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Event-Probabilistic Unification of Heterogeneous Sensor Data for Decision-Support Systems: A Conceptual Framework and Illustrative Numerical Experiment

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ABSTRACT:

Modern info communication, sensing, and cyber-physical systems increasingly rely on heterogeneous data streams originating from channels of different physical nature, sampling rates, reliability levels, and uncertainty characteristics. Direct fusion of such data in conventional artificial intelligence pipelines often yields decision outputs that are difficult to interpret, calibrate, and trust, especially in safety-related or security-related applications. This work proposes an event-probabilistic approach to the unification of heterogeneous sensor data for decision-support systems. The main idea is to transform heterogeneous sensor observations into a common space of event-oriented probability estimates, which can then be integrated using reliability-aware weighting. In this form, the system can generate not only a final recommendation, but also supporting metrics, including event likelihood, risk level, uncertainty, data quality, and inter-channel conflict. The paper formulates the conceptual and architectural basis of the proposed framework and discusses its compatibility with further Bernoulli encoding and stochastic processing. An illustrative numerical experiment involving four sensor channels and three representative scenarios is used to demonstrate the behavior of the framework. The results show that adaptive reliability-aware weighting improves the stability of the integrated event probability under channel degradation, while explicit conflict assessment prevents unjustified automatic decisions under contradictory sensor evidence. The proposed framework may serve as a basis for future stochastic and photonic-stochastic decision-support systems in access control, industrial monitoring, transport infrastructure, and critical-infrastructure applications.

KEYWORDS: heterogeneous sensor data, event-probabilistic representation, decision-support systems, sensor fusion, uncertainty-aware decisions, stochastic computing, Bernoulli bitstreams, access control.

INTRODUCTION

Contemporary sensor-rich systems increasingly operate in environments where decisions must be formed on the basis of multiple heterogeneous information sources. Such systems arise in info communication networks, access-control systems, industrial monitoring platforms, intelligent transport infrastructure, security systems, and cyber-physical environments. Their input channels may include visual observations, motion data, identification signals, telemetry, physical measurements, contextual information, and event logs. Although multisensor fusion has long been studied as an important engineering problem, the growing diversity of sensing modalities and decision contexts creates new challenges for robust and interpretable data integration [1], [2].

A major difficulty is that heterogeneous sensor channels differ not only in physical nature, but also in sampling rate, uncertainty, susceptibility to noise, delay, and semantic role in decision formation. Classical fusion and multimodal machine learning methods provide powerful tools for combining information [2], [3], but in many practical cases the final output is still treated as a hard classification result or a confidence score that does not explicitly reflect the quality of the incoming evidence, the level of conflict between channels, or the uncertainty of the decision. This limitation becomes especially relevant in systems where the consequences of an erroneous automatic decision may be significant.

A related trend in modern sensing concerns event-based and asynchronous data representation, which has demonstrated clear advantages in terms of temporal responsiveness and efficient information extraction [4], [5]. At the same time, trustworthy and risk-aware artificial intelligence increasingly emphasizes the need for transparency, uncertainty handling, calibration, and risk management [6], [7]. These developments suggest that decision-support systems should not rely solely on direct end-to-end classification. Instead, they require an intermediate representation capable of unifying heterogeneous sensor evidence in a controlled and interpretable manner.

This paper proposes such an intermediate layer in the form of event-probabilistic unification. In the proposed approach, each sensor channel is mapped not directly to a final class label, but to a set of event-oriented probability estimates. These probabilities are then combined in a common probabilistic space using channel-dependent weights reflecting reliability, data quality, freshness, and inter-channel consistency. The resulting framework produces not only an integrated event likelihood, but also additional metrics such as risk level, uncertainty, data quality, and conflict level. This makes the output more informative and better suited for decision-support tasks than a rigid class assignment alone.

The contribution of this work is twofold. First, it formulates the conceptual and architectural foundations of event-probabilistic unification of heterogeneous sensor data. Second, it provides an illustrative numerical experiment that demonstrates the behavior of the proposed framework under representative normal, degraded, and conflicting sensing conditions. A broader set of modelling directions is also outlined as a perspective for subsequent full-scale validation.

The remainder of the paper is organized as follows. Section 2 formulates the problem addressed by the work. Section 3 presents the proposed event-probabilistic approach. Section 4 describes the generalized architecture of the framework. Section 5 discusses the perspective of stochastic representation via Bernoulli streams. Section 6 considers an example application in access control. Section 7 presents an illustrative numerical experiment. Section 8 outlines further research perspectives and directions for extended validation. Section 9 discusses advantages, limitations, and applications. Section 10 concludes the paper.

