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Review

Ontology in Hybrid Intelligence: A Concise Literature Review

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Abstract: In the context of the constant evolution and proliferation of AI technology, hybrid intelligence is gaining popularity in reference to a balanced coexistence between human and artificial intelligence. The term has been extensively used over the past two decades to define models of intelligence involving more than one technology. This paper aims to provide (*i*) a concise and focused overview of the adoption of ontology in the broad context of hybrid intelligence regardless of its definition and (*ii*) a critical discussion on the possible role of ontology to reduce the gap between human and artificial intelligence within hybrid-intelligent systems, as well as (*iii*) the identification of possible future research directions in the field. Alongside the typical benefits provided by the effective use of ontologies at a conceptual level, the conducted analysis has highlighted a significant contribution of ontology to improving quality and accuracy, as well as a more specific role to enable extended interoperability, system engineering and explainable/transparent systems. Additionally, an application-oriented analysis has shown a significant role in present systems (70+% of cases) and, potentially, in future systems. However, despite the relatively consistent number of papers on the topic, a proper holistic discussion on the establishment of the next generation of hybrid-intelligent environments with a balanced co-existence of human and artificial intelligence is fundamentally missed in the literature. Last but not the least, there is currently a relatively low explicit focus on automatic reasoning and inference in hybrid-intelligent systems.

Keywords: artificial Intelligence; hybrid intelligence; ontology; semantic web; interoperability; explainability; knowledge representation

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1. Introduction

Artificial intelligence is constantly evolving [1] towards a more and more sophisticated technology [2]. It is generating a disruptive innovation in most application domains, such as, among others, medicine [3]/healthcare [4], education [5], finance [6], transportation [7] and manufacturing [8]. Indeed, the last generation of AI-powered systems is having a clear impact in solving real-world problems, also including tangible contributions in situations of major crisis [9], and, in general terms, is probably generating unprecedented expectations.

The current socio-technological climate is characterised by an imperishable mix of enthusiasm and concern. A concrete example is generative AI [10], such as ChatGTP, an AI program that has become a cultural sensation in less than 2 months [11]. By automatically creating text based on written prompts, ChatGTP has also revealed the potential of AI to non-expert users, which has further increased concerns on possible and probable misuse, as well as on the collateral effects for society. The classic debate, involving experts from academia and industry around ethics and possible regulations, has now somehow extended to involve a much broader audience in a kind of public debate.

The rise of AI has also led to an increasing popularity of hybrid solutions, normally referred to as hybrid intelligence [12]. This is an evidently less radical concept that assumes a model of intelligence based on a balanced co-existence of humans and machines. It is important to remark that the concept has been extensively used in the past two decades to define models of intelligence involving more than one technology.

Born in philosophy, ontology is also a relatively consolidated concept used in computer science [13], where it is extensively adopted to formalize a given domain within computer systems [14]. In practice, ontologies are rich data models that allow the specification of machine-processable "semantics". While their primary purpose is machine-to-machine interaction, ontological modelling also enables extended capabilities in terms of human–computer interaction by fostering the same representation of knowledge for humans and machines. While ontology actively contributes in general in the context of intelligent systems at a different level, its specific potential within hybrid intelligence is probably not fully exploited and could play a significant role within next-generation systems.

In the context of the constant evolution and proliferation of AI technology, this paper aims to provide (*i*) a concise and focused overview of the adoption of ontology in the broad context of hybrid intelligence regardless of its definition and (*ii*) a critical discussion on the possible role of ontology to reduce the gap between human and artificial intelligence, as well as (*iii*) the identification of possible future research directions in the field.

The relevance of this study resides mostly in a need for a consolidated approach for hybrid intelligence that may assure an evolution according to current society needs.

1.1. Why Hybrid Intelligence?

Regardless of concrete implementations, hybrid solutions are normally designed to take advantage of the characteristics of multiple approaches/technologies or to optimise some kind of key trade-off. In the context of the huge proliferation of HI, hybrid intelligence is mostly emerging as a result of two possible main paths: (i) *current limitations of AI technology* and/or (ii) *lack of trust in fully AI-based solutions*. While the relevance of the former trend is naturally expected to decline with the evolution of AI, a more sophisticated AI technology could have an overall unclear impact on the latter as a more powerful AI could further increase concerns for sensitive applications.

1.2. Why Ontology?

Ontology may be considered a consolidated asset within the semantic web [15]. It is contributing more in general to solving problems in computer science (e.g., data integration [16]) and is extensively adopted in a broad range of disciplines and application domains (e.g., bio-informatics) [17], and it is also the object of constant research interest, as specialised journals and conferences clearly demonstrate. Despite its already mentioned consolidated value within computer systems, ontology is evolving as a response to emerging problems and major technology trends. For instance, its convergence with machine learning is remarkable (e.g., Ref. [18], among many others), as is its intrinsic relation with knowledge graphs [19], as well as its contribution at an application level to emerging systems (e.g., digital twins [20]).

1.3. Structure of the Paper

The Section 1 of the paper follows, with a brief presentation of the background concepts (Section 2). Methodological aspects are discussed in Section 3, while Section 4 provides an overview of the contributions on the topic in the literature; such a body of knowledge is discussed in quantitative and qualitative terms in Section 5. Finally, the paper ends with the Section 6.

2. Background Concepts

The root of this review is intrinsically related to the very generic concepts of *intelligence* and *semantics*, which have an extremely broad scope in the context of modern systems. The focus is explicitly on more narrowed concepts, an more concretely on the intersection between *hybrid intelligence* and *ontology*. Such an approach allows the identification of a body of knowledge. However, hybrid-intelligent systems may be defined in different ways and quite often present blurred boundaries; furthermore, ontologies may refer to the more generic and conceptual knowledge representation as well as to the more technology-specific semantic web.

While methodological aspects are proposed later on (Section 3), this section aims to provide an overview of the central concepts. An in-depth exhaustive discussion is out of the scope of this paper.

