## Using AI to Understand Intelligence: The Search for a Catalog of Intelligence Capabilities

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Abstract. Artificial Intelligence (AI) algorithms permeate many of the systems and devices we interact with in everyday life. Since its conception as a field, a wide variety of these intelligent algorithms have sought to simulate or even surpass human cognitive abilities and behavior. However, there is as yet no widely accepted definition of what intelligence in machines means, nor of human intelligence. The primary goal of this paper is to propose an *intelligence vocabulary* or *catalog* in the quest for the boundaries that shape the current discourse of the experts on intelligence. The idea is to provide and inform researchers, practitioners, journalists, and policymakers, among many others, with a terminology that can be used when defining intelligence. Considering these challenges, we analyze the data from hundreds of experts around the world, provided when they were asked to give both their opinions on existing definitions of intelligence in the scientific literature and their own suggested definitions. All of the answers that were gathered (despite being subjective views) were evaluated using stateof-the-art text analytics processing and AI mechanisms. This ensures objectivity and allows us to extend (or even reproduce) the study in the future. Ultimately, our work contributes to strengthen the bridge between human and automatic reasoning: we examine experts' opinions on definitions of human and machine intelligence with both manual and automatic methods. Some linguistic tasks like normalizing and clustering the opinions are performed automatically, thereby the twofold goal being to find an overview and to enable a drill-down to the most interesting answers. These individual artefacts are then interpreted manually. We hope that the proposed intelligence vocabulary will not only contribute to defining (machine) intelligence better but also to an understanding of both the current views of experts on intelligence and intelligence itself. This would help to frame a common language around AI, which has unfortunately been absent thus far. In the future, extending the procedure presented in this paper might lead to an interdisciplinary machine-assisted method for extracting knowledge from subjective opinions.

Keywords: Intelligence  $\cdot$  Human intelligence  $\cdot$  Machine intelligence  $\cdot$  NLP  $\cdot$  Intelligence catalog.

## **1** Introduction

Over the last 100 or so years, the concept of intelligence has been defined on numerous different occasions and in different fields, both formally and informally. There are many informal definitions of both human and machine or artificial intelligence (AI). For example, Legg and Hutter [11] collected 71 definitions that were divided into three broad categories: *collective definitions, psychologists' definitions*, and *AI researchers' definitions*. Despite many attempts and suggestions, there is still no generally accepted definition of intelligence. Defining intelligence has been a rather controversial topic in the AI community, and this is one of the fundamental problems that has remained unsolved since the creation of the field. It is also a perceived stumbling block to the pursuit of understanding intelligence and building machines that replicate and exceed human intelligence, as addressed by Brooks [4]. In their study more than 25 years later, Wollowski et al. [27] outlined a stark difference of opinion with respect to the definition of AI. Very little has changed since, and this gap is further reflected in a recent research study on defining intelligence [19].

Several works have tried to characterize and structure the field of AI. For example, researchers at Elsevier [6] have applied text mining and machine learning techniques for this purpose. The authors first identified meaningful concepts and then extracted field-specific keywords from relevant and non-relevant AI publications that reflect four *perspectives* on AI: how it is taught, researched, talked about in the media, and described in patents. As a result, a diverse *AI vocabulary* was created and then used to shape AI subfields and areas of research. The authors wondered, however, about the greater divergence than commonality that arises when comparing the four perspectives, and noted that the absence of a common language around AI was a missing piece for a wide-ranging understanding.

This was not the first time that the evolution of AI as a discipline had been the focus of research. In [15], relevant AI publications were investigated, and information was drawn from two leading AI conferences and around 50 years of documents from the AAAI's AITopics database on research, people, and applications of AI.<sup>4</sup> Martínez-Plumed et al. propose a framework for defining this field that consists of nine facets (or intersections between multiple dimensions), such that those that help to characterize the functionality of AI systems, their generalizability when solving problems, and the paradigm or approach used, among others. By plotting the relevance of field-specific words (although these were limited to substrings appearing in titles, abstracts, keywords, and conference topics), the authors analyzed AI past trends and theorized about its future. Other authors have also used AI to analyze and track the development of specific AI areas, such as deep learning [10], and even to predict the decline in their popularity [9]. A more ambitious initiative even aimed to create an atlas or map of intelligence [3] that allowed for the categorization, specification, comparison, and experimental reproduction not only of artificial intelligent systems but also of other kinds of intelligence.

