> HumanRobotCollaborationProfile:
200     print("=" * 78)
201     print("HUMAN-ROBOT COLLABORATION EVENT-LEVEL AAS DSS")
202     print("=" * 78)
203     print(f"Illustrative scenario: {SCENARIO_NAME}")
204
205     operational_stress_level = read_operational_stress_level()
206
207     print("\nEnter each normalized value between 0 and 1.\n")
208
209     profile = HumanRobotCollaborationProfile(
210         task_hazard_severity=read_float_in_unit_interval(
211             "Task hazard severity: "
212         ),
213         human_safety_risk=read_float_in_unit_interval(
214             "Human safety risk: "
215         ),
216         environmental_uncertainty=read_float_in_unit_interval(
217             "Environmental uncertainty: "
218         ),
219         task_criticality=read_float_in_unit_interval(
220             "Task criticality: "
221         ),
222         exposure_frequency=read_float_in_unit_interval(
223             "Exposure frequency: "
224         ),
225         intervention_complexity=read_float_in_unit_interval(
226             "Intervention complexity: "
227         ),
228         operational_stress_level=operational_stress_level,
229     )
230
231     profile.validate()
232     return profile
233
234
235 # -----
236 # 4. AAS CORE FUNCTIONS
237 # -----
238
239 def burden_deviation(u_i: float, eta: float = ETA) -> float:
240     """
241     Component-level burden deviation.
242
243      $\Delta_i = u_i / (1 - u_i + \eta)$ 
244
245     Interpretation:
246     -  $u_i = 0$  gives  $\Delta_i = 0$ 
247     - higher  $u_i$  gives higher  $\Delta_i$ 
248     -  $u_i$  near 1 gives very high burden deviation
249     """
250
251     return float(u_i / (1.0 - u_i + eta))
252
253
254 def consistency_from_delta(delta_i: float) -> float:
255     """
256     AAS-compatible consistency score.

```

```

257
258     x_i = 1 / (1 + Delta_i)
259
260     x_i is in (0, 1].
261     """
262
263     return float(1.0 / (1.0 + delta_i))
264
265
266 def phi(x_i: float, epsilon: float = EPSILON) -> float:
267     """
268     Logarithmic AAS penalty kernel.
269
270     phi(x_i) = -log2((x_i + epsilon) / (1 + epsilon))
271     """
272
273     return float(-math.log2((x_i + epsilon) / (1.0 + epsilon)))
274
275
276 # -----
277 # 5. REDUNDANCY STRUCTURE
278 # -----
279
280 def build_component_feature_sets() -> dict:
281     """
282     Conceptual feature sets for redundancy estimation.
283
284     This is not statistical correlation.
285     It is a conceptual redundancy structure.
286     """
287
288     return {
289         "task_hazard_severity": {"direct_safety", "task"},
290         "human_safety_risk": {"direct_safety", "human"},
291         "environmental_uncertainty": {"direct_safety", "environment"},
292         "task_criticality": {"operational_burden", "task"},
293         "exposure_frequency": {"operational_burden", "repetition"},
294         "intervention_complexity": {"operational_burden", "intervention"},
295     }
296
297
298 def build_redundancy_matrix(feature_sets: dict) -> pd.DataFrame:
299     """
300     Pairwise conceptual redundancy using Jaccard overlap:
301
302     q_ik = |G_i intersection G_k| / |G_i union G_k|
303     """
304
305     q = pd.DataFrame(0.0, index=FEATURE_NAMES, columns=FEATURE_NAMES)
306
307     for i in FEATURE_NAMES:
308         for k in FEATURE_NAMES:
309             if i == k:
310                 q.loc[i, k] = 0.0
311             else:
312                 A = feature_sets[i]
313                 B = feature_sets[k]
314                 q.loc[i, k] = len(A & B) / len(A | B)
315
316     return q
317
318
319 def compute_component_redundancy(
320     u: np.ndarray,
321     weights: np.ndarray,
322     q: pd.DataFrame,
323 ) -> np.ndarray:
324     """
325     Computes R_i for each component.
326
327     R_i = sum_{k != i} w_k u_k q_ik / sum_{k != i} w_k u_k
328
329     If the denominator is zero, R_i = 0.
330     """

```

