

UNIVERSIDADE TECNOLÓGICA FEDERAL DO PARANÁ

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**SEMANTIC-RELATED CHALLENGES IN COMPUTATIONAL
INTELLIGENCE: A TRANSDISCIPLINARY APPROACH**

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**SEMANTIC-RELATED CHALLENGES IN COMPUTATIONAL
INTELLIGENCE: A TRANSDISCIPLINARY APPROACH**

**Desafios relacionados à semântica na inteligência computacional:
uma abordagem transdisciplinar**

Tese apresentada como requisito para obtenção do título (grau) de Doutor em Ciências, do Programa de Pós-Graduação em Engenharia Elétrica e Informática Industrial, da Universidade Tecnológica Federal do Paraná (UTFPR).

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CURITIBA

2023



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TIAGO BUATIM NION DA SILVEIRA

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Trabalho de pesquisa de doutorado apresentado como requisito para obtenção do título de Doutor Em Ciências da Universidade Tecnológica Federal do Paraná (UTFPR). Área de concentração: Engenharia De Computação.

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“No puede ser, pero es. El número de páginas de este libro es exactamente infinito. Ninguna es la primera; ninguna la última. No sé por qué están numeradas de ese modo arbitrario. Acaso para dar a entender que los términos de una serie infinita admiten cualquier número.”

—Jorge Luis Borges, *El Libro de Arena*

RESUMO

DA SILVEIRA, Tiago Buatim Nion. **Desafios relacionados à semântica na inteligência computacional: uma abordagem transdisciplinar**. 2023. 171 f. Tese (Doutorado em Engenharia Elétrica e Informática Industrial) – Universidade Tecnológica Federal do Paraná. Curitiba, 2023.

Nesta tese são identificados e abordados os desafios semânticos em inteligência computacional, especialmente aqueles relacionados ao processamento de linguagem natural e à visão computacional, conhecidos como *gap semântico*. Partindo da hipótese de que a atribuição semântica é um comportamento inteligente, e considerando que o termo inteligência é utilizado sob diferentes perspectivas na psicologia e na computação, foi realizada uma extensa pesquisa através da qual identificou-se que não há consenso para inteligência. Para atender a esta necessidade, foi proposto uma definição abrangente de inteligência, formalizada como a capacidade de um agente autônomo de processar informações externas e internas para obter uma adaptação ótima ao ambiente. Esta definição se aplica a qualquer agente, para o qual se propõe a categorização em agentes inteligentes humanos, artificiais e biológicos. Nesta tese, o modelo de inteligência CHC é citado como o padrão-ouro em estudos de inteligência e avaliação psicológica. Sua aplicação na área computacional, porém, é ainda desafiadora. Sendo assim, foram caracterizados os seus 83 fatores em 5 aspectos da inteligência: recursos formais, semânticos, contextuais, sociais ou afetivos, e de processamento. O foco passa a ser, então, apenas a inteligência semântica, a qual foi abordada a partir de uma perspectiva transdisciplinar. O desafio de tal abordagem é que diferentes áreas possuem diferentes bases epistêmicas, o que foi superado ao ser proposta a análise paradigmática: a identificação de estudos e teorias em três grupos de paradigmas relacionados à semântica: ontológicos, sobre a natureza do significado e que pode ser objetivo ou subjetivo; de medição, sobre a observação do significado, que pode ser determinístico ou inferencial; e computacional, sobre a decisão ou atribuição de significado, que pode ser lógico-formal ou baseada no processamento de informações. Usando esta metodologia, foi explorado e categorizado de forma abrangente as teorias relacionadas à semântica da linguística e da psicologia. A organização do conhecimento entre estas áreas é uma das principais contribuições desta tese, trazendo novas perspectivas para a pesquisa semântica. Consequentemente, conclui-se que nem todos os paradigmas podem representar o conteúdo semântico de outra forma que não parcialmente. Sendo assim, foi proposto um modelo formal de atribuição semântica, no qual o conteúdo semântico é decomposto em seus componentes objetivo, subjetivo e contextual. Este modelo é verificado por meio de uma análise fatorial das Normas de Glasgow — um corpus que relaciona palavras a diferentes variáveis psicolinguísticas. Utilizando estes fatores, foi proposta uma análise e classificação do conteúdo semântico. Por fim, ofereceu-se uma reinterpretação do *gap semântico*, frequentemente encontrado em tarefas de inteligência computacional. Tal reinterpretação foi realizada por meio da análise paradigmática dos estudos pesquisados e da análise dos parâmetros ontológicos que influenciam a semântica, em um experimento explorando a pareidolia. A tese conclui propondo uma nova definição para o *gap semântico* sustentada no modelo formal desenvolvido para a semântica.

Palavras-chave: Atribuição semântica. Inteligência. Gap Semântico. Conteúdo semântico. Semântica.

ABSTRACT

DA SILVEIRA, Tiago Buatim Nion. **Semantic-related challenges in computational intelligence: a transdisciplinary approach**. 2023. 171 p. Thesis (Doctorate in Computer Engineering) – Universidade Tecnológica Federal do Paraná. Curitiba, 2023.

In this thesis, we identify and address semantic challenges in computational intelligence, especially those in natural language processing and computer vision, known as the semantic gap. Starting from the hypothesis that semantic attribution is intelligent behavior and that the term intelligence is used from different perspectives in psychology and computing, we carried out in-depth research through which we identified that there is no consensus for intelligence, even in the same area. To meet this need, we proposed a comprehensive definition of intelligence, formalized as the ability of an autonomous agent to process external and internal information to obtain optimal environmental adaptation. This definition applies to any agent, for which we propose categorization into human, artificial, and biological intelligent agents. In our review, the CHC model of intelligence is cited as the gold standard in intelligence studies and psychological assessment. However, its application in the computational area is challenging. Furthermore, we categorized its 83 factors into five aspects of intelligence: formal, semantic, contextual, social or affective, and processing resources. Our focus then becomes only semantic intelligence, which we approach from a transdisciplinary perspective. The challenge of such an approach is that different areas have different epistemic bases, which we overcome by proposing paradigmatic analysis: the identification of studies and theories in three groups of paradigms related to semantics: ontological, about the nature of meaning and which can be objective or subjective; of measurement, on the observation of meaning, which can be deterministic or inferential; and computational, about the decision or attribution of meaning, which can be formal-logical or based on information processing. We comprehensively explore and categorize semantics-related theories from linguistics and psychology using this methodology. The organization of knowledge between these fields is one of the main contributions of this thesis, bringing new perspectives to semantic research. Consequently, we found that not all paradigms can represent semantic content other than partially. In this way, we proposed a formal model of semantic attribution, in which the semantic content is decomposed into its objective, subjective, and contextual components. The proposed model is verified through a factor analysis of the Glasgow Norms – a corpus that relates words to different psycholinguistic variables. Using these factors, we proposed a semantic content analysis and classification. Finally, we offer a reinterpretation of the semantic gap, often found in computational intelligence tasks. Such reinterpretation was carried out through the paradigmatic analysis of the studies researched and the analysis of the ontological parameters that influence semantics through pareidolia. The thesis concludes by proposing a new definition for the semantic gap sustained in the formal model developed for semantics.

Keywords: Semantic attribution. Intelligence. Semantic gap. Semantic content. Semantics.

LIST OF ALGORITHMS

Algorithm 1 – Semantic Attribution Process by an agent a	104
Algorithm 2 – Exploratory Factor Analysis (EFA).	108

LIST OF FIGURES

Figure 1 – Semantic attribution process and its related issues. Circles represent agents, while diamonds (\diamond) represent the agents' private semantic representation. The dashed line represents H.1's motor pathways to the drawing action; the continuous lines represent the perception of the object's properties by the agents' sensory inputs.	19
Figure 2 – Organization of language as a set of phonological, syntactic, and conceptual rules (semantics) with their related structures.	23
Figure 3 – The main NLP applications according to their purpose category.	24
Figure 4 – NLP pipeline for semantic-related applications.	25
Figure 5 – Taxonomy of the state of the art DNN models applied to contextual understanding.	29
Figure 6 – GPT architecture.	30
Figure 7 – Timeline of the main evaluation metrics for NLP tasks: Text Summarization, Machine Translation, Document Similarity, Image Captioning, Video Captioning, and Text Generation.	30
Figure 8 – Frequency of occurrence in books, from 1940 to 2019, of the terms <i>natural language processing</i> (in green), <i>image retrieval</i> (in red) and <i>semantic gap</i> (in blue). The frequency of occurrence of the last term has a $10\times$ gain so as to appear in the frequency range as the other terms.	32
Figure 9 – Examples of deceived deep learning in medical applications: a perturbation on the input image or an image rotation leads to wrong prediction.	36
Figure 10 – Attack on Attention (AoA): the image of a salamander on the left is correctly identified by all considered DNN. After the AoA, the resulting image on the right leads to a classification error in all the DNNs tested.	37
Figure 11 – Number of publications in each research area from 1966 to 2021. Data obtained from WoS search query for "semantic AND intelligence." Computer science and engineering lead, followed by psychology and neurosciences, then distributed along different applications. Some documents can be attributed to more than one category.	41
Figure 12 – Co-occurrence network for the author's keywords from WoS _{DB1200} dataset.	43
Figure 13 – Sources coupling analysis: Higher coupling values indicate that publications from these sources share references at a given level.	45
Figure 14 – Diagram of a model-based, utility-based agent. An intelligent agent perceives its environment through sensors and acts in this environment through actuators in a way that maximizes its utility.	48
Figure 15 – Relationship between biological (B), artificial (A), and computational (C) organizations of neural networks (NN), pattern recognition (PR), and intelligence (I).	48
Figure 16 – CHC theory of intelligence. Strata I represents the narrow abilities, as defined and detailed in (SCHNEIDER; MCGREW, 2012). Strata II represents the broad abilities, grouped by (FLANAGAN; DIXON, 2014) in reasoning (Gf), acquired knowledge (Gc, Gkn, Gq, Grw), memory and efficiency (Gsm, Glr), sensory (Gv, Ga, Go, Gh), motor (Gp, Gk), and speed and efficiency (Gs, Gt, Gps). Strata III represents the factor <i>g</i> of general intelligence.	55

Figure 17 – Subtests composing the instruments for intelligence assessment based on the Wechsler scale, including the Wechsler Adult Intelligence Scale-Fourth Edition (WAIS-IV) and the Wechsler Intelligence Scale for Children-Fourth Edition (WISC-IV). Adapted from (WEISS <i>et al.</i> , 2006).	57
Figure 18 – Semantic attribution relates to fields of study supported by different paradigms.	70
Figure 19 – Categorization of the main semantic-related paradigms.	71
Figure 20 – Semantic-related theories in linguistics can be distinguished into two main groups: formal theories and cognitive theories. The former is generally supported by objective and formal-logical paradigms, while subjective and information processing paradigms support the latter.	81
Figure 21 – Semantic-related theories in psychology and their respective paradigms.	87
Figure 22 – Freudian representation scheme: the word presentations are associated with the object presentations through a secondary process, i.e., not directly associated with the sensory inputs.	91
Figure 23 – Psychometry is a sub-area of psychology sustained by theories and axioms from mathematics and statistics, which settles it in the information processing and probabilistic paradigms. The main epistemological basis and theories of psychometry only differ in the ontological paradigm.	95
Figure 24 – Underlying paradigms for semantics: the semantic content has objective, subjective, and contextual portions, each supported by other distinct paradigms. The dashed lines indicate that the same paradigm can be applied to different ontological perspectives.	98
Figure 25 – Scree plot for the exploratory factor analysis with 8 psycholinguistic dimensions. Factors with eigenvalues lower than 1.0 are not recommended for selection.	109
Figure 26 – Orthogonal and oblique factor rotation for exploratory factor analysis.	109
Figure 27 – Points relating to the top-50 and bottom-50 words with the highest and lowest scores in F_Objectivity, F_Subjectivity, and F_Context factors, respectively.	111
Figure 28 – Distribution of F_Objectivity and F_Subjectivity for the Glasgow Norms corpus.	112
Figure 29 – Semantic Component Analysis: classification of semantic content in quadrants generated by the medians of the plane formed by F_Objectivity and F_Subjectivity.	113
Figure 30 – Semantic component analysis of words related to child and childhood activities.	114
Figure 31 – Semantic component analysis of words related to suffering-pleasure in bodily and psychic aspects.	114
Figure 32 – Error between relatedness score (normalized_score) from SICK database and similarity score calculated via SpaCy (similarity_STD).	120
Figure 33 – Randomly selected pairs of images from the original dataset with illusory faces through pareidolia (images <i>a, c, e, g, i, k</i>) and their corresponding matched objects (images <i>b, d, f, h, j, l</i>).	126

LIST OF TABLES

Table 1 – Summary of studies exploring semantic-related issues in CI surveyed in this work.	32
Table 1 – Summary of studies exploring semantic-related issues in CI surveyed in this work.	33
Table 2 – WoS results for "semantic AND intelligence" search query. The research areas were grouped into technology, cognitive science, and application.	42
Table 3 – Most relevant sources from WoS query and its classification according to the technology, cognitive science, and application categories. PSD stands for “Publication in the Sampled Data”. PQD stands for “Publication in the Queried Data”.	46
Table 4 – Intelligence definitions from computational intelligence and their respective authors. Intelligence scope can be general (G), open-domain (OD), or specific-domain (SD). The modeling approach can be information processing (IP), formal-logical (FL), factor-analytical (FA), interactionist (INT), instrumentalist (INS), or skill-based (SB). The measurement approach can be performance metrics (PM), psychometric (PSY), or observational (OBS). Related applications are detailed for each author.	60
Table 5 – Intelligence definitions from psychology and their respective authors. Intelligence scope can be general (G), open-domain (OD), or specific-domain (SD). The modeling approach can be information processing (IP), formal-logical (FL), factor-analytical (FA), interactionist (INT), instrumentalist (INS), or skill-based (SB). The measurement approach can be performance metrics (PM), psychometric (PSY), or observational (OBS). Related applications are detailed for each author.	61
Table 6 – Relationship of the five aspects of intelligence with the CHC model. Each CHC factor (Stratum II) has <i>n</i> Stratum I items. The value of each proposed aspect indicates its correlation with the CHC factor.	67
Table 7 – Categorization criteria for paradigms. Each study surveyed is categorized into 4 levels according to these criteria.	80
Table 8 – Psycholinguistic dimensions rated in the Glasgow Norms dataset.	106
Table 9 – Descriptive statistics of the psycholinguistic dimensions of Glasgow Norms.	106
Table 10 – Distribution of VAL and DOM variables after transformation via smooth customized scaler.	107
Table 11 – Factor loadings for EFA. Values > 0.5 highlighted in orange, values < -0.5 highlighted in red.	110
Table 12 – Calculated factor variance for EFA.	110
Table 13 – Analysis of F_Objectivity and F_Subjectivity scores for polysemous words 'charge' and 'club' with their contextual distinctions. SCA_id refers to the word index in the SCA dataset.	116
Table 14 – Model performance summary of the Semantic Content Classifier.	118
Table 15 – Model performance summary of the enhanced Semantic Content Classifier.	119
Table 16 – Analysis of semantic content categories and their impact on error rates and similarity scores.	121

Table 17 – Categorization of the main paradigms underlying each reviewed study, ordered by publication year. The acronyms stand for (SD) semantic definition; (EC) empirical comparison; (DM) decision-making; (CV) computer vision; (NLP) natural language processing; (O) objective paradigm; (S) subjective paradigm; (D) deterministic paradigm; (FI) frequentist inference paradigm; (BI) Bayesian inference paradigm; (FL) formal-logical paradigm; (IP) information processing paradigm. The adherence of each study to a given paradigm is indicated on a scale from 0 to 4, according to the criteria presented in Table 7.	123
Table 18 – Experiment with pareidolia: number of faces and objects detected by HIA and AIA on illusory and matched objects images, respectively. Data synthesized from Appendix D.	125
Table 19 – Top 50 words with the highest score in F_Objectivity factor.	159
Table 20 – Top 50 words with the highest score in F_Subjectivity factor.	160
Table 21 – Top 50 words with the highest score in F_Context factor.	161
Table 22 – Bottom 50 words with the lowest score in F_Objectivity factor.	162
Table 23 – Bottom 50 words with the lowest score in F_Subjectivity factor.	163
Table 24 – Bottom 50 words with the lowest score in F_Context factor.	164
Table 25 – Responses and face detection by intelligent agents for the illusory images set . The Image ID corresponds to those of Figure 33. VS stands for Vision Studio.	170
Table 26 – Responses and face detection by intelligent agents for the matched objects set . The Image ID corresponds to those of Figure 33. VS stands for Vision Studio.	171

LIST OF ACRONYMS

AGI	Artificial General Intelligence
AI	Artificial Intelligence
AIA	Artificial Intelligent Agents
AoA	Attack of Attention
BIA	Biological Intelligent Agents
BoW	Bag of Words
CAPA	Computer-Assisted Psychological Assessment
CFA	Confirmatory Factor Analysis
CHC	Cattel-Horn-Carroll
CI	Computational Intelligence
CIQ	Control Intelligence Quotient
CMIR	Cross-Modal Image Retrieval
CTT	Classical Test Theory
CV	Computer Vision
DL	Deep Learning
DM	Decision-Making
DNN	Deep Neural Networks
EFA	Exploratory Factor Analysis
EQCA	Expert Questionnaire on Cognitive Ability
FNN	Feedforward Neural Network
FSIQ	Full-Scale IQ
GloVe	Global Vectors
GPT	Generative Pre-training Transformer
HAL	Hyperspace Analogue to Language
HIA	Human Intelligent Agents
HIQ	Human Intelligence Quotient
I	Intelligence
i.i.d.	independent and identically distributed
IQ	Intelligence Quotient
IRT	Item Response Theory
KMO	Kayser-Meyer-Olkin Test
LLM	Large Language Models
LSTM	Long-Short Term Memory

MAD	Median Absolute Deviation
MIQ	Machine Intelligence Quotient
ML	Machine Learning
MLP	Multi-Layer Perceptron
NLG	Natural Language Generation
NLP	Natural Language Processing
NLU	Natural Language Understanding
NN	Neural Networks
PIQ	Performance IQ
POS	Part-of-Speech
PR	Pattern Recognition
PRI	Perceptual Reasoning Index
PSI	Processing Speed Index
RNN	Recurrent Neural Network
SCA	Semantic Component Analysis
SCC	Semantic Component Classifier
USE	Universal Sentence Encoder
VCI	Verbal Comprehension Index
VIQ	Verbal IQ
WAIS	Wechsler Adult Intelligence Scale
WISC	Wechsler Intelligence Scale for Children
WISC-V	Wechsler Intelligence Scale for Children - 5th Edition
WMI	Working Memory Index
WoS	Web of Science

CONTENTS

1	INTRODUCTION	17
1.1	SEMANTIC ATTRIBUTION	18
1.2	RESEARCH HYPOTHESIS AND OBJECTIVES	20
1.3	THESIS STRUCTURE	21
2	SEMANTIC-RELATED WORKS	22
2.1	A BRIEF INTRODUCTION FOR SEMANTICS	22
2.2	COMPUTATIONAL MODELS FOR SEMANTIC APPLICATIONS	23
2.2.1	Pre-Processing	25
2.2.2	Representation or feature extraction	26
2.2.3	NLP Modeling	28
2.2.4	NLP Evaluation	29
2.3	SEMANTIC-RELATED CHALLENGES IN CI	31
2.3.1	Semantic gap	31
2.3.2	Deceived deep learning models	35
2.3.3	AI hallucinations	37
2.3.4	Other semantic issues	38
3	AN INTELLIGENCE-CENTRIC PERSPECTIVE OF SEMANTICS	40
3.1	EXPLORATORY DATA ANALYSIS	41
3.1.1	Conceptual analysis	42
3.1.2	Contextual analysis	44
3.2	A JOINT PERSPECTIVE FOR INTELLIGENCE	45
3.2.1	Definitions from computational intelligence	47
3.2.2	Definitions from psychology	49
3.2.3	Intelligence measurement	54
3.2.3.1	Intelligence measurement in computational intelligence	54
3.2.3.2	Intelligence measurement in psychology	56
3.2.3.3	Intelligence measurement between humans and artificial systems	58
3.2.4	There is no consensus for intelligence	60
3.3	A PROPOSAL FOR A BROADER DEFINITION OF INTELLIGENCE	63
3.3.1	Categories of intelligent agents	64
3.3.2	Categories of intelligence	65
3.4	CONTRIBUTIONS FROM THIS CHAPTER	66
4	A TRANSDISCIPLINARY APPROACH FOR SEMANTICS	69
4.1	EPISTEMIC PERSPECTIVES ON SEMANTICS	70
4.1.1	Epistemological preamble	71
4.1.2	Ontological paradigms	72
4.1.3	Measurement paradigms	73
4.1.3.1	Probabilistic approach	73
4.1.3.2	Deterministic approach	74
4.1.4	Computational paradigms	75
4.1.4.1	Formal-logical paradigm	75
4.1.4.2	Information processing paradigm	77

4.1.5	A proposal of criteria for a paradigmatic analysis	79
4.2	SEMANTICS AND THE PARADIGMS OF LINGUISTIC THEORIES	79
4.2.1	Formal Theories	81
4.2.2	Cognitive Theories	85
4.3	SEMANTICS AND THE PARADIGMS OF PSYCHOLOGICAL THE- ORIES	87
4.3.1	Classical Theories	88
4.3.2	Behavioral Theories	89
4.3.3	Psychodynamics and representations	90
4.3.4	Cognitive Theories	92
4.3.5	Psychometry and semantic evaluation	94
4.4	AN APPROPRIATE SETTING OF PARADIGMS FOR SEMANTICS	96
4.5	CONTRIBUTIONS FROM THIS CHAPTER	99
5	A PROPOSAL FOR MEASURING SEMANTICS OBJECTIVELY . . .	100
5.1	A FORMAL MODEL FOR SEMANTIC ATTRIBUTION	100
5.2	UNPACKING THE SEMANTIC CONTENT DIMENSIONS	104
5.2.1	Psycholinguistic dimensions	104
5.2.2	Factor analysis of semantic dimensions	107
5.2.3	Semantic Component Analysis (SCA)	111
5.2.4	Applying SCA to sequences of words	113
5.3	A SEMANTIC CONTENT CLASSIFIER	115
5.3.1	Word embedding-based classifier	115
5.3.2	General classifier based on Universal Sentence Encoder	118
5.3.3	Consistency of the Semantic Content Classifier	119
5.4	A REINTERPRETATION OF THE SEMANTIC GAP	121
5.4.1	Paradigmatic analysis of the semantic gap studies	122
5.4.2	Observing the semantic gap through pareidolia	125
5.4.3	Proposing a new definition for the semantic gap	128
5.5	CONTRIBUTIONS FROM THIS CHAPTER	128
6	CONTRIBUTIONS AND FUTURE WORK	130
6.1	RESEARCH CONTRIBUTIONS	130
6.2	FUTURE WORKS	132
	REFERENCES	135
	APPENDIX	152
	APPENDIX A – CHATGPT-3.5 PROMPT	153
	APPENDIX B – WORDS WITH HIGHEST FACTOR SCORES	159
	APPENDIX C – SEMANTIC CONTENT CLASSIFIER MODELS	165
	APPENDIX D – RESULTS OF THE EXPERIMENT WITH PAREI- DOLIA	170

1 INTRODUCTION

Der liebe Gott steckt im detail.

The devil is in the details.

God is in the details.