However, although there has been a recent and growing interest in characterizing, structuring and tracking the evolution of AI in particular and of intelligent systems in

<sup>&</sup>lt;sup>4</sup> See https://aitopics.org/ for more.

general, there has been very little research on finding a common language around intelligence and AI. The two-fold purpose of this paper is therefore to use AI to understand intelligence and to help to frame a common language around defining it. To reach these goals, we apply various AI techniques to extract the most representative verbs, nouns, adjectives, and adjective-noun phrases contained in experts' opinions that might indicate cognitive and behavioral abilities (or capabilities) that could be used when defining intelligence.

#### 1.1 Data and Relevance of the Study

Our research starts with the analysis of two data sources: respondents' *written opinions* to the AGISI research survey "Defining (machine) Intelligence" [19] to justify their level of agreement with definitions of human and machine intelligence from the literature; and respondents' *suggested definitions* of human and machine intelligence, i.e. new suggestions for defining intelligence. Both these data sources and the definitions from the literature that were provided in the survey were made available by the survey's authors.

The diversity of opinions that were collected reflects the current vastly mixed landscape of research, development and theory in AI. Most of the respondents to the survey were AI experts with several years of experience in the field, and an overwhelming majority were explicitly invited to participate in the survey due to their research in AI or intelligence-related areas. They originated from 57 different countries and more than 184 institutions around the world. They worked mainly in academia (N=441, 79.3%) and industry (N=114, 20.5%), and had primary roles as researchers (N=424, 76.3%) and/or educators (N=193, 34.7%). This was the first time that such a contemporary collection of opinions on and new suggested definitions of human and machine intelligence had been gathered.

A thorough analysis of this information could have a significant impact on the AI field for several reasons. Firstly, to obtain clarity around defining intelligence (and AI as a field), we must consider experts' opinions and the current debate on AI. Definitions of intelligence (and especially machine intelligence) should not rely solely on published content, since the scientific literature does not fully reflect the evolving dynamics of the field. Shaping the boundaries of the current scientific discourse is necessary, and thus is important for the advancement of the field.

Secondly, there is no consensus definition of AI, let alone of intelligence; this is primarily because the former has evolved with a *fluid* definition due to the varied human conceptions of the latter [15]. Furthermore, the interdisciplinary nature of the field may conspire against the possibility of a consensus definition [14]. This has both positive and negative implications; as mentioned in [23], "the lack of a precise, universally accepted definition of AI probably has helped the field to grow, blossom, and advance at an ever-accelerating pace." However, there are several pressing reasons for coming to a consensus definition that can help to tackle the various well-known limitations on the development of the field, such as the poor public knowledge and understanding of AI [20] and the often misleading media coverage that generates misconceptions about what is and what is not AI [1,5,13,22], to name only a few. An examination of experts'

opinions and suggested definitions may contribute to better insights into intelligence and to a wider understanding of the current discourse on AI.

Thirdly, it matters *how* and *by whom* the AI field is defined [15]. There is no monolithic approach to the development of AI, although this has historically been concentrated on a few actors worldwide. The current AI landscape shows not only uneven progress within and among a variety of application domains [6,23] but also different interests and research focus together with different perceptions of how and by whom AI is being developed. This also directly affects how AI is being defined; sounded experts' opinions are simply a reflection of the key cultural, societal, and technological differences driving AI.