2.1. Defining "Intelligence"

The definition of "intelligence" has historically been the object of discussion and controversy. While it is probably not possible to provide universally accepted formal definitions, it is interesting to look at the understanding of intelligence in the context of a more and more technology-intensive society. Looking intrinsically at intelligent systems, whose definition is also constantly evolving and may significantly vary depending on the context of use, this section addresses the concept of intelligence. While a comprehensive analysis is out of the scope of this paper, a clear understanding of the logical relationship existing between human and artificial intelligence to establish intelligent systems in the current socio-technological landscape is a critical aspect for hybrid solution engineering.

2.1.1. Human and Artificial Intelligence

Human (or natural) intelligence is normally associated with the ability to generate an abstracted mental model of a given reality and perform mental simulations accordingly. It underlays the common notions of thinking and reasoning [21], enabling human skills in terms of problem analysis/solving and decision making [22].

Although such considerations may be considered a common assumption, it is also well known that human intelligence goes beyond its "analytical" component to also embrace "emotional" intelligence [23], which is based on emotions (e.g., empathy) to enable a unique and strictly human way to behave, reason and decide, resulting from a mix of rational elements and "gut feelings" [24]. This more comprehensive understanding of intelligence plays a key role, given the increasing dehumanization within society, which is also pushed by technology [25].

There are at least two critical complementing considerations: on one side, all human beings have their own consciousness and unique ways of thinking [21]; on the other side, individuals belong to a social context, which affects the way reality is perceived and consequently the way people think. This naturally leads to the concept of "collective" intelligence [26], which puts emphasis on the added, if not determinant, value of collectivity to establish a level of intelligence higher than the correspondent to any individual. Collective intelligence becomes even more critical in the context of an always connected world with unprecedented interaction possibilities enabled by the evolution of the web [27] and social websites operating at a global scale [28].

Computers have intrinsically generated the idea of machines able to "reason" like humans. Indeed, Alan Turing, often considered the father of computer science, formulated the question "can machines think?", which led to the famous "Turing Test", where a human tries to distinguish between a computer and a human response in a conversation [29]. Since then, the intuitive concept of artificial intelligence has evolved in the scientific context and very many definitions have been provided. For instance, "AI is the science and engineering of making intelligent machines, especially intelligent computer programs" [30].

Given the huge availability of data and computational resources, the most recent advances in the field are producing an actual new generation of solutions, which are often converted to services or tools potentially available to the general public, such as the already cited ChatGPT. The main stakeholders are actively involved in a constant debate, with a mixture of excitement and concern. This is triggering different feeling and perceptions in the broader social context.

2.1.2. Hybrid Intelligence

As part of the ongoing debate, more and more questions are being raised. Among them, and because of a number of evident concerns are, *how are human and artificial intelligence going to co-exist?* and *how is such a "relationship" going to evolve in the future?*

An interesting (and also very intuitive) concept in this broader context is probably hybrid intelligence, which focuses on expanding the human intellect with AI, instead of replacing it [31]. The authors in [12] characterise hybrid intelligence through a comparative analysis.

This more recent understanding and definition of hybrid intelligence as a combination of human and machine intelligence also reflects an evolution of the concept. Indeed, that same term has been extensively adopted more or less informally in the last two decades to indicate the engineering of systems whose "intelligence" results from the combined application of more than one technology.

2.1.3. Intelligent Systems

The concept of intelligence is also extremely popular in the context of system engineering to address advanced capabilities of artificial intelligent systems to perceive and respond to the world around them. Integrated architectures [32] enable cutting-edge solutions to solve real-world problems by combining optimised techniques and features.

The apparent "simplicity" of the concept, both with the genericness common to the many existing definitions, actually hides an inherent complexity, due to the adaptive nature of intelligence and the underlying techniques to synthesise effective solutions. It normally advises a domain-specific approach, such as, among many, the classic applications in process engineering [33] or the relatively more novel ones in tourism [34]. Recent advances in machine learning [35] and related models (e.g., Ref. [36]) are quickly enabling a new generation of intelligent systems, whose potentialities are still largely unexploited and, in most cases, even unexplored.

2.2. Semantics, Ontology and Semantic Web

Born as the branch of metaphysics dealing with "the nature of being", ontology is a philosophical concept often associated with a formal conceptualization of a given domain. According to that same holistic approach, ontology became part of the computer world [13] to provide machine-processable conceptualizations.

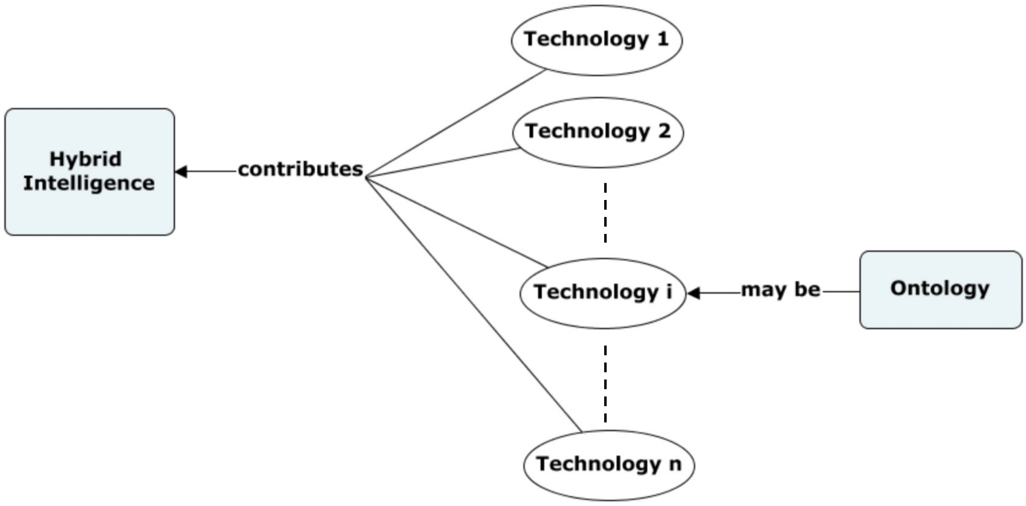
An ontology-based approach to knowledge representation allows one to specify "semantics" within computer systems and, indeed, ontology is a key asset within the semantic web [15] and its variants, such as in [37]. The semantic web adopts the web infrastructure and standard languages to formalise a common understanding of data and to achieve "intelligence" via interoperability and inference. Ontologies are extensively adopted in a wide range of domains and applications, and they also play a role in establishing advanced data ecosystems, such as open data [38] and linked data [39].