—Popular sayings

The upwelling of Artificial Intelligence (AI) dates back to the mid-twentieth century and has even contributed to the rise of cognitive sciences (RUSSELL; NORVIG, 2010). Still, only at the beginning of this century terms such as neural networks, machine learning, and deep learning became popular and strongly associated with Computational Intelligence (CI).

Despite all the excellence of these technologies in applications such as electronic games (YANNAKAKIS; TOGELIUS, 2015) and autonomous cars (JO; SUNWOO, 2014), to mention just a few, the CI developers have been faced with a recurring challenge when dealing with applications that seek to emulate human cognitive behavior, such as Computer Vision (CV), Natural Language Processing (NLP), and decision-making under uncertainty or with affective bias.

The difficulty of computationally addressing a meaning to an image, word, or action – namely, semantic attribution – has been demonstrated in several works where trivial methods can fool trained deep learning models by adding a stick to an image or adding white noise to an audio (HEAVEN, 2019). Recent studies have evidenced that more elaborated techniques, such as adversarial networks, can be used to fool trained CI models (WIYATNO *et al.*, 2019).

It is worth noting that semantic attribution is usually pointed out as a secondary, or even implicit, process of their respective main functions: CV seeks to emulate human vision in tasks such as object recognition and categorization. In contrast, in NLP, the main tasks seek to automate the translation, generation, and understanding of natural language.

Nevertheless, we must remember that semantic attribution and natural language are, in general, human phenomena. To enable them in computational agents, it seems necessary to investigate such phenomena in the light of linguistics – an area of knowledge that seeks to characterize the nature of semantics and the structure of natural language – and of psychology – an area that, in turn, strive to understand the mechanisms by which humans acquire, process, and understand natural language (ANDERSON, 2009).

On the other hand, the role of CI is to emulate or simulate the semantic attribution

process in computational or artificial agents according to the needs and possibilities of cutting-edge technologies. Thus, the performance of CI applications related to semantics is proportional to the completeness and validity of the models employed to explain or generate those phenomena.

This thesis points to the need to explore the problem of semantic attribution crossing the borders of a single area of knowledge. Such a transdisciplinary¹ approach settles semantic attribution as the intersection between computational intelligence, linguistics, and psychology. However, even though these fields of knowledge share semantics as an object of study and application, they are not supported by the same epistemological assumptions – which challenge the proper use of the scientific method and hinder the cross-fertilization between these areas.

In this chapter, we introduce the semantic attribution problem in Section 1.1. Based on this, we delineate in Section 1.2 the research hypothesis and objectives we sought to fulfill in this thesis. An overview of how this thesis is structured is presented in Section 1.3.

1.1 SEMANTIC ATTRIBUTION

To illustrate the semantic attribution process, we will use a simple adaptation of *Pictionary* – a word guessing game created by Robert Angel². In this game, participants endeavor to guess the word or phrase conveyed by a teammate’s drawing. As pointed out by Thøgersen (2012), it is important to note that the translation of a word into an image can vary among different players, introducing an element of unpredictability or uncertainty. Consequently, the accurate assignment of meaning plays a pivotal role in determining the game’s outcome, with victory going to the player who successfully interprets the drawings with the highest precision.

To align with the objectives of our research, we will expand upon the traditional setup involving two human players (H.1 and H.2) by introducing a third participant: a computational intelligence application (C.1). The task assigned to C.1 mirrors that of human player H.2 – namely, the accurate interpretation of the visual representation created by H.1. In other words, it must effectively ascribe semantics to the object represented in the drawing, matching the intended meaning of H.1.

¹ Alvargonzalez (2011) distinguishes the terms multidisciplinary, interdisciplinarity, and transdisciplinarity as follows. Multidisciplinary is referred to as the “knowledge from different disciplines” that “stays within the boundaries of those fields.” Interdisciplinarity stands for analyzing, synthesizing, and harmonizing knowledge “between different disciplines into a coordinated and coherent whole.” Lastly, “transdisciplinarity integrates the natural, social, and health sciences in a humanities context, and in doing so transcends each of their traditional boundaries.”

² For a detailed overview of the game, refer to <https://en.wikipedia.org/wiki/Pictionary>.

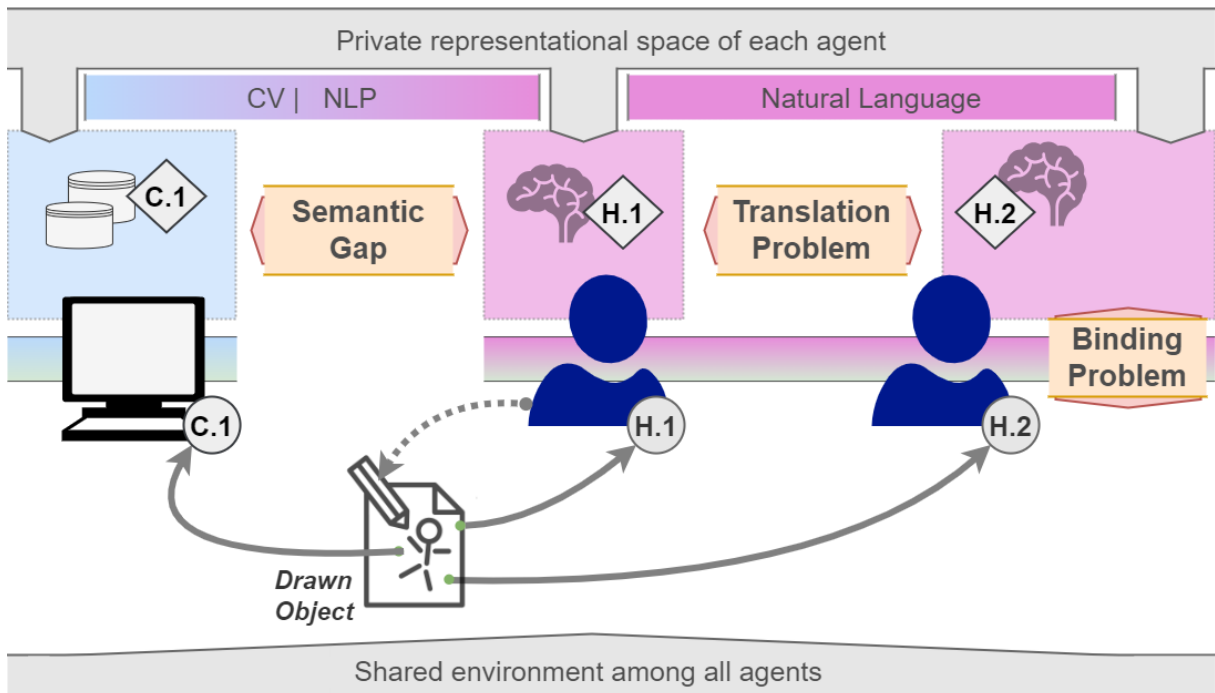


Figure 1 – Semantic attribution process and its related issues. Circles represent agents, while diamonds (◇) represent the agents' private semantic representation. The dashed line represents H.1's motor pathways to the drawing action; the continuous lines represent the perception of the object's properties by the agents' sensory inputs.

Source: Created by the author.

This scenario is visually depicted in Figure 1 and serves as a foundational context for the theoretical frameworks explored in this thesis. Starting with a private conceptualization of the subject to be depicted, human player H.1 translates their mental representation onto a sheet of paper placed on an environment shared by all agents involved. This process unfolds through motor pathways responsible for executing the drawing action, as illustrated by the dashed line in Figure 1.

The object – i.e., the drawing – possesses inherent, objective, and quantifiable attributes that agents perceive through their sensory inputs. These sensory inputs are depicted in Figure 1 and represented by the continuous lines. Notably, each agent denoted by the circles bearing the acronyms C.1, H.1, and H.2 maintains an associated semantic representation, visualized in Figure 1 as diamonds (◇) with their respective acronyms.

The transduction process involves the conversion of signals coming from the object within the shared environment into representations within each agent's private conceptual space. It can be classified as computation, or data processing, by C.1, and cognitive processing by H.1 and H.2. It is worth highlighting that this transduction process is intimately connected to the underlying ontological characteristics of each agent. In broad terms, computational agents

are distinguished using formal reasoning, binary coding, electrical signals, and semiconductor components. In contrast, human agents rely on a combination of formal and affective reasoning, intricate firing coding³, electrochemical signals, and chains of amino acids, as elucidated by Sterling and Laughlin (2015).

Turning our attention to the interaction among agents, Figure 1 emphasizes those elements that somehow relate to this study. Among human agents, the primary mode of interaction is through natural language, while CV or NLP serves as the intermediary application facilitating communication between humans and computational agents.

From this hypothetical scenario, we can identify three fundamental challenges in the realm of semantic attribution:

- (i) **The semantic gap:** the distance, or error, between low-level features of images and their high-level semantics in a given situation (BAËZAOUË *et al.*, 2018), a gap that computational intelligence strives to minimize;
- (ii) **The translation problem:** an issue dealt with by linguistics when studying the impossibility of translating terms in a deterministic way (QUINE, 1969);
- (iii) **The binding problem:** a subject of study in neuroscience and psychology, which aims to understand the process by which sensory attributes (e.g., image, sound, touch) are transformed into mental perceptions (ANDERSON, 2009).

In this thesis, our primary focus is the study of semantic attribution issues in CI, as such, the semantic gap. However, its inherent relationship with the translation problem (from linguistics) and the binding problem (from neuroscience and psychology) bring fresh insights to the formulation of hypotheses and the exploration of the topic under study.

1.2 RESEARCH HYPOTHESIS AND OBJECTIVES

Generally speaking, this thesis seeks to contribute to understanding semantic attribution applied to computational intelligence. More specifically, in CV and NLP applications, and their related issues, such as the semantic gap. Therefore, the following hypotheses are taken as starting points for this research:

³ Firing rate “is the number of electrical impulses a neuron generates in a given amount of time (e.g., spikes per second).” (PALMER, 1999). The variance of such impulses encodes information.

- (i) Semantic attribution is an intelligent behavior.
- (ii) The formal-logical paradigm cannot represent semantics.
- (iii) All semantic content comprises an objective and subjective portion.
- (iv) Subjective semantic content cannot be determined, only inferred.

In particular, this work seeks to meet the following specific objectives:

- 1.2.1 Conduct a critical analysis of the main issues and challenges related to semantic attribution in CI.
- 1.2.2 Offer a global definition for intelligence based on bibliometric analysis and corresponding theoretical articulation.
- 1.2.3 Identify the epistemological divergences when dealing with the semantic attribution process, thus understanding the causes of the semantic gap problem in CI and figuring out possible solutions.
- 1.2.4 Investigate and validate the underlying (latent) factors of the semantic content.
- 1.2.5 Develop methods to quantify the semantic content experimentally, validating the proposed approaches using publicly available datasets.

1.3 THESIS STRUCTURE

This thesis is organized as follows: in Chapter 2, we attend to objective 1.2.1 by delving into the landscape of semantic-related works, drawing insights from computational models and highlighting the challenges faced in CI. In Chapter 3, we attend to objective 1.2.2 by examining the definitions and measurements of intelligence while proposing a novel definition and categorization. In Chapter 4, attending to objective 1.2.3, we explore the semantic attribution by intelligent agents through paradigmatic analysis and empirical studies, aiming to characterize the semantic content and contribute to bridging the semantic gap. In Chapter 5, we attend to the objectives 1.2.4 and 1.2.5, proposing a formal model for semantics and proposing strategies to objectively measure subjectivity. Finally, in Chapter 6, we present the conclusions drawn from this research, outlining contributions to the field and suggesting future research directions.

2 SEMANTIC-RELATED WORKS

It is pointless to ask whether a model is real, only whether it agrees with observation.

—Stephen Hawking & Leonard Mlodinow, *The Grand Design*

Over the years, the semantic representation and its treatment in CI has evolved significantly. Section 2.1 gently introduces the theme with an overall definition of semantics. Section 2.2 reviews the main computational models for semantic applications. Although their satisfactory performance in NLP tasks, some emerging problems are explored in Section 2.3, of which we highlight the semantic gap problem and the strategies used to circumvent the weakness of Deep Learning (DL) architectures.

2.1 A BRIEF INTRODUCTION FOR SEMANTICS

According to Anderson (2009, p.325), “one goal of linguistics is to discover a set of rules that will account for both the productivity and the regularity of natural language, (..) referred to as a grammar.” Therefore, a grammar contains three sets of rules: phonological, syntactic, and semantic or conceptual, as depicted in Figure 2. The first, phonology, acts on the sound structure of sentences. The second, syntax, deals with word order and inflection. The last, semantics, provides the study and understanding of the meaning of sentences.

Recent studies suggest that formal rules only partially represent language, as they pertain solely to linguistic structures, which can be viewed as an organization of conceptual knowledge (DAVIS; GILLON, 2004, p.329). Semantics is redefined as the domain of meaning that relates expressions to what they stand for in the world, encompassing not only the literal interpretation of words and sentences but also the inferred meanings that arise from context. Semantics involves the mapping of linguistic expressions to their corresponding meanings, serving as the foundation for understanding how language conveys information about the world.

Conceptual structures go beyond semantics by integrating linguistic meanings with broader cognitive processes. These structures are not entirely dependent on language; they serve as “an interface between linguistic information and information germane to other capacities such as vision and action.” (DAVIS; GILLON, 2004). In this light, semantics is concerned with the meaning of symbols and the relationship between expressions and their meanings, while conceptual knowledge encompasses a wider range of cognitive processes that extend beyond the

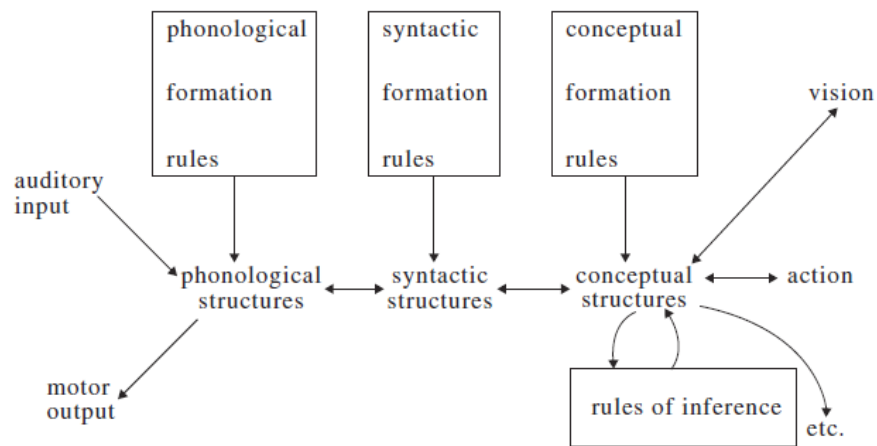


Figure 2 – Organization of language as a set of phonological, syntactic, and conceptual rules (semantics) with their related structures.

Source: (DAVIS; GILLON, 2004).

scope of linguistic meaning alone.

In summary, while semantics focuses on the meaning of linguistic symbols and their relationships, conceptual knowledge involves a broader spectrum of cognitive understanding that transcends linguistic expressions to include context, inference, and their integration with other cognitive domains.

2.2 COMPUTATIONAL MODELS FOR SEMANTIC APPLICATIONS

In the pathway to treat and emulate natural language, CI practitioners developed a plethora of methods for NLP that deal with distinct aspects of language, from phonetics (as in speech recognition) to semantics. Jurafsky and Martin (2006) categorized NLP methods according to their purpose: Natural Language Understanding (NLU), when the main focus is to comprehend human natural language, and Natural Language Generation (NLG), when it is expected to communicate with humans.

On the other hand, Cambria and White (2014) categorized these methods based on their linguistic ability, what they called NLP development curves: the syntactic curve, which the authors associated with the bag-of-words¹ paradigm; the semantic curve, associated with the bag-of-concepts paradigm; and, finally, the pragmatic curve, idealized as the bag-of-narrative paradigm. The first paradigm sought to find meaning based on language's lexical and syntactic aspects, such as the distributional structure proposed by Harris (1954). The second one, bag-of-

¹ Bag-of-words here refers to a linguistic context, as proposed by Harris (1954), who was trying to find a structure for meaning. It is important to distinguish here from the Bag-of-Words (BoW) model, a word embedding technique later explored in Section 2.2.2.

concepts, leaves the formal logic and endeavors on statistical NLP. The third, bag-of-narratives, should represent any piece of text as interconnected episodes. As claimed by Cambria and White (2014), “while the bag-of-concepts model helps to overcome problems such as word-sense disambiguation and semantic role labeling, the bag-of-narratives model will enable tackling NLP issues such as co-reference resolution and textual entailment.”

Choosing a model or architecture for a NLP task depends mainly on the intended application. There are several studies surveying NLP methodologies for a given field, such as for opinion mining (SUN *et al.*, 2017), biomedical applications (HOUSSEIN *et al.*, 2021), innovation management (i.e., patent retrieval) (CASOLA; LAVELLI, 2022), and so forth. We provide below a brief description of some of the most common tasks and applications, as depicted in Figure 3, according to their purpose category (i.e., NLU, or NLG):

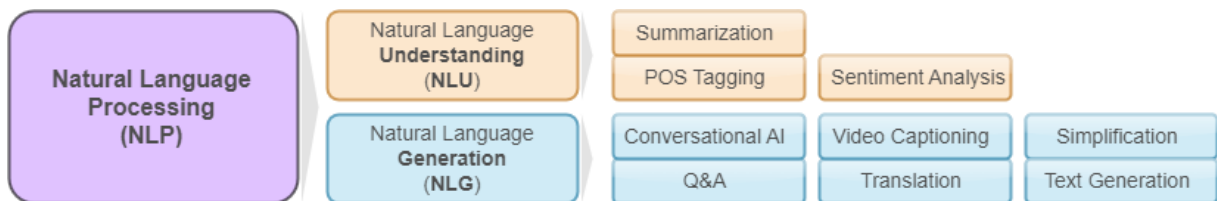


Figure 3 – The main NLP applications according to their purpose category.

Source: Created by the author.

- NLU Tasks:
 - **POS Tagging:** consists of labeling each word or element of a sentence with its syntactic category, choosing the proper tag for the context (JURAFSKY; MARTIN, 2006, p.297).
 - **Text Summarization:** consists of providing a piece of text that contains the main information from a given corpus in the more concise, dense, and less redundant way (CASOLA; LAVELLI, 2022).
 - **Sentiment Analysis:** consists of classifying a word or sentence polarity (PATIL *et al.*, 2023). There can be found variations for hate speech detection and toxicity classification (SUBRAMANIAN *et al.*, 2023).
- NLG Tasks:
 - **Conversational AI:** aims to enable more natural and contextually relevant interactions between humans and machines, advancing virtual assistants and human-robot communication (e.g., chatbot) (FU *et al.*, 2022).

- **Question and Answering systems:** relate to conversational applications, although limited to interpreting the users’ questions and providing useful information to them, through a reliable information retrieval (SINGH; MAHMOOD, 2021).
- **Video Captioning:** aims to provide a textual description for video sequences, thus associating CV and NLP tasks (INACIO; LOPES, 2023).
- **Machine Translation:** has been significantly improved by providing better context-aware translations through the use of transformers (TRIPATHY *et al.*, 2021).
- **Simplification:** in contrast to the summarization task, aims to keep the whole original information but now written in a simplified manner (CASOLA; LAVELLI, 2022).
- **Text Generation:** is a broad task that consists of generating a text based on given parameters and contexts. Different adaptations of Generative Pre-training Transformer (GPT) models have been applied for text generation (TRIPATHY *et al.*, 2021).

We will now introduce some of the main techniques and methods from NLP following the steps of a traditional Machine Learning (ML) pipeline (LIU *et al.*, 2020), as illustrated in Figure 4: pre-processing, in Subsection 2.2.1; representation or feature extraction, in Subsection 2.2.2; modeling, in Subsection 2.2.3; and evaluation, in Subsection 2.2.4.

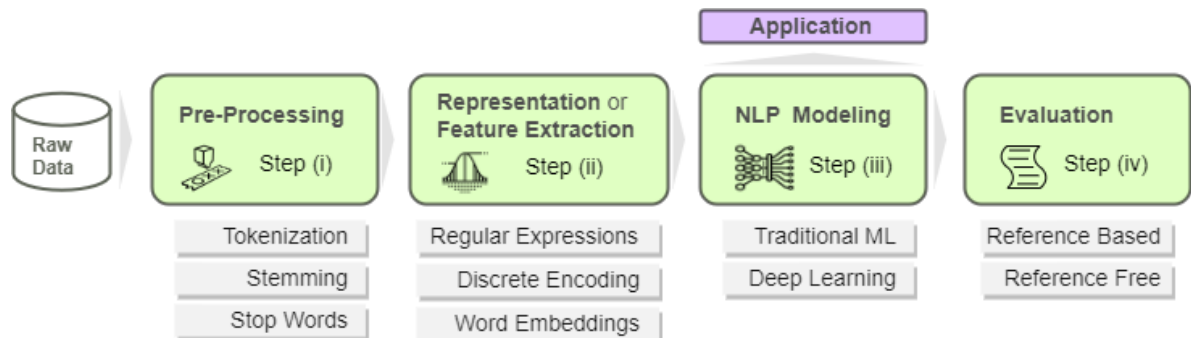


Figure 4 – NLP pipeline for semantic-related applications.

Source: Created by the author.

2.2.1 Pre-Processing

Preprocessing techniques prepare textual raw data to be processed by feature extractor algorithms. Three main procedures are used: tokenization, stemming, and stop-word removal (JURAFSKY; MARTIN, 2006).

Tokenization consists of dividing sentences and words into minimal textual elements called tokens. Different tokenization methods and computational implementations exist (e.g., NLTK library²).

Stemming relates to the morphological aspects of the language. Its purpose is to provide the single root form of a word (e.g., the three terms *process*, *processing*, and *processed* can be stemmed to the single *process* form).

Lastly, stop word removal consists of eliminating punctuations, non-meaningful words such as prepositions, and other spurious words that may increase the error rate of NLP algorithms. The need for a pre-processing step depends significantly on the model architecture and, sometimes, it is dispensable, as in some DL architectures.

2.2.2 Representation or feature extraction

Feature extraction is the fundamental step in NLP applications. Its importance lies in extracting the text's lexical, syntactic, or semantic representation and, therefore, enabling its analysis or modeling. Goodfellow *et al.* (2016, p.354) affirm that “in the context of machine learning, (..) a good representation is one that makes a subsequent learning task easier.” In this step, distinct classes of techniques can be used for NLP: regular expressions, discrete encoding, and word embeddings. The latter can be classified into static or dynamic embeddings (PATIL *et al.*, 2023).

Regular expressions consist of finding patterns or sequences of patterns in a given document. It comprises all rule-based strategies for feature extraction. Discrete encoding techniques, in turn, are statistical methods that represent words as numerical vectors. By doing so, a corpus becomes a matrix of vectors. Patil *et al.* (2023) emphasizes the following algorithms in this category: one hot embedding, Bag of Words (BoW), category-based embedding, N-grams, term-frequency embedding, inverse document frequency, and Hyperspace Analogue to Language (HAL).

Initially used by Hinton *et al.* (1986), the representation of words in a vector space – namely, word embedding – has been applied in different ways using statistical models based on frequency, such as the Latent Semantic Analysis (LSA) and N-grams (BRANTS *et al.*, 2007), as well as non-linear models based on distributed representation (BENGIO *et al.*, 2003). However, it was only from the log-linear models proposed by Mikolov *et al.* (2013a) that the vector

² NLTK is a python library available at <https://www.nltk.org/>.

representation of a large volume of text could be effectively constructed.