Due to the overwhelming response rate to the survey, a manual analysis of the data was difficult. We therefore decided to apply AI techniques ourselves, and to use text mining to analyze the results. The following sections describe in more detail how these techniques were applied to extract and analyze the experts' opinions on and their new suggested definitions of intelligence, as introduced above. As a result of this work, an intelligence catalog that includes cognitive and behavioral capabilities is proposed that can be considered when defining intelligence, and this forms the main contribution of this work. With this, we hope to contribute to a common language around both intelligence and AI.

## 2 Data Pre-Processing

Two corpora were created: the first consisted of 4,041 experts' opinions, of which 2,424 were on definitions of machine intelligence (*MI*) and 1,617 on definitions of human intelligence (*HI*) from the literature; the second consisted of 338 new, suggested definitions of intelligence, of which 213 were suggested for machine intelligence and 125 for human intelligence. The easiest way to look at the data in these corpora was by applying simple text analytics techniques for gathering information about the number of words that are used, together with their frequency of occurrence, the number of sentences and so on. The corpus of opinions, for example, contains more than 71,000 words. This work would be very exhausting to do manually, and the separation of verbs, nouns, and other parts of the speech into unigrams, bigrams, etc. for later processing would be very difficult and time-consuming. Other techniques and algorithms should therefore be used instead.

Our pre-processing of the data from the corpora consisted of the following phases and steps (see Figure 1):

**Data preparation:** First, the raw data from the survey was converted into a format ready for further processing. Then, all personal information about the survey participants (like name, age, ethnicity, institution, email, etc.), available in separate fields, was removed.

**Cleaning:** The data was cleaned. For example, opinions containing a URL as only content were deleted. Some intelligence-specific words might be losing their significance if they are not spell checked or have grammatical errors in their occurrences. Thus, a spelling and grammar check was carried out.

**Natural Language Processing (NLP):** Part-of-speech (POS) tagging was performed. This allows for the identification of verbs, adjectives, nouns, etc. in a sentence according to their meaning and context. Other techniques that were applied in this phase included tokenization and lemmatization. Stop words and unimportant characters like non-printable characters and emojis were also removed.

**Analysis:** This phase comprises the following steps: i) *Statistical analysis:* Word clouds, heat maps and histograms were generated, among other graphics, together with some general statistics. This allowed for an initial understanding of the data and the subsequent inclusion of other analyses; ii) *Unsupervised learning:* We used a slight modification of topic modeling, aggregating the content written by individual authors and using these documents as basis. We refer to these as data-driven persona models; iii) *Semantic analysis:* A word embedding was created and trained to convert words to vectors. This is useful for finding semantic relations between definitions of intelligence, respondents' opinions, etc. We started with a simple bag-of-words model and refined it using TF-IDF to penalize frequent words with little distinction quality. To obtain a better understanding of the semantics, we analyzed both unigrams and bigrams.

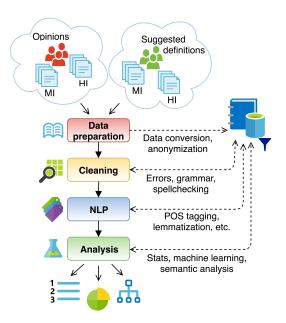


Fig. 1: Pre-processing phases and steps in analyzing the corpora of intelligence data.

Our analysis pipeline depended mainly on open source software. Data preparation was carried out with Pandas (https://pandas.pydata.org), and for cleaning we used GNU Aspell (http://aspell.net). NLP was carried out using spaCy (https://spacy.io) and we chose scikit-learn (https://scikit-learn.org) for machine learning and topic modeling. Semantics were extracted using word2vec [17], especially to detect *phrases*, what worked well despite the very domain-specific, small vocabulary. Even though the dataset is not very large, the vocabulary is highly repetitive which makes word2vec a suitable technology. We also used Jupyter notebooks (https://jupyter.org) as an integration platform.<sup>5</sup>

## **3** Data Analysis

Our initial approach to interpreting the data consisted of the analysis of 18 word clouds created in the final phase of the pre-processing. They included the most common verbs, nouns, adjectives, and adjective-noun combinations used in the *experts' opinions* on definitions of human and machine intelligence from the literature, the most common verbs used in opinions about the three *most agreed upon definitions* of human intelligence (Gottfredson's [8], Anastasi's [2], and Wechsler's [25]) and machine intelligence (Wang's [24], Winston's [26], and Legg and Hutter's [11]), and the most common words used in *all new, suggested definitions* of human and machine intelligence.

