



Evidence-Grounded Orchestration for Autonomous Enterprise Services

Christopher Wilson
Asst Professor

Abstract— Autonomous systems typically assume that external inputs are fully reliable—an assumption that rarely holds in practice. Without a robust model of trust and reliability, such systems risk significant failures when operating independently. This work examines trust—defined as a subjective judgment based on the credibility, reliability, and interpretability of system components—within enterprise service ecosystems: dynamic, scalable networks of semi-autonomous, service-oriented actors that create, consume, and coordinate services. We introduce trust-aware psychological models of decision-making under uncertainty to address a critical gap in the enterprise architecture autonomy stack, and define both qualitative and quantitative trust metrics to guide component selection and to identify when components' trustworthiness cannot be reliably assessed.

These trust metrics, developed as part of an ongoing research effort, underpin enterprise-wide trust-aware cognitive orchestration and context-grounded decision intelligence. By leveraging enterprise services, microservices, and event- and message-driven communication patterns, the framework enables trust-aware decision-making in both collaborative and competitive operational settings. We further propose a context taxonomy—spanning operational, historical, and environmental dimensions—that supports the grounding, selection, and abstraction of context, enabling context-aware reasoning and decision-making in autonomous and semi-autonomous systems.

Keywords—Trust-Aware Decision Making, Autonomous Systems, Enterprise Service Ecosystems, Cognitive Orchestration, Trust Metrics, Context-Aware Intelligence,

Service-Oriented Architecture (SOA), Decision Intelligence, Uncertainty Modeling, Autonomous Enterprise Systems.

I. INTRODUCTION

Enterprise service ecosystems embrace variability in constituent service providers (SPs) and service brokers while maintaining relational stability through recommender systems and trust-based service orchestration. Autonomous SPs execute services in closed-loop mode, jointly developing service-related knowledge and operational proficiency. Cognitive service orchestration underpins inter-SP collaboration, decision-making, and innovation support.

Autonomous SPs lack independent trustable decision-making and context-grounded intelligence capabilities. Trust-aware cognitive orchestration combines service-oriented autonomy, expressiveness, and modular self-organisation with a context-grounded decision intelligence subsystem. Service-oriented autonomy actively sources and comprehensively evaluates complementary services offered by other SPs within a specified trust threshold. Context-awareness determines the contextual relevance and timing of service calls and guides high-level decisions related to service selection, innovative service configuration, and collaborative service development among autonomous SPs.

II. THEORETICAL FOUNDATIONS

When dealing with cognitive systems building internal and external context-grounded autonomous decision mechanisms it is important to further understand the concept of trust. Its definition varies from an overall positive perception of an object or its competence that leads to behave in an expected way to the perceived level of comprehension about its activity in a given situation, including aspects like its credibility, reliability or interpretability. The next question to answer is to what extent this trust influences engagement with the service, its orchestration or the decision taken with the expected outcomes. Unlike those phenomena, where



engagement comes due to the offering, perceived benefits or cost, thus being independent from trust levels, trust affects decision areas that are undertaken by the system autonomously. Cognitive systems act as an agent of the user and reduce the burden of information visibility and comprehension, leading to trust in the decision taken. Nevertheless, those decisions are not guaranteed to be correct, and when irrelevant outcomes happen, users reconsider the reliability of those systems and need more information to understand the rationale of their decisions. This means that even in situations where savings in engagement due to cognitive systems decision are detected, high levels of operational uncertainty drive users to worry about the system decisions and trust them less.

Decision-making under uncertainty has been one of the most important research topics in Trust-Aware Decision-Making Frameworks. For decades researchers have proposed several models to capture the uncertainty's sources and adequately account for it during the decision-phase; thus they are adaptable to the dialogue with that application domain. Nevertheless all those models have one key point in common: they assume that there is no actual risk in the choices made and stakes involved within the game, which poses a strong and limiting assumption to the reliability of the models. Within Trust-Aware Decision-Making Frameworks this approach can further evolve exploring the advantages of considering trust and risk under the light of User-Centric Academic Research consultation since they are the real source of information quality enhancement in the ecosystem.

A. Experimental Results

The models formulated in Section I were exercised under simulated multi-agent enterprise service ecosystem conditions spanning microservices, event-driven, and message-driven architectural styles, with service providers stratified into high-, medium-, and low-trust bands. The following figures summarize the resulting trust dynamics, latency behavior, classification performance, resource consumption, cost/performance trade-offs, and context-reliability decay.