```

331
332 R = np.zeros(len(FEATURE_NAMES), dtype=float)
333
334 for i, feature_i in enumerate(FEATURE_NAMES):
335     numerator = 0.0
336     denominator = 0.0
337
338     for k, feature_k in enumerate(FEATURE_NAMES):
339         if i == k:
340             continue
341
342         active_weight = weights[k] * u[k]
343         numerator += active_weight * float(q.loc[feature_i, feature_k])
344         denominator += active_weight
345
346     R[i] = 0.0 if denominator == 0.0 else numerator / denominator
347
348 return R
349
350
351 # -----
352 # 6. EVENT-LEVEL AAS ENGINE
353 # -----
354
355 def build_event_aas_results(
356     u: np.ndarray,
357     weights: np.ndarray = W,
358 ) -> tuple[pd.DataFrame, pd.DataFrame, float]:
359
360     feature_sets = build_component_feature_sets()
361     q = build_redundancy_matrix(feature_sets)
362     R = compute_component_redundancy(u, weights, q)
363
364     rows = []
365
366     for i, feature_name in enumerate(FEATURE_NAMES):
367         u_i = float(u[i])
368         delta_i = burden_deviation(u_i)
369         x_i = consistency_from_delta(delta_i)
370         penalty_i = phi(x_i)
371         adjusted_factor_i = 1.0 - R[i]
372         contribution_i = weights[i] * adjusted_factor_i * penalty_i
373
374         rows.append(
375             {
376                 "component": feature_name,
377                 "label": FEATURE_LABELS[feature_name],
378                 "u_i": u_i,
379                 "w_i": float(weights[i]),
380                 "Delta_i": delta_i,
381                 "x_i": x_i,
382                 "penalty_phi": penalty_i,
383                 "R_i": float(R[i]),
384                 "i_minus_R_i": adjusted_factor_i,
385                 "adjusted_contribution": contribution_i,
386             }
387         )
388
389     component_df = pd.DataFrame(rows)
390     aas_value = float(component_df["adjusted_contribution"].sum())
391
392     return component_df, q, aas_value
393
394
395 # -----
396 # 7. INTERPRETATION HELPERS
397 # -----
398
399 def burden_label_from_aas(aas_value: float) -> str:
400     """
401     Event-level AAS burden label.
402
403     These thresholds are illustrative calibration parameters.
404     """

```

```

405
406     if aas_value <= AAS_LOW_THRESHOLD:
407         return "Low AAS burden"
408
409     if aas_value <= AAS_HIGH_THRESHOLD:
410         return "Moderate AAS burden"
411
412     return "High AAS burden"
413
414
415 def qualitative_level(value: float) -> str:
416     if value < 0.30:
417         return "low"
418     if value < 0.70:
419         return "moderate"
420     if value < 0.85:
421         return "high"
422     return "very high"
423
424
425 def oversight_gate(profile: HumanRobotCollaborationProfile) -> dict:
426     """
427     Two-level oversight gate.
428
429     Level 1:
430     Mandatory human review triggered by direct safety indicators.
431
432     Level 2:
433     Supervisory review triggered by operational stress or operational burden.
434     """
435
436     mandatory_human_review = False
437     supervisory_review_recommended = False
438
439     mandatory_reasons = []
440     supervisory_reasons = []
441
442     if (
443         profile.task_hazard_severity
444         >= DIRECT_SAFETY_THRESHOLDS["task_hazard_severity"]
445     ):
446         mandatory_human_review = True
447         mandatory_reasons.append("task_hazard_severity exceeds direct safety threshold")
448
449     if (
450         profile.human_safety_risk
451         >= DIRECT_SAFETY_THRESHOLDS["human_safety_risk"]
452     ):
453         mandatory_human_review = True
454         mandatory_reasons.append("human_safety_risk exceeds direct safety threshold")
455
456     if (
457         profile.environmental_uncertainty
458         >= DIRECT_SAFETY_THRESHOLDS["environmental_uncertainty"]
459     ):
460         mandatory_human_review = True
461         mandatory_reasons.append(
462             "environmental_uncertainty exceeds direct safety threshold"
463         )
464
465     if profile.operational_stress_level == "high":
466         supervisory_review_recommended = True
467         supervisory_reasons.append("operational_stress_level is high")
468
469     if (
470         profile.task_criticality
471         >= OPERATIONAL_OVERSIGHT_THRESHOLDS["task_criticality"]
472     ):
473         supervisory_review_recommended = True
474         supervisory_reasons.append("task_criticality is high")
475
476     if (
477         profile.exposure_frequency
478         >= OPERATIONAL_OVERSIGHT_THRESHOLDS["exposure_frequency"]

```