#### 3.1 Most used Verbs when Defining Intelligence

Intelligent capabilities are mostly described in ostensive and operational ways, i.e. by exemplifying and using the cognitive and behavioral characteristics of humans, agents, or intelligent systems in general that denote or are important in achieving intelligence [7]. Verbs are often used to denote which these intelligent capabilities should be. Figure 2 shows the word clouds for the verbs in the experts' opinions on definitions of human and machine intelligence from the literature, and in their new, suggested definitions, as created in the pre-processing phase.

A first analysis of these verb word clouds indicates the presence of two types of verbs used by experts in their arguments for or against existing definitions and in their suggested definitions: not only verbs that exemplify intelligent capabilities, such as *think, anticipate*, and *feel*, but also those that complement respondents' written speech when justifying their opinions, such as *define, agree*, and *include*. The former are important in constructing a catalog of intelligence. Furthermore, the verbs used in the suggested definitions shape the current discourse on intelligence, whilst those used when criticizing definitions from the literature may refer to issues that are no longer relevant or that should not be considered when defining intelligence.

It is worthwhile to analyze in depth those definitions for which the level of agreement was positive, and thus less polarized. Although comments expressing positive agreement were many fewer than those expressing disagreement [18], and "[a] good argument is an argument that is not refuted" [16], we expected that they would contain words that both supported the positive opinion of their authors and indicated what should be considered when defining intelligence, rather than what should not.

<sup>&</sup>lt;sup>5</sup> The source code and data are available upon request.

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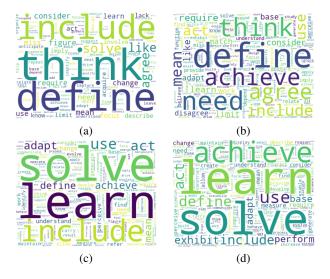


Fig. 2: Verb word clouds for (a) all opinions on the definitions of human and (b) machine intelligence from the literature, and for the new, suggested definitions of (c) human and (d) machine intelligence.

A closer look at the verbs used in the comments on the most agreed-upon definitions shows a similar trend. Again, two types of verbs can clearly be identified. The process of constructing the catalog of intelligence should identify only those verbs that denote cognitive and behavioral capabilities. This is not a task that can be automated easily, however, and depends heavily on the context. There are sometimes verbs that could be of both types, such as *define*: compare "*The goal is to define intelligence easily*" to "*An agent can define its own goals*." In the latter example, there is a cognitive capability that could denote intelligence. This would mean that the data pre-processing and application of NLP techniques in conjunction with visualization using word clouds can provide "the first filter," but the remainder would mostly depend on human work.

#### 3.2 Most used Adjectives and Adjective-Noun Bigrams

Other words besides verbs can indicate cognitive and behavioral capabilities that denote intelligence, for example adjective and nouns. We analyzed the most commonly used adjectives and their combinations with nouns for all of the experts' comments on definitions of intelligence from the literature and for their suggested definitions in the corpora. Again, the most frequently used words included the two types discussed above: those that could be used when constructing the catalog of intelligence, and those used to complement the respondents' written speech. For example, the adjectives *cognitive*, *rational*, and *adaptive* may be related to properties of intelligence, but *vague*, *fuzzy*, and *restrictive* may form part of a negative opinion on a concrete definition that is being criticized. A property of intelligence should not be vague, although a definition may be

vague. This distinction is more evident in the adjective-noun phrases, since bigrams give more information about the context than unigrams. Furthermore, adjectives and nouns arise in respondents' opinions for or against definitions from the literature that are used to qualify those definitions (for example *good*, *narrow*, *general definition*) and that are not used at all in the respondents' new, suggested definitions of intelligence. Thus, the parts of speech from the latter can better contribute to a catalog of intelligence.