The primary application context for ontology is machine-to-machine interaction. However, through a proper knowledge engineering process, it is possible to assume a "shared" vision of a given knowledge for humans and machines. This can be further fostered by different kinds of abstractions and visualizations [40].

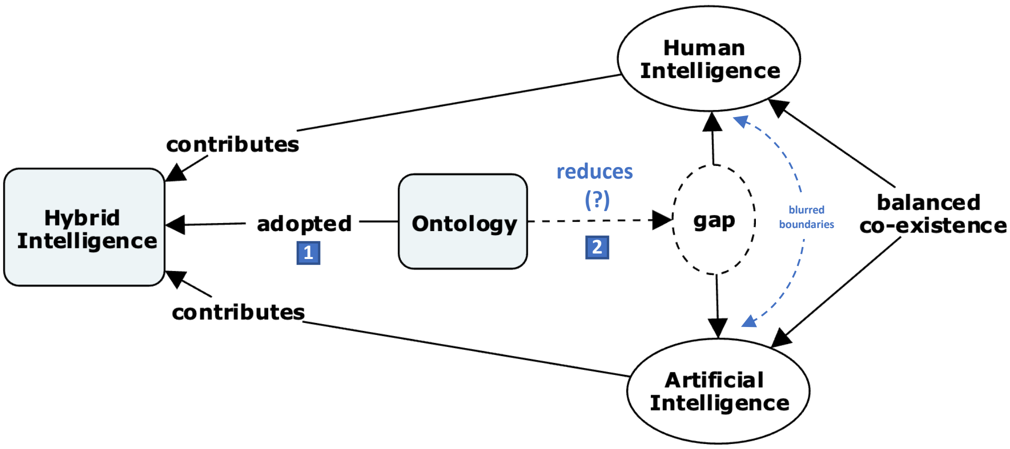
3. Methodology and Approach

This paper aims to provide (*i*) a concise and focused overview of the adoption of ontology in the broad context of hybrid intelligence and (*ii*) a critical discussion on the possible role of ontology to reduce the gap between human and artificial intelligence within hybrid-intelligent systems, as well as (*iii*) the identification of possible future research directions in the field.

A simplified conceptualization of the main objectives and scope by adopting an enriched conceptual map [41] is proposed in Figure 1b. The underlying idea assumes intelligence enabled in a heterogeneous context, either involving multiple technologies or a coexistence of human and artificial intelligence.



(**a**)



(**b**)

Figure 1. Conceptualization of the main objectives and scope of the review through the analysis of the HI concept evolution. (**a**) Historical common understanding of HI and related ontology role. (**b**) HI evolution with the proliferation of AI technology and related ontology role.

Because of the potentially broad scope, looking at that specific context, the literature review was conducted assuming the following selection criteria:

SC.1 Selected papers have an explicit focus on hybrid intelligence, regardless of its contextual definition.

SC.2 Selected papers explicitly address the role of ontology.

SC.3 The role of ontology is relevant in the context of the contribution, and its value can be identified.