PROBLEM STATEMENT

i. Heterogeneity of sensor channels:

In practical decision-support systems, input information may arrive from multiple heterogeneous channels, including: video or image sensors; motion or trajectory sensors; identification channels; radio-frequency or telemetry channels; channels measuring physical parameters of the object or environment; contextual information sources; event logs and historical system records.

Each of these channels carries useful information, but in a different representational form. For example, a visual channel may provide object shape or appearance, a motion channel may describe velocity or trajectory patterns, an identification channel may confirm or reject authorization, and a contextual channel may indicate whether the object behavior is admissible for a given time, zone, or operational mode.

ii. Main difficulties of direct data fusion

The direct fusion of such channels is complicated by several factors [1–3]:

- Different physical units and semantics. Sensor outputs may represent intensities, coordinates, codes, logical states, or contextual descriptors.
- Different sampling rates and update frequencies. Some channels provide nearly continuous data, whereas others update only occasionally or asynchronously.
- Different noise and uncertainty levels. Visual channels may degrade under poor lighting or occlusion, identification channels may be intermittent, and contextual data may be incomplete or delayed.

- Missing data and temporary channel failure. One or more channels may become unavailable without warning.
- Delays and temporal misalignment. Reliable fusion may require synchronization or explicit handling of freshness.
- Contradictions between sources. Different channels may support incompatible conclusions.
- Different informativeness for different decisions. The same channel may be highly informative in one scenario and weakly informative in another.

iii. Insufficiency of direct classification

In many applied systems, an output of the form “the object belongs to class A” is not sufficient. For decision-support applications, especially those related to safety, security, or controlled access, it is important to know:

- how likely the inferred event is,
- how large the associated risk is,
- how uncertain the decision remains,
- whether the data quality is adequate,
- whether the channels agree or conflict,
- whether a fully automatic decision is justified.

These considerations motivate the introduction of an intermediate decision-support representation in which heterogeneous sensor inputs are mapped into a common, interpretable, and probabilistically meaningful space.

PROPOSED EVENT-PROBABILISTIC APPROACH

i. From sensor signals to events

The central idea of the proposed framework is to interpret each sensor channel not merely as a stream of raw values, but as a source of event-oriented evidence. Instead of directly fusing heterogeneous physical measurements, the system identifies relevant events associated with the decision problem.

Examples of events may include:

E1: the object is detected,
E2: the object shape corresponds to an admissible class,
E3: the object speed is within the allowed range,
E4: the trajectory is typical,
E5: the identification channel is confirmed,
E6: the sensor data quality is insufficient,
E7: a conflict between channels is detected.

This representation allows heterogeneous channels to be described in a common event-based language.

ii. Event probabilities

For the i-th channel, the event-related probability is written as

$$p_i(t) = P(E_i \mid S_i(t)) \tag{1}$$

where:
S_i (t)denotes the data of the i-th sensor channel at time t,
E_i is the corresponding event;
p_i (t) is the time-dependent probability associated with that event.
This transformation maps heterogeneous sensor information into a common probabilistic space.

iii. Unified event vector

At each time instant, the current event state of the system may be represented by the vector

$$p(t) = [p_1(t)\ p_2(t)\ \dots\ p_n(t)]. \tag{2}$$

This vector provides a unified description of the object or situation from the perspective of multiple heterogeneous channels.

iv. Reliability-aware weighting

The channels generally differ in reliability, data quality, recency, and consistency with other sources. Therefore, a reliability-aware weight $w_i(t)$ is introduced for each channel. Such a weight may reflect:

- noise level,
- current quality of the channel,
- freshness or recency of the data,
- delay and synchronization quality,
- consistency with other channels,
- prior reliability of the source.

The integrated event assessment can then be represented in the general form

$$P_{event}(t) = F(w_1(t)p_1(t)\ w_2(t)p_2(t)\ \dots\ w_n(t)p_n(t)) \quad (3)$$

where F(·) denotes the fusion function.

To clarify how heterogeneous data are transformed into the proposed event-probabilistic representation, Table 1 provides representative examples of sensor inputs, corresponding event-oriented features, and probabilistic parameters.