In a simplified description, the models proposed in (MIKOLOV *et al.*, 2013a) make it possible to train a word embedding from a large volume of text to predict a word based on its context (continuous bag of words, CBOW) or, based on a given word, predict the context in which it is inserted (Skip-gram).

Let us consider a sequence of N words from a corpus $T = w_t \mid 0 \leq t \leq N$. To each word w_t , there is an associated context c_{w_t} given by its neighboring words, taken from a selection window of size $d = 2j$, where j is an arbitrary value that indicates the number of words considered in each direction:

$$c_{w_t}(w_t) = w_{t-j}, \dots, w_{t-1}, w_{t+1}, \dots, w_{t+j}. \quad (1)$$

The skip-gram model can be understood as a Multi-Layer Perceptron (MLP) where the input layer is a vector representing the word w_t . Once the MLP has been trained for the N selected words and their respective contexts, the hidden layer of the neural network (i.e., the projection layer) will be equivalent to the word embedding W of the respective corpus T , with dimension $N \times d$.

Regarding the training of word embeddings, considering D the set of all pairs $(w_t, c(w_t))$ extracted from T , the objective of the *skip-gram* model is to determine the θ parameter in order to maximize the following probability distribution function (GOLDBERG; LEVY, 2014):

$$\operatorname{argmax}_{\theta} \prod_{(w,c) \in D} p(c|w,\theta). \quad (2)$$

In its basic implementation, the parameterization of the Equation 2 is given through the *softmax* function, so that $p(c|w, \theta)$ is defined as:

$$p(c|w,\theta) = \frac{\exp^{v_c \cdot v_w}}{\sum_{c' \in C} \exp^{v_{c'} \cdot v_w}}, \quad (3)$$

where C is the set of all possible contexts, v_w is the vector representation of words, and v_c is the vector representation of contexts. The parameters corresponding to θ are v_{c_i}, v_{w_j} , for $w \in W$, $c \in C$, considering $0 \leq i < d-1$, and $0 \leq j < N-1$.

From this formulation, the computation of the probability distribution $p(c|w)$ has a cost proportional to the size of the word embedding W , which makes it unfeasible for large data sets. However, Mikolov *et al.* (2013b) suggested different strategies, such as (i) hierarchical softmax; (ii) Noise Contrastive Estimation (NCE); (iii) Negative sampling (NEG); and (iv) subsampling of frequent words.

Patil *et al.* (2023) offer a comprehensive survey on the available word embeddings for NLP tasks, categorizing them as feature-based embeddings, which can be static (e.g., Word2Vec, GloVe, FastText) or dynamic (e.g., Context2Vec, Generative Pre-Training (GPT), Bidirectional Encoder Representations from Transformers (BERT)), and fine-tune based embeddings, which can be cross-lingual, knowledge enriched, domain-specific, multi-modal, and language-specific.

2.2.3 NLP Modeling

As shown in Figure 4, the third step of an NLP pipeline consists of modeling the representations or features extracted in the previous step to fulfill a desired application. Different strategies have been used during the NLP development. As claimed by Cambria and White (2014), the models from the syntactic curve that were mainly based on rules – such as the first generation algorithms for Part-of-Speech (POS) tagging – started being replaced by traditional ML methods for supervised and unsupervised learning (BISHOP, 2006) – such as *k-means* for feature clustering and *naive Bayes* for sentiment analysis classification.

In addition to the traditional approach, DL architectures – also called Deep Neural Networks (DNN) – have been substantially employed in developing NLP models (TRIPATHY *et al.*, 2021), with particular interest in the recent transformer architectures that gave rise to applications such as ChatGPT.

Tripathy *et al.* (2021) bring a comprehensive analysis of DNN models applied to contextual understanding, as summarized in Figure 5. The authors categorized contextual-based DNN models for NLP as (i) purely recurrent models, those employing Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM) architectures; (ii) attention mechanisms, which applied a new hidden state to the LSTM architecture, thus providing encoder-decoder architectures that include local attention, global attention (e.g., the Global Vectors (GloVe) model), and transformers; and (iii) linear transformations models, which use some linear operations (e.g., Fourier transform as in the FNet model proposed by Lee-Thorp *et al.* (2022)) in the DNN to improve time and processing performance.

Although the attention mechanisms brought impressive results to NLP tasks, Tripathy *et al.* (2021) observe “they hit a certain limit after which an increase in the training dataset or increase in training time would not increase the overall score achieved by the model.” Such a situation led to a pre-trained strategy, where embeddings would be fine-tuned in downstream

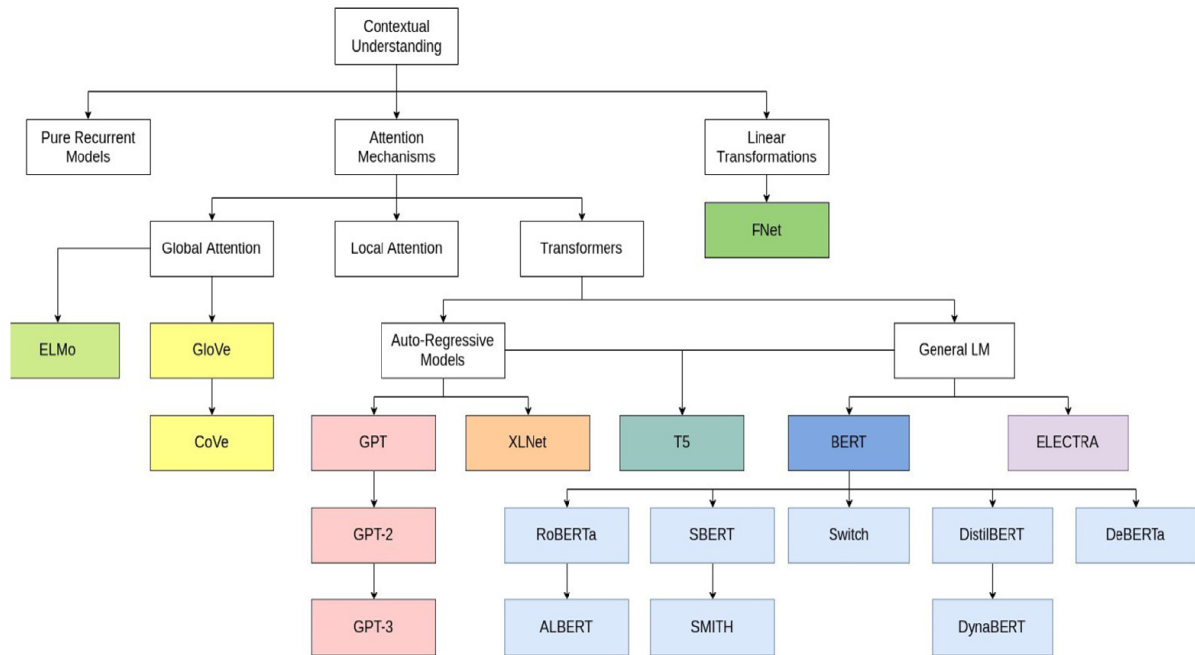


Figure 5 – Taxonomy of the state of the art DNN models applied to contextual understanding.

Source: (TRIPATHY *et al.*, 2021).

tasks. For instance, Figure 6 shows the GPT³ architecture, where multi-transformers blocks are applied on the input pre-trained embedding, stacked with multi-head attention blocks and point-wise Feedforward Neural Network (FNN)⁴. As described by Tripathy *et al.* (2021), “to use the GPT for fine-tuning tasks, the inputs are processed by the pre-trained GPT model and then followed by a linear+softmax layer.”

2.2.4 NLP Evaluation

The success of a NLP application mainly depends on the data quality, the chosen architecture, and the resources available. However, evaluating its results and measuring its performance is still challenging in CI. Evaluation methodologies can be broadly categorized into “Reference Based” and “Reference Free” approaches, as depicted in 4. Reference-based evaluations compare system outputs against pre-defined reference answers, using metrics such as BLEU, ROUGE, and METEOR⁵ to assess similarity. Conversely, reference-free approaches, also known as intrinsic evaluations, assess the quality of outputs based on internal criteria such

³ An interactive introduction on how GPT models work can be found at <https://ig.ft.com/generative-ai/>.

⁴ FNN is also known as the multilayer perceptron (MLP). “In fact, ‘multilayer perceptron’ is really a misnomer because the model comprises multiple layers of logistic regression models (with continuous nonlinearities) rather than multiple perceptrons (with discontinuous nonlinearities).” (BISHOP, 2006)

⁵ The definitions and detailed explanations of evaluation metrics such as BLEU, ROUGE, METEOR, among others mentioned in Figure 7, can be found in the comprehensive survey by Inacio and Lopes (2023).

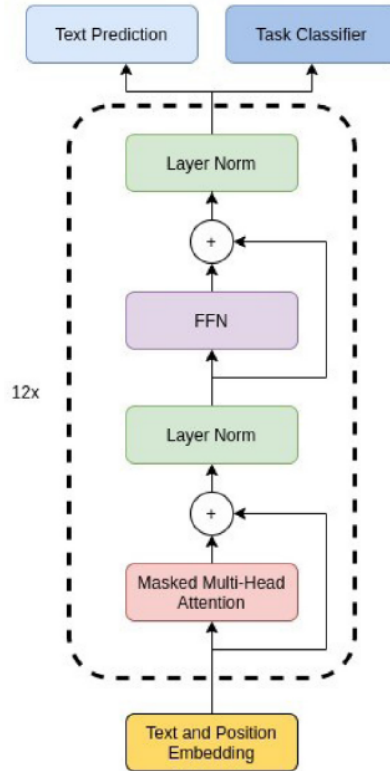


Figure 6 – GPT architecture.
 Source: (TRIPATHY *et al.*, 2021).

as fluency and coherence without relying on external references. Recently, Inacio and Lopes (2023) elaborated on this problem by surveying the evaluation metrics for video captioning, as depicted in Figure 7, which also apply for NLP as a whole.

Recently, Martinez-Gil (2022) argued for the use of stacking methods for semantic

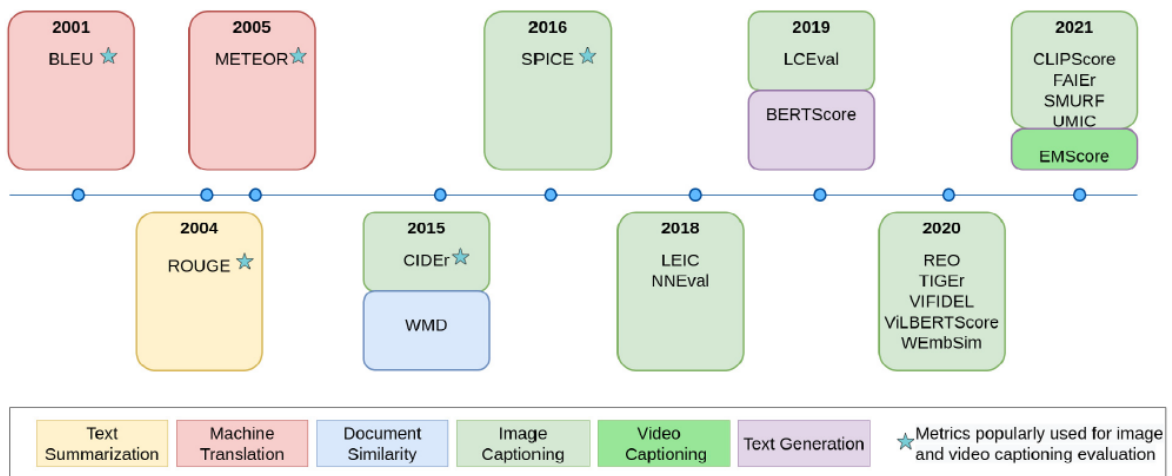


Figure 7 – Timeline of the main evaluation metrics for NLP tasks: Text Summarization, Machine Translation, Document Similarity, Image Captioning, Video Captioning, and Text Generation.
 Source: (INACIO; LOPES, 2023).

similarity, i.e., “a class of methods called ensembles that base their operation on an underlying formula capable of aggregating the predictions of an indeterminate number of basic algorithms.” According to the author, such a strategy “is inspired by some studies that show that the decision-making ability of a group of people is usually higher than the individual ability of each member, provided that certain conditions are met.”⁶ A stacking method could then result in a meta-model with improved simplicity, robustness, accuracy, interpretability, and transferability.

2.3 SEMANTIC-RELATED CHALLENGES IN CI

In this thesis, we explore four main semantic-related challenges: the semantic gap (see Section 2.3.1), adversarial attack (see Section 2.3.2), AI hallucination (see Section 2.3.3), and representation learning (see Section 2.3.4). Table 1 summarizes, in reverse chronological order, the studies considered throughout this Section, pointing to the respective issues explored by them. Along with it, we brought the journal and the publication year of each study. The reader should note that AI hallucination is a quite recent term, mainly influenced by Large Language Models (LLM) research and applications. The other issues have been actively researched for more than a decade.

2.3.1 Semantic gap

The semantic gap is a recurring challenge that CI developers face when dealing with CV and NLP. Considering that both applications are closely related to human sensory-perceptive activities, one could define the semantic gap as the distance (or error) resulting from the computational emulation of human intelligence.

The first reference to semantic gap appeared in books⁷ in the 1940s, as shown in Figure 8. A noticeable increase in its frequency – observed from the 1970s – is correlated with the advent of NLP. By the end of the last century, another correlation was observed for image retrieval techniques – resulting from the popularization of digital media and the rising of DL architectures.

A general definition for the semantic gap considers it as “the difference between low-level features of images and their high-level semantics in a given situation.” (BAËZAOUË *et al.*,

⁶ We attribute these results to the subjective factor, which will be discussed in Chapter 4.

⁷ We analyzed data from Google Books Ngram Viewer, a tool available at <https://books.google.com> with a database from 1500 to 2019.

Table 1 – Summary of studies exploring semantic-related issues in CI surveyed in this work.

Author	Journal	Year	Semantic Issue
Ji <i>et al.</i>	ACM Computing Surveys	2023	AI hallucination
Chen <i>et al.</i>	IEEE Transactions on Pattern Analysis and Machine Intelligence	2022	Adversarial attack
Haque <i>et al.</i>	IEEE Access	2021	Semantic gap
Li <i>et al.</i>	IEEE Access	2021	Semantic gap
Xu <i>et al.</i>	IEEE Access	2021	Semantic gap
Song <i>et al.</i>	IEEE Access	2020	Semantic gap
Xu <i>et al.</i>	International Journal of Automation and Computing	2020	Adversarial attack
Wiyatno <i>et al.</i>	arXiv	2019	Adversarial attack
Zhang <i>et al.</i>	IEEE Access	2019	Semantic gap
Li <i>et al.</i>	IEEE Transactions on Cybernetics	2019	Semantic gap
Zhang <i>et al.</i>	IEEE Access	2019	Semantic gap
Finlayson <i>et al.</i>	Science	2019	Adversarial attack
Yuan <i>et al.</i>	IEEE Transactions on Neural Networks and Learning Systems	2019	Adversarial attack
Vaduva <i>et al.</i>	IEEE Access	2018	Semantic gap
BAËZAOUË <i>et al.</i>	Expert Systems With Applications	2018	Semantic gap
Aytar <i>et al.</i>	IEEE Transactions on Pattern Analysis and Machine Intelligence	2018	Semantic gap
Eykholt <i>et al.</i>	IEEE/CVF Conference on Computer Vision and Pattern Recognition	2018	Adversarial attack
Tu <i>et al.</i>	Expert Systems With Applications	2017	Semantic gap
Zhang <i>et al.</i>	Neurocomputing	2017	Semantic gap
Cai <i>et al.</i>	Neurocomputing	2016	Semantic gap
Calumby <i>et al.</i>	Neurocomputing	2016	Semantic gap
Guo <i>et al.</i>	Neurocomputing	2016	Semantic gap
Pandey <i>et al.</i>	Journal of Visual Communication and Image Representation	2016	Semantic gap
Zhang <i>et al.</i>	Neurocomputing	2016	Semantic gap
Goodfellow <i>et al.</i>	MIT Press Cambridge	2016	Representation learning
Kumar and Ravi	Knowledge-Based Systems	2016	Representation learning
Jain <i>et al.</i>	IEEE Security and Privacy	2015	Semantic gap
Bahmanyar <i>et al.</i>	IEEE Geoscience and Remote Sensing Letters	2015	Semantic gap
Shao <i>et al.</i>	IEEE Transactions on Neural Networks and Learning Systems	2015	Representation learning
Cambria and White	IEEE Computational Intelligence Magazine	2014	Semantic gap

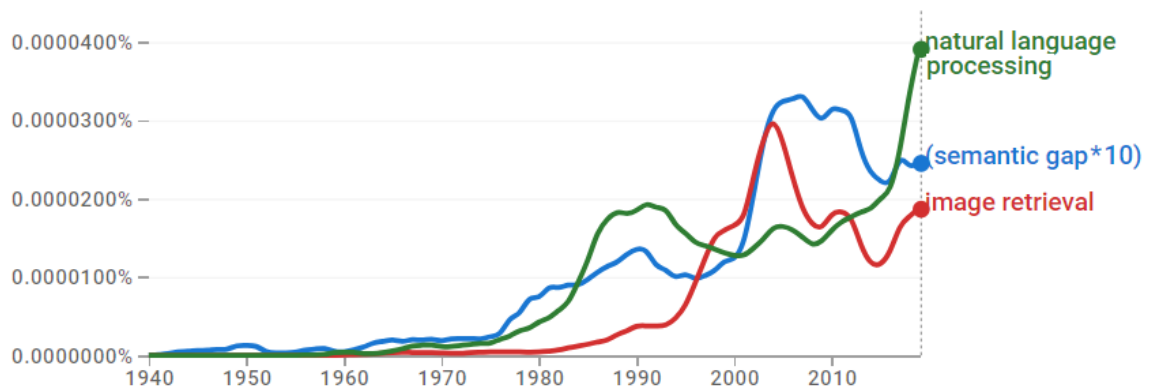


Figure 8 – Frequency of occurrence in books, from 1940 to 2019, of the terms *natural language processing* (in green), *image retrieval* (in red) and *semantic gap* (in blue). The frequency of occurrence of the last term has a 10× gain so as to appear in the frequency range as the other terms.

Source: Google Books Ngram Viewer.

Table 1 – Summary of studies exploring semantic-related issues in CI surveyed in this work.

Author	Journal	Year	Semantic Issue
Kurtz <i>et al.</i>	Journal of Biomedical Informatics	2014	Semantic gap
Bastinos and Krisper	Information Sciences	2013	Semantic gap
Andreopoulos and Tsotsos	Computer Vision and Image Understanding	2013	Semantic gap
Szegedy <i>et al.</i>	arXiv	2013	Adversarial attack
Mikolov <i>et al.</i>	Proceedings of Neural Information Processing Systems	2013	Representation learning
Tang <i>et al.</i>	IEEE Transactions on Image Processing	2012	Semantic gap.
Tousch <i>et al.</i>	Pattern Recognition	2012	Semantic gap
Lang <i>et al.</i>	Expert Systems with Applications	2012	Semantic gap
Hein	Abstracts of the 2010 Forum on Philosophy, Engineering Technology	2010	Semantic gap
Pan and Yang	IEEE Transactions on Knowledge and Data Engineering	2010	Representation learning
Deng <i>et al.</i>	IEEE Conference on Computer Vision and Pattern Recognition	2009	Representation learning

Source: Created by the author.

2018, p.11). Similar definitions relating to low-level features of images are found in Tousch *et al.* (2012), Xu *et al.* (2021), Pandey *et al.* (2016), Cai *et al.* (2016), Zhang *et al.* (2019), Zhang *et al.* (2017), Song *et al.* (2020), Li *et al.* (2021).

According to Tang *et al.* (2012), the differences mentioned before refer to the many interpretations that the same visual data evoke in different contexts. These authors also observe that “an image is relevant to multiple semantic concepts while different concepts have different sizes of semantic gaps.”

Another definition sets the semantic gap as “the difference between user and computer interpretation of an image.” (BAHMANYAR *et al.*, 2015, p.2046). The same authors also referred to the linguistic semantic gap derived from subjective biases when interpreting recorded signals from sensors.

On the other hand, Cambria and White (2014) explored the high-level symbolic capabilities required for NLP, as found in humans, but lacking in syntax-based algorithms. They called this difference the cognitive gap. Hein (2010) established the semantic gap as the difference of meaning between constructs formed within distinct representational systems, such as the natural language or the formal language. Zhang *et al.* (2016) added visual and linguistic experiences to the musical one, exploring the semantic distance between acoustic features and emotions.

Lang *et al.* (2012) defined the semantic gap as “semantic related visual variance”. A more restrictive definition was given by Bastinos and Krisper (2013, p.596), who attributed it to the semantic differences and “incompatible data between the information system and the decision-making system”. A similar definition was given by Kurtz *et al.* (2014).

According to Andreopoulos and Tsotsos (2013, p.885), the semantic gap can be understood as “the inability of less complex but easily extractable indexing primitives to be grouped/organized so that they provide more high-level and more powerful indexing primitives.”

Considering the image-retrieval context, Calumby *et al.* (2016, p.7) explain the semantic gap as when “the user receives the group of items retrieved and judges their relevance in relation to the information need”.

Cross-Modal Image Retrieval (CMIR) consists of the automatic search for visual elements in a given database through metadata, photographs, sketches, or its textual description (AYTAR *et al.*, 2018). The semantic gap resulting from this application can thus be characterized as equivalent to the binding problem (see Section 1.1). The same considerations apply to the strategies proposed by Haque *et al.* (2021) to overcome the semantic gap in image captioning tasks.

In the same context of vision-to-language tasks, Li *et al.* (2019) offer a relational definition of the semantic gap, stating that “every word in captions or every question should only correspond to one or several regions of an image.” Although slightly situated in the formal-logical paradigm, this perspective is strongly objective and deterministic.

Vaduva *et al.* (2018) explore current techniques for Earth observation, pointing out its main shortcomings due to the different human and sensor perceptions of objects, which they define as sensory and semantic gaps. They present a compound framework based on the information theory to overcome it. Such an approach made by Vaduva *et al.* (2018), altogether with those found in Cambria and White (2014) and Tang *et al.* (2012), are the closest to what we propose in Section 5.4.

An unusual definition of the semantic gap was given by Jain *et al.* (2015) in the context of computer networks. Those authors considered it as the mismatch between the low-level features of a virtual machine instance and the high-level abstractions, such as process descriptors and open files, from the perspective of a virtual infrastructure manager.

Some authors (ZHANG *et al.*, 2019; TU *et al.*, 2017; GUO *et al.*, 2016) do not explicitly define the semantic gap but seek DL architectures to bridge it. Such studies are inserted into the information processing paradigm (i.e., semantic information is modeled as inputs and outputs of a DNN). In addition, they demonstrate the possibility of dealing with the semantic gap from an empirical approach, where the problem is computationally treated indirectly, i.e., without a concise definition of its causes. For these cases, however, it is observed that the subjective

portion of the semantic content needs to be adequately represented.

From our point of view, although all these surveyed studies and definitions aim at the central problem of the semantic gap, they need to be clarified, leading to significant theoretical and practical consequences.

2.3.2 Deceived deep learning models

When dealing with semantic attribution (see Section 1.1), DL architectures are limited mainly by two factors: (i) an intrinsic one, known as semantic gap, previously introduced in Section 2.3.1, and (ii) an intentional one, known as adversarial example and deliberately applied to lead a DL model to a flawed behavior. These factors differ not only in their nature but also in the understanding available about them. While the semantic gap causes are still undefined and demand interdisciplinary investigation, the intentional strategies consist of input tricks or the use of generative models, an approach self-contained in the CI field.