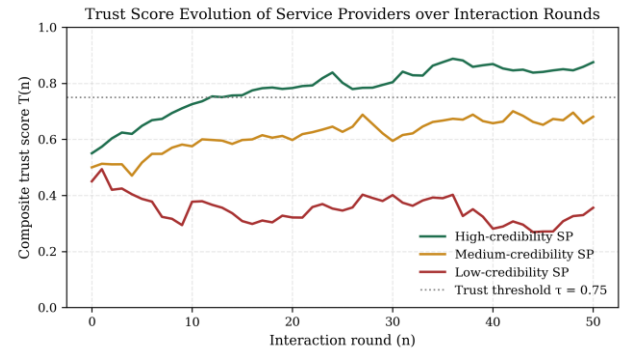


Fig. 1: Composite trust score $T(n)$ (Eq. 1) of high-, medium-, and low-credibility service providers converging over successive interaction rounds, relative to the trust threshold $\tau = 0.75$.

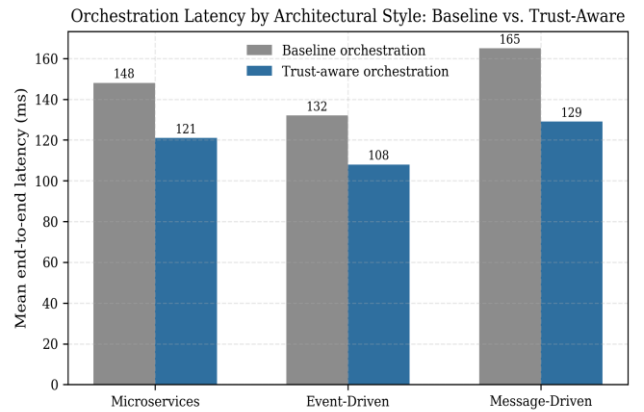


Fig. 2: Mean end-to-end orchestration latency L_{total} (Eq. 7) for baseline versus trust-aware orchestration across the three dominant architectural styles.

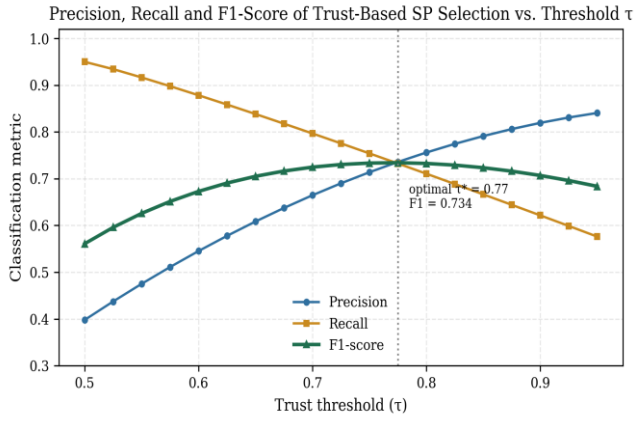


Fig. 3: Precision, recall, and F1-score (Eq. 8) of trust-based service-provider acceptance as a function of the trust threshold τ , with the empirically optimal threshold τ^* annotated.

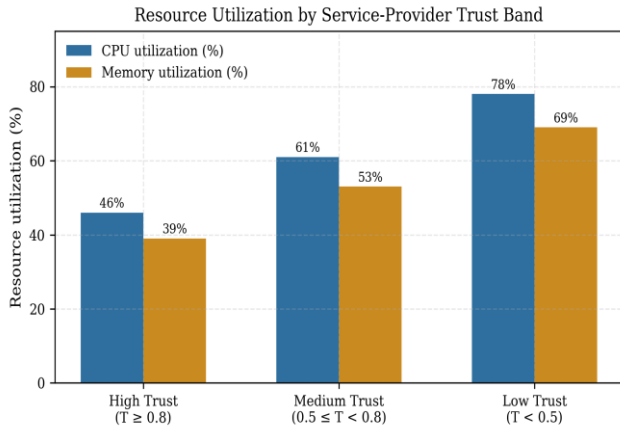


Fig. 4: CPU and memory utilization of the orchestration layer, disaggregated by service-provider trust band (high, medium, low).