### 3.3 Measuring Similarity Between Experts' Opinions

Figure 3 shows a heat map of the similarities between the opinions given by respondents to the definitions of human (top left side) and machine (bottom right side) intelligence, in descending order of similarity in each category. The higher the similarity values (i.e. closer to 1), the more similar the level of agreement between two definitions. The similarity values were calculated using the cosine similarity measure of summed TF-IDF vectors. These vectors give information on the frequency of the words used by respondents in their opinions against their importance with respect to the other opinions in the corpus. No other similarity measures were considered at this stage; further work could include an extended comparison to other methods.

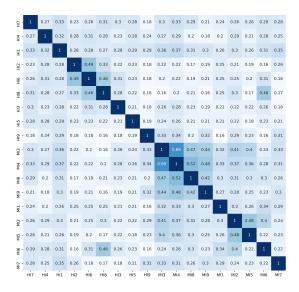


Fig. 3: Heat map of the cosine similarities between experts' opinions. The x- and y-axis use the order of perceived similarity between definitions.

There is a remarkable low similarity in the opinions on definitions of machine intelligence and those given for human intelligence. The similarities between the arguments that were given to justify the level of agreement with definitions of machine intelligence (lower right-hand side) are much more evident (have higher values) than when they are compared to human intelligence (lower values in the top right and lower left quadrants). Correspondingly, the similarities between the opinions given for definitions of human intelligence (top left-hand side) are similar to each other but not to the opinions given for machine intelligence (except for HI8 and MI6). Once again, this confirms the findings in [12] and supports the need for two separate definitions of machine and human intelligence: it is clear that we view, understand, react to, and judge these differently. In other words, a definition of intelligence may need to differentiate between machine and human intelligence. Furthermore, the heat map shows that the arguments provided by respondents to justify their level of agreement with definition MI7 (Russell and Norvig's [21] definition of machine intelligence) are the least similar to other comments, i.e. the similarity values to other opinions are the lowest on average (see the last column and last row of the heat map). Since this definition was both the most commented on and second least accepted definition overall, a possible explanation for these low similarity values may be that the polarized comments contain "special" information about what should not be considered when defining intelligence that the other comments do not include. This may have an explanation that is consistent with results from argumentative theory: "When participants want to prove a conclusion wrong, they will find ways to falsify it [...] If they disagree with [the conclusion], they try to prove it wrong" [16], i.e. by providing counterexamples that falsify the wrong conclusion. In this case, we expect that the counterexamples use a (different) vocabulary that contradicts the conclusion.

# 3.4 Measuring Similarity Between Experts' Opinions and Their Suggested Definitions of Intelligence

Figure 4 shows a heat map of the similarities between the experts' opinions and their new, suggested definitions of machine and human intelligence; the higher the similarity values, the more similar the terminology used in the opinions on the definitions in the literature to the new, suggested definitions. As can be interpreted from the figure, the respondents tended to (re-)define both machine and human intelligence using much of the same terminology (and thus intelligent capabilities) that was used when commenting on definitions of *machine* intelligence from the literature (see the higher similarity values on the left-hand side). However, the vocabulary used in their opinions on the definitions of human intelligence was much less often used in their suggestions for new definitions (see lower similarity values on the right-hand side). In other words, the suggested definitions of both machine and human intelligence seem to require much of the same vocabulary that was previously used to subjectively evaluate definitions of machine intelligence from the research literature. This may be another reason for supporting two separate definitions of intelligence. We note that 41.9% of the respondents to the research survey on defining intelligence supported the need for only one definition, in contrast to 48.2% who preferred two separate definitions, as concluded in [19].

Interestingly, the new, suggested definitions of human intelligence used a vocabulary that was very similar to that used to comment on the definitions of machine intelligence that *were not* the most agreed upon. Three of the four highest similarity values

(see the darker colors at the top left-hand side of Figure 4) corresponded to opinions given on the definitions of machine intelligence that were not the most agreed upon.<sup>6</sup>



Fig. 4: Heat map of the cosine similarities between experts' opinions (horizontal axis) and their new, suggested definitions of intelligence (vertical axis).