Adversarial examples were first coined by Szegedy *et al.* (2013). They realized that minor disturbances in an input image could modify the model's output (i.e., its prediction error). In the following years, as pointed out by Heaven (2019), several studies identified similar flaws and exploited them – what was called adversarial attacks. Finlayson *et al.* (2019) exemplified some of these attacks in medical machine learning, as shown in Figure 9. Such vulnerabilities could lead to the wrong diagnosis, adulterated abuse risk evaluation, and fraud in reimbursement processes.

Similar attacks were studied by Eykholt *et al.* (2018), whose proposal introduced perturbations on physical-objects images, such as traffic signs. By adding sticks in stop sign images, the authors led a trained model to classify them as “Speed Limit 45” signs – a critical misbehavior if considering applications such as autonomous cars.

Xu *et al.* (2020) presented a systematic review of adversarial attacks in multiple data domains, such as images, graphs, and text. Besides the attacks, the authors also explored some defense strategies, which they grouped into gradient masking, robust optimization, and detection.

Wiyatno *et al.* (2019) compiled a comprehensive list of adversarial attacks in CV. While warning that there are no proven defensive techniques, they point to Bayesian inference as a possible direction in its development. Also, Yuan *et al.* (2019) have extensively reviewed adversarial attack techniques in applications such as reinforcement learning, generative modeling, face recognition, object detection, semantic segmentation, reading comprehension, and malware

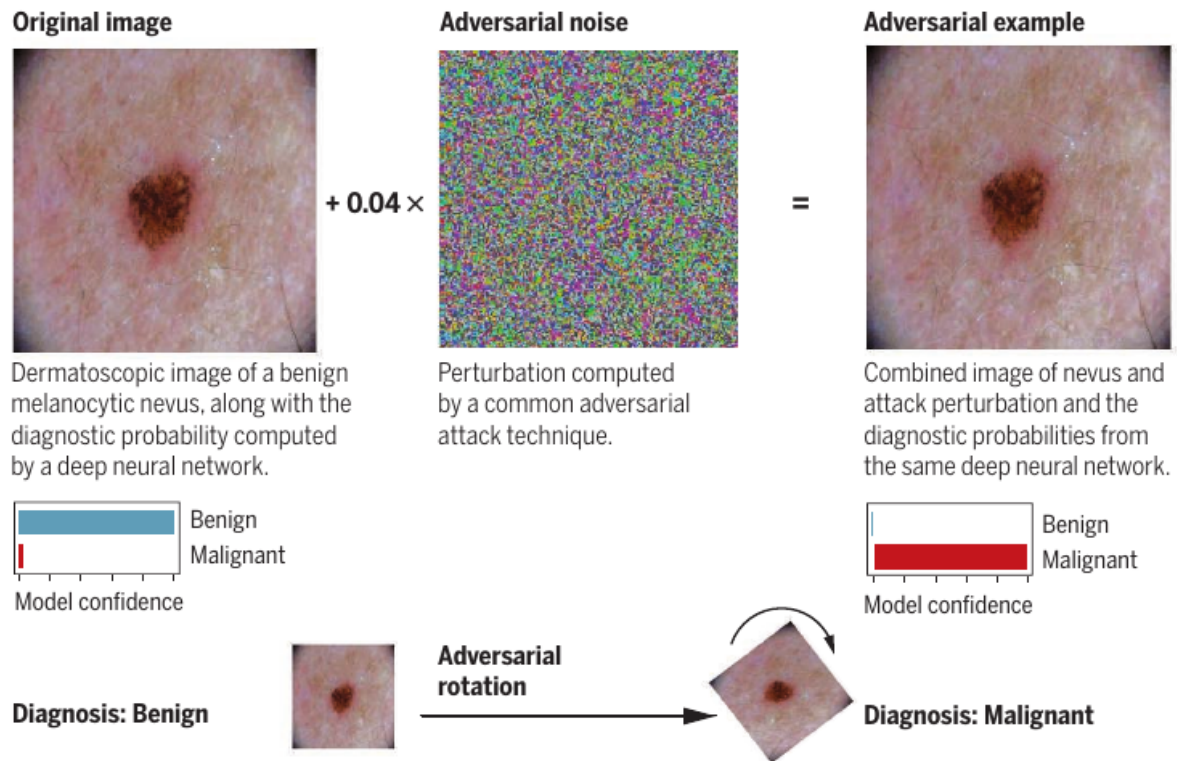


Figure 9 – Examples of deceived deep learning in medical applications: a perturbation on the input image or an image rotation leads to wrong prediction.

Source: Adapted from (FINLAYSON *et al.*, 2019).

detection. Except for the last one, all of them are semantic-related applications. The authors list the adversarial methods employed against each application, as well as the perturbation characteristics.

Recently, Chen *et al.* (2022) published their study on an adversarial attack that resulted in the DAmageNet – a dataset with 50,000 adversarial samples, each one a modified version from ImageNet data (DENG *et al.*, 2009). Assuming that semantic attribution by humans is due to attention, Chen *et al.* proposed the Attack of Attention (AoA) method, where the attention heatmap – obtained “by calculating the relevance between adjacent layers from the output to the input” (CHEN *et al.*, 2022, p.3) – is attenuated, thus distracting a computer vision model. Figure 10 exemplifies this kind of attack: the original sample, on the left, is correctly classified by all considered deep neural networks (VGG19, InceptionV3, InceptionResNetV2, ResNet152, and Xception). However, after the AoA, all models failed to identify the target, even though there was a very slight change for the human perception.

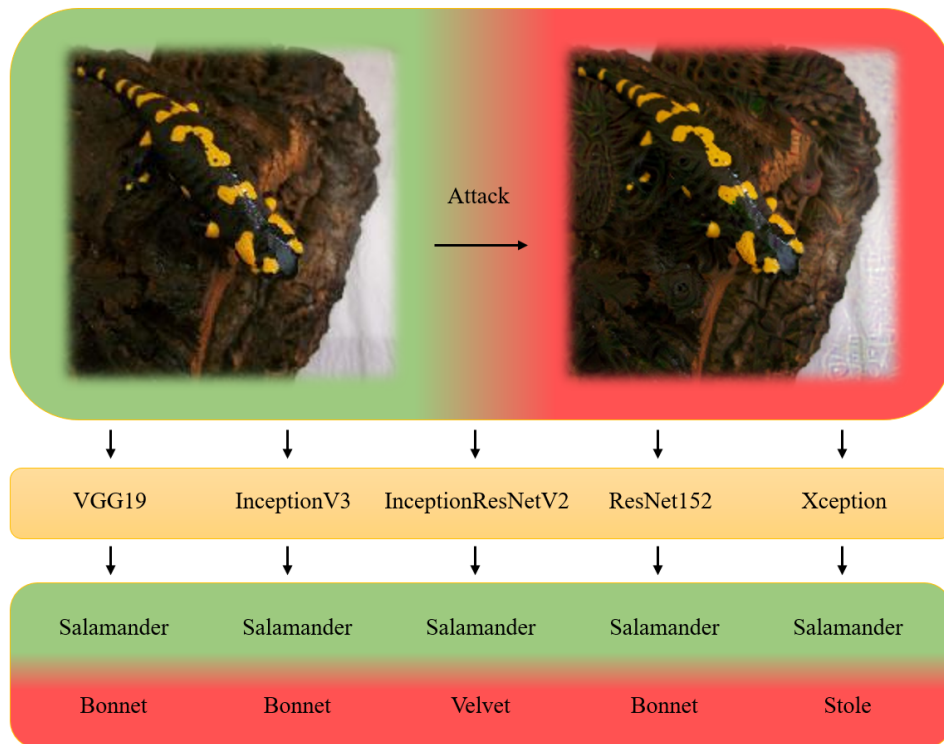


Figure 10 – Attack on Attention (AoA): the image of a salamander on the left is correctly identified by all considered DNN. After the AoA, the resulting image on the right leads to a classification error in all the DNNs tested.

Source: (CHEN *et al.*, 2022).

2.3.3 AI hallucinations

Advanced ML models, especially those applied to NLG, have ushered in challenges and phenomena known as AI hallucinations, which happen when DNNs generate outputs that exhibit patterns, structures, or information that do not exist in the training data. These spurious, fabricated, or hallucinated features emerge during the model’s generation process, often causing erroneous or nonsense outcomes. AI hallucinations challenge the reliability and interpretability of ML models since they “hinder performance and raise safety concerns for real-world applications” (JI *et al.*, 2023).

According to Ji *et al.* (2023), AI hallucinations can be categorized into (i) intrinsic hallucination, when the generated output is contradictory to the source information, or (ii) extrinsic hallucination, when there is no way to verify the generated information. The same authors state that those hallucinations can originate from data (e.g., heuristic data collection or innate divergence) or training and inference processes (e.g., imprecise representation learning, erroneous decoding, exposure bias, or parametric knowledge bias).

AI hallucinations represent a pressing challenge in CI, with implications for ML models’

reliability, safety, and ethical use. Therefore, a better comprehension of the semantic attribution processes and the development of robust metrics for their evaluation are reasonable strategies for mitigating and controlling AI hallucinations.

2.3.4 Other semantic issues

When discussing architectures for representation learning, Goodfellow *et al.* (2016) define the problem of transfer learning and domain adaptation, as well as contextualizing it for applications related to semantics:

Transfer learning and domain adaptation refer to the situation where what has been learned in one setting (e.g., distribution P_1) is exploited to improve generalization in another setting (say, distribution P_2). (...) In transfer learning, the learner must perform two or more different tasks, but we assume that many of the factors that explain the variations in P_1 are relevant to the variations that need to be captured for learning P_2 . This is typically understood in a supervised learning context, where the input is the same, but the target may be of a different nature (GOODFELLOW *et al.*, 2016, p.526-527).

Following the previous quote, the authors exemplify the transfer of learning through a CV architecture first trained with a set containing two classes (e.g., dogs and cats) and then another set (e.g., ants and wasps). The authors note that low-level features, such as borders, shapes, and lighting patterns, are shared between different categories of images.

For high-level characteristics – which the authors associate with the semantics of the output – it is recommended that transfer learning algorithms use the layers closest to the network's output and some pre-processing strategies at the input. They exemplify such application as follows:

A speech recognition system needs to produce valid sentences at the output layer, but the earlier layers near the input may need to recognize very different versions of the same phonemes or subphonemic vocalizations depending on which person is speaking (GOODFELLOW *et al.*, 2016, p.527).

From the above definitions and examples brought by Goodfellow *et al.*, one could question whether this tacit and implicit definition of semantics applies, in the same way, to the process of understanding natural language. Put another way, would language and the attribution of meaning in human communication also occur through some transfer learning process?

Pan and Yang (2010) present a more comprehensive but strictly computational view. These authors define transfer learning or knowledge transfer as the methods and strategies needed to test or apply models in a given domain or feature space different from those used for training.

Shao *et al.* (2015) explore transfer learning techniques applied to visual categorization, splitting them into cross-domain and cross-view methods.

Concept drift is a related problem that results from gradual changes in the data distribution (GOODFELLOW *et al.*, 2016, p.528). Gunn *et al.* (2018) explore this problem in the context of a data streaming classifier. The concept drift could occur in the following process: (i) a data point $x \in \mathbf{R}^d$ is observed at a time t ; (ii) the point is labeled by the classifier since there is no label available at the considered time t ; (iii) before the next point to be classified, a true label is obtained by the system, thus changing its meaning. Based on this scheme, Gunn *et al.* determine four types of concept drift: sudden or abrupt, incremental, gradual, or recurring. Such categorization is approached only quantitatively, i.e., without defining meaning or semantics.

3 AN INTELLIGENCE-CENTRIC PERSPECTIVE OF SEMANTICS

I could not see the trees because I was looking for a forest.

—James Flynn, *What is intelligence?*

The interpretation of dreams and symbols demands intelligence.

—Carl G. Jung, *The Man and his Symbols*

Recently, the excitement caused by generative models such as Dall-E and ChatGPT for image and text generation, respectively, has contributed to reinforcing the idea of a possible human-like general intelligence with comparable semantic comprehension abilities – especially those related to CV and NLP tasks.

Before discussing the validity of a “general” intelligence, it is of fundamental importance to primarily discuss the generalization of the concept of intelligence since many of them lack formalization, empirical evidence, or a measurement strategy. We assume that intelligence is a quality or ability of a given agent or system (human, biological, or artificial). Therefore, in this research, we seek to equalize such definitions of intelligence from the perspectives of CI and psychology, thus contributing to the cross-fertilization between these areas, especially for semantic-based applications.

This Chapter is organized into three main Sections. Section 3.1 aims to verify and bring data evidence that the term intelligence is used across different areas – more than this, that the term is applied in the same sense, which presumes that studies from different fields would share the same sources. Such an exploratory data analysis is also helpful for observing the co-occurrence of the terms intelligence and semantics, both keywords of this thesis. Following this, Section 3.2¹ discusses intelligence through a joint perspective between CI and psychology, thus proposing a comprehensive definition for intelligence based on the Cattell-Horn-Carroll (CHC) model, the current most important theory of intelligence from psychology. Section 3.3, in turn, offers an adaptation of the CHC model to enable a broader definition of intelligence.

¹ The content of Section 3.2 was originally published in (SILVEIRA; LOPES, 2023).

3.1 EXPLORATORY DATA ANALYSIS

Our main goal in leading this analysis is to find the relationship between intelligence and semantics and how it manifests through the different areas of knowledge. To provide worthy information, we queried the Clarivate Analytics Web of Science (WoS) database with the terms “semantic AND intelligence” in all available fields, thus refining the search by document types (only article or review) and language (only in English). This search query resulted in 5,548 documents from 1966 to 2021, comprehending 1,361 distinct sources and 14,117 authors. This amount of documents is distributed along 296 research areas – the 15 most relevant great areas are depicted in Figure 11. It is important to observe that WoS categorization allows for superimposition, i.e., a document can pertain to one or more research areas.

Aiming at conciseness and objectivity, we grouped the different areas of research into just three classes: (a) technology, including the major areas of computer science, engineering, and

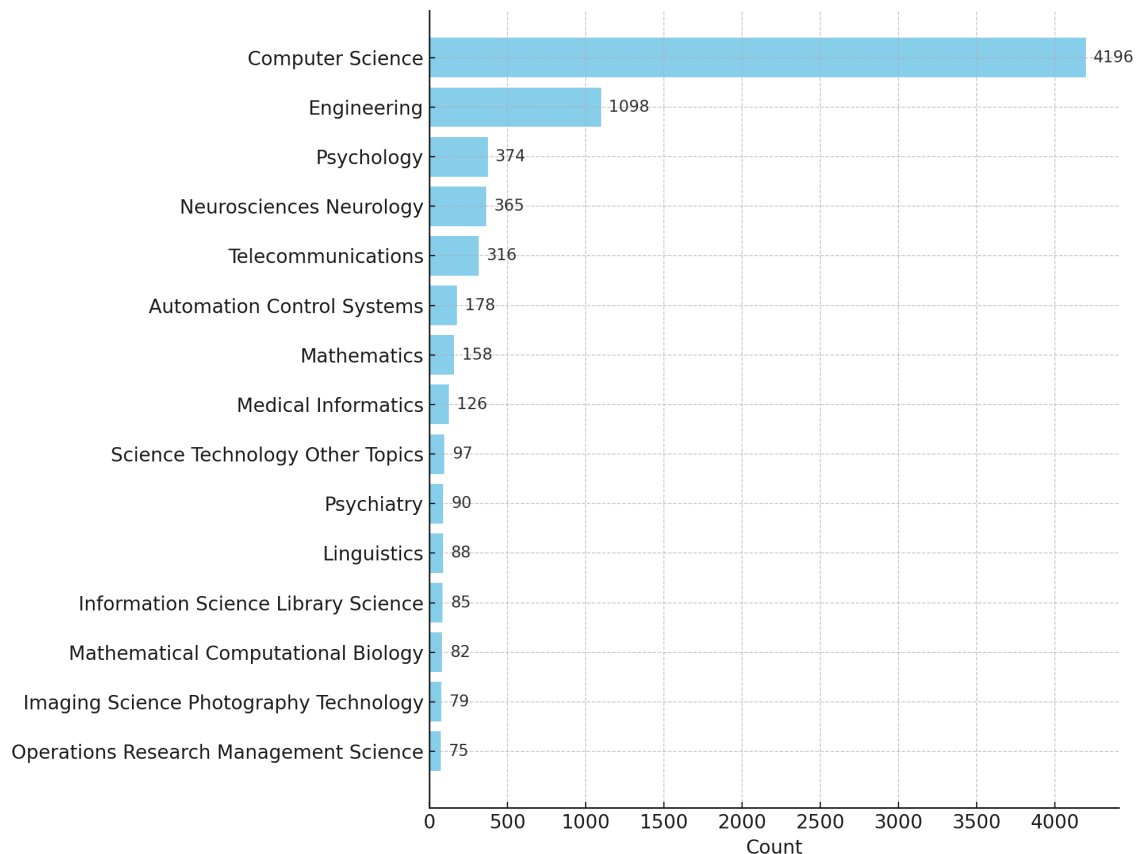


Figure 11 – Number of publications in each research area from 1966 to 2021. Data obtained from WoS search query for "semantic AND intelligence." Computer science and engineering lead, followed by psychology and neurosciences, then distributed along different applications. Some documents can be attributed to more than one category.

Source: Clarivate Analytics Web of Science.

Table 2 – WoS results for "semantic AND intelligence" search query. The research areas were grouped into technology, cognitive science, and application.

	Number of documents	Total times cited	Citations mean rate	Number of cited reference	Referencing mean rate
Technology	4,312	73,406	17.02	157,009	36.41
Cognitive Science	753	21,750	28.88	41,710	55.49
Application	483	6,358	13.16	22,863	47.34

Source: Created by the author.

telecommunications; (b) cognitive science, including the major areas of psychology, neuroscience, and neurology; and (c) application, including all other major areas shown in Figure 11.

This grouping is summarized in Table 2, where we can see an imbalance between the number of documents in each research group. However, considering the average number of citations per document, cognitive science publications are cited 1.7 times more than technology publications and 2.2 times more than application publications. We attribute this difference to epistemological concerns: theoretical sciences demand greater discussion and foundation, usually resulting in wider repercussions. On the other hand, applied sciences share a greater consensus and have their repercussions restricted to their field. On average, cognitive science uses 50% more references than technology publications, while 17% more references than application publications.

Since we sought to precisely explore the transdisciplinary relationship of the theme, to overcome the imbalance of categories, we selected the first 400 most relevant documents from each research group, thus leading a balanced database with 1,200 publications (we called this dataset WoS_{DB1200}), on which we applied (i) conceptual analysis; and (ii) contextual analysis. All of them were conducted by manipulating and preparing data using the Pandas library (MCK-INNEY, 2010), from the Python language, and the Bibliometrix library (ARIA; CUCCURULLO, 2017), from the R language. It is crucial to note that this exploratory data analysis should not be regarded as a bibliometric study, as it does not adhere to the stringent criteria of bibliometric principles.

3.1.1 Conceptual analysis

The purpose of this analysis is to check whether a subject from one document relates to another one. Co-occurrence terms network is proposed by Aria and Cuccurullo (2017) as a tool for science mapping, thus available in the Bibliometrix R library. As the authors define, “connections of different attributes can be represented through a matrix $Document \times Attribute$,”

called A . For the conceptual analysis, we choose as attributes the author's keywords, thus obtaining:

$$\mathbf{A}_{\text{Keywords}} = \begin{matrix} & \text{keyword}_1 & \text{keyword}_2 & \dots & \text{keyword}_j \\ \text{doc}_1 & \left[\begin{array}{cccc} a_{1,1} & a_{1,2} & \dots & a_{1,j} \\ \dots & \dots & \dots & \dots \\ \text{doc}_i & a_{i,1} & a_{i,2} & \dots & a_{i,j} \end{array} \right. & \end{matrix} \quad (4)$$

Based on this, we performed an analysis to map the conceptual structure among the publications through the word co-occurrence matrix \mathbf{B}_{coc} :

$$\mathbf{B}_{\text{coc}} = \mathbf{A}'_{\text{Keywords}} \times \mathbf{A}_{\text{Keywords}}. \quad (5)$$

From Equations (4) and (5), one observes that regardless of the number of documents analyzed, the matrix \mathbf{B}_{coc} will be symmetric, representing each term's co-occurrence. In turn, its diagonal will indicate the number of documents in which the respective word was used.

By using the Bibliometrix functions, the \mathbf{B}_{coc} calculated from the WoS_{DB1200} dataset allows us to generate the co-occurrence network, as depicted in Figure 12. The co-occurrence values were normalized through association strength between the words and clustered using the edge betweenness algorithm (75 nodes; minimum edge value between nodes of 3).

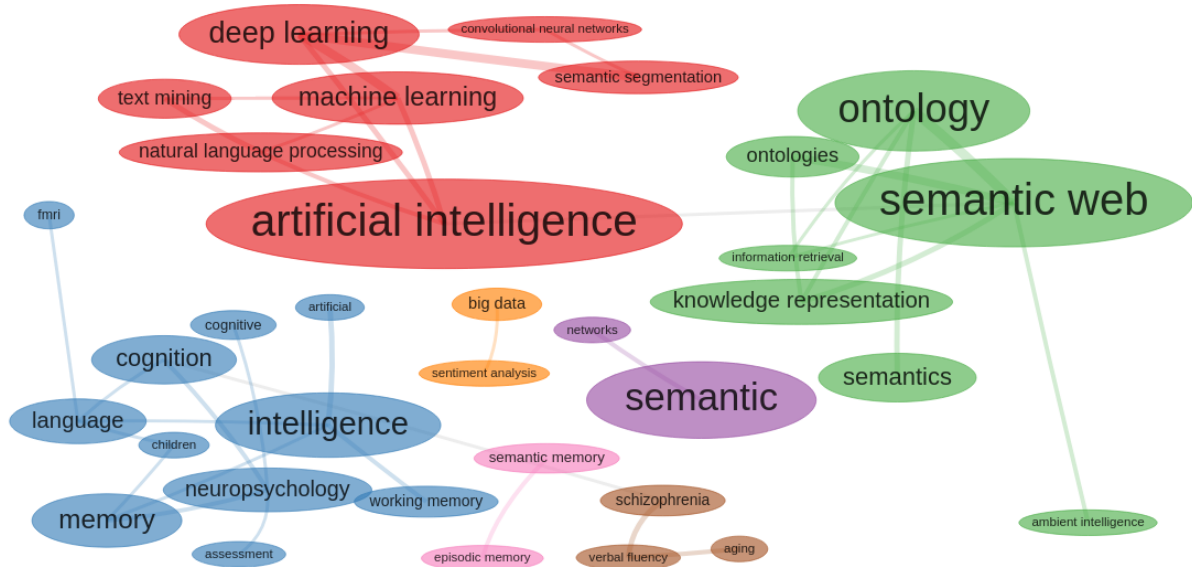


Figure 12 – Co-occurrence network for the author's keywords from WoS_{DB1200} dataset.

Source: Created by the author.

In Figure 12, we can observe three main clusters: the blue one, related to cognitive science and centralized on the word intelligence; the red one, associated with technology and centralized on artificial intelligence, relating to ML, DL, NLP, text mining, convolutional neural

networks, and semantic segmentation; and the green one, associated with formal logic, centralized in semantic web and related to ontology and knowledge representation.