Table1. *Representative mapping of heterogeneous sensor inputs into event-oriented probabilistic parameters.*

Sensor channel	Initial data	Event-oriented feature	Probabilistic parameter
Visual channel	Shape, size, contour, visual appearance	Object corresponds to an admissible class	$p_{shape}(t)$
Motion channel	Velocity, acceleration, trajectory	Motion behavior is normal or admissible	$p_{motion}(t)$
Identification channel	ID code, RFID tag, digital credential, authorization signal	Identification is confirmed	$p_{id}(t)$
Physical-parameter channel	Distance, dimensions, temperature, vibration, other measurable parameters	Physical parameters are within admissible limits	$p_{phys}(t)$
Contextual channel	Time, access zone, operating mode, environmental conditions	Context is admissible for the current decision	$p_{context}(t)$
Data-quality channel	Noise level, completeness, freshness, sensor status	Data quality is sufficient for decision support	$p_{quality}(t)$
Inter-channel consistency block	Comparison of event probabilities from different channels	No significant conflict between channels	$p_{cons}(t)$, $1 - C_{conflict}(t)$

The table illustrates that physically different input data can be mapped into a unified probabilistic event space. This representation enables further reliability-aware weighting, uncertainty estimation, conflict analysis, and optional Bernoulli encoding for stochastic processing.

v. Additional decision-support metrics

The proposed approach is intended not only to form an integrated event likelihood, but also to provide a richer set of metrics:

$P_{event}(t)$ — probability of the target event,
$P_{risk}(t)$ — probability of a risky state,
$U(t)$ — uncertainty estimate,
$Q_{data}(t)$ — data quality indicator,
$C_{conflict}(t)$ — level of conflict between channels.

This set of outputs makes the decision process more transparent and controllable.

ARCHITECTURE OF THE DECISION-SUPPORT FRAMEWORK

The generalized architecture of the proposed framework is shown in Figure 1. It consists of the following functional blocks:

- Heterogeneous sensor channels,
- Preprocessing,
- Event extraction,
- Probabilistic normalization,
- Unified event vector formation,
- Reliability-aware weighting,
- Weighted fusion,
- Risk / uncertainty / conflict assessment,
- Decision-support module.
-

The processing chain may be summarized as:

Sensor channels→preprocessing→event extraction→probabilisticnormalization→weighted integration→decision support.

An important feature of the proposed architecture is the explicit separation between event-probability generation and final decision support. This makes it possible to preserve interpretability and to use additional criteria before allowing or blocking a decision.

The architecture also leaves open the possibility of further representing event probabilities as Bernoulli streams for stochastic or photonic-stochastic processing, as discussed in Section 5.