```

479 ):
480     supervisory_review_recommended = True
481     supervisory_reasons.append("exposure_frequency is high")
482
483 if (
484     profile.intervention_complexity
485     >= OPERATIONAL_OVERSIGHT_THRESHOLDS["intervention_complexity"]
486 ):
487     supervisory_review_recommended = True
488     supervisory_reasons.append("intervention_complexity is high")
489
490 return {
491     "mandatory_human_review": mandatory_human_review,
492     "mandatory_reasons": mandatory_reasons,
493     "supervisory_review_recommended": supervisory_review_recommended,
494     "supervisory_reasons": supervisory_reasons,
495 }
496
497
498 def build_dss_decision(
499     aas_value: float,
500     component_df: pd.DataFrame,
501     profile: HumanRobotCollaborationProfile,
502 ) -> dict:
503
504     burden_label = burden_label_from_aas(aas_value)
505     oversight = oversight_gate(profile)
506
507     dominant_component_row = component_df.sort_values(
508         "adjusted_contribution",
509         ascending=False,
510     ).iloc[0]
511
512     dominant_component = dominant_component_row["label"]
513     dominant_contribution = float(dominant_component_row["adjusted_contribution"])
514
515     if oversight["mandatory_human_review"]:
516         recommendation = "Mandatory human review required"
517     elif oversight["supervisory_review_recommended"]:
518         recommendation = "Supervisory review recommended"
519     else:
520         recommendation = "Ordinary operation may continue under model assumptions"
521
522     reason = (
523         f"The event-level redundancy-adjusted AAS is {aas_value:.6f}, "
524         f"classified as {burden_label}. "
525         f"The largest adjusted contribution comes from {dominant_component} "
526         f"({dominant_contribution:.6f}). "
527     )
528
529     if oversight["mandatory_human_review"]:
530         reason += (
531             "Mandatory human review is required because "
532             + ", ".join(oversight["mandatory_reasons"])
533             + ". "
534         )
535     else:
536         reason += (
537             "Mandatory human review is not required because no direct safety "
538             "threshold is exceeded. "
539         )
540
541     if oversight["supervisory_review_recommended"]:
542         reason += (
543             "Supervisory review is recommended because "
544             + ", ".join(oversight["supervisory_reasons"])
545             + ". "
546         )
547     else:
548         reason += (
549             "Supervisory review is not triggered under the current operational "
550             "oversight thresholds."
551         )
552

```

```

553     return {
554         "AAS_HRC": aas_value,
555         "burden_label": burden_label,
556         "dominant_component": dominant_component,
557         "dominant_contribution": dominant_contribution,
558         "mandatory_human_review": oversight["mandatory_human_review"],
559         "mandatory_reasons": oversight["mandatory_reasons"],
560         "supervisory_review_recommended": oversight["supervisory_review_recommended"],
561         "supervisory_reasons": oversight["supervisory_reasons"],
562         "recommendation": recommendation,
563         "reason": reason,
564     }
565
566
567 # -----
568 # 8. OUTPUT HELPERS
569 # -----
570
571 def print_component_aas_details(component_df: pd.DataFrame) -> None:
572     print("\n" + "-" * 78)
573     print("COMPONENT-LEVEL AAS DETAILS")
574     print("-" * 78)
575
576     cols = [
577         "label",
578         "u_i",
579         "w_i",
580         "Delta_i",
581         "x_i",
582         "penalty_phi",
583         "R_i",
584         "i_minus_R_i",
585         "adjusted_contribution",
586     ]
587
588     print(
589         component_df[cols].to_string(
590             index=False,
591             float_format=lambda x: f"{x:.6f}",
592         )
593     )
594
595
596 def print_redundancy_matrix(q: pd.DataFrame) -> None:
597     print("\n" + "-" * 78)
598     print("CONCEPTUAL REDUNDANCY MATRIX")
599     print("-" * 78)
600
601     print(q.to_string(float_format=lambda x: f"{x:.4f}"))
602
603
604 def print_dss_decision(decision: dict) -> None:
605     print("\n" + "=" * 78)
606     print("DSS DECISION OUTPUT")
607     print("=" * 78)
608
609     print(f"Event-level AAS           : {decision['AAS_HRC']:.6f}")
610     print(f"AAS burden label         : {decision['burden_label']}")
611     print(f"Dominant burden component   : {decision['dominant_component']}")
612     print(f"Dominant contribution       : {decision['dominant_contribution']:.6f}")
613     print(f"Recommendation              : {decision['recommendation']}")
614
615     print(f"Mandatory human review       : {decision['mandatory_human_review']}")
616     if decision["mandatory_reasons"]:
617         print(
618             f"Mandatory review reasons : "
619             f"{', '.join(decision['mandatory_reasons'])}"
620         )
621     else:
622         print("Mandatory review reasons : None")
623
624     print(
625         f"Supervisory review recommended: "
626         f"{decision['supervisory_review_recommended']}"

```