#### 3.5 Analyzing Other Variables

The question arose as to whether the ratings given by experts, i.e. their level of agreement with the definitions of intelligence from the literature, were correlated with the number of words they wrote in their opinions. However, these were not correlated, i.e. a significant relationship between the length of the opinions and the level of agreement was not observed. Due to space constraints, detailed results are not include here. The interested reader can receive more information about the concrete calculations upon request.

Does the vocabulary used in the opinions depend on respondents' years of experience in the field? To answer this question, we again aggregated the TF-IDF vectors, but this time for respondents with similar numbers of years of experience. It turns out that novices with less than five years of experience and experts used a similar vocabulary.<sup>7</sup> The same is true for respondents with a considerable amount of experience. However,

<sup>&</sup>lt;sup>6</sup> The most agreed upon were MI3 [24], MI1 [26], and MI2 [11], in that order.

<sup>&</sup>lt;sup>7</sup> Respondents without experience in AI used a different vocabulary and were viewed as outliers.

the similarity values decreased with the level of experience in the field. One possible explanation is that greater expertise not only means a deepened knowledge of AI but also a wider knowledge of other fields, which may enrich the experts' point of view. This may empower the use of a more sophisticated, distinctive or selective vocabulary that occasionally also contributes to the discourse with new terminology. We can surmise that experts not only have knowledge that goes beyond others' grasp, but that they also use it actively to produce new information, in this case opinions on definitions of intelligence from the scientific literature.

## 4 Intelligence Vocabulary or Catalog

The intelligence catalog was created with the most representative verbs, nouns, adjectives, and adjective-noun phrases (i.e. bigrams) that were extracted after applying text mining and machine learning techniques, and the analysis introduced above. They were manually filtered out from the top 100 occurrences of each word type after considering the techniques presented in this paper. These extracted words help us to distinguish the boundaries of the discourse around definitions of intelligence from the scientific literature and to shape the current experts' view around how intelligence should be defined instead. Figure 5 shows the main categories and subcategories of the intelligence catalog and Table 1 shows a list with the most common words that were extracted. For example, the top five verbs that are related to the internal processing of the intelligent entity are *learn*, *solve*, *achieve*, *adapt*, and *understand*, in this order. The more general categories are a suggestion from the authors and relate to their expert knowledge in the intelligent agents and multi-agent systems domains (i.e. they are not extracted automatically nor any ontology engineering is used, yet).

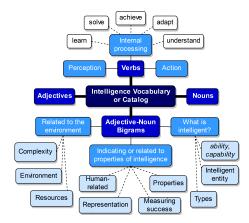


Fig. 5: Intelligence vocabulary or catalog: categories and subcategories for the corpus of experts' suggested definitions.