Isolated clusters also associate big data with sentiment analysis and semantics with networks. However, all documents in WoS_{DB1200} contain the words intelligence and semantic at least once in the title, keywords, or abstract. It means at least two words connect all documents, and such cluster isolation can be justified by the parameters chosen to build the network (e.g., number of nodes, minimum edge values).

3.1.2 Contextual analysis

The previous analysis grouped the publications into three main clusters: technology, cognitive science, and applications (see Figure 12). Now, we seek to measure how close or far the considered research areas are. Different strategies can be applied to this aim. Aria and Cuccurullo (2017) suggest, among others: (i) co-citation analysis, where co-cited articles are both found in the references of a third article; (ii) collaboration analysis, where the network nodes represent authors and the links their coauthoring; and (iii) coupling analysis, where one considers the cited sources shared among different publications.

Since our query in the WoS database comprehended several research areas, we opted to perform a coupling analysis on the most relevant sources ($n=35$) from the WoS_{DB1200} dataset. The results are shown on the heatmap of Figure 13, where the source IDs are mapped to the source name in Table 3, where each source is categorized into technology, cognitive science, or application, according to the conceptual analysis in Section 3.1.1. Table 3 also exposes, for each source, the number of publications in the sampled data (WoS_{DB1200} , $N=1,200$) and the queried data (WoS , $N=5,548$).

The joint analysis of Figure 13 and Table 3 allows us to measure how the studied theme is distributed among different research areas. As expected, sources from the same category present higher coupling values, roughly distinguishing two groups: cognitive science (sources [1]-[15]) and technology (sources [16]-[31]). A visual inspection of Figure 13, though, indicates there are sources with a distributed coupling value over all the other ones (sources [1], [3], [19], [21], [23], and [29]). Such a visualization confirms the transdisciplinarity with these areas and suggests research opportunities.

3.2 A JOINT PERSPECTIVE FOR INTELLIGENCE

On the one hand, divergences and contradictions in the definition of concepts between areas of knowledge can be ignored or minimized when such areas have little or no relationship (e.g., structure in civil engineering carries a different meaning of structure in psychology). On the other hand, it is necessary to be careful when a given concept is used in areas of distinct epistemic bases but with very related applications. This is the case with intelligence, as shown in Section 3.1. From the etymological point of view, the term intelligence originates from the Latin language and designates the ability to understand. Over the years, the term has been used for the most diverse areas, from military strategies to business. Today, from a cognitive perspective, its lay use has been most associated with logic, good grades, and problem-solving abilities (COHEN

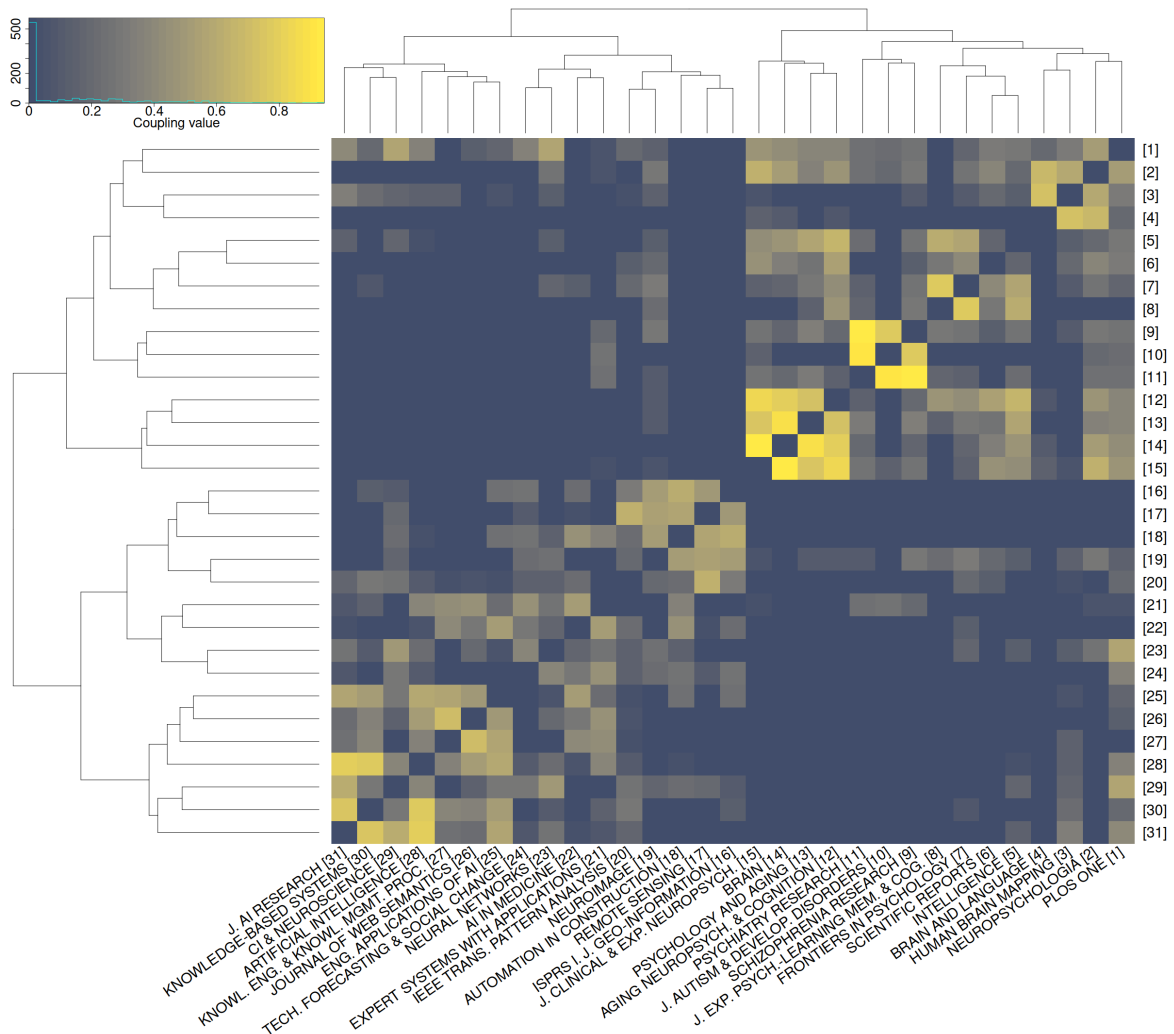


Figure 13 – Sources coupling analysis: Higher coupling values indicate that publications from these sources share references at a given level.

Source: Created by the author.

et al., 2009).

It is essential to notice that intelligence has historically been associated with formalism (FLYNN, 2007), resulting from a positivist perspective that originated, among other things, computing itself. Computer science is formalist by definition (SIPSER, 2006), although disciplines such as CI are primarily based on the information theory (SHANNON, 1948). Psychology, on the other hand, started from a solid positivist influence and began considering different epistemic bases in its studies since the emergence of psychodynamics (SOLMS; TURNBULL, 2002).

In this Section, we start by reviewing the main concepts and definitions of intelligence found in CI (Section 3.2.1) and psychology (Section 3.2.2) that support or oppose each other.

Table 3 – Most relevant sources from WoS query and its classification according to the technology, cognitive science, and application categories. PSD stands for “Publication in the Sampled Data”. PQD stands for “Publication in the Queried Data”.

	Source category	Source name	PSD	PQD
[1]	Application	Plos One	20	21
[2]	Cognitive Science	Neuropsychologia	12	21
[3]	Cognitive Science	Human Brain Mapping	7	11
[4]	Cognitive Science	Brain and Language	7	10
[5]	Cognitive Science	Intelligence	9	14
[6]	Application	Scientific Reports	10	13
[7]	Cognitive Science	Frontiers in Psychology	8	13
[8]	Cognitive Science	Journal of Experimental Psychology-Learning Memory & Cognition	6	7
[9]	Cognitive Science	Schizophrenia Research	8	8
[10]	Cognitive Science	Journal of Autism and Developmental Disorders	6	6
[11]	Cognitive Science	Psychiatric Research	8	11
[12]	Cognitive Science	Aging Neuropsychology and Cognition	9	11
[13]	Cognitive Science	Psychology and Aging	6	6
[14]	Cognitive Science	Brain	6	6
[15]	Cognitive Science	Journal of Clinical and Experimental Neuropsychology	9	10
[16]	Application	ISPRS International Journal of Geo-Information	7	7
[17]	Application	Remote Sensing	13	16
[18]	Application	Automation in Construction	8	8
[19]	Cognitive Science	Neuroimage	11	17
[20]	Technology	IEEE Transactions on Pattern Analysis and Machine Intelligence	68	171
[21]	Technology	Expert Systems With Applications	8	46
[22]	Technology	Artificial Intelligence in Medicine	10	73
[23]	Cognitive Science	Neural Networks	6	13
[24]	Application	Technological Forecasting and Social Change	8	8
[25]	Technology	Engineering Applications of Artificial Intelligence	10	111
[26]	Technology	Journal of Web Semantics	7	21
[27]	Technology	Knowledge Engineering and Knowledge Management Proceedings: Ontologies and the Semantic Web	7	35
[28]	Technology	Artificial Intelligence	44	131
[29]	Cognitive Science	Computational Intelligence and Neuroscience	8	36
[30]	Technology	Knowledge-Based Systems	13	60
[31]	Technology	Journal of Artificial Intelligence Research	20	75

Source: Created by the author.

Following this, we present the main strategies for measuring intelligence in Section 3.2.3. These various definitions led us to state, in Section 3.2.4, that there is no consensus for intelligence.

3.2.1 Definitions from computational intelligence

As defined by Russell and Norvig (2010), an intelligent agent is an entity that perceives and acts in a given environment through sensors and actuators, respectively. In this definition, the agent function, particular to each agent, determines the action to be taken by the agent in response to any perceived stimulus and is implemented through a program – the latter running on a hardware architecture containing sensors and actuators. The authors point out countless ways to implement the same agent function so that the programs present differences in efficiency, compactness, and flexibility. Therefore, the appropriate program design that will implement the agent function will depend on the nature of the environment in which this agent will be inserted. In the authors' view, this process defines AI, which they establish as the science of designing agents.

The same authors suggest that intelligent agents can be categorized into (i) simple reflex agents when they respond directly to perceptions; (ii) model-based reflex agents, when the responses to perceptions occur through internal states that are not evident; (iii) goal-based agents, whose actions are directed to achieve a previously-defined objective; and, finally, (iv) utility-based agents, who try to maximize their expected utility. In any case, the agent reads the environment state through sensors and acts on the environment through actuators, as shown in Figure 14. In this conception, agents improve themselves through learning, usually based on penalties and rewards. Interestingly, the categorization of intelligent agents into reflex, goal-based, and utility-based types echoes the concept of behaviorism in psychology, where behavior is understood as a response to stimuli in the environment, directed towards a goal or outcome, and shaped by rewards and punishments.

From the Russell and Norvig (2010)'s conception, a human would be defined as a utility-based agent: from an internal model of the world (i.e., the environment), the agent would choose the action that would maximize the expected utility, computed through the average of all possible output states and weighted by the probability of each output. The authors consider happiness as the agent function, which means a human agent would operate to become happier. It should be noticed that the attribution of happiness to the expected utility corroborates the ideas from behaviorism (SKINNER, 1965), but does not correspond to the subjective conceptions of

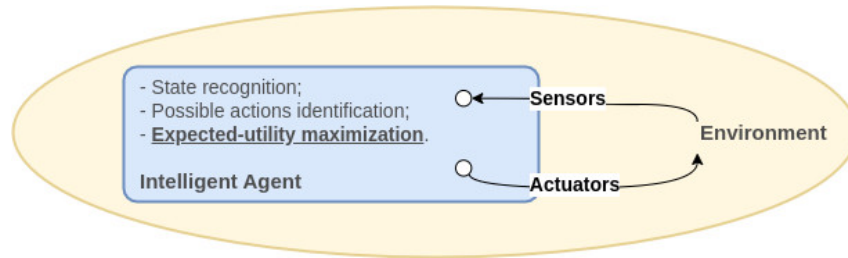


Figure 14 – Diagram of a model-based, utility-based agent. An intelligent agent perceives its environment through sensors and acts in this environment through actuators in a way that maximizes its utility.

Source: (SILVEIRA; LOPES, 2023)

happiness or pleasure that can be found in Freud (1920), Siegel (2010) nor by the concept of expected utility in situations of uncertainty addressed by Gilboa (2010).

Bezdek (1992) proposed the distinction between artificial (A), biological (B), and computational (C) intelligence – what he called the “ABCs of Neural Networks (NN), Pattern Recognition (PR), and Intelligence (I),” categorizing them according to their functional and structural complexity, as shown in Figure 15. Such a categorization, in terms of complexity CI, associated with a numeric structure, is a subset of AI, associated with symbolic structure, which, in turn, is a subset of biological intelligence, associated with organic structure. The exact relationship is established for NN: a subset of PR, and, again, in terms of complexity, a subset of I. In a more recent publication on the subject, Bezdek (2016) recognizes that, although this distinction remains valid, the borders between AI and CI are increasingly blurred.

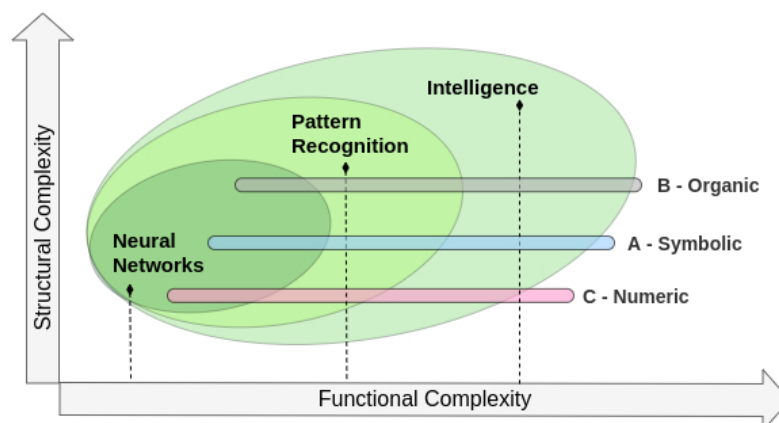


Figure 15 – Relationship between biological (B), artificial (A), and computational (C) organizations of neural networks (NN), pattern recognition (PR), and intelligence (I).

Source: (SILVEIRA; LOPES, 2023)

For instance, DNNs, which are a cornerstone of modern AI, are inspired by the structure and function of the human brain, blurring the line between artificial and biological intelligence. Similarly, CI techniques such as fuzzy logic and genetic algorithms have found applications in a

wide range of fields, from finance to medicine, demonstrating the versatility and power of these approaches. Therefore, while the distinction between artificial, biological, and computational intelligence remains a practical conceptual framework, it is crucial to recognize that the boundaries between these domains are constantly evolving and shifting.

Without explicitly defining intelligence, Shneiderman (2020) proposes an alternative categorization for AI based on goals. This author distinguishes AI research into two major groups: (i) those seeking to emulate human intelligence – for which the author includes “aspiration for humanoid robots, natural language and image understanding, commonsense reasoning, and artificial general intelligence” – and (ii) those seeking to build valuable applications, i.e., “AI-guided products and services” such as “instruments, apps, orthotics, prosthetics, utensils, or implements.”

Pandl *et al.* (2020) bring an implicit definition of intelligence by stating that “AI enables computers to execute tasks that are easy for people to perform but difficult to describe formally.” To this end, the authors segment artificial intelligence into (i) Artificial General Intelligence (AGI), an open-domain approach defined by Goertzel and Monroe (2017) as the human-like design of self-organizing and complex adaptive systems, and (ii) narrow artificial intelligence, a domain-specific approach in which the authors include knowledge bases and machine learning methods.

More recently, a conceptualization of intelligence based on its measurement was suggested by Chollet (2019, p.27), who stated that “intelligence of a system is a measure of its skill-acquisition efficiency over a scope of tasks, with respect to priors, experience, and generalization difficulty.” Such a definition is quite similar to the instrumentalist attempt from psychology to define intelligence, as we will describe in the next Section.

3.2.2 Definitions from psychology

Psychology approaches intelligence as a construct ². Cohen *et al.* (2009) bring the concept of interactionism to explain those theories that attribute intelligence to the interaction between people, consisting of biological and social factors, and these with the environment. In addition, those authors group factor-analytical theories as those concerned with identifying which factors or sets of skills express intelligence. Finally, they call information processing

² A construct is a psychometric concept designed to explain or understand a psychological phenomenon (i.e., the latent trait) from its indirect manifestations (i.e., the overt behavior).

theories those that study the mental processes that result in intelligence.

Historically, intelligence assessment has played an important and controversial role in psychology. Some authors (SIMONTON, 2003; COHEN *et al.*, 2009) attribute to Francis Galton the beginning of the scientific study of individual differences, who established mathematical techniques such as correlation to measure it – a method that later on would be improved by Pearson and Spearman.

In 1904, Spearman (1927, p.260) formulated the “two-factor theory” of intelligence, which included the specific factor (*s*), based on the unique ones and the general factor of intelligence, or *g* factor, which would be common to any intelligent ability and thus able to measure it.

Arthur Jensen delved into the *g* factor theory, thus defining intelligence operationally as “the first principal component of an indefinitely large number of highly diverse mental tasks” (JENSEN, 1978, p.112).

In 1905, Alfred Binet and Theodore Simon published a measuring scale of intelligence applied to Parisian children – the first to use a standardized Intelligence Quotient (IQ) scale. Instead of defining intelligence, Binet limited himself to describing its components: “reasoning, judgment, memory, and abstraction” (COHEN *et al.*, 2009, p.292). For them, intelligent behavior was a joint result of these abilities, countering Galton’s idea that each could be assessed separately.

The indiscriminate and uncritical use of psychological tests in the early twentieth century led Boring (1961) to state, in 1923, that “measurable intelligence is simply what the tests of intelligence test,” thus claiming for a better definition. Flynn (2007) has called this perspective “instrumentalism”, defined by him as the attempt “to measure by referring to the readings of the measuring instrument,” which is thus “subject to devastating critique.”

In 1939, David Wechsler designed an intelligence test that could be applied to adults, defining intelligence as “the aggregate or global capacity of the individual to act purposefully, to think rationally, and to deal effectively with his environment” (WECHSLER, 1958). His work originated the gold-standard tests for intelligence known as Wechsler Adult Intelligence Scale (WAIS) and Wechsler Intelligence Scale for Children (WISC). Wechsler’s definition stands out since it does not restrict intelligence to cognitive and executive functions but also considers the role of conative functions, i.e., those related to affection (COHEN *et al.*, 2009, p.52).

In the 1940s, Cattell (1941) started a work, which was later developed by Horn (1965), that led to a model where two skills were defined: crystallized intelligence (*Gc*), which includes

acquired vocabulary and knowledge, and fluid intelligence (Gf), which is non-verbal and has few cultural influences, such as the numerical memory (CARROLL, 2003). Horn later added other factors: visual processing (Gv), auditory processing (Ga), quantitative processing (Gq), processing speed (Gs), facility with reading and writing (Grw), short-term memory (Gsm), and long-term storage and retrieval (Glr) (COHEN *et al.*, 2009, p.297).

In the 1950s, Jean Piaget elaborated his theory of intelligence development in children (PIAGET, 2003). For him, learning would occur through assimilation and accommodation processes. The first consists of absorbing new data to fit it into already-known information. The second consists of changing the registered information to fit the new one. Piaget's theory of cognitive development has influenced the understanding of human intelligence and its development.

The information processing paradigm, described by Palmer (1999, p.70) as “a way of theorizing about the nature of the human mind as a computational process”, started to be employed in psychological theories from the middle of the twentieth century. Alexander Luria, considered the precursor of neuropsychology (COHEN *et al.*, 2009, p.300), was the first to conceptualize intelligence from this approach. Luria has demonstrated two ways of information processing: (i) simultaneous or parallel and (ii) successive or sequential. The first would be associated with semantic attribution tasks, while the second would involve tasks that demand attention and linear execution, such as spelling a word.

Such a paradigm provides a framework for understanding how intelligent systems process information. The simultaneous or parallel processing, which is associated with semantic attribution tasks, can be linked to approaches such as deep learning in computational intelligence, where multiple layers of neurons process information simultaneously to extract features of different abstraction levels. The successive or sequential processing, associated with tasks that demand attention and linear execution, can be linked to approaches such as reinforcement learning, where an agent learns by interacting with an environment in a sequential manner.

Gottfredson (1997) defined intelligence as “a highly general information processing capacity that facilitates reasoning, problem-solving, decision-making, and other higher order thinking skills.” Also situated in the information processing paradigm, Sternberg (2003) proposed the triarchic theory of intelligence, composed of analytical, creative, and practical aspects. Later, Sternberg (2019) proposed the theory of adaptive intelligence, questioning the general factor of intelligence, its metrics, and theoretical assumptions. His thesis is related to the environmental

impact caused by humanity and questions how intelligent such actions are. Thus, he promotes a debate between such conceptions of intelligence from a biological and optimal perspective.

The consideration of a general intelligence factor, the *g factor*, started to be used again after Carroll's work, which divided intelligence into three strata of abilities: specific, broad, and general (CARROLL, 2003). Flynn (2007, p.48) argued against the *g* factor, stating it does not provide a robust definition of intelligence but limits it to a comparison approach. He also claimed that intelligence's social and physiological aspects are reduced to the possibility of enhancing or not the significance of *g*. As an alternative, FLYNN proposes a theory that integrates physiological, individual, and social aspects of intelligence, which he calls the BIDS model – an acronym indicating the brain; the individual differences, which he associates with the *g* factor; and the society.

Recently, McGrew (2009) unified the theories of Cattell-Horn and Carroll in what he called the CHC-Theory. The Cattell-Horn model considered a total of eight abilities distributed through crystallized (*Gc*) and fluid (*Gf*) factors of intelligence. In turn, Carroll's model proposed that intelligence should be divided into three hierarchical strata: the first, of specific skills; the second, of complex factors such as *Gf* and *Gc*; and the third, the general intelligence factor, or *g*.