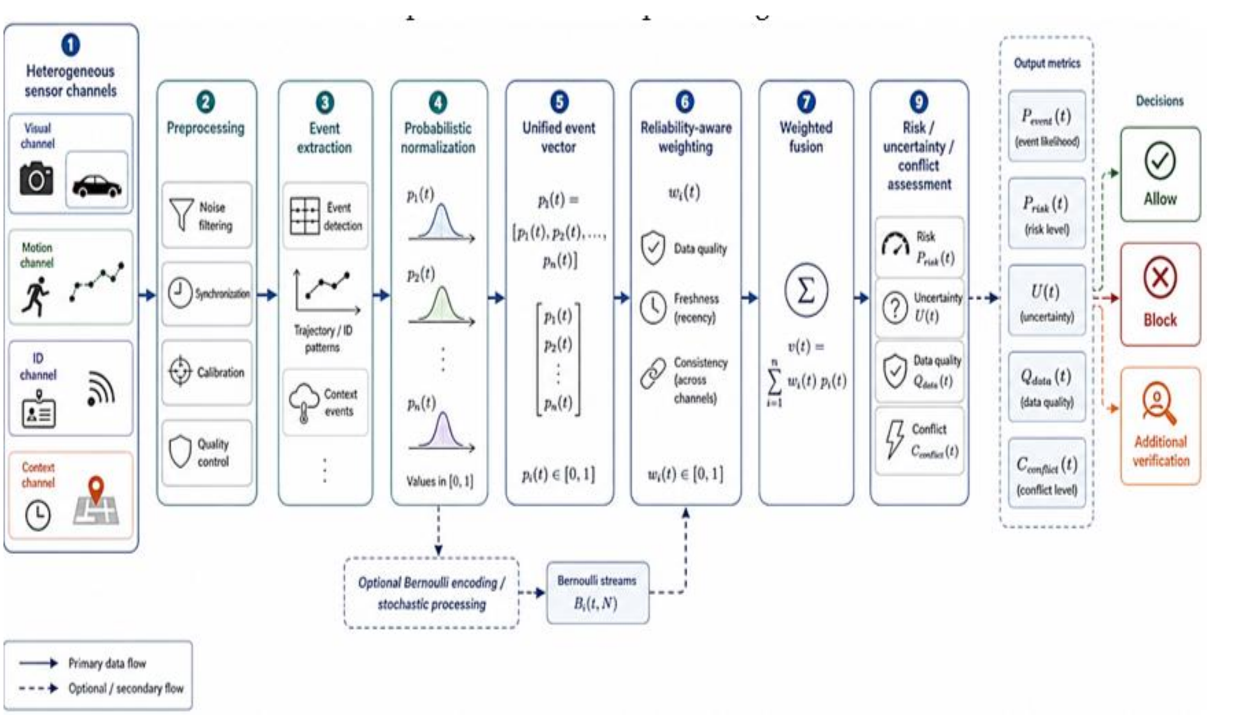

Figure 1. *Generalized architecture of the proposed event-probabilistic decision-support framework. Heterogeneous sensor data are preprocessed, transformed into event-oriented features, normalized into event probabilities, integrated using reliability-aware weights, and further used to estimate event likelihood, risk, uncertainty, data quality, and inter-channel conflict before generating a decision-support recommendation. An optional branch illustrates the possibility of Bernoulli encoding and stochastic processing.*

The final outputs of the decision-support layer include the metrics P_{event} (t), P_{risk} (t), U(t), Q_{data} (t), and $C_{conflict}$ (t). On this basis, the system may generate one of three recommendation modes:

Allow,

Block,
Additional verification.
The third mode is especially important, because it prevents the system from being forced into an automatic decision when the available evidence is insufficient or contradictory.

PERSPECTIVE OF STOCHASTIC REPRESENTATION

The event probabilities generated by the proposed framework may be further represented in stochastic form as Bernoulli streams. For a given event probability $p_i(t)$, the corresponding stochastic representation may be written as

$$p_i(t) \rightarrow B_i(t, N) \tag{4}$$

where B_i (t,N) denotes a Bernoulli bitstream of length N. If p_i (t)=0.75, then ideally approximately 75% of the bits in the stream take the value 1.
This representation offers several possible advantages [8–10]:

- a unified representation for different data types,
- compatibility with stochastic logic operations,
- suitability for efficient hardware implementation,
- potential compatibility with photonic-stochastic modules,
- support for parallel processing of event streams.

At the same time, several limitations must be acknowledged:

- the estimation error depends on the stream length N,
- correlation between stochastic streams must be controlled,
- the event-probability mapping must be properly calibrated,
- uncertainty estimation remains necessary.

Thus, Bernoulli encoding is not a replacement for the event-probabilistic layer, but rather a possible next representation stage for downstream stochastic processing.

APPLICATION EXAMPLE: ACCESS-CONTROL SYSTEM

To illustrate the practical relevance of the proposed framework, consider an access-control system. In such a system, a controlled object may be characterized by:

- object shape and visual features,
- dimensions,
- trajectory,
- speed,
- identification signal,
- contextual information.

The task of the system is not merely to classify the object, but to determine whether automatic access should be granted, denied, or postponed pending further verification.
Representative event features in this context may include:

- the object belongs to an admissible class,
- identification is confirmed,
- the trajectory is normal,
- the speed is within the permissible range,
- the channels do not contradict one another.

The possible decision modes are:

Allow access: high admissible-event probability, low risk, and acceptable uncertainty;
Block access: high risk or critical non-compliance;
Additional verification: high uncertainty, degraded data quality, or significant conflict.
between channels.

This example demonstrates why a decision-support formulation is more appropriate than direct hard classification in applications where decision accountability and safety matter.

ILLUSTRATIVE NUMERICAL EXPERIMENT

i. Purpose of the experiment

A complete validation of the proposed framework may include a broad range of modeling studies. However, for the purposes of the present preprint, it is sufficient to provide one representative numerical experiment that directly illustrates the core idea of the event-probabilistic decision-support approach.

The selected experiment was chosen because it verifies the most important practical claim of the paper: reliability-aware event-probabilistic fusion can maintain interpretable decision support under normal and degraded sensing conditions and can prevent unjustified automatic decisions under sensor conflict.

ii. Simulation setup

The illustrative experiment uses four sensor channels:

- **visual channel**, represented by p_{shape} (t),
- **motion channel**, represented by p_{motion} (t),
- **ID channel**, represented by p_i d(t),
- **context channel**, represented by $p_{context}$ (t).

Two fusion modes are compared:

- **Equal-weight fusion**, in which all channels have the same contribution,
- **Reliability-aware adaptive weighting**, in which the contribution of a channel is reduced when its quality decreases, its evidence conflicts with other channels, or its reliability becomes questionable.