While the search criteria have been designed accordingly to systematically retrieve papers which simultaneously contain the keywords "*Hybrid Intelligence*" and "*Ontology*", acceptance is based on a qualitative assessment by the author of the criteria *SC.1*, *SC.2* and *SC.3*. However, as ontology and hybrid intelligence can be indirectly referred to in different ways within the current technological context, the query has been extended to include possible common equivalent/strictly related concepts as follows:

```
(‘‘Hybrid Intelligence’’ OR ‘‘Hybrid Intelligent’’)
    AND
(‘‘Ontology’’ OR ‘‘Semantic Web’’)
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On the other hand, very generic keywords, such as "knowledge representation", have not been used for retrieval.

In order to further enhance a critical discussion in context, selected papers, wherever possible, are associated with a generic domain, or even with a more specific application. Additionally, as part of the adopted framework, the different contributions are classified depending on their focus (conceptual/theoretical or application-focused) and on the provided value in a given system. This light classification model contributes to generating a structured overview and a conceptualised analysis. On the other hand, classifications are arbitrary and may present some overlapping.

The combined application of the mentioned selection criteria results in a relatively restrictive retrieval strategy that significantly limits the number of papers that can be included in the literature review. In this specific case, this approach assures a focused discussion within a broad topic, mostly characterised by the blurred boundaries of hybrid intelligence.

A further level of analysis has been established by critically assessing the relevance of ontology in the different systems. The assessment framework aims to capture the main benefit(s) provided by the adoption of ontologies in a given context and assumes a classification based on three main categories (knowledge representation, automatic reasoning and other features). Such a simplified approach allows a reasonable classification based on the interpretation of the claims by authors, while a more fine-grained level of description could result as being unrealistic, especially for those papers that do not address details. Last but not least, the quantitative assessment in a range of 0–4 has been performed, looking holistically at the different systems to capture the effective relevance of ontologies in context. Intuitively, a value of 0 is associated with no contribution, 1 with supporting features, and 2 and 3 with relevant and very relevant functionalities, respectively.

4. Ontology in Hybrid Intelligence

An overview of the major contributions retrieved from the most common scientific databases is proposed in Tables 1 and 2, which report conceptual and application-focused papers, respectively. In order to provide a grounded discussion, they are addressed separately in the next two sub-sections.

4.1. A Conceptual Perspective

Table 1 reports the contributions in the literature that present a more theoretical/conceptual approach. Although they do not have a specific application-focus and should allow a certain generalization of the insight, where specified, the original domain/application is still reported.

In [42], the authors propose a design principle: "*Provide the Hybrid Intelligence DSS with an ontology-based representation to transfer an entrepreneur's assumptions and create a shared understanding among the mentors, the machine, and the entrepreneur*". Despite the domain/application-specific focus, the use of ontologies to create a shared understanding among all stakeholders (also including machines) can be applied in general terms.

Table 1. Overview of the selected contributions with a conceptual focus.

Contr.	Domain	Application	Focus	Value (Main)
[42]	Business	Decision Support System	Conceptual	Interoperability
[43]	N\A	N\A	Conceptual	Interoperability
[44]	N\A	N\A	Conceptual	Interoperability
[45]	Healthcare	Explainable models	Conceptual	Explainability
[31]	N\A	Explainable models	Conceptual	Explainability
[46]	Education	System Thinking	Conceptual	System Engineering
[47]	Smart Systems	Ambient Assisting Living	Conceptual	System Engineering
[48]	N\A	N\A	Conceptual	Explainability
[49]	N\A	Collective Intelligence	Conceptual	Quality and Accuracy
[50]	N\A	Knowledge Graph	Conceptual	Explainability
[51]	N\A	Collective Intelligence	Conceptual	Quality and Accuracy
[52]	N\A	N\A	Conceptual	Quality and Accuracy
[53]	N\A	N\A	Conceptual	System Engineering
[54]	N\A	N\A	Conceptual	System Engineering

Another principle assumes interoperability as one of the key factors behind the development of hybrid intelligence [43]. An effective machine-to-machine model to assure interoperability among different systems leads to a central role of ontologies to enable sophisticated approaches (semantic interoperability [55]). Additionally, also for interoperability, a multi-stakeholder vision fundamentally applies to real-world scenarios that typically involve machines and designers, subject matter experts and final users [44].

Looking at the current technological climate, one aspect of increasing interest is the potential role of ontology to reduce the fear of AI by pushing more intelligible explainable models [45,48]. This would enable more transparent and trusting environments for an effective co-existence of human and artificial intelligence, especially if considered with knowledge graphs [50]. Moreover, a wider perspective to the possible evolution of AI that implies an increasing convergence of data, such as AI 2.0 [49], is worthy of mention.