The CHC model integrates them in the way schematically represented in Figure 16. Some broad abilities (stratum II) are composed of narrow abilities (stratum I) as follows:

- **Fluid intelligence (*Gf*)** relates to induction (I), general sequential reasoning (RG), and quantitative reasoning (RQ);
- **Crystallized intelligence (*Gc*)** relates to general (verbal) information (KO), language development (LD), lexical knowledge (VL), listening ability (LS), communication ability (CM), grammatical sensitivity (MY), and oral production and fluency (OP);
- **General (domain-specific) knowledge (*Gkn*)** relates to foreign language proficiency (KL), knowledge of signing (KF), skill in lip-reading (LP), geography achievement (AS), general science information (K1), mechanical knowledge (MK), and knowledge of behavioral content (BC);
- **Quantitative knowledge (*Gq*)** relates to mathematical knowledge (KM), and mathematical achievement (A3);
- **Reading/writing ability (*Grw*)** relates to reading decoding (RD), reading comprehension

(RC), reading speed (RS), spelling ability (SG), English usage knowledge (EU), writing ability (WA), and writing speed (WS);

- **Short-term memory (Gsm)** relates to memory span (MS), and working memory (MW);
- **Long-term storage and retrieval (Glr)** relates to associative memory (MA), meaningful memory (MM), free-recall memory (M6), naming facility (NA), associational fluency (FA), expressional fluency (FE), sensitivity to problems/alternative solution fluency (SP), originality/creativity (FO), ideational fluency (FI), word fluency (FW), and figural fluency (FF);
- **Visual processing (Gv)** relates to visualization (Vz), speeded rotation (spatial relations) (SR), closure speed (CS), flexibility of closure (CF), visual memory (MV), spatial scanning (SS), serial perceptual integration (PI), length estimation (LE), perceptual illusions (IL), perceptual alternations (PN), and imagery (IM);
- **Auditory processing (Ga)** relates to phonetic coding (PC), speech sound discrimination (US), resistance to auditory stimulus distortion (UR), memory for sound patterns (UM), maintaining and judging rhythm (U8), absolute pitch (UP), musical discrimination and judgment (U1 U9), and sound localization (UL);
- **Olfactory processing (Go)** relates to olfactory memory (OM);
- **Tactile abilities (Gh)** has no narrow ability;
- **Psychomotor abilities (Gp)** relates to static strength (P3), multilimb coordination (P6), finger dexterity (P2), manual dexterity (P1), arm-hand steadiness (P7), control precision (P8), aiming (A1), and gross body equilibrium (P4);
- **Kinesthetic abilities (Gk)** has no narrow ability;
- **Processing speed (Gs)** relates to perceptual speed (P), rate-of-test-taking (R9), number facility (N), reading speed (fluency) (RS), and writing speed (fluency) (WS);
- **Decision speed/reaction time (Gt)** relates to simple reaction time (R1), choice reaction time (R2), semantic processing speed (R4), mental comparison (R7), and inspection time (IT);

- **Psychomotor speed (Gps)** relates to speed of limb movement (R3), writing speed (fluency) (WS), speed of articulation (PT), and movement time (MT).

In fact, the CHC model adds the g factor to Cattell-Horn's theory and seeks for empirical evidence for its validation. For each broad ability (stratum II) in the CHC model, a set of narrow abilities (stratum I) is considered. As observed by Flanagan and Dixon (2014), the CHC theory is "a dynamic model that is continuously reorganized and restructured based on current research", a statement reaffirmed by the last update on the CHC model where some factors were removed or rearranged (SCHNEIDER; MCGREW, 2012).

For last, we must consider that human intelligence allows us to handle both accurate and vague information by computing with numbers and words. This is consistent with the Bayesian brain theory (FRISTON, 2010; POUGET *et al.*, 2013), one of the most accredited theories in neuroscience sustaining "the brain both represents probability distributions and performs probabilistic inference" based on sensory input and prior models. Human decision-making based on incomplete information is also well-modeled by fuzzy logic (ZADEH, 2000). Recently, a close link between Fuzzy logic and Bayesian inference has been established (GENTILI, 2021), shedding light on a possible unified perspective for intelligent behavior.

3.2.3 Intelligence measurement

As claimed by Cohen *et al.* (2009, p.303), "how one measures intelligence depends in large part on what one conceives intelligence to be." That said, in this Section, we will describe the main intelligence measures supported by the theories and definitions given in the former Sections 3.2.1 and 3.2.2.

3.2.3.1 Intelligence measurement in computational intelligence

Russell and Norvig (2010) bring an economic perspective to the field. To them, a performance measure is necessary to evaluate a given agent's behavior in a given environment. Therefore, a rational agent would act to maximize its expected value as a performance measure, that is, maximize its expected utility. According to Gilboa (2010), such a proposition is only reasonable when we understand the utility's meaning and know the probability of such an event, which usually does not occur when dealing with applications under uncertainty.

Inspired by the g factor of intelligence and its measure, the IQ, some researchers

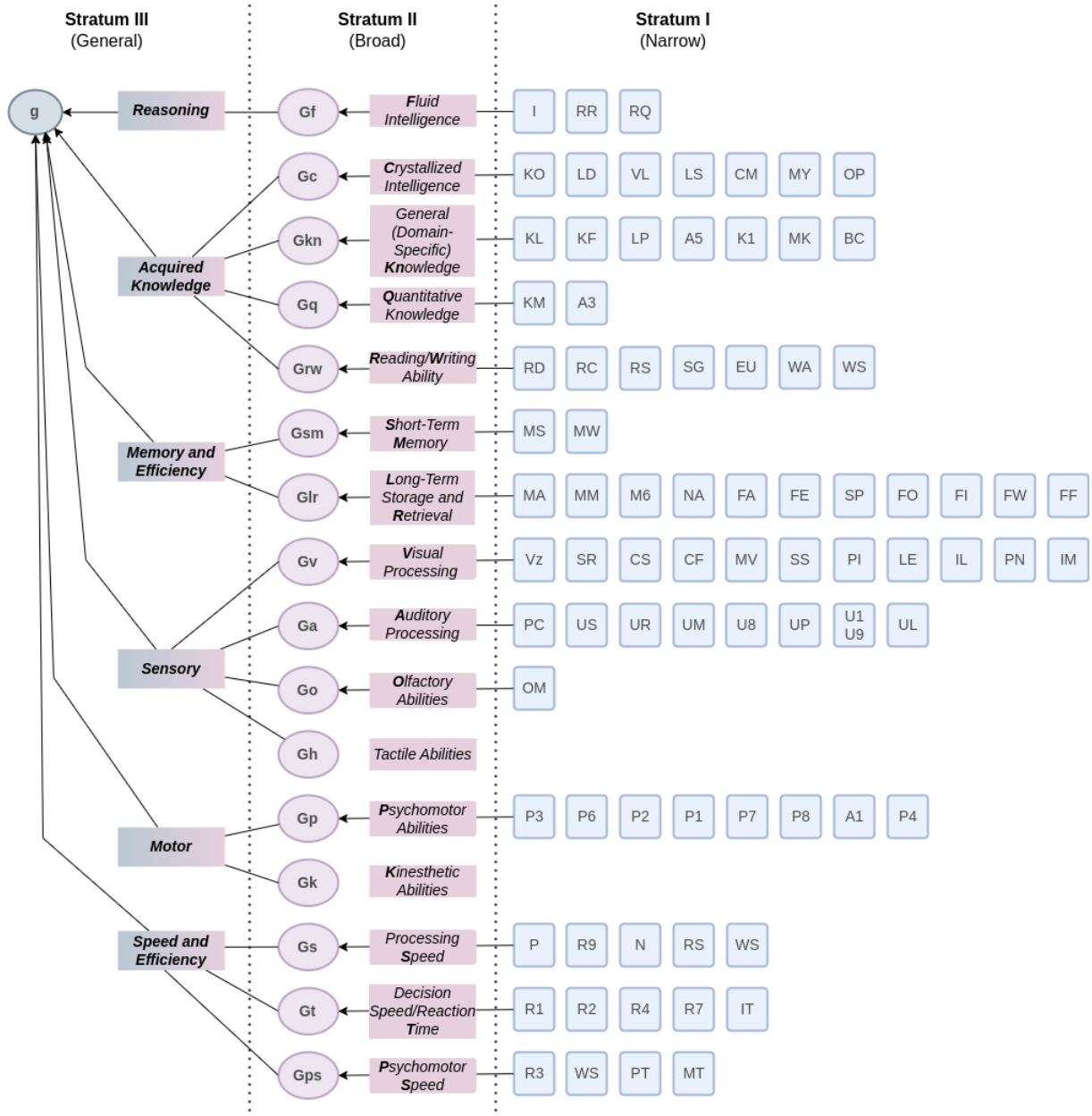


Figure 16 – CHC theory of intelligence. Strata I represents the narrow abilities, as defined and detailed in (SCHNEIDER; MCGREW, 2012). Strata II represents the broad abilities, grouped by (FLANAGAN; DIXON, 2014) in reasoning (Gf), acquired knowledge (Gc, Gkn, Gq, Grw), memory and efficiency (Gsm, Glr), sensory (Gv, Ga, Go, Gh), motor (Gp, Gk), and speed and efficiency (Gs, Gt, Gps). Strata III represents the factor *g* of general intelligence.

Source: (SILVEIRA; LOPES, 2023)

proposed an equivalent metric for AI: the Machine Intelligence Quotient (MIQ). Park *et al.* (2001) proposed a framework for MIQ measurement in human-machine cooperative systems. These authors affirm that “machine intelligence is the ability to replicate the human mental faculty and to perform human-like.” Following it, they define MIQ as “the measure of autonomy and performance for unanticipated events.” From their definitions, both intelligence uses relate to different constructs or phenomena.

Another approach is offered by Ozkul (2009), who defines MIQ as the difference between the Control Intelligence Quotient (CIQ) and Human Intelligence Quotient (HIQ). In his work, HIQ is posed as “the intelligence quantity needed from the human controller for controlling the system.” In contrast, CIQ is defined as “the total intelligence required for carrying out all the tasks in the man-machine cooperative system.” Notice that an independent definition of intelligence was not provided.

Liu and Shi (2014), in turn, compare the performance of the Internet with that of the human brain network and propose a shallow equivalence with the human IQ without accounting for the assumptions of validity and precision necessary in psychometry.

Regarding ML and DL, the measurement of intelligence is replaced by some kind of performance evaluation. As pointed out by Goodfellow *et al.* (2016), the performance measure is usually task-specific, and it is obtained through well-defined measurements such as accuracy, precision, and recall.

3.2.3.2 Intelligence measurement in psychology

If, on the one hand, a definition of intelligence is essential for computation to develop better systems and agents, on the other hand, for psychology, its primary justification comes from the need to assess both children and adults to identify their abilities and limitations due to traumas, illness, special skills, and any other diagnostic requirement.

Most of the theories for intelligence discussed in Section 3.2.2 sustain an intelligence measuring instrument. It is not the scope of this work to detail each of them. For illustrative purposes, we will follow the discussion based on Wechsler’s subtests, whose structure is depicted in Figure 17. In this instrument, the g factor is measured as the Full-Scale IQ (FSIQ), which is calculated from the Verbal IQ (VIQ) and Performance IQ (PIQ). VIQ is obtained by two factors (latent variables): the Verbal Comprehension Index (VCI), whose observable variables are the results of the tests of vocabulary, similarities, information, and comprehension; and the Working Memory Index (WMI), whose observable variables are the results for arithmetic, digit-span, and letter-number sequencing. PIQ is also obtained by two factors: the Perceptual Reasoning Index (PRI), calculated over the results for picture completion, block design, matrix reasoning, visual puzzles, and figure weights; and the Processing Speed Index (PSI), calculated over the results for coding, symbol search, and cancellation.

Nowadays, Wechsler’s tests validity is supported by the CHC theory (WEISS *et al.*,

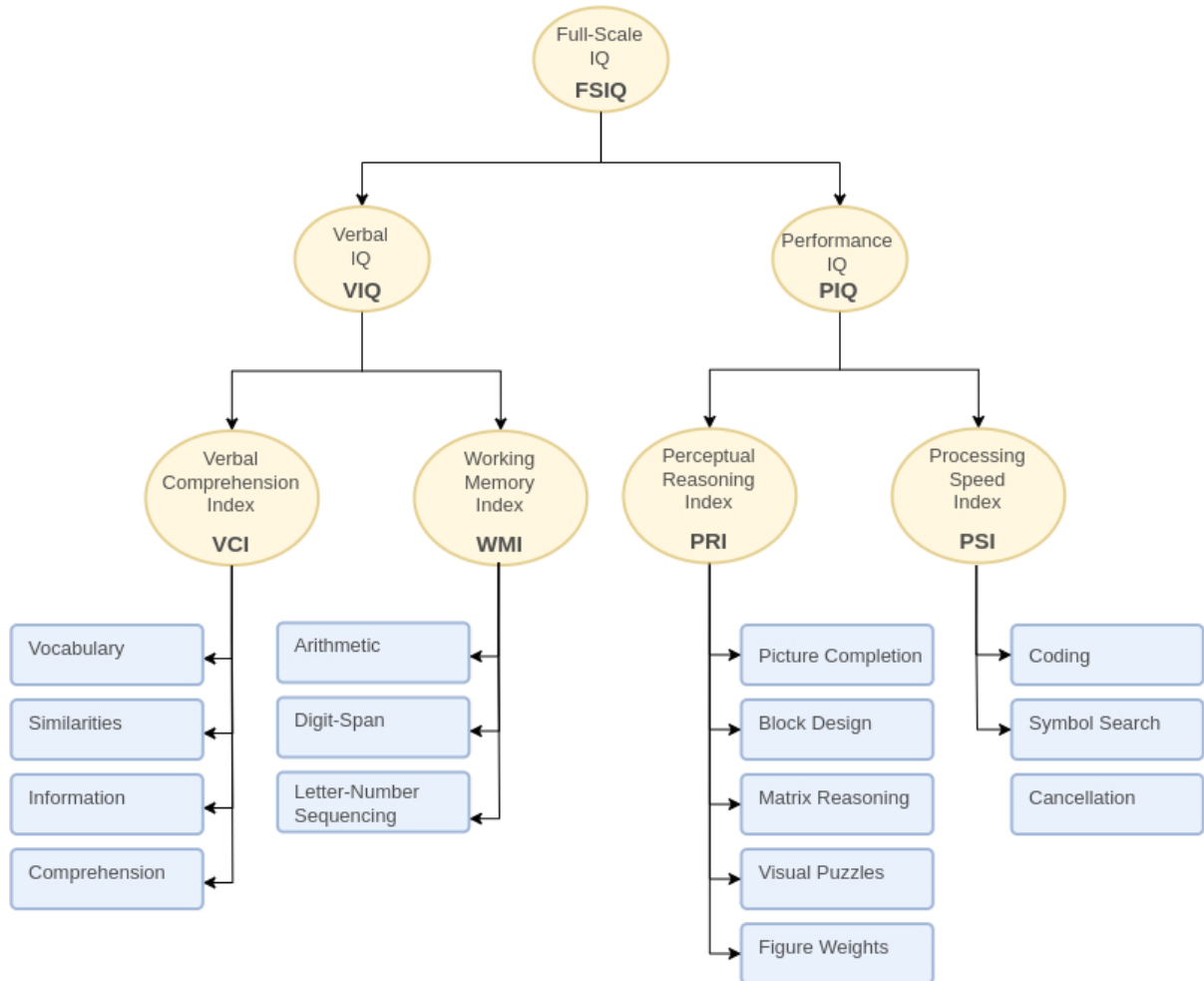


Figure 17 – Subtests composing the instruments for intelligence assessment based on the Wechsler scale, including the Wechsler Adult Intelligence Scale-Fourth Edition (WAIS-IV) and the Wechsler Intelligence Scale for Children-Fourth Edition (WISC-IV). Adapted from (WEISS *et al.*, 2006).

Source: Created by the author.

2006; GRÉGOIRE, 2013; SCHEIBER, 2016). The following relationship is suggested by Grégoire (2013): the VCI relates to crystallized intelligence (G_c); the WMI relates to short-term memory (G_{sm}); the PRI relates to fluid intelligence (G_f) and visual processing (G_v), and the PSI relates to processing speed (G_s). However, Scheiber (2016) suggests a slightly different relationship with the CHC model for the arithmetic subtest of the Wechsler Intelligence Scale for Children - 5th Edition (WISC-V), which would measure not only short-term memory (G_{sm}) but also fluid intelligence (G_f) and crystallized intelligence (G_c).

Incidentally, the study of psychic abnormalities and their correlation with neural anatomy – i.e., the anatomy-clinical method – has led to remarkable findings from Charcot³

³ Jean-Martin Charcot (1825-1893) was a French neurologist who is considered a pioneer in the field of clinical neurology. He is known for his contributions to the understanding and treatment of several neurological disorders, including multiple sclerosis and Parkinson's disease. He was also a teacher and mentor to many influential figures in medicine, including Sigmund Freud.

to modern computational neuroscience (GOETZ, 2009). An example of the before-mentioned correlation between adjacent neural processes and intelligence tests is found in the following quote:

“The Picture Vocabulary subtest was developed to further reduce the nonspecific language demands of the Vocabulary test. (..) The child must have the capacity to interpret pictures into their semantic representation. (..) For the vocabulary subtests, there are a number of hypotheses to test when the examinee receives a low score (..): are low scores due to impaired auditory or semantic decoding, semantic productivity, access to semantic knowledge and/or executive functioning, or limited auditory working memory capacity?” (WEISS *et al.*, 2006, p.217).

The above description indicates how semantic processes relate to the sensory inputs of vision, hearing, and executive, memory, and language functions. Therefore, the relevance of such diagnostic hypotheses goes beyond clinical assessment. It can inspire and direct research on the issues presented in Chapter 1, as the enhancement of computational models to explain semantic attribution and to enable semantic emulation in CI applications.

Finally, it is worth mentioning another point of convergence between the areas we are working with: the Computer-Assisted Psychological Assessment (CAPA), which includes not only the test administration but also scoring, interpretation, and development. Such an approach can be exemplified by the recent works from Martins and Baumard (2022) and (LUO *et al.*, 2020). As pointed by Cohen *et al.* (2009, p.78), “CAPA has become more the norm than the exception.” However, the authors identify issues regarding this strategy that need to be addressed: information security concerns, comparability between the pencil-and-paper test and its computerized version, the validity of test interpretations by computational intelligence methods, and the unprofessional use of online psychological tests.

3.2.3.3 Intelligence measurement between humans and artificial systems

Two theoretical tests played an important role in AI development and speculated its limits: the Turing test and Searle’s Chinese room. Initially published as “the game of imitation,” the Turing test proposes that a human observer interrogates a computer and another human without knowing their identities. Once the computer deceives the human observer, it could be claimed that it thinks or expresses human intelligent behavior (TURING, 2012).

Later, in the 1980s, when criticizing functionalism ⁴ John Searle defended the idea

⁴ Functionalism is a theory of mind that assumes that two isomorphic systems, given the same sensory inputs, would have identical mental states

of biological naturalism – in which mental states are high-level abstractions that emerge from low-level instances, physically supported on neurons. For this, he proposed the Chinese room experiment, where a human knowing only the English language and equipped with an instruction book would perform operations written in Chinese. For an outside observer, the English-speaking human would be understanding Chinese and would pass the Turing test. However, the mere manipulation of symbols would not guarantee him any understanding (RUSSELL; NORVIG, 2010, p.1031).

From a practical standpoint, rough comparisons are often used when evaluating the interface between humans and artificial systems. For example, human performance is compared to computational performance in formal reasoning tasks like arithmetic. In semantic-related applications, the algorithm’s performance is typically measured against a dataset that one or more humans have annotated. These practical comparisons contrast the philosophical debates about whether artificial intelligence can fully replace or emulate human intelligence, often centered around the Turing test and the Searle’s Chinese room experiment.

It sounds plausible to include in this Section the answer given by an AI agent itself, the ChatGPT^{5,6} (OPENAI, 2023), when asked about the differences between human and AI:

(...) “Human intelligence is the product of the complex interactions between the brain’s neurons and the environment, resulting in the ability to learn, reason, and solve problems. On the other hand, AI refers to the ability of machines or computer systems to perform tasks that typically require human-like intelligence, such as language processing, visual perception, decision-making, and problem-solving. (...) Finally, human intelligence is influenced by factors such as emotion, motivation, and context, whereas AI is typically designed to operate in a context-free environment and lacks emotional awareness or subjective experience.”

The above answer appears satisfactory and could easily be alleged to a student. In other words, it passes the Turing test, but as Searle advocated, it is nothing else than complex and effective symbol manipulation. From this perspective, a lack of a standard definition of intelligence between areas with distinct epistemic bases, as introduced at the beginning of Section 3.2, sustains the problem posed by Searle. Computing seeks to generalize intelligence through its codification in algorithms. In formal reasoning (e.g., arithmetic), indeed, the result must be unanimous and general. However, on the other hand, evaluating the semantic performance of an algorithm trained from a dataset annotated by humans implies assuming that such annotations would be similar throughout humanity. It may be for some concepts, but numerous studies expose

⁵ ChatGPT is “a large-scale, multimodal model which can accept image and text inputs and produce text outputs,” (OPENAI, 2023) developed and trained under a deep learning perspective, as introduced in Section 2.2.3.

⁶ The full transcript of the interaction with the ChatGPT-3.5 prompt is available in Appendix A.

the subjective and particular character of any meaning attribution (LAKOFF, 1990). This topic will be further approached in Chapter 4.

3.2.4 There is no consensus for intelligence

We presented and discussed the main theories for intelligence, summarized in Table 4 for CI and, in Table 5, for psychology. We propose a categorization of the intelligence scope based on the theory extension: general (G), open-domain (OD), or specific-domain (SD). Following this, we also categorized the modeling approach based on the epistemic foundations in the definition or theorization of intelligence, which can be either formal-logical (FL), instrumentalist (INS), information processing (IP), interactionist (INT), factor-analytical (FA), or skill-based (SB). We also identified the measurement approach for each author, whether through psychometric, observational, or performance metrics.

Table 4 – Intelligence definitions from computational intelligence and their respective authors. Intelligence scope can be general (G), open-domain (OD), or specific-domain (SD). The modeling approach can be information processing (IP), formal-logical (FL), factor-analytical (FA), interactionist (INT), instrumentalist (INS), or skill-based (SB). The measurement approach can be performance metrics (PM), psychometric (PSY), or observational (OBS). Related applications are detailed for each author.

Authors	Intelligence Definition	Intel. Scope	Mod. Approach	Meas. Approach	Related Applications
Bezdek (1992)	Distinguishes artificial, biological, and computational intelligence, according to their complexity, in a hierarchical structure.	G, OD, SD	IP	PM	Neural networks, pattern recognition, and general and specific-domain intelligences.
Russell and Norvig (2010)	The ability to perceive and act in a given environment through sensors and actuators, respectively, maximizing its expected utility.	OD, SD	FL	PM	Defines: simple reflex agents; model-based reflex agents; goal-based agents; and utility-based agents.
Chollet (2019)	Intelligence of a system measures its skill-acquisition efficiency over a scope of tasks.	G	FL, IP, FA	PSY, PM	The author proposes the Abstraction and Reasoning Corpus (ARC) as a benchmark dataset for general intelligence. Uses the CHC model as a reference in his work.
Shneiderman (2020)	Categorizes AI into: (i) emulation goal and (ii) application goal.	OP	FL	PM	For emulation: intelligent agent, humanoid robot, etc. For application: powerful tool, teleoperated device, etc.
Pandl <i>et al.</i> (2020)	Execution of tasks that are easy for people to perform but difficult to describe formally.	G, SD	FL, IP	PM	AGI (e.g., self-organizing and complex adaptive systems), and narrow AI (e.g., machine learning).

Source: Created by the author.

Table 5 – Intelligence definitions from psychology and their respective authors. Intelligence scope can be general (G), open-domain (OD), or specific-domain (SD). The modeling approach can be information processing (IP), formal-logical (FL), factor-analytical (FA), interactionist (INT), instrumentalist (INS), or skill-based (SB). The measurement approach can be performance metrics (PM), psychometric (PSY), or observational (OBS). Related applications are detailed for each author.