Three representative scenarios are considered:

- **Normal admissible object,**
- **Visual-channel degradation,**
- **Visual-ID conflict.**

The output metrics are the integrated event probability P_{event} (t), the risk probability P_{risk} (t), the uncertainty estimate U(t), the average data quality Q_{data} (t), and the conflict indicator $C_{conflict}$ (t).

The final recommendation is determined using a simple three-state logic:

Allow, if admissible-event probability is high and risk remains low,

Block, if risk becomes high,

Additional verification, if uncertainty or conflict exceeds the admissible threshold.

iii. Normal admissible scenario

Figure 2: shows the time evolution of the principal output metrics for the normal admissible-object scenario. The event probability increases as more evidence is accumulated, whereas the risk and uncertainty remain relatively low. In this case, the system converges toward a stable admissible decision.

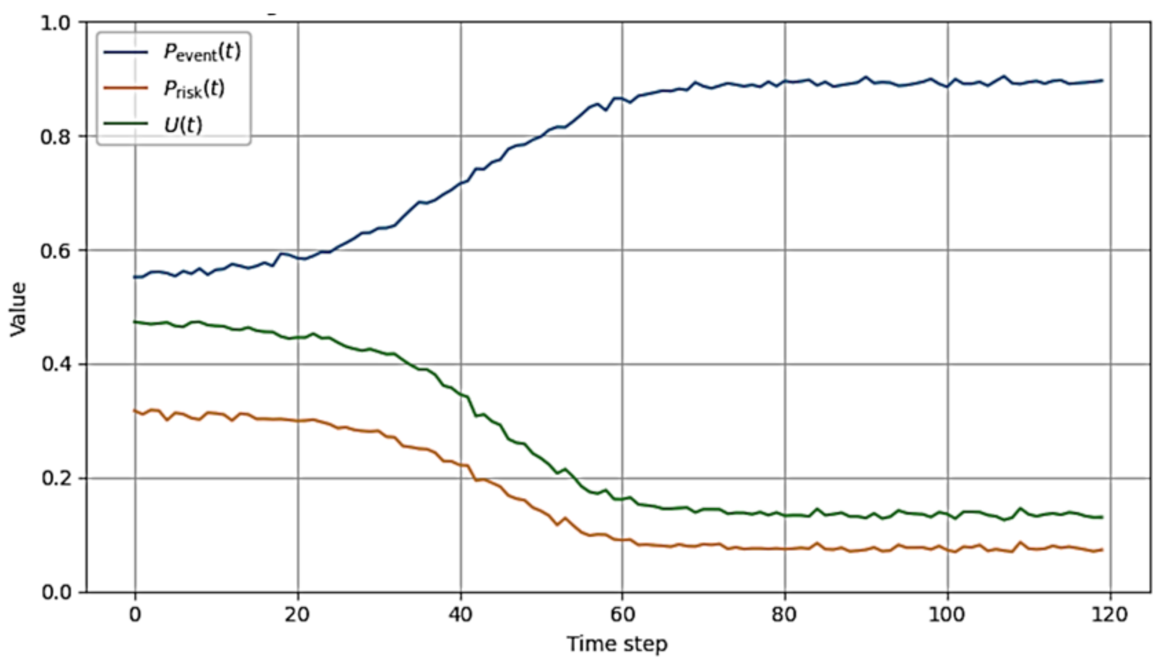

Figure 2: *Time evolution of P_{event} (t), P_{risk} (t), and U(t) for the normal admissible-object scenario using*

adaptive weighting. The event probability rises and stabilizes as evidence accumulates, while the risk and uncertainty remain low.

For the evaluation interval corresponding to the stabilized stage of this scenario, the integrated admissible-event probability equals 0.884 for equal-weight fusion and 0.894 for adaptive weighting. The corresponding risk levels are 0.080 and 0.075, respectively. In both cases the decision is Allow, although the adaptive scheme provides a slightly better overall estimate.

iv. Degradation of one channel

In the second scenario, the visual channel is intentionally degraded during a finite time interval. The purpose of this test is to evaluate whether adaptive weighting can reduce the negative influence of the degraded channel.

Figure 3 compares the integrated event probability under equal-weight and adaptive fusion. During channel degradation, equal-weight fusion becomes more sensitive to the unreliable visual evidence, while adaptive weighting better preserves the stability of the decision variable.