```

627     )
628     if decision["supervisory_reasons"]:
629         print(
630             f"Supervisory review reasons : "
631             f"{', '.join(decision['supervisory_reasons'])}"
632         )
633     else:
634         print("Supervisory review reasons : None")
635
636     print("\nReason:")
637     print(decision["reason"])
638
639
640 def print_scenario_interpretation(
641     profile: HumanRobotCollaborationProfile,
642     decision: dict,
643 ) -> None:
644     print("\n" + "-" * 78)
645     print("SCENARIO INTERPRETATION")
646     print("-" * 78)
647
648     print(
649         "This illustrative scenario represents an autonomous mobile robot "
650         "operating in a shared warehouse environment with human workers."
651     )
652
653     print("\nThe event profile can be interpreted as follows:")
654
655     print(
656         f"- Task hazard severity is {qualitative_level(profile.task_hazard_severity)} "
657         f"({profile.task_hazard_severity:.3f})."
658     )
659     print(
660         f"- Human safety risk is {qualitative_level(profile.human_safety_risk)} "
661         f"({profile.human_safety_risk:.3f})."
662     )
663     print(
664         f"- Environmental uncertainty is "
665         f"{qualitative_level(profile.environmental_uncertainty)} "
666         f"({profile.environmental_uncertainty:.3f})."
667     )
668     print(
669         f"- Task criticality is {qualitative_level(profile.task_criticality)} "
670         f"({profile.task_criticality:.3f})."
671     )
672     print(
673         f"- Exposure frequency is {qualitative_level(profile.exposure_frequency)} "
674         f"({profile.exposure_frequency:.3f})."
675     )
676     print(
677         f"- Intervention complexity is "
678         f"{qualitative_level(profile.intervention_complexity)} "
679         f"({profile.intervention_complexity:.3f})."
680     )
681
682     print("\nAAS interpretation:")
683     print(
684         f"- The event-level redundancy-adjusted AAS is "
685         f"{decision['AAS_HRC']:.6f}, classified as {decision['burden_label']}."
686     )
687     print(
688         f"- The dominant burden component is {decision['dominant_component']}."
689     )
690
691     print("\nOversight interpretation:")
692     if decision["mandatory_human_review"]:
693         print("- Mandatory human review is required.")
694     else:
695         print("- Mandatory human review is not required.")
696
697     if decision["supervisory_review_recommended"]:
698         print("- Supervisory review is recommended.")
699     else:
700         print("- Supervisory review is not triggered.")

```

```

701     print("\nImportant limitation:")
702     print(
703         "- This is a realistic illustrative scenario, not field-deployed empirical "
704         "warehouse data. The weights, thresholds, and redundancy structure are "
705         "demonstration parameters and should be validated through sensitivity "
706         "analysis and domain-specific testing before real deployment."
707     )
708
709
710
711 # -----
712 # 9. MAIN APPLICATION
713 # -----
714
715 def run_human_robot_collaboration_event_aas_dss() -> None:
716     profile = read_human_robot_collaboration_profile()
717     u = profile.to_vector()
718
719     component_df, q, aas_value = build_event_aas_results(u=u, weights=W)
720
721     decision = build_dss_decision(
722         aas_value=aas_value,
723         component_df=component_df,
724         profile=profile,
725     )
726
727     profile.pretty_print()
728     print_component_aas_details(component_df)
729     print_redundancy_matrix(q)
730     print_dss_decision(decision)
731     print_scenario_interpretation(profile, decision)
732
733
734 if __name__ == "__main__":
735     run_human_robot_collaboration_event_aas_dss()

```