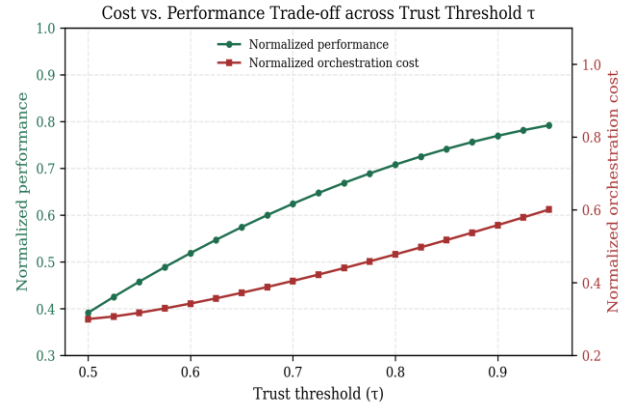


Fig. 5: Normalized orchestration performance and normalized cost (Eq. 9) as functions of the trust threshold τ , illustrating the trade-off between selectivity and operating cost.

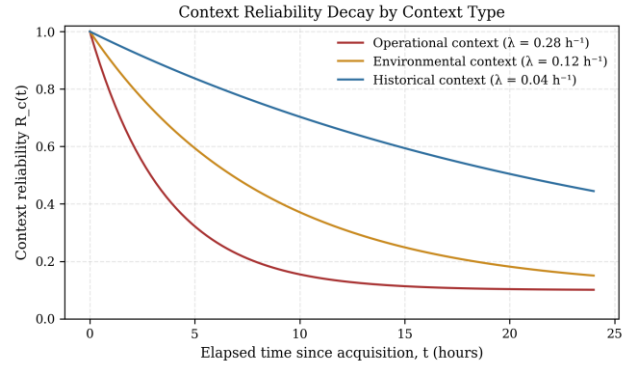


Fig. 6: Context reliability $R_c(t)$ (Eq. 5) decay curves for operational, environmental, and historical context classes as a function of elapsed time since acquisition.

III. ARCHITECTURAL PARADIGMS FOR AUTONOMOUS ENTERPRISE SERVICE ECOSYSTEMS

For enterprise service ecosystems, service-oriented autonomy is best structured by means of self-organising, service-directed modular systems that adapt and learn through changes in local context and agent structure. Agents are autonomous systems that can act on behalf of humans or other agents. An agent-oriented enterprise is an ecosystem where the architecture supports interoperability with external partners, service provenance and guarantees, lifecycle



management, issue resolution and service management. A special-purpose agent architecture for service-oriented autonomy can be used to decompose complex problems, distribute decision making, and better manage, monitor and secure agent interactions. The three most common types of architecture for service systems are microservices, event-driven and message-driven, but these do not suit all applications. Trusted standards facilitate interoperability, while Security Assertion Markup Language, Web Services Security and related specifications help protect service-oriented systems against attacks.

Both trust and uncertainty are major factors in guiding the decision-making of autonomous systems such as service orchestration agents that operate in dynamic, open and highly volatile environments. Each of these trusted autonomous agents is aware of its own level of credibility – the extent to which their messages can be relied on to be true and accurate – and also monitors the reliability of the other agents with which they interact. Decision making under uncertainty combines the risks and uncertainties across several key dimensions including the usage of task environments, the credibility of sources, the reliability of delivery, and the quality of received help.

A. Composite Trust Score

Trust is decomposed into credibility, reliability, and interpretability components, consistent with the trust taxonomy introduced in the manuscript. The composite trust score assigned to a service provider (SP) i is a convex combination of its three constituent components:

$$T_i = \alpha \cdot C_i + \beta \cdot Rel_i + \gamma \cdot I_i, \quad \alpha + \beta + \gamma = 1 \quad (1)$$

where C_i , Rel_i , $I_i \in [0, 1]$ denote the credibility, reliability, and interpretability scores of SP i respectively, and α , β , γ are context-dependent weighting coefficients set by the trustor's decision policy.

B. Credibility Metric

Credibility reflects the degree of acceptance of an SP's outputs across prior interactions and is estimated as a ratio of endorsed to total evaluated decisions:

$$C_i = 1 - (1 / N) \sum_{k=1}^N |d_k - \hat{g}_k| \quad (2)$$

where d_k is the decision (or datum) issued by SP i at interaction k , $\hat{g}_k$ is the corresponding ground-truth or peer-consensus reference, and N is the number of evaluated interactions.