A relatively more classic contribution is in the engineering of systems adopting hybrid intelligence, where ontology can contribute to formalizing the specification of requirements [47]. This is in line with the typical benefits of ontology in the generic system [56]/software [57] engineering, as well as in the more specific field of requirement engineering [58]. Given the recent advancements in AI and the peculiarities of hybrid intelligence, the role of ontology throughout the design process could be remarkable (e.g., contributing to the formalization of problems [54]) and could also eventually provide a linkage to the different principles, such as ethics. In [46], the authors further extend the intent and the extent within system engineering by dealing with requirements and challenges and addresses the need for automatic reason.

Last but not least, ontologies may contribute to enabling and sustaining the quality of knowledge-based systems. For instance, argumentation can be adopted to address inconsistencies in knowledge bases [31].

Ref. [51] deals with the interesting concept of hybrid collective intelligence and the consequent need for knowledge convergence; in addition, [52] discusses the augmentation of hybrid intelligence by collaboration and cognition with the extensive use of semantic artefacts. In general terms, ontology-based models are extensively used in hybrid learning [53].

4.2. An Application Perspective

An overview of applications is summarised in Table 2. Such an application perspective shows a clear generic focus on knowledge representation.

Table 2. Overview of the selected contributions with an application focus.

Contr.	Domain	Application	Focus	Value (Main)
[59]	N\A	Blockchain	Application	Automatic Reasoning
[60]	Software	Programming	Application	Knowledge Representation
[61]	Agriculture	Recommender Systems	Application	Semantic Similarity
[62]	Security	Intrusion Detection/Prevention	Application	Modelling
[63]	Security	Critical Infrastructure Protection	Application	Information Standardization
[64]	Smart Systems	Assistive Technology	Application	Knowledge Representation
[65]	Healthcare	Drug Discovery	Application	Analysis
[66]	Management	Decision Support Systems	Application	Knowledge Representation
[67]	Business	Automated Enterprise Modeling	Application	Automated Reasoning
[68]	Healthcare	Decision Support Systems	Application	Knowledge Representation
[69]	Science	N\A	Application	Knowledge Representation
[70]	N\A	Data Integration	Application	Knowledge Representation
[71]	Business	Assistive Technology	Application	Semantic Similarity
[72]	Law	Text mining	Application	Knowledge Representation
[73]	N\A	Information Systems	Application	Knowledge Representation
[74]	N\A	Internet of Things	Application	Knowledge Representation
[75]	N\A	Multi-agent Systems	Application	Semantic Similarity
[76]	N\A	Data Analysis	Application	Knowledge Representation
[77]	Healthcare	Automated Learning	Application	Knowledge Representation
[78]	N\A	Multi-agent Systems	Application	Automated Reasoning
[79]	Smart Systems	Control Systems	Application	Knowledge Representation
[80]	N\A	Multi-agent Systems	Application	Semantic Similarity
[81]	N\A	Multi-agent Systems	Application	Knowledge Representation
[82]	Business	Multi-agent Systems	Application	Knowledge Representation
[83]	N\A	Multi-agent Systems	Application	Knowledge Representation
[84]	N\A	Multi-agent Systems	Application	Knowledge Representation
[85]	N\A	Multi-agent Systems	Application	Knowledge Representation
[86]	N\A	Multi-agent Systems	Application	Automated Reasoning
[87]	N\A	Decision Support Systems	Application	Knowledge re-use and Sharing
[88]	N\A	Data Mining	Application	Automated Reasoning
[89]	Healthcare	Recommender Systems	Application	Modelling
[90]	N\A	Information Systems	Application	Knowledge Representation
[91]	Agriculture	Control Systems	Application	Knowledge Representation
[92]	N\A	Collaborative Systems	Application	Knowledge Representation
[93]	Business	Recommender Systems	Application	Knowledge Representation
[94]	Software	Software Engineering	Application	Automated Reasoning
[95]	N\A	Data Mining	Application	Knowledge Representation
[96]	Manufacturing	Industry 4.0	Application	Knowledge Representation
[97]	Smart Systems	Energy Systems	Application	Knowledge Representation
[98]	N\A	Information Systems	Application	Knowledge Representation
[99]	Management	Decision Support Systems	Application	Knowledge Representation
[100]	Business	Business Intelligence	Application	Automated Reasoning

Indeed, knowledge representation is seen as an essential asset to trace the provenance of data and knowledge and to link the accountability of humans and machine-based agents [59]. Such a type of integrated approach is a major prerequisite to establishing trust in hybrid systems [59]. These generic considerations apply in a different way within concrete application domains (e.g., science [69]). For instance, in certain programming environments based on semantically enriched compound objects, "the confidence of users in making decisions is based on access to previous decisions of others, on quick perception and understanding these decisions and on their transformations leading to new models and algorithms" [60]. Additionally, the adoption of shared ontologies for different purposes, such as upper, domain, communication and state annotation, is a relatively established pattern [64].

Within the broad knowledge representation context, it is possible to define a set of more fine-grained capabilities. For instance, Ref. [61] proposes a model based on semantic similarity to generate a knowledge base in the field of agriculture from multiple sources. Solutions for agriculture are also proposed in [91]. Semantic similarity [75,80] and negotiation techniques [78,84] are considered in multi-agent systems. More in general, multi-agent systems extensively adopt ontology-based representations [81–83,85].

Ref. [62] adopts an ontological model for intrusion detection. The work proposed in [63] addresses the significant issues related to information standardization and ontology-based representation in the security domain, while in [65] the emphasis is on analysis.