Authors	Intelligence definition	Intel. Scope	Mod. Approach	Meas. Approach	Related Applications
Binet (1905) apud Cohen <i>et al.</i> (2009)	It is compounded by reasoning, judgment, memory, and abstraction.	G	INT	PSY	Has published the first IQ scale.
Boring (1961)	Criticized intelligence definitions: it is what tests test.	G	INS	PSY	Claimed for a better definition from the scientific community.
Spearman (1927)	There is a general factor <i>g</i> correlated with all its manifestations.	G	INS	PSY	Two-factor theory and <i>g</i> factor.
Wechsler (1958)	The aggregate or global capacity to act purposefully, think rationally, and deal effectively with the environment.	G, SD	INT, FA	PSY	Modeled the cognitive, executive, and conative aspects. Created the first editions of the WISC/WAIS psychometric tests.
Cattell (1941)	Intelligence has crystallized and fluid aspects.	OD	FA	PSY	The Gc-Gf model is part of the modern CHC model.
Piaget (2003)	It is developed through assimilation and accommodation processes.	OD, SD	INT	OBS	Psychology of intelligence through its development stages.
Horn (1965)	Added many specific factors to Cattell's theory of Gc-Gf.	OD, SD	FA	PSY	This theory became known as the Cattell-Horn model and did not admit the <i>g</i> factor.
Luria (1973)	Intelligence results from two ways of information processing: parallel or sequential.	OD, SD	IP	PSY, OBS	Luria is considered the precursor of neuropsychology.
Jensen (1978)	Intelligence is the first principal component of an indefinitely large number of highly diverse mental tasks.	G	FA	PSY	Distinguished intelligence from memory and learning. Also defined mental and physical abilities.
Gardner (1983) apud Jensen (1978)	Defines multiple intelligences, including art and spirituality.	OD	SB	OBS	There are several critics of his work due to the lack of psychometric validity.
Sternberg (2003), Sternberg (2019)	Compounded by analytic, creative, and practical aspects. Intelligence is defined through a biological and optimal perspective.	G, SD	IP	PSY, OBS	The triarchic theory of intelligence (2003). Theory of adaptive intelligence (2019).
Carroll (2003)	Intelligence is divided into general, broad, and specific abilities.	G, OD, SD	FA	PSY	The three-stratum model is part of the modern CHC model.
Gottfredson (1997)	A highly general information processing capacity.	G, SD	FA, IP	PSY	Gottfredson advocates for the <i>g</i> factor.
Flynn (2007)	It integrates physiological, individual, and social aspects.	G, SD	IP	PSY	BIDS model and the Flynn effect.
McGrew (2009)	Unified the theories of Cattell-Horn and Carroll, creating the CHC model.	G, OD, SD	FA, IP	PSY, OBS, PM	This theory is the gold-standard reference for intelligence assessment in psychology.

Source: Created by the author.

As a matter of fact, Tables 4 and 5 lack a standard and general definition for intelligence, comprehensive to both, CI (mostly objective and formal) and psychology (mostly subjective).

Since long ago, (NEISSER, 1979; NEISSER *et al.*, 1996) emphasized many times in his studies that a widely accepted definition of intelligence remains a challenge. In this thesis, we reinforced such an idea by showing the many conceptualizations and divergences around this subject.

Flynn (2007) observed that Jensen stopped using the term intelligence due to its lack of precision and consensus when referring to mental abilities, the construct measured by *g*. Recently, the same absence was pointed out by Rindermann *et al.* (2020) in a survey from the Internet-based Expert Questionnaire on Cognitive Ability (EQCA), where participants' opinions on the *g* factor, intelligence measurement, and controversial issues were collected. Thus the models that define – and therefore explain – intelligence still need to be further elaborated. Other issues must also be taken into account, such as cross-cultural variation and human-machine interfaces. Flynn (2007, p.54) says that “different societies have different values and attitudes that determine what cognitive problems are worth the investment of mental energy.” Following this, one can wonder if it is reasonable to think about a general intelligence.

Garlick (2002), after reviewing the main theories and models regarding intelligence, proposes a conceptual integration of the models from neural and cognitive sciences with the psychometric-based theory of general intelligence:

“These approaches initially seem contradictory because neuroscience and cognitive science argue that different intellectual abilities would be based on different neural circuits and that the brain would require environmental stimulation to develop these abilities. In contrast, intelligence research argues that there is a general factor of intelligence and that it is highly heritable. However, it was observed that if people differed in their ability to adapt their neural circuits to the environment, a general factor of intelligence would result. Such a model can also explain many other phenomena observed with intelligence that are currently unexplained” (GARLICK, 2002, p.131).

As the author emphasizes, further research is needed to provide an intelligence model that satisfactorily explains its manifestations. In neuropsychology, the CHC model has been considered the most robust and efficient one – we highlight here the role of psychological assessment and psychometrics to validate the theory a test is based upon since it brings empirical evidence. However, despite the broad and narrow abilities proposed by the CHC model, depicted in Figure 16, many of them are still unexplored by intelligence measurement instruments in psychology and even more rarely discussed in CI applications.

The naiveness of the concept of intelligence in computing is deeply debated in recent works (KORTELING *et al.*, 2021; ZHAO *et al.*, 2022). Its relationship with human intelligence is observed, for instance, from the following statement:

“In the early days of artificial intelligence, the field rapidly tackled and solved problems that are intellectually difficult for human beings but relatively straight-

forward for computers — problems that can be described by a list of formal, mathematical rules. The true challenge to artificial intelligence proved to be solving the tasks that are easy for people to perform but hard for people to describe formally — problems that we solve intuitively, that feel automatic, like recognizing spoken words or faces in images (GOODFELLOW *et al.*, 2016, p.1)”.

Since many AI and CI applications are related to cognitive and neuropsychic functions, such as vision, language, and decision-making, the equivalent robustness of the term intelligence found in psychology – mainly represented by the CHC model – must be sought in computing for a consensus in the definition and measurement of intelligence among all its related areas.

3.3 A PROPOSAL FOR A BROADER DEFINITION OF INTELLIGENCE

We have explored what intelligence is in both CI and psychology, demonstrating the lack of consensus even within the same field. Since divergent concepts about intelligence can distort measurements and mislead applications, we propose a broader definition based on how autonomous agents process information.

According to Franklin and Graesser (1997, p.25), an autonomous agent is “a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future.” Not only is the environment changed by the autonomous agent, but the agent is also susceptible to environmental changes and may even be extinguished by them. A taxonomy proposed by Franklin and Graesser (1997) classifies autonomous agents into biological, robotic, or computational ones. Each agent structure admits the existence of subagents – i.e., instances internal to the agents – and agent societies. The latter results from interactions between agents in the same environment or system.

Such conception enables any intelligent system to be modeled as an information processing system so that any information perceived by the agent from its environment is encoded singularly through distinct representational structures. Based on this, we define:

Definition 3.1 (Ontology). The totality of principles and mechanisms that explain or are responsible for the inherent properties of a system, being, or agent – represented by a given set of parameters Ω .

Definition 3.2 (Autonomous Agent). A system that can continuously perceive the environment it is situated within and act on it according to its own ontology:

$$F = A(\Omega, \mathcal{E}), \quad (6)$$

where F is the agent’s action and A is the agent’s autonomous decision, which is a function of their ontological parameters Ω and the environment states \mathcal{E} .

Definition 3.3 (Intelligence). The ability of an autonomous agent to process external and internal information to find an optimum adaptation (decision-making) to the environment, thus decoding this information as an output action:

$$F_I \stackrel{I}{=} \text{optimal } A(\Omega, \mathcal{E}|I), \quad (7)$$

where F_I is the agent’s intelligent action resulting from the optimized agent’s autonomous decision A given the intelligence factors I .

It is crucial to distinguish between computational ontology and the broad sense of ontology. In AI, ontology may refer to “a set of representational primitives with which to model a domain of knowledge or discourse.” (GRUBER, 2008) These primitives are usually defined in terms of classes, properties, and relations among them. Such a definition sustains the object-oriented programming paradigm and semantic web⁷ research (CAMBRIA; WHITE, 2014). In a broader sense, which we claim for in Definition 3.1, ontology refers to the totality of principles and mechanisms that lead to an agent’s constitution.

3.3.1 Categories of intelligent agents

Considering the ontological aspects of a given agent, the structural complexity defined by Bezdek (2016) and discussed by Sterling and Laughlin (2015), and the information theory (MACKAY, 2003; STONE, 2015), we propose the following categorization of intelligent agents:

- **Artificial Intelligent Agents (AIA):** All those autonomous and adaptive agents whose ontological bases are in the context of AI, CI, and robotics.
- **Human Intelligent Agents (HIA):** Once humans perceive and act on their environment, they are settled as autonomous agents. The ontology of such agents is a fundamental topic in different fields of study, including philosophy and psychology. In Section 3.2.1, we have already mentioned the utility-based perspective proposed by Russell and Norvig (2010) and also found in behaviorist theories (SKINNER, 1965) – an ontological basis from

⁷ For instance, the terms ontology and ontologies found in Figure 12 relate to the semantic web, which can be understood as a markdown language aiming to classify semantic elements.

a formal-logical perspective. In this work, we rely on perspectives from computational neuroscience and psychodynamic theories, detailed in Section 4.3.

- **Biological Intelligent Agents (BIA):** Any biological agent other than human. Like HIA, the ontological bases of a BIA, be it an insect or a mammal, can also be described through information processing approaches.

Concerning the categories of autonomous agents, it is crucial to distinguish intelligence from consciousness. SETH (2021) states that “consciousness has more to do with being alive than with being intelligent.” In other words, consciousness requires the agent to have a self-perception ability found in HIA and BIA, as is the case for mammals. However, being conscious is not a condition for intelligence.

3.3.2 Categories of intelligence

Although the Definition 3.3 is compatible with the CHC model, applying it to any category of intelligent agent can be arduous, given that CHC model was developed for HIA who have considerably distinct ontological and epistemological bases. Therefore, we propose in Silveira and Lopes (2023) a categorization of intelligence in the following aspects:

- (i) **Formal**, based on reasoning and logical representation;
- (ii) **Semantic**, characterized by meaning attribution for both vague and accurate information;
- (iii) **Contextual**, an optimization scheme that takes into account an agent’s ontology and the state of the environment;
- (iv) **Social or Affective**, which involves interaction between agents and is dependent on their respective ontologies; and
- (v) **Processing Resources**, the substrates that enable any intelligent expression (e.g., biological or digital).

The proposed categorization results from a theoretical synthesis of the studies presented in this thesis while also considering the prevailing scientific paradigms and their inherent conflicts⁸, such as objectivism versus subjectivism, determinism versus indeterminism, and formal-logics versus information processing.

⁸ An in-depth discussion of paradigms related to intelligence and semantics is given in Section 4.1.

The relationship between CHC factors and those five proposed aspects of intelligence are synthesized in Table 6. It was obtained based on the opinion of two experts when relating each item from Stratum I of the CHC model with the proposed factors. The markings were then grouped according to Stratum II and normalized by the number n of Strata I for a given factor. By observing Table 6, one can affirm that **formal intelligence** relates mainly to reasoning (fluid intelligence, Gf) and acquired knowledge (quantitative knowledge, Gq); **semantic intelligence** relates mainly to acquired knowledge (crystallized intelligence, Gc, and general knowledge, Gkn) and sensory (olfactory abilities, Go, and visual processing, Gv); **contextual intelligence** relates mainly to motor (kinesthetic abilities, Gk) and memory and efficiency; **social and affective intelligence** relates mainly to sensory (olfactory abilities, Go) and acquired knowledge (crystallized intelligence, Gc); **processing resources**, in turn, relates primarily to speed and efficiency but also to sensory, motor, memory and efficiency, and acquired knowledge.

It is worth mentioning that such categorization has some known limitations that will be addressed in future works: the number of expert judges must be improved; appropriate methods should be employed to validate the inner consistency of the factors, as well as more empirical evaluation of its validity and precision. In any case, establishing a relationship between the CHC factors and the proposed categorization shed light on developing intelligence assessment instruments also for AIA.

Our proposal raises several research questions, including the possibility of a unified concept of intelligence that abstracts the ontology of each agent (i.e., the biological constitution versus digital) and how to unify the measurements of this single theory. Additionally, we need to evaluate and differentiate narrow abilities from computational and human agents. Notably, the CHC model is a robust theory for intelligence. However, many of its broad and narrow abilities are still underexplored in psychology and rarely mentioned in computational intelligence applications. These remaining questions must be addressed in future research.

3.4 CONTRIBUTIONS FROM THIS CHAPTER

Throughout this Chapter, we explored what intelligence is both in computational intelligence and psychology. Our first contribution was to show that, although these areas have a strong relationship, a common definition for intelligence is still needed. In the same way, we explored how intelligence is measured in these areas through instruments supported by the given theories. Secondly, we showed that there is no consensus for intelligence even in the same area.

Table 6 – Relationship of the five aspects of intelligence with the CHC model. Each CHC factor (Stratum II) has n Stratum I items. The value of each proposed aspect indicates its correlation with the CHC factor.

		Proposed Intelligence Categorization					
		n	Formal	Semantic	Contextual	Social / Affective	Resources
CHC Factors	Acquired Knowledge	23	0,39	0,87	0,26	0,35	0,43
	Gc	7	0,29	1,00	0,43	0,57	0,29
	Gkn	7	0,43	1,00	0,14	0,43	0,29
	Gq	2	1,00	0,50	0,00	0,00	0,50
	Grw	7	0,29	0,71	0,29	0,14	0,71
	Memory and Efficiency	13	0,38	0,62	0,08	0,00	0,77
	Glr	11	0,36	0,64	0,00	0,00	0,73
	Gsm	2	0,50	0,50	0,50	0,00	1,00
	Motor	9	0,11	0,00	0,44	0,00	1,00
	Gk	1	0,00	0,00	1,00	0,00	1,00
	Gp	8	0,13	0,00	0,38	0,00	1,00
	Reasoning	3	1,00	0,00	0,00	0,00	0,00
	Gf	3	1,00	0,00	0,00	0,00	0,00
	Sensory	21	0,43	0,48	0,19	0,05	0,57
	Ga	8	0,50	0,25	0,38	0,00	0,88
	Gh	1	0,00	0,00	0,00	0,00	1,00
	Go	1	0,00	1,00	0,00	1,00	1,00
	Gv	11	0,45	0,64	0,09	0,00	0,27
	Speed and Efficiency	14	0,21	0,36	0,07	0,00	1,00
	Gps	4	0,00	0,00	0,00	0,00	1,00
	Gs	5	0,40	0,60	0,00	0,00	1,00
Gt	5	0,20	0,40	0,20	0,00	1,00	
Total CHC Factors		83					

Source: Created by the author.

This fact shows the need for a common concept to guide human and computational intelligence since divergent concepts about intelligence can bias measurements and mislead applications.

Therefore, to meet this need, we proposed a comprehensive definition of intelligence, which we formalized as the ability of an autonomous agent to process internal and external information in order to find an optimum adaptation to the environment. This is accomplished by decoding the input information as an output action. Such a definition extends to any autonomous agent, which we propose to be classified as AIA, HIA, and BIA. Finally, to make this conceptualization applicable in areas with different epistemologies, we proposed reducing the CHC model of intelligence into just five aspects: formal, semantic, contextual, social or affective, and processing resources. Such a reduction will be validated in future studies. Furthermore, given the

fact that the CHC model is considered the gold standard in the study of intelligence, the visual organization of its 83 factors that make up the model, as shown in Figure 16, is also a relevant contribution of this study.

Considering the definitions and terminologies discussed in this Chapter, especially the definitions brought by Bezdek (2016) and presented in Section 3.2.1, from now on, our context of action will be restricted to CI and no longer to AI, as a whole. This refinement in focus is crucial for the subsequent chapters, as it allows us to delve deeper into the specific challenges and opportunities within the realm of CI.

In the next Chapter, we will delve deeper into the semantic aspects of intelligence, seeking to understand the characteristics that compose it and that are inherent to HIA, as well as establishing the methods and resources necessary for improving its emulation in AIA. From now on, we can state that semantic attribution is an aspect of intelligent behavior. Nevertheless, it is not an exclusive factor of intelligence: other aspects are also constitutive, and therefore, there may be intelligent agents without the ability to attribute or interpret semantics.

4 A TRANSDISCIPLINARY APPROACH FOR SEMANTICS

The limits of my language mean the limits of my world.

—Ludwig Wittgenstein, *Tractatus Logico-Philosophicus*

So far, we have discussed what intelligence is and how an intelligent agent attributes semantics, whether artificial, human, or biological. It is worth remembering that, in general, semantic attribution and language are natural human phenomena. In Chapter 1, we settle semantics as the intersection between linguistics, psychology, and computational intelligence, which justifies our transdisciplinary approach. As outlined in Figure 18, linguistics mainly studies language’s grammatical, syntactic, semantic, and phonological rules. Psychology, in turn, is dedicated to studying cognition, representations, and mental constructs, seeking to understand the process of language acquisition. CI is mainly dedicated to the development of ML and DL methods, interfacing with linguistics on the formalization of language (e.g., syntactic rules) and the discussion of semantics itself. CI interfaces with psychology in a range of applications related to CV, NLP, among others.

However, even though CI, linguistics, and psychology relate to intelligence and share semantics as an object of study or application, they are not supported by the same epistemological assumptions. As pointed out by Belz (2022), such a fact may be challenging for reproducibility and replicability. It turns out that the procedures used to treat semantics in computational applications are sustained by insufficient or inappropriate paradigms.

This thesis aims to address an important issue: how one could minimize the impact of epistemic divergences while ensuring cross-fertilization between these areas to solve the semantic attribution problem? Our proposed solution initially seeks to outline the scientific precepts of each area and then offer common alternatives. To do so, we use the definition of a scientific paradigm explored in Section 4.1, where we propose a categorization for the main paradigms related to semantics, as depicted in Figure 19. More than that, we establish criteria for identifying these paradigms – a method of epistemological analysis, synthesized in Table 7, that will be used in the subsequent sections of this Chapter. Based on our paradigmatic analysis, we explore the main semantic-related theories from linguistics (Section 4.2) and psychology (Section 4.3).

In this Chapter, we adopt a conversational style, aiming to dialogue with the reader to convey the appropriate idea of paradigms, semantics, and meaning. Furthermore, to understand

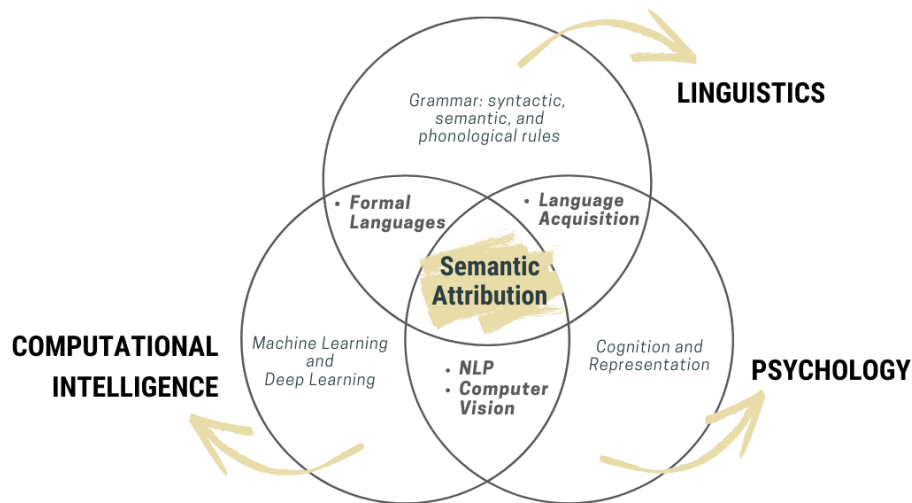


Figure 18 – Semantic attribution relates to fields of study supported by different paradigms.

Source: Created by the author.

and reflect on the paradigms that support a given theory, it is essential to look back at the ideas that led to its theorization.

This extensive literature review consolidated the main theories associated with semantics in linguistics and psychology and their respective paradigms, as organized in Figures 20, 21, and 23. Based on this review, we present, in Section 4.4, a discussion of which paradigms are appropriate for semantic representation. This is the main theoretical contribution of this work.

4.1 EPISTEMIC PERSPECTIVES ON SEMANTICS

To overcome the epistemological divergences that underlie the disciplines considered in this work, we structured our analysis based on the idea of paradigm, which is understood as the set of assumptions a group of researchers shares about a given field. In the context of semantics, the categorization of paradigms that we propose seeks to organize how one can:

- Understand the nature of meaning – ontological¹ paradigms, discussed in Subsection 4.1.2;
- Observe the meaning – measurement paradigms, discussed in Subsection 4.1.3;
- Decide about a meaning – computational paradigms, discussed in Subsection 4.1.4.

¹ In this work, ontology refers to the philosophical concern about the nature of meaning, for which an elaborated discussion is given by Davis and Gillon (2004). The reader should not be confused with the homonymous term used in computing to represent the data model in object-oriented programming (e.g., web-ontology language).

Each of these paradigms is represented by an icon in Figure 19, which will be used to reference them in the other figures in this Chapter.

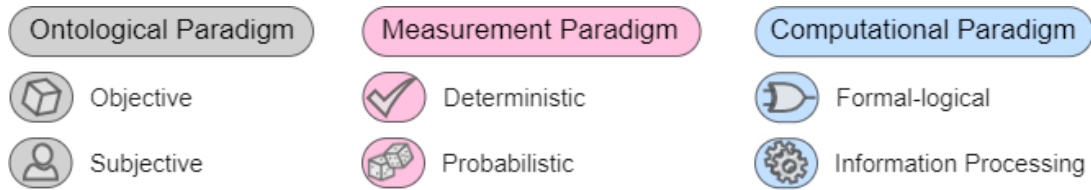


Figure 19 – Categorization of the main semantic-related paradigms.

Source: Created by the author.

4.1.1 Epistemological preamble

At the beginning of the 20th century, the prevailing scientific thought was based on objectivism and formalism. These two ideas gave rise to logical positivism, which comprises a universalization of rationality and excludes any psychological or historical element from its arguments (LEAL, 2011).

Later, in 1934, Karl Popper formulated his “critical rationalism,” establishing the scientific endeavor as the realization of experiments, the formulation of theories, and their subjection to falsifiability. According to Popper (2002), every discovery contains an irrational element, a reason why rationality could not be universalized but, rather, used for the logical evaluation of theories.

These two currents of scientific thought (logical positivism and critical rationalism) played an essential role in developing exact and natural sciences and still influence many semantic-related studies. However, such epistemic approaches were insufficient to support social and human sciences research nor to elucidate divergences in all these fields. New proposals would emerge, therefore, to resolve these epistemic limitations, as follows.

Kuhn (1962) observed that a given corpus of knowledge is shared by a scientific community, which he called paradigm:

“On the one hand, it [paradigm] stands for the entire constellation of beliefs, values, techniques, and so on, shared by the members of a given community. On the other, it denotes one sort of element in that constellation, the concrete puzzle-solutions which, employed as models or examples, can replace explicit rules as a basis for the solution of the remaining puzzles of normal science.” (KUHN, 1962)

Based on the concept of paradigm, Kuhn termed a scientific revolution: the transition from one paradigm to another when the former fails to solve problems through its established

models or examples.

Contemporary to Kuhn, Feyerabend also criticized all previous epistemological approaches – not the rationality itself, but the universality of the scientific method proposed by them (FEYERABEND, 2010). He tried to demonstrate that “all methodologies, even the most obvious ones, have their limits.” (FEYERABEND, 2010). In doing so, he argued for theoretical and methodological pluralism and proposed counterinduction. This method could be synthesized by applying counter rules, that is, introducing hypotheses that are inconsistent with the well-established theories and facts. Feyerabend also defined incommensurability: the fact that the concept from one theory renders meaningless the concept of another (FEYERABEND, 2010). For him, incommensurability between theories is a positive thing for science.

Feyerabend also suggests a contextualized rationality, in which different apprehensions of reality could be exercised through theoretical and methodological pluralism, including subjectivity and irrational influences such as propaganda, emotions, and even prejudices. Feyerabend refused Popper’s assertion that “what is true in logic is true in psychology, ... in the scientific method, and the history of science” by stating that there is not a single logic that permeates all these domains, but many different systems of logic (FEYERABEND, 2010).