Verbs related to perception	(with at least five occurrences)	:			
perceive [19]	acquire [7]	recognize [5]			
Verbs related to the internal	l processing of the intelligent e	ntity (top 15 and with at leas	t five occurrences):		
learn [54]	adapt [26]	improve [14]	evolve [10]	think [9]	explain [5]
solve [52]	understand [20]	generate [14]	reason [9]	plan [6]	predict [5]
achieve [37]	find [15]	maintain [13]			
Verbs related to action (top	10 and with at least five occurr	ences):			
act [32]	exhibit [17]	behave [9]	interact [7]	execute [5]	respond [5]
change [20]	perform [15]	pursue [8]	communicate [7]		
Nouns (top 30):					
machine [284]	system [82]	information [45]	reasoning [34]	learning [29]	context [23]
ability [146]	behavior [77]	time [42]	agent [34]	capacity [28]	situation [23]
human [96]	capability [60]	action [36]	world [32]	decision [28]	range [22]
environment [96]	knowledge [55]	process [35]	experience [30]	reason [27]	domain [21]
goal [96]	problem [54]	task [34]	artificial [30]	resource [24]	entity [21]
Adjectives (top 30):					
human [183]	wide [21]	real [18]	specific [12]	effective [11]	mental [9]
cognitive [32]	physical [21]	computational [17]	limited [12]	optimal [11]	right [8]
general [24]	complex [20]	social [15]	available [12]	adaptive [10]	possible [8]
artificial [24]	good [19]	rational [14]	capable [11]	evolutionary [10]	autonomous [7]
high [22]	broad [18]	natural [14]	useful [11]	efficient [9]	biological [7]
Bigrams indicating or relate	ed to properties of intelligence:				
Properties:					
prior knowledge [5]	future behavior [3]	adaptive behavior [3]	previous experience [3]	common sense [2]	
social interaction [4]	autonomous behavior [2]				
Measuring success:					
right thing [4]	right time [3]	efficient plan [2]	effective goal [2]	useful action [2]	
meaningful existence [4]	ongoing success [2]				
Representation:					
own goal [7]	short goal [3]	new solution [3]	heuristic approach [3]	current state [2]	inner narrative [2
Human-related:					
human level [15]	human being [10]	human condition [6]	human observer [3]	natural language [3]	
Bigrams related to the envir	ronment, thus external to the int	telligent entity:			
Environment:					
real time [11] Complexity:	real world [4]	natural world [3]	physical world [2]		
complex problem [4]	new situation [3]	different situation [3]	recurrent situation [3]	complex dimension [2]	
complex problem [4] complex environment [3]	unknown situation [2]	and on situation [5]	recurrent situation [5]	complex unichsion [2]	
Availability of resources:	anknown anuauon [2]				
wide range [12]	limited resource [5]	wide variety [4]	sensory information [4]	available resource [3]	
broad range [6]	limited information [3]	wide variety [4]	sensory mornation [4]	available resource [5]	
What is intelligent?					
Types of intelligence:					
human intelligence [22]	artificial intelligence [17]	general intelligence [9]	high intelligence [3]		
Intelligent entity:	5	0 11			
intelligent behavior [11]	intelligent machine [9]	machine intelligent [8]	intelligent system [7]	system intelligent [4]	artificial agent [2
ability, capability:					
cognitive capability [6]	cognitive process [4]	cognitive ability [3]	human capability [3]	broad capability [2]	

Table 1: *Intelligence vocabulary or catalog*: top words extracted from the corpus of experts' suggested definitions that may be considered when defining intelligence. The words are ordered based on their frequency; some of them could be related to more than one category.

## 5 Conclusions

The findings presented in this paper clearly suggest that the current discourse on intelligence (and on AI) requires a deeper analysis of how intelligence is defined. This should be the first step in understanding intelligence. The aim of the present study was therefore to use AI in helping to frame a common language around AI and intelligence by analyzing thousands of experts' opinions on definitions from the scientific literature and their new, suggested definitions of intelligence. As a result, an intelligence vocabulary is suggested that could be used when defining intelligence.

The possible uses of such a vocabulary are many. For example, it could be used by lecturers when introducing the concept of (machine) intelligence in their courses; or by researchers when defining the goals of their artificial intelligence-related research; or by journalists when reporting scientific results in the neurosciences, psychology, or AI fields, to name a few; or by policy makers, lawyers, and ethicists when delineating recommendations and regulations on how to design, deploy, and use intelligent systems, because for regulating something, that something must be well-defined. In short, we are of the opinion that the intelligence vocabulary could be essential when developing a common language around AI and intelligence.

A wider discussion remains open, however, and it includes questions such as: to what degree can the resulting capabilities be considered properties of intelligence? Which capabilities or parts of the intelligence catalog are related to which specific areas from the AI field? Is there any distinction between capabilities that relate only to humans or only to machine or non-human intelligence? The intelligence vocabulary offers one of several initial approaches to these questions, but further research is needed before we can achieve a common language around AI and a satisfactory understanding of what intelligence is.

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