In general terms, automation plays a key role in modern systems. For instance, Ref. [67] proposes an approach for automated enterprise modelling, ref. [86] presents a technique for component integration, ref. [70] approaches problems related to metadata management in data exchange and integration, while ref. [68] deals with the automated annotation and ontological mapping of clinical texts. Additionally, the system proposed in [79] has an explicit focus on automated control, and as [88,95] addresses hybrid-intelligent data mining.

In line with the more theoretical analysis previously proposed, the work presented in [66] focuses on the explanation of hybrid intelligence systems with an extensive use of semantic web technology, and the value of semantics in human–machine collaboration is highlighted in [71]. Semantic web technology is adopted to support hybrid systems in the law domain [72], within more generic information systems [73,90,98] and internet of things [74].

The system proposed in [76] adopts ontology to generate and classify vehicle driver profiles. Ontology matching is a central concept in the automated medical-learning approach proposed in [77].

Ref. [87] implicitly refers to hybrid intelligence and addresses the relevance of knowledge re-use and sharing.

Fuzzy-logic and ontological modelling are combined in [89] to implement sophisticated recommendations in healthcare. Solutions for recommendation systems are also the object of other works (e.g., Ref. [93]).

Ontology-based meta-modelling is adopted in [92] to support machine-to-machine as well as human–machine interaction. There are also remarkable applications in the areas of software engineering [94] and advanced manufacturing (e.g., Industry 4.0 [96]), energy systems [97], crisis management/prevention [99] and business intelligence [100].

5. Gap Identification and Challenges

This section aims to quantitatively and qualitatively analyse the identified body of knowledge and to critically discuss major gaps, with an outlook on challenges.

5.1. A Quantitative Analysis

The proposed analysis has been conducted on 56 different papers on the topic. As expected, most contributions (75%) present an application focus. However, the relatively consistent amount of more conceptual papers has provided significant insights (Section 5.2).

The classification by macro domain (Figure 2) is relatively distributed and does not allow the identification of major patterns or trends. Almost half of the papers cannot be clearly associated with a macro-domain. There is a prevalence of contributions in business (11%), healthcare (9%) and smart systems (7%).

Similar considerations also apply to a quantitative analysis by application (Figure 3), which presents a low percentage (13%) of unclassified papers and shows a major number of contributions in multi-agent systems (16%) and decision support systems (9%).

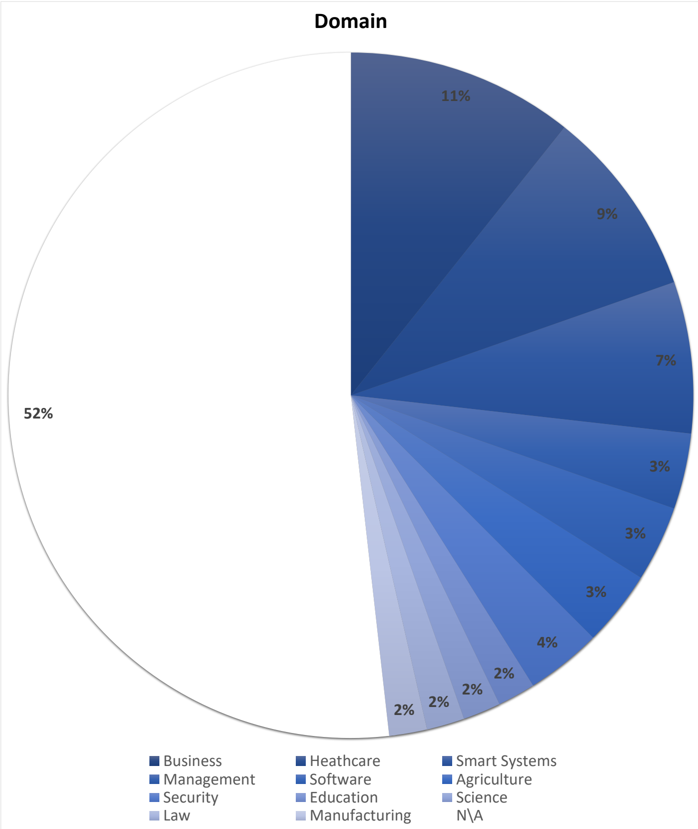

Figure 2. Quantitative analysis by macro-domain.

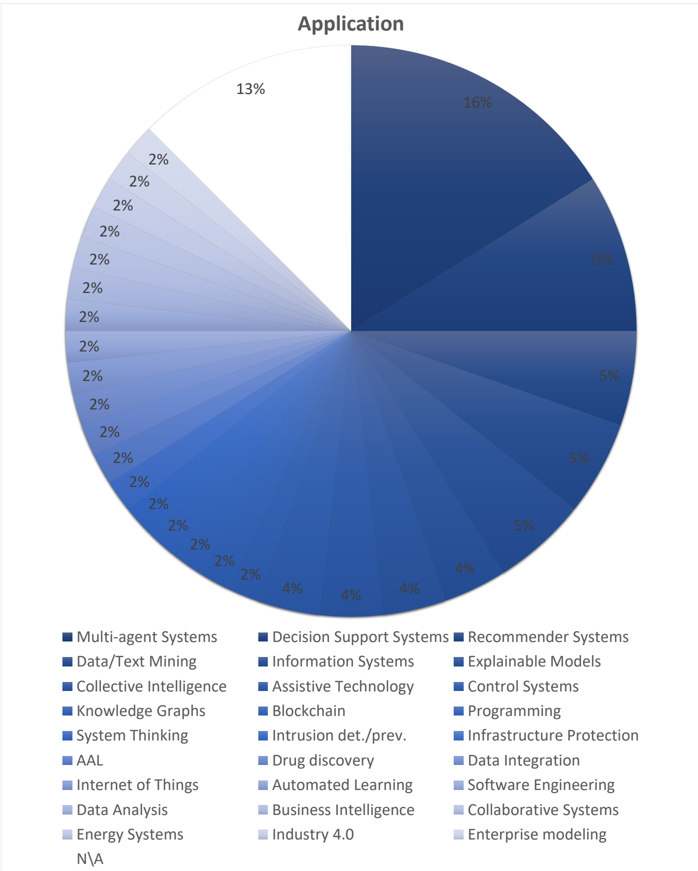

Figure 3. Quantitative analysis by application.

An analysis by "provided value" is reported in Figure 4. In quantitative terms, the papers' objects of analysis deal with the four different identified categories uniformly. Such contributions are discussed in qualitative terms later on in the paper. An application-oriented perspective points out a high number of works on generic knowledge representation, while there is much less explicit focus on other aspects, including automatic reasoning.

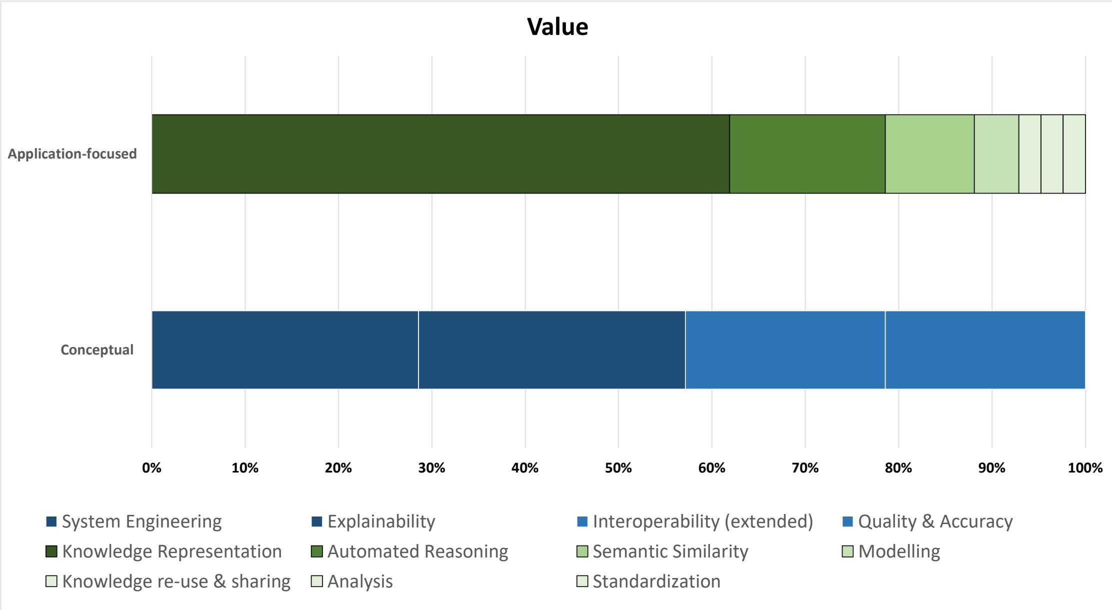

Figure 4. Quantitative analysis of the provided value from a conceptual and an application perspective.

5.2. A Qualitative Analysis

From a conceptual point of view, four key aspects have been identified as follows:

CP.1 *Interoperability as a key factor*. This includes interoperability among systems as well as a shared understanding between humans and machines. Interoperability is a concept classically associated with ontology. However, in the specific field of hybrid intelligence, there is a clear emphasis on human–machine interaction. This may have implications on knowledge engineering, as well as on the evolution of ontology-related technology.

CP.2 *Explainable and transparent models*. The use of ontologies to support some kind of intelligible synthesis of a given analysis or process is not an absolute novelty. For instance, knowledge graphs [101] are extensively adopted in several disciplines and applications and may be underpinned by formal ontologies to deal with the underlying complexity [40]. In most cases, such a presentation level is designed ad-hoc to optimally match the requirements within a system. Explainable and transparent models in AI (and hybrid AI) usually require a more systematic approach.

CP.3 *System Engineering*. The contribution of ontology within system/software engineering is well known and extensively documented in the literature. This review, conducted in the specific context of hybrid intelligence, has highlighted a potential extended and enhanced scope to include a linkage to different aspects, such as design and ethic principles and challenges.

CP.4 *Quality and Accuracy (including evolution)*. This last aspect has a less specific scope than the previous ones as it addresses the contributions of ontology to do "better". In practice, it may refer to support advanced functionalities and features or to drive the evolution of a system. A typical practical example that emerged from the conducted review is the collaborative approach which, in general terms, requires extended and more sophisticated semantics, as well as a certain level of interoperability. That is, normally, a value provided by ontologies.

A more extended qualitative analysis of applications aims to estimate the relevance of ontology in a given context. A summary is reported in Table 3. The relevance of knowledge representation, automated reasoning or other features has been informally evaluated without specific criteria independently for each pertinent system in order to support a more holistic assessment. In at least 70+% of cases, the role of ontology may be considered relevant or critical.