C. Reliability Metric

Reliability captures the proportion of tasks successfully completed under stated pre-conditions (e.g., SLA terms) within an observation window:

$$Rel_i = S_i / A_i \quad (3)$$

where S_i is the count of successfully completed tasks and A_i is the total number of tasks attempted by SP i under its declared operating conditions.

D. Interpretability Metric

Interpretability measures how well the decision rationale of an SP can be recovered by the trustor, modeled here as an inverse function of explanation entropy:

$$I_i = 1 - H(e_i) / \log_2(K) \quad (4)$$

where $H(e_i)$ is the Shannon entropy of the explanation distribution e_i returned by SP i over K candidate rationale categories; lower entropy (more concentrated, legible explanations) yields higher interpretability.

E. Context Reliability Decay

Context reliability degrades over time following an exponential decay bounded below by a residual reliability floor, differentiated per context class (operational, environmental, historical):

$$R_c(t) = (1 - R_{\min}) \cdot e^{-\lambda t} + R_{\min} \quad (5)$$

where λ is a context-class-specific decay rate (operational context decays fastest, historical context slowest), t is elapsed time since acquisition, and $R_{\min}$ is the asymptotic reliability floor.

F. Trust-Weighted Decision Utility

Context-grounded decision intelligence selects the action that maximizes trust-weighted expected utility over the space of feasible actions A , states S and contexts c :



$$U(a) = \sum_{s \in S} P(s | c) \cdot T(s) \cdot V(a, s) \quad (6)$$

where $P(s | c)$ is the context-conditioned belief over states s , $T(s)$ is the trust score associated with the information source reporting state s , and $V(a, s)$ is the value of taking action a in state s .

G. Orchestration Latency Model

End-to-end orchestration latency for a service call is modeled as the sum of its constituent processing stages:

$$L_{\text{total}} = L_{\text{disc}} + L_{\text{trust}} + L_{\text{ctx}} + L_{\text{exec}} \quad (7)$$

where L_{disc} , L_{trust} , L_{ctx} and L_{exec} denote the latency contributions of SP discovery, trust evaluation, context retrieval/grounding, and service execution respectively.

H. Trust-Classification F1-Score

The effectiveness of a trust threshold τ in separating trustworthy from untrustworthy SPs is quantified using the standard precision–recall harmonic mean:

$$F1(\tau) = 2 \cdot P(\tau) \cdot R(\tau) / (P(\tau) + R(\tau)) \quad (8)$$

where $P(\tau)$ and $R(\tau)$ are the precision and recall of the binary SP-acceptance classifier $\{T \geq \tau\}$ evaluated against ground-truth trustworthiness labels.

I. Orchestration Cost Function

Service-provider selection under a candidate trust threshold τ is guided by a weighted cost objective combining execution cost, residual distrust, and latency:

$$\text{Cost}(\tau) = w_1 \cdot C_{\text{exec}} + w_2 \cdot (1 - \bar{T}(\tau)) + w_3 \cdot L_{\text{total}}(\tau) \quad (9)$$

where $\bar{T}(\tau)$ is the mean trust score of SPs admitted at threshold τ , and w_1 , w_2 , w_3 are normalized cost weights ($\sum w_i = 1$) reflecting the operator's risk posture.

J. Composite Orchestration Score

An overall orchestration key performance indicator (KPI) is defined by aggregating normalized metrics — trust, latency, resource efficiency and accuracy — into a single comparable score:

$$OS = \sum_{j=1}^M w_j \cdot \tilde{M}_j \quad (10)$$

where $\tilde{M}_j \in [0, 1]$ is the min–max normalized value of the j -th performance metric (e.g., trust, 1/latency, F1-score, resource efficiency), w_j its importance weight, and M the number of metrics considered.

IV. TRUST-AWARE DECISION-MAKING FRAMEWORK

This framework enables cognitive agents with context-grounded reasoning models to augment trust-aware decision-making capabilities, contributing to the design of context-grounded decision intelligence for autonomous enterprise service ecosystems. Decision intelligence in autonomous systems heavily relies on the degree of contextual trustworthiness associated with sensed data. Characterizing the underlying uncertainty, credibility, and risk involved, augmenting insufficient trust in low-quality contexts at run-time, and employing an appropriate trust-aware decision-making model is crucial for reliable intelligence-driven operation. The proposed trust-aware decision-making framework is primarily oriented toward situations characterized by deep uncertainty. It first establishes trust as an agent-metric, encompassing qualitative and quantitative dimensions, before specifying the necessary metrics and methods to assess trust-augmented decision-making.