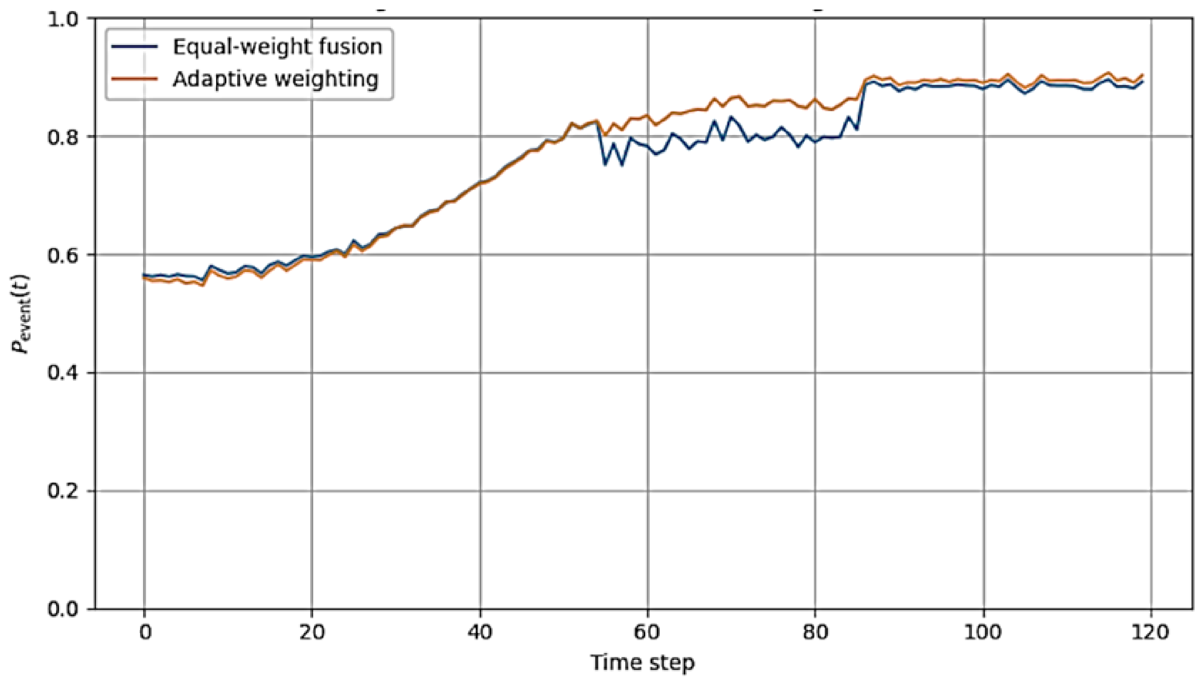

Figure 3. *Effect of visual-channel degradation on the integrated event probability P_{event} (t). Adaptive weighting reduces the negative influence of the degraded channel and yields a more stable estimate than equal-weight fusion.*

Averaged over the degradation interval, the event probability is 0.796 for equal-weight fusion and 0.849 for adaptive weighting. The corresponding risk levels are 0.234 and 0.211. Thus, both schemes still produce the decision Allow, but the adaptive scheme is more robust and more clearly separates the admissible state from a potential failure.

v. Conflict scenario and additional verification

In the third scenario, the visual channel supports an admissible object, while the ID channel rejects authorization. This case models contradictory sensor evidence, which is especially important for access-control applications.

Figure 4 shows that the conflict indicator rises significantly, and the system does not force an automatic permissive decision. Instead, it transitions into the ***Additional verification*** mode.