This evaluation is merely indicative and reflects a fundamental lack of detail about the semantic infrastructure and its actual role in many proposed systems.

Table 3. Assessment of the relevance of ontology within the considered systems.

Ontology Relevance				
Title	**KR**	**AR**	**Other**	**Overall**
Supporting Trust in Hybrid Intelligence Systems Using Blockchains [59]	•••	•••	-	•••
*Hybrid Intelligence Aspects of Programming in * AIDA Algorithmic Pictures* [60]	••	-	-	••
HIAS: Hybrid Intelligence Approach for Soil Classification and Recommendation of Crops [61]	•••	-	•••	••
Towards an Ontology-Based Intelligent Model for Intrusion Detection and Prevention [62]	•••	•••	-	•••
Hybint: A Hybrid Intelligence System for Critical Infrastructures Protection [63]	-	-	•	•
Hybrid Intelligence for Driver Assistance [64]	•	-	-	•
Stargazer: A Hybrid Intelligence Platform for Drug Target Prioritization and Digital Drug Repositioning using Streamlit [65]	-	-	•	•
Explaining Scientific and Technical Emergence Forecasting [66]	•	-	-	•
Automatic Generation of Conceptual Enterprise Models [67]	•	-	-	•
Assessing the Impact of Automated Suggestions on Decision Making: Domain Experts Mediate Model Errors but Take Less Initiative [68]	••	-	-	••
The Noosphere Paradigm of the Development of Science and Artificial Intelligence [69]	•••	-	-	•••
Combining OWL Ontology and Schema Annotations in Metadata Management [70]	•••	-	-	•••
Human–Machine Collaboration in Online Customer Service–A Long-Term Feedback-Based Approach [71]	•	-	•••	•••
The Text Fragment Extraction Module of the Hybrid-Intelligent Information System for Analysis of Judicial Practice of Arbitration Courts [72]	•••	-	-	•••
The hybrid-intelligent Information System Approach as the Basis for Cognitive Architecture [73]	•••	-	-	•••
The Social Web of Things (SWoT)-Structuring an Integrated Social Network for Human, Things and Services [74]	•••	-	-	•••
Similarity Measure of Agents' Ontologies in a Cohesive Hybrid-Intelligent Multi-Agent System [75]	••	-	•••	•••
Context Aware Ontology-Based Hybrid-Intelligent Framework for Vehicle Driver Categorization [76]	•••	-	-	•••
Hybrid-Intelligent Framework for Automated Medical Learning [77]	•••	-	-	•••
Agents' Ontologies Negotiation in Cohesive Hybrid-Intelligent Multi-Agent Systems [78]	••	••	-	•••
HVAC Control via Hybrid-Intelligent Systems [79]	•••	-	-	•••
Estimation of the Similarity of Agents' Goals in Cohesive Hybrid-Intelligent Multi-Agent System [80]	••	-	•••	•••
Cohesive Hybrid-Intelligent Multi-Agent System Architecture [81]	•	-	-	•
An Agent-Based Hybrid-Intelligent System for Financial Investment Planning [82]	•	-	-	•
Modeling Team Cohesion using Hybrid-Intelligent Multi-Agent Systems [83]	•	-	-	•
Ontology Support for Communicating Agents in Negotiation Processes [84]	•••	-	-	•••
Visualization of Team Cohesion in Hybrid-Intelligent Multi-Agent Systems [85]	•	-	-	•
Integration of Knowledge Components in Hybrid-Intelligent Control Systems [86]	•••	•••	-	•••

Table 3. *Cont.*

Ontology Relevance				
Title	**KR**	**AR**	**Other**	**Overall**
Using a CBR Approach based on Ontologies for Recommendation and Reuse of Knowledge Sharing in Decision Making [87]	• • •	-	• • •	• • •
Ontology—Guided Intelligent Data Mining Assistance: Combining Declarative and Procedural Knowledge [88]	•	••	• • •	••
A Hybrid Fuzzy-Ontology-Based Intelligent System to Determine Level of Severity and Treatment Recommendations for Benign Prostatic Hyperplasia [89]	• • •	•	• • •	• • •
Using a Hybrid-Intelligent Information System Approach for Text Question Generation [90]	•	-	-	•
A Hybrid-Intelligent Multiagent System for the Remote Control of Solar Farms [91]	• • •	••	-	• • •
Ontology-Based Meta-Model for Hybrid Collaborative Scheduling [92]	• • •	-	-	• • •
An Agent-Based Hybrid-Intelligent System for Financial Investment Planning [93]	•	-	-	•
A Generic Architecture for Hybrid-Intelligent Test Systems [94]	•	• • •	-	• • •
Constructing Hybrid-Intelligent Systems for Data Mining from Agent Perspectives [95]	•	-	-	•
Efficient Services in the Industry 4.0 and Intelligent Management Network [96]	• • •	••	-	• • •
A Fog-Based Hybrid-Intelligent System for Energy Saving in Smart Buildings [97]	•	-	-	•
DSS-Based Ontology Alignment in Solid Reference System Configuration [98]	• • •	-	-	• • •
Design and Conceptual Development of a Novel Hybrid-Intelligent Decision Support System Applied towards the Prevention and Early Detection of Forest Fires [99]	••	-	-	••
A Hybrid Reasoning Architecture for Business Intelligence Applications [100]	• • •	••	-	• • •

KR = Knowledge Representation, AR = Automatic Reasoning. (• • •) = critical, (••) = relevant, (•) = supporting.

5.3. Major Research Gaps

The literature review conducted has also allowed the identification and the consequent formulation of a number of research gaps as follows:

G.1 The understanding of hybrid intelligence in a specific context or system is not always explicitly defined but rather intuitive. This makes it hard to understand the effective relevance and role of ontologies within the broader system to solve a given problem or address a given challenge.

G.2 Many contributions address and empathise the added value provided by ontologies. However, there is often a fundamental lack of detail to support the corresponding claims.

G.3 The contribution of ontologies to achieve hybrid environments where human and artificial intelligence co-exist and co-operate is not fully addressed, although the review has highlighted a relevant insight at a conceptual level.

G.4 An implicit role of ontologies as an interface between humans and machines in hybrid systems emerged from the conducted literature review. However, looking at existing solutions, the actual potential seems largely unexplored, especially at an application level.

G.5 Lack of focus on automatic reasoning and inference.