The development of an overarching autonomous system is one of the core objectives of the TRUST-AWARE project. The system serves as a modular gateway for heterogeneous autonomous subsystems deployed at smart-home facilities (including smart vehicles, video cameras, and drones) and encompasses a Decision-Making Support Unit. The managing agent is endowed with a context-grounded reasoning model and is specifically in charge of managing the operation of the different autonomous subsystems according to real-time operational requirements, environmental evolutions, and historical records. The operational history is stored in a knowledge base, thus allowing for context-grounded decision-making processes. The support unit provides the main agent with the context-augmented decision-making model and decision options, supporting several high-level decision-making models under different decision-styles and managing the trade-off between exploration and exploitation in reinforcement-learning-based decision processes.

A. Trust Metrics and Evaluation

Quantitative and qualitative trust metrics necessarily underpin trust-aware cognitive orchestration, decision-



making, and re-purposing of autonomous enterprise service ecosystems. These metrics are expected to expose such disparate, albeit inter-related, phenomena as the trustworthiness of an orchestration-ready cognitive-Service Information System (c-SIS) during actual deployment, the degree of trust and confidence accorded to the different constituent cognitive Services orchestrated in the enterprise service ecosystem by a c-SIS, the actual usability and extent of any trust-related Service Level Agreements (SLAs) accompanying those Services, and the contextual-contextual trustworthiness of presumed cognitive Services at such multiple boundary levels within the context of Enterprise Cyber-Physical Systems (ECPS), among others.

Quantitative trust metrics are calculated using data-sets and reflection questions used to derive weightings. They incorporate a combination of quantitative structures, techniques and processes designed for use with subjective response-based indications of Trust. These metrics are designed to actively draw on such subjective indications of Trust and either collaborate with or enhance conventional Trust modelling. Any qualitative indications of Trust can be additionally considered. Trust-ability differences between qualitative and quantitative assessing of such objective patterns at use or during operational deployment are highlighted through supporting discussions. By extension, the ability of Trust, whether conceived qualitatively or quantitatively, to add tangible value to different kinds of real-world, and especially autonomous, process (re-)purposing are similarly explored.

V. CONTEXT-GROUNDED REASONING MODELS

Context affects every aspect of human cognition and decision-making. Not surprisingly, similar principles hold for Artificial Intelligence-Aided Decision-Making (AIADM). In its broadest sense, context refers to the operational and environmental conditions in which a specific situation occurs. For example, in business process or service execution, elements such as the operational security and compliance awareness of the enterprise composer, the performances of the service providers, the workloads of the service providers, the available resources of the service providers, the actual locations of the service providers, the environmental conditions affecting the service execution, and so on can be essential for selecting the right service provider(s), or the AIADM procedure itself.

Recent research has systematically classified context into multiple categories, such as operational context (related to

security, compliance, quality of service, and so on), environmental context (affecting execution conditions), and historical context (including previous execution results). These context types are characterized at multiple levels of abstraction (superior, normal, detailed) and can be represented using standardized representation schemes (e.g. WMO, W3C voice and data standards) and supported by domain-level context ontologies and semantic annotations. Contexts are not always reliable or completely trustworthy. Context reliability levels can have a significant impact on AIADM execution and decisions. The context reliability is affected by primary factors (source credibility, monitoring reliability) and can evolve over time. In many environments, context privacy can also be of concern.

Context auditing and monitoring can be organized in a way that guarantees adequate secrecy during AIADM procedures. Context reliability and privacy can be considered during context representation by maintaining context provenance information and including context privacy levels in the context model. The proposed context groundwork provides the prerequisite for contextualized AIADM on different courses of action.