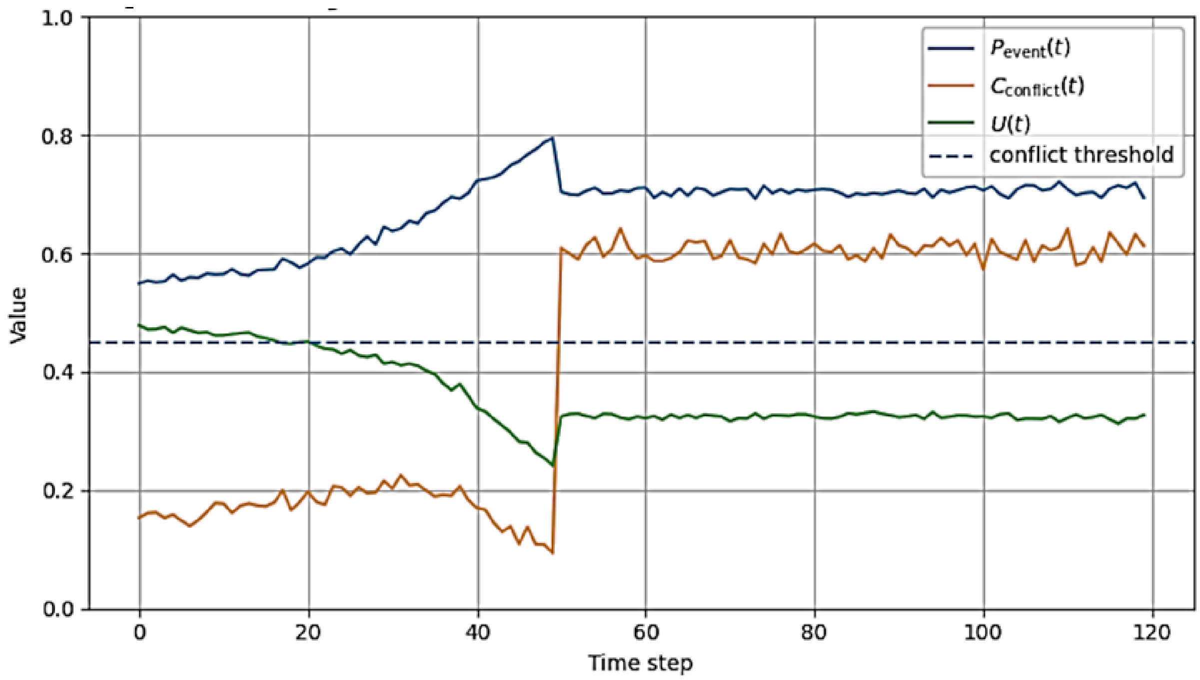

Figure 4: *Conflict scenario and transition to additional verification. Although the event probability remains moderate, the conflict indicator Cconflict (t) rises above the admissible level, which prevents an unjustified automatic decision*.

For the conflict interval, the average conflict level reaches 0.607 in both fusion modes, which is substantially higher than in the normal scenario. The event probabilities are 0.682 and 0.706 for equal-weight and adaptive fusion, respectively, but the system does not interpret this as sufficient evidence for automatic access. Instead, the decision becomes ***Additional verification***.

vi. Summary of numerical results

The numerical results of the three scenarios are summarized in Table 2.

Table 2: *Summary of decision outcomes for the illustrative numerical experiment. The table compares equal-weight and adaptive fusion for three representative scenarios using scenario-specific evaluation windows. The adaptive weighting scheme improves the stability of the integrated event probability in the degraded-channel scenario, while explicit conflict handling drives the decision into additional verification in the contradictory-evidence scenario*.

Scenario	Fusion mode	P_{event}	P_{risk}	U	Q_{data}	$C_{conflict}$	Evaluation window	Decision
Normal admissible object	Equal-weight	0.884	0.080	0.135	0.933	0.040	90–119	Allow
Normal admissible object	Adaptive	0.894	0.075	0.135	0.933	0.040	90–119	Allow
Visual-channel degradation	Equal-weight	0.796	0.234	0.324	0.753	0.267	60–80	Allow
Visual-channel degradation	Adaptive	0.849	0.211	0.324	0.753	0.267	60–80	Allow
Visual-ID conflict	Equal-weight	0.682	0.376	0.324	0.900	0.607	70–119	Additional verification
Visual-ID conflict	Adaptive	0.706	0.365	0.324	0.900	0.607	70–119	Additional verification

The illustrative experiment confirms three important points:

- the framework behaves as expected in a normal admissible scenario,
- adaptive weighting improves robustness when one channel degrades,
- explicit conflict assessment prevents a potentially unsafe automatic decision in the presence of contradictory evidence.

FURTHER MODELLING PERSPECTIVES

The illustrative experiment presented in Section 7 provides only a representative proof of concept. A broader validation of the proposed framework should include a wider range of modeling scenarios.

i. Extended robustness analysis

A more comprehensive study should consider:

- increasing noise in individual sensor channels,
- temporary loss of one or more channels,
- missing or stale data,
- asynchronous sensor updates,
- stronger inter-channel contradictions,
- variable data freshness.

These studies would allow the robustness of the framework to be characterized more systematically.

ii. Comparison of weighting strategies

In the present paper, only two fusion modes were compared: equal weighting and adaptive reliability-aware weighting. Future work may extend this comparison to:

- fixed expert-defined weights,
- reliability-only weighting,
- freshness-aware weighting,
- combined reliability-freshness weighting,
- context-dependent weighting policies.