G.6 Lack of focus on ontological modelling. It reflect a fundamental lack of big picture, meaning that within certain systems ontologies are seen within specific components rather than at a more holistic level.

5.4. Towards a Principled Approach

The HI definition in very generic terms is intuitive and somehow consolidated, even in the context of the current AI mainstream. A further consolidation step from a conceptual perspective is to establish a reasonable set of principles to characterise hybrid-intelligent technology.

A preliminary critical analysis performed in the context of this review has led to the definition of three principles, as follows:

P.1 Human input is determinant to generate a solution.

P.2 Automated solutions are not acceptable solutions to final users.

P.3 Rules/conditions to keep the system as hybrid are identified.

That same analysis has allowed the identification of a number of open issues at a conceptual level, as reported in Table 4. In the table, each question is associated with a relevant aspect, a brief rationale, a link with identified principles and the potential/expected contribution of ontology. According to this holistic analysis framework, the proposed principles mostly cover the definition of HI in an application context, while ontology is expected to contribute mainly to engineering aspects by facilitating a better integration between human and machine capabilities, to acceptance through more transparent models and to exploitation by contributing to the generation of dynamic frameworks. On the other hand, as briefly discussed in previous sections, an assessment of the evolution of HI in response to advancements in AI is probably unrealistic.

Table 4. Open questions on HI from a conceptual perspective.

Open Question	Aspect	Rationale	Principle	Ontology
When can a system be considered to be hybrid intelligent?	***Definition***	Certain HI-based implementations could be AI solution de facto	P.1, P.2, P.3	-
How to fully exploit the potentiality of AI within HI solutions?	***Engineering***	An effective engineering of HI solutions is a critical issue	-	✓
Would such a type of technology be "accepted"?	***Acceptance***	It could be perceived as a kind of "downgrade" from AI	-	✓
How to identify critical applications?	***Exploitation***	Criteria may vary very much from case to case and HI is not always applicable	-	✓
How will HI evolve?	***Evolution***	A more and more advanced AI technology could need a constant re-focus and re-engineering of HI solutions	-	-

5.5. Future Research Directions

The previously conducted analysis has highlighted significant research gaps at different levels. Indeed, the theoretical gap identified within the current body of knowledge mirrors a significant knowledge gap, due to the intrinsically evolving nature of intelligent systems. Looking at this specific aspect, additional research is needed to consolidate such knowledge in context and to bridge the corresponding gap (practical knowledge) accordingly. Ontologies could be one of the key factors to enable effective implementations for modern hybrid solutions. However, there is still a fundamental lack of experimental evidence that suggests the need for deeper and more specific research in the field considering the intrinsic contextual gaps that are currently preventing more systematic approaches.

The different research lines across hybrid system development and ontology-based solutions should progressively facilitate an alignment with the last AI generation and associated applications. However, additional research efforts are needed to maximise the value of hybrid intelligence and develop convergent solutions that are effective and competitive in the modern business world. This requires re-thinking through more holistic research and the definition of more specific methodologies to address peculiarities, straights/weaknesses, as well as principles and ethical frameworks.

6. Conclusions

In the context of constant evolution and proliferation of AI technology, hybrid intelligence is gaining popularity to refer a balanced coexistence between human and artificial intelligence. That same concept has often been used in the recent past to define a model of intelligence resulting from multiple technologies.

By adopting a soft methodology, this paper proposes a literature review that aims to provide (*i*) a concise and focused overview of the adoption of ontology in the broad context of hybrid intelligence regardless of its definition and (*ii*) a critical discussion on the possible role of ontology to reduce the gap between human and artificial intelligence within hybrid-intelligent systems.

Alongside the typical benefits provided by an effective use of ontologies, at a conceptual level the analysis conducted has highlighted a significant contribution to quality and accuracy, as well as a more specific role to enable extended interoperability, system engineering and explainable/transparent systems. On the other hand, an application-oriented analysis has shown a significant role in present systems (70+% of cases) and, potentially, in future systems.

At a more holistic and conceptual level, ontology is expected to contribute to better engineering, as well as to the acceptance and exploitation of hybrid-intelligent technology.

As extensively discussed in the paper, the concept of hybrid intelligence is evolving to meet the requirements of a new generation of systems that may present blurred boundaries. A proper holistic discussion on the establishment of the next generation of hybrid-intelligent environments with a balanced co-existence of human and artificial intelligence is fundamentally missed in the literature, as is the consequent analysis on the role of ontology. Additional research efforts are required to maximise the value of hybrid systems within a business world and to re-think hybrid solutions, looking at the constantly evolving socio-technological landscape.

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