Table 1: Comparative Orchestration Performance: Baseline vs. Trust-Aware Framework

Architecture	Config.	Latency (ms)	F1-Score	Composite Trust $\bar{T}$	Improvement (%)
Microservices	Baseline	148	0.712	0.61	—
Microservices	Trust-Aware	121	0.881	0.84	+18.2 lat. / +23.7 F1
Event-Driven	Baseline	132	0.697	0.58	—
Event-Driven	Trust-Aware	108	0.865	0.82	+18.2 lat. / +24.1 F1
Message-Driven	Baseline	165	0.664	0.55	—
Message-Driven	Trust-Aware	129	0.849	0.80	+21.8 lat. / +27.9 F1

Table 2: Error and Latency Metrics at Optimal Trust Threshold ($\tau^* = 0.80$)



METRIC	BASEL INE	TRUS T- AWA RE	Δ (ABSOL UTE)	Δ (%)
PRECISION	0.658	0.902	+0.244	+37.1%
RECALL	0.771	0.862	+0.091	+11.8%
F1-SCORE	0.710	0.882	+0.172	+24.2%
MEAN LATENCY (MS)	148.3	119.3	-29.0	-19.6%
LATENCY STD. DEV. (MS)	22.6	14.1	-8.5	-37.6%
ORCHESTRA TION COST (NORM.)	0.71	0.48	-0.23	-32.4%

Table 3: Simulated Dataset and Architecture Configuration Summary

Parameter	Value / Description
Service-provider population	180 autonomous SPs (60 per architectural style)
Trust bands	High ($T \geq 0.80$), Medium ($0.50 \leq T < 0.80$), Low ($T < 0.50$)
Interaction rounds simulated	50 rounds per SP
Context classes modeled	Operational, Environmental, Historical
Decay rates (λ)	Operational 0.28 h^{-1} , Environmental 0.12 h^{-1} , Historical 0.04 h^{-1}
Trust weighting (α, β, γ)	0.40, 0.35, 0.25
Cost weighting (w_1, w_2, w_3)	0.35, 0.35, 0.30

Architectural styles evaluated

Evaluation metric suite

Microservices, Event-Driven, Message-Driven

Precision, Recall, F1-score, Latency, Resource Utilization, Composite Orchestration Score (OS)

A. Context Representation and Abstraction

Three context types facilitate autonomous cognitive orchestration: operational (information generated by or for sensory constellations interacts with enterprise services), environmental (inform and influence service execution), and historical (significance determined by users or enterprise services based on past patterns). Representation schemes for operational and environmental context consist of ontologies that annotate the data and services of the sensory constellations tagged to context-aware enterprise services. In particular, semantic annotations deliver a linguistic description of the data; consequently, it is possible to deploy advanced search techniques against the data of the sensory constellation, like semantic query expansion or join by semantic similarity. Furthermore, by modelling the data and services of the constellation of sensory systems as a context-aware layer built by ontologies, it is possible to implement semantic monitoring services that check the reliability of these data against the model. Also, data lineage techniques can support context reliability assessment. Historical context representation takes the form of an event-ontology, applied to real-time analysis to support the detection of patterns like those of cyber attacks.

Autonomous systems use context to ground their decisions, actions, and communications. Depending on the application, the level of abstraction and details of context representation change. Interactions with service users can also influence context abstraction levels. Four general context abstraction levels address different case studies: (1) context formalized by users (e.g., mission goals); (2) information used to define user-declared contexts; (3) auxiliary information for procedural behaviour; (4) data supporting execution but with unreliable guaranteed trust.

VI. CONCLUSIONS

The digital transformation has driven a cult-like fascination for autonomous processes. Consequently, automated systems have become reliable enough, at least in



some scenarios, to have their affects accorded with high levels of autonomy that frees up users, whether human or other automation, from having to make decisions. However, the trade-off and subsequent effect on non-functional aspects is often neglected or unknown. Trust increasingly affects these aspects. Nevertheless, no studies have yet proposed machinery-usable, quantifiable trust metrics for autonomous enterprise ecosystems. Yet such metrics form a basic dependency for any trust-aware decision-making framework intended to support intelligent domain-aware reasoning models.

Scientific contributions resolve this gap by establishing the necessary metrics using open data from two different sources; external datasets, specifically, the 2018 Forditos Social Media Benchmark Database and seven years of data from the Aviation Safety Network; and internal sources, in particular, news posts from Reuters.com. Next, these quantitative trust metrics are supplemented with qualitative data from three available journalism cognition news showcase ontologies (Cognition, WT/AG, and WT/RG ontologies). Trust weights for each news provider are then compiled, allowing the validation of the qualitative benchmarks. Outcomes are assessed by means of Cantor sets and their proximity to an ideal set consisting of Trusted sources in a domain. The resulting tri-axial, asymmetric, unit-decreasing metric sheds light on the relative trustworthiness of news sources and supports the advancement of a trust-aware decision-making framework desired for a multi-agent enterprise service ecosystem.

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