Such analysis would clarify which weighting strategy is most appropriate for different classes of decision-support systems.

iii. Extended uncertainty and risk modelling

Another important direction concerns the refinement of uncertainty estimation and risk modeling. In addition to the simple illustrative formulation used here, future studies may explore:

- probabilistic calibration of event scores,
- Bayesian uncertainty estimation,
- evidence-theoretic conflict measures,
- explicit cost-sensitive risk models.

These developments are important for trustworthy and accountable AI-assisted decision support [6], [7], and may be complemented by evidence-theoretic approaches, such as Dempster-Shafer-based combination of evidence, for conflict-sensitive decision support [11].

vi. Stochastic and Bernoulli-based analysis

Since the event-probabilistic interface is compatible with Bernoulli encoding, a natural next step is to study:

- the influence of Bernoulli-stream length N,
- the effect of inter-stream correlation,
- error versus processing-time trade-offs,
- the robustness of stochastic decision logic under degraded inputs.

Such studies would create a direct bridge toward hardware-efficient stochastic or photonic-stochastic implementations.

v. Toward full-scale validation

Thus, the broader program of future work includes not only extended numerical modelling, but also the eventual development of a full validation study in which multiple datasets, parameter regimes, and decision criteria are systematically compared. The current preprint should therefore be viewed as a conceptual and methodological foundation accompanied by an illustrative numerical example, while the outlined studies constitute the natural continuation toward a full-scale publication.

DISCUSSION

The proposed event-probabilistic framework provides a structured way to unify heterogeneous sensor data without collapsing them too early into a single hard decision. Its main advantage is that it preserves intermediate information about event likelihood, channel reliability, data quality, uncertainty, and inter-channel conflict.

A key benefit of the framework is the explicit representation of data quality and channel consistency. In many traditional systems, degraded inputs still influence the final output without being separately identified. In contrast, the proposed architecture introduces dedicated indicators such as $Q_{data}(t)$, $U(t)$, and $C_{conflict}(t)$, which can be used both by a human operator and by a higher-level control module.

Another important feature is that the decision is formed as a probability-oriented recommendation rather than a rigid class label. For safety-aware and security-aware systems, this distinction is essential. The framework supports not only the decisions ***Allow and Block***, but also the intermediate mode ***Additional verification***, which is necessary when the evidence remains insufficient or contradictory.

The illustrative numerical experiment, although compact, supports this interpretation. It shows that adaptive weighting improves the robustness of the integrated event probability under channel degradation. It also shows that even when the integrated admissible-event probability remains moderate, a high conflict level can override the temptation to produce a direct automatic decision. This is precisely the type of controlled behavior expected from a trustworthy decision-support framework.

The proposed methodology is not limited to access control. The same logic may be applied to:

- industrial monitoring,
- Internet-of-Things systems,
- transport infrastructure,
- security and surveillance systems,
- critical-infrastructure monitoring,
- cyber-physical systems.

At the same time, some limitations should be acknowledged. First, the quality of the overall framework depends on the correctness of event extraction from raw data. Second, weighting strategies require proper calibration and validation. Third, the current numerical experiment is illustrative rather than exhaustive. Fourth, if Bernoulli encoding is introduced, stream-length effects and correlation control become essential. These limitations do not weaken the conceptual value of the framework, but they do define the scope of the next research stage.

CONCLUSIONS

1. A framework for the unification of heterogeneous sensor data based on event-probabilistic representation has been proposed. The main idea is to map heterogeneous sensor observations into a common set of event-oriented probability estimates.
2. It has been shown that heterogeneous channels of different physical nature can be represented in a unified probabilistic event space, which supports interpretable decision-support processing.
3. The need for reliability-aware weighting has been substantiated. Such weighting allows the framework to account for channel quality, data freshness, and inter-channel consistency.
4. The framework produces not only an integrated event likelihood, but also additional decision-relevant metrics, including risk level, uncertainty, data quality, and inter-channel conflict.
5. An illustrative numerical experiment has shown that adaptive weighting improves robustness under channel degradation, while explicit conflict assessment prevents unjustified automatic decisions in contradictory sensing conditions.
6. The proposed framework is compatible with Bernoulli encoding and may serve as a basis for future stochastic and photonic-stochastic decision-support architectures.
7. The presented preprint should be viewed as a conceptual and methodological foundation accompanied by a representative numerical demonstration, while broader validation remains a subject of future full-scale investigation.

Data and code availability: The Python scripts, processed numerical outputs, and figure data used in the illustrative experiment are provided as supplementary material to this preprint.
Conflicts of Interest: The authors declare no conflict of interest

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