In this study, we propose a paradigmatic analysis based on two of the currents mentioned above of epistemology: (i) the idea of paradigm, proposed by Kuhn, and (ii) the plural interaction between scientific paradigms, suggested by Feyerabend. The choice of the paradigms undertaken in this study comes from fundamental aspects of science introduced by Kuhn and Feyerabend: the similarity between theories and assumptions shared between researchers – the paradigms – and the incommensurability between them.

4.1.2 Ontological paradigms

When dealing with semantics, an essential question is about the nature of meaning: does it exist inherently in what is being signified, or does it depend on who is signifying it? Fostering this debate goes beyond the scope of this thesis, which is why we will limit ourselves to introducing two fundamental paradigms that will sustain, from an ontological perspective, the entire development of this study: (i) objective paradigm and (ii) subjective paradigm.

The objective paradigm is centered on the object, which is assumed to have its attributes and qualities. In this perspective, meaning is inherent to the object. Saying that someone (a subject) assigns meaning to something (an object) implies the recognition or identification of

the properties of an object. It also means the recognition of the reality of such an object in an environment shared by all types of agents (subjects and objects) and whose properties are available to all.

The subjective paradigm, in turn, is centered on the subject – i.e., the autonomous agent according to Definition 3.2 (Section 3.3). Such an agent has a private space available only to itself. In this perspective, the meaning attributed by a subject to an object is an internal representation exclusive to the subject.

The above conceptions, although presented here in an oversimplified way, constitute the central debate in the philosophy of mind and the philosophy of language. The intention, however, is to sensitize the reader that such paradigms have a strong influence not only on theories and conceptions about what meaning is (i.e., ontological perspective) but also on strategies to measure or observe it (i.e., measurement perspective), as well as on the decision problems related to meaning (i.e., computational perspective).

4.1.3 Measurement paradigms

When discussing how to measure or to observe the meaning attributed to a concept, there are two main approaches to take: the probabilistic one, which relates to uncertainty and is presented in Subsection 4.1.3.1; or the deterministic approach, which in turn refers to unpredictability and is explored in Subsection 4.1.3.2.

Understanding the measurement paradigm that underlies a semantic model is also crucial to recognize what happens when it fails. In a probabilistic-based model, inaccuracy is due to uncertainty, whereas in a deterministic model, the failures would be attributed to unpredictability. More than that, since semantic attribution is still an open problem, establishing the paradigms to work on is fundamental for developing and improving any measurement method.

4.1.3.1 Probabilistic approach

Statistical inference is the method by which, from the probability distribution of a known sample (or evidence) of the population, one can estimate the entire population's probability distribution. According to Russell and Norvig (2010), probability is the third major contribution of mathematics to the AI field, following logic and computation.

There are two main strands within the probabilistic or statistical inference: the traditional

or frequentist paradigm and the Bayesian paradigm. In the first, we assume the existence of a probability distribution for the population, which can be inferred through independent and identically distributed (i.i.d.) random variables. This paradigm is supported by the law of large numbers and the central limit theorem (GILBOA, 2010).

The Bayesian paradigm, in turn, refers to the same inference problem relying on Bayes' theorem to find the probability P that a given hypothesis X is true from the collected evidence E . Since P is just available after knowing E , it is called *posterior* probability $P(X|E)$ and is given by:

$$P(X|E) = \frac{P(X) * P(E|X)}{P(E)}. \quad (8)$$

The term $P(X)$ represents the *prior* probability of the hypothesis to be true, i.e., the information previously known about X without knowing E . In turn, $P(E|X)$ indicates how likely is E given X , while $P(E)$ denotes the probability that E will occur, regardless of X .

The central aspect of the Bayesian approach is that prior beliefs are changed by the evidence, thus resulting in posterior beliefs that may change again on the occurrence of new evidence, and so on.

In this approach, the law of large numbers does not apply since a random variable is equivalent to a prior belief, and, thus, the i.i.d. condition is not met. There are many situations where the population distribution parameters are not known, a fact that does not guarantee the samples are independent – or more strictly, that they are i.i.d. In such cases, as demonstrated by Gilboa (2010, p.41), the Bayesian approach becomes more appropriate.

In addition, the ability of the Bayesian approach to apprehend even subjective information makes it quite suitable for semantic modeling:

Classical statistics is a collection of tools for a society to agree on what can be stated as officially established, with the understanding that this society includes different people with different beliefs and goals. Bayesian statistics is the tool for individual reasoners or decision-makers who attempt to sort out their knowledge, belief, evidence, and intuition. As such, classical statistics aspires to be objective. Bayesian statistics, by contrast, hopes to capture all beliefs and intuition, whether objective or subjective (GILBOA, 2010, p.46).

4.1.3.2 Deterministic approach

The second approach relies on determinism and opposes the idea of statistical inference, whether frequentist or Bayesian. Generally speaking, the deterministic view implies that initial causes and conditions determine any event. One could predict past and future states by pursuing

a model representing a given phenomenon. The prediction errors of such models, in turn, can be attributed to the imperfection of the model (and the errors statistically evaluated by their frequency of occurrence), or one may assume, under certain conditions such as non-linearity, that the phenomenon is chaotic. Chaos, in this context, refers to “deterministic systems whose time evolution has an extreme dependence on initial conditions,” as stated by Cattani *et al.* (2017), thus making them unpredictable yet still deterministic.

The idea of determinism naturally arises when we consider static and constant factors. However, decisions involving dynamic and adaptive systems – as those related to language – require us to deal with the problem more elaborately, which can be either through chaotic or stochastic models.

4.1.4 Computational paradigms

In short, computation relates to solving a decision problem. Information, in turn, is the amount of choice available to a given problem. It turns out that computation can be based on the formal-logical paradigm, mainly represented by the formalism offered by Alan Turing (SIEGELMANN, 1995) and detailed in Subsection 4.1.4.1, or based on the information processing paradigm, an approach inspired on the information theory defined mathematically by Shannon (1948) and detailed in Subsection 4.1.4.2.

In the extent of semantics, the computational paradigm considered for a given model will justify how meaning is attributed to an object, image, sound, or word: a decision process resulting from a formal logical operation or, else, the output of an information processing. Piccinini and Scarantino (2011) bring critical elucidations about the different forms of computation (e.g., digital or generic) and information (e.g., Shannonian or semantic), that will be discussed throughout this work.

4.1.4.1 Formal-logical paradigm

This paradigm is derived from the formalism or axiomatization of mathematics by Hilbert (1902) and the establishment of symbolic logic by Frege (1980), at end of the 19th century. Its predominant belief was that the first-order logic could solve any well-defined problem. Such ideas led Hilbert, in 1928, to pose what would become his famous decision problem: the challenge of finding an algorithm capable of outputting yes or not for any description in a formal

language received as input, according to its veracity (HILBERT; ACKERMANN, 1999).

Later, in 1930, Kurt Gödel proved that such axiomatization was possible. However, his fame arose in 1931 when he published the incompleteness theorem (GÖDEL, 1931, p.37), demonstrating that any axiomatic system could not be both complete and consistent. In other words, a complete system could not prove itself, thus being inconsistent, while in a consistent system, there are propositions that could not be proved, thus being incomplete. As an example of its current scope, Gödel's theorem is routinely applied in ML for a classifier evaluation: it will be complete if it is capable of classifying all the elements of the dataset domain (i.e., offering an answer), while it will be consistent if it correctly classifies all the elements (which is only guaranteed in closed domains or overfitted models).

Gödel's incompleteness theorem demonstrated the limitations of formal logic. However, in 1936, Alan Turing applied formal logic to the concept of algorithms by proposing the Universal Turing Machine (TURING, 2012), resulting in great achievements that masked such limitations.

Briefly, a Turing machine consists of a program that, in its initial state, reads an instruction tape. Depending on the symbol read, the machine can change its status, write a symbol, or move left or right. The computation stops when it reaches an end state, thus accepting or rejecting the input. A formal definition of a Turing machine requires, first, the definition of an *alphabet* Σ as a finite set of symbols or characters. A *word* w is defined as a chain of juxtaposed symbols belonging to this alphabet, in the way that $w \in \Sigma$. A *language* L is defined over an alphabet as a set of words from it, thus $L \subseteq \Sigma$. Therefore, a Turing machine M is defined as the 8-tuple shown in Eq. (9):

$$M = (\Sigma, Q, \Pi, q_0, F, V, \beta, \otimes), \quad (9)$$

where Q is the finite set of possible machine states; Π is the program or transition function; $q_0 \in Q$ represents the initial state; $F \in Q$ is the set of ending states; V is an auxiliary alphabet; β represents a white symbol; and \otimes is the initial tape marker.

Such formalization is capable of offering an analysis of the computability, complexity, and tractability of any decision problem formally written (SIPSER, 2006). However, it should be noted that not every class of problems (e.g., a subset of NP-hard²) is computable – i.e., there is no guarantee that there exists at least one algorithmic solution to the decision, localization, or optimization problem. This is one of the limitations of the formal-logical paradigm, which is

² In complexity theory, P is the class of problems solvable in polynomial time. NP is the class of problems whose solutions can be verified in polynomial time. NP-hard includes problems to which any NP problem can be reduced in polynomial time, indicating possible intractability.

also a direct consequence of Gödel's incompleteness theorem.

Although computation has become less naive after Gödel's demonstrated his incompleteness theorem, the practical implications of Turing's machines were extensive, effectively overshadowing any inherent constraints. Formal logic subsequently became the cornerstone of computer science, and its influence extended to various domains, including studies of mind (LACAN *et al.*, 1988), visual perception (PALMER, 1999), and language (CHOMSKY; KEYSER, 1987).

4.1.4.2 Information processing paradigm

This paradigm has consolidated from the so-called cognitive science (PALMER, 1999; RUSSELL; NORVIG, 2010) and is sustained by the decision theory and the information theory.

Decision theory traditionally relied on a deterministic and rational approach (e.g., the principle of expected utility maximization, as discussed in Section 3.2.1), fully supported by the formal-logical paradigm (PETERSON, 2017). However, the information processing paradigm demands a non-deterministic view of the decision process based on the amount of perceived information. In this case, as presented by Gilboa (2010), decisions must be evaluated under uncertainty, which is made through a probabilistic approach (see Section 4.1.3.1).

Information theory, in turn, was formulated by Shannon (1948) and relates information to the number of possible states from a given system, which implies possibilities for a choice, i.e., for decision-making. Such a relationship is clarified by Stone (2015): "if you have to choose between m equally probable alternatives, then you need $n = \log_2 m$ bits of information," where a *bit* stands for the amount of information required when choosing among two equally probable alternatives³.

According to Shannon's theory, information is a measure of surprise: low probability events are surprising, thus carrying high information, while high probability events are unsurprising, thus carrying low information. In other words, the more certain we are about the occurrence of an event, the less chance there is of surprise events, which means lower possible states or lower information. Putting this formally (STONE, 2015): a random variable X with probability distribution $p(X) = \{p(x_1), \dots, p(x_m)\}$, which we define here as a random signal, has a Shannon

³ Bit, in this case, relates to the information unit also known as Shannon (Sh). Although related, it is not the same as the contraction of binary digit, which refers to a binary variable.

information $H(X)$, which is the average measure of surprise, given by:

$$H(X) = - \sum_{i=1}^m p(x_i) \log_2 p(x_i), \quad (10)$$

where $p(x_i)$ refers to the probability of each of the m possible values for the random variable X .

Shannon information is also called entropy due to its similarity with the same formulation from thermodynamics. In short, the lower the entropy, the lower the uncertainty. It is precisely the idea of entropy that enables a unified understanding between information theory and thermodynamics, as the “free-energy principle” presented in Friston (2010) which accounts for action, perception, and learning. The same formulation is applied for performance metrics in statistical NLP (CAMBRIA; WHITE, 2014; SUN *et al.*, 2017).

The information theory developed by Shannon not only provided a measure of uncertainty – and thus a measure of the information gain – but also formalized how information flows between systems. According to Russell and Norvig (2010), “Shannon showed that no matter how noisy the channel, it is possible to recover the original message with an arbitrarily small error if we encode the original message in a redundant enough way.”

From a practical point of view, the information processing paradigm explores how a system deals with its input and output information. Ogata (1997) defines a system as a “combination of components that act together and perform a certain objective.” A system is made up of representation structures and processes. Representation relates to how a given system encodes or stores information. A process, in turn, corresponds to the functional elements of a system, i.e., how it handles information and its representations.

Lastly, we must recognize, though, that the concept of information from Shannon’s theory differs from that of common sense – i.e., that information is the amount of knowledge or the content in a message. Regarding this, Piccinini and Scarantino (2011) distinguish Shannon information from semantic information:

“Semantic notions of information pertain to what a specific signal broadcast by an information source means. To address the semantics of a signal, it is neither necessary nor sufficient to know which other signals might have been selected instead and with what probabilities. (...) Semantic and nonsemantic notions of information are both connected with the reduction of uncertainty. In the case of nonsemantic information, the uncertainty has to do with which among many possible signals is selected. In the case of semantic information, the uncertainty has to do with which among many possible states of affairs is the case.”

Studying complex representations, such as language, requires more comprehensive models to relate semantic information to Shannon information.

4.1.5 A proposal of criteria for a paradigmatic analysis

Throughout this Section, we presented the main paradigms related to semantic attribution, which we grouped into ontological, measurement, and computational paradigms. For each of them, we explored the main theories and arguments that support them, as well as point out their relationship with semantics.

However, identifying and delimiting paradigms, as well as establishing whether a theory or application belongs to one or the other, becomes a posteriori task. This is instigated by the identification of ideas anomalous to a given paradigm and which are subsequently established in larger sets. As pointed out by Kuhn (1962) in the final chapters of his essay, the incommensurability of scientific standards makes any objective assertion about paradigms unfeasible.








Given that paradigms play a central role in this thesis, we propose a scale to assess the relevance of a given concept or work to each of the paradigms studied. These criteria are summarized in Table 7, indicating adherence to the respective paradigms on a scale from 1 to 4. The lower the scale, the lower the relationship between a given theory and its respective paradigm. In this sense, level 1 indicates few statements or related references. Level 2 comprises the inclusion of the most generalizable ideas of a given paradigm but without the commitment to be coherent with its central ideas. Level 3, in turn, indicates that a given paradigm occupies a central position in that study or theory. Finally, level 4 indicates full compliance with the ideas supported by the given paradigm. In Subsection 5.4.1, we will also apply this proposed paradigmatic analysis to studies related to the semantic gap.

4.2 SEMANTICS AND THE PARADIGMS OF LINGUISTIC THEORIES

Our starting point is to observe the differences between phonological⁴, syntactic, and semantic levels of language. As defined by Anderson (2009, p.326), “phonology concerns the sound structure of sentences,” while “syntax concerns word order and inflection.” Semantics, in turn, is the interpretative level and “concerns the meaning of sentences.” The semantic attribution problem was introduced in Chapter 1 as the ability to assign a meaning to an object. To elaborate on what semantic content (or semantic representation) is and which are the appropriate models

⁴ Although phonology is directly associated with the auditory-vocal system, there is evidence that both auditory and visual stimuli constitute language (KUHL; DAMASIO, 2013, p.1358). The visual aspect of language is also discussed in (PALMER, 1999, p.453) from the problem of identifying letters and words.

Table 7 – Categorization criteria for paradigms. Each study surveyed is categorized into 4 levels according to these criteria.

	 Objective	 Subjective	 Deterministic	 Frequentist Inference	 Bayesian Inference	 Formal-logical	 Information Processing
1	<i>Few related statements or references.</i>	<i>Few related statements or references.</i>	<i>Few related statements or references.</i>	<i>Few related statements or references.</i>	<i>Few related statements or references.</i>	<i>Few related statements or references.</i>	<i>Few related statements or references.</i>
2	Theory or study assumes that objects or phenomena external to the observer are real and independent.	Theory or study assumes that perception is dependent on the observer.	Theory or study attempts to model a given phenomenon through a deterministic perspective, thus concluding its causes.	i. There is the moderate use of tests, tools, and analysis based on frequentist statistics (e.g., p-values in hypothesis testing); or ii. There are a few assumptions in the study regarding uncertainty.	i. There is the moderate use of tests, tools, and analysis based on Bayesian statistics (e.g., Bayesian networks, naive Bayes); or ii. There are a few assumptions in the study regarding prior knowledge changed by evidence.	Theory or study is implicitly based on symbolic and formal logic.	Theory or study implicitly establishes an information flow on a computational, algorithmic, or implementational level.
3	i. Objective aspects of the studied phenomena prevail ; or ii. Theory or study firmly grounded on the physicalist paradigm.	i. Subjective aspects of the studied phenomena prevail ; or ii. Theory or study firmly grounded on perception.	Theory or study makes explicit that any object, event, or phenomenon addressed in the study could be entirely determined and predicted by an appropriate model.	i. There are many applications of tests, tools, and analysis based on frequentist statistics ; or ii. Theory or study is partially based on stochastic processes.	i. There are many applications of tests, tools, and analysis based on Bayesian statistics ; or ii. Theory or study explicitly makes use of Bayesian reasoning.	i. Theory or study presents a definition for a formal language ; or ii. Theory or study is firmly based on symbolic and formal logic.	i. Theory or study is partially defined through Shannon's information theory ; or ii. Theory or study has most of its information flow established on a computational, algorithmic, or implementational level.
4	i. The main ideas are built over the materialist monism or the substance dualism paradigm; or ii. Although considering subjective phenomena, the theory or study is centered on an objective perspective.	i. The main ideas are built over the idealistic monism or the dual-aspect monism paradigm; or ii. Although considering objective phenomena, the theory or study is centered on a subjective perspective.	Theory or study considers advanced approaches to the deterministic paradigm , such as deterministic chaos and co-determinism.	i. Causality is determined whether a statistical test is in a confidence interval or not; and ii. Theory or study obeys the law of large numbers and the central limit theorem ; or iii. Theory or study is entirely based on stochastic processes.	i. Causality is understood as a degree of belief ; or ii. Theory or study is entirely based on subjective Bayesianism.	Theory or study is fully defined through symbolic and formal-logical paradigms.	Theory or study is fully defined through Shannon's information theory.

Source: Created by the author.

to represent it, we should first explore language and its underlying paradigms.

The split of language study into these three fields (phonology, syntactic, and semantics) began in the early 20th century, during the apogee of the formal-logical paradigm. Later on, cognitive theories were established under the information processing paradigm.

In this context, we can settle two distinct groups of theories from linguistics that will provide us with a better comprehension of semantics, both represented in Figure 20: the formal theories (Subsection 4.2.1) and the cognitive theories (Subsection 4.2.2). Still, in Figure 20, notice that for each group of theories, we identified the underlying paradigms according to the symbols defined in Figure 19 and the criteria established in Table 7.

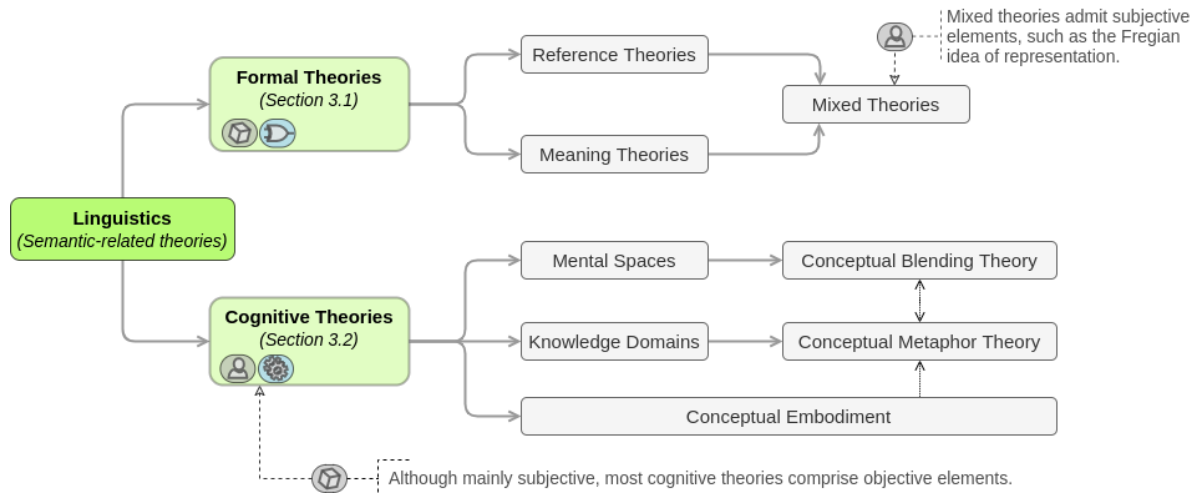


Figure 20 – Semantic-related theories in linguistics can be distinguished into two main groups: formal theories and cognitive theories. The former is generally supported by objective and formal-logical paradigms, while subjective and information processing paradigms support the latter.

Source: Created by the author.

4.2.1 Formal Theories

This group includes the reference, meaning, and mixed theories, all sustained by objective and formal-logical paradigms.

From lectures between 1906 and 1911, Saussure stated that language is a compound of signs, and those, in turn, are compound of a signifier (i.e., the sound, the acoustic image) and a signified (i.e., the concept) (SAUSSURE, 1916). Saussure's main contribution to linguistics was to abandon the idea that language mapped words to objects, treating both aspects of signs – signified and signifier – as mental entities. However, although there is a place for subjectivity in Saussure's theory, it is profoundly sustained by a structuralist and objective paradigm – i.e., language can be split up into constituent structures and analyzed independently⁵ (CRYSTAL, 2015).

The dominance of structuralism in linguistics had its apogee with the *Tractatus Logico Philosophicus* of (WITTGENSTEIN, 1922), which extended the analytical empiricism to language. To Wittgenstein, the world is built of facts from which we access through propositions. The language, in turn, would be made by structured and logical propositions.

Two decades before, in the early 1900s, the formal-logical paradigm had arisen from the meeting of Frege's logical system with the formalism proposed by Hilbert (1902). In addition

⁵ Structuralism concerns an epistemological paradigm – i.e., the way knowledge is apprehended – and not always a structuralist paradigm is superimposed to an objective one. However, in the structuralism of language presented by Saussure, the constituent structures would be independent of each other and from any observer, which places it as an objective theory instead of a subjective one.

to his axiomatization system, Hilbert proposed that mathematical demonstrations should be considered exclusively as matters of form. That is, syntax problems could be solved through mathematics, while semantic problems should be dealt with metamathematics.

Thus, from the 1930s, syntax and semantics were defined as two separate fields that could be independently studied. More than that, this paradigm has identified rationality with formal syntactic activity, giving new scope to the old metaphor that the mind is a machine. Cognitive processes, at this time, were assumed to be algorithmic in nature, and thinking would be nothing less than manipulating symbols. The computer had become a strong metaphor for the brain.

The semantic solution that formal languages have adopted is to consider that meaning is a relationship established between a linguistic expression and a non-linguistic thing. This idea originated a family of theories – called correspondence theories – which started from the following principle: meaning is the relationship between the symbols of a language and certain entities that are independent of that language (DAVIS; GILLON, 2004). Ideally, this relationship could be seen as referential, i.e., linguistic expressions refer to extra-linguistic entities, whatever these entities may be: objects, events, or properties in the present world or in some possible world, images of real or fictional objects, ideas, feelings or experiences perceived by individuals.

Formal theories have adopted the correspondence solution for semantics: meaning is a relationship established between a linguistic expression and a non-linguistic thing (i.e., any other entity, concrete or abstract, that is not a linguistic element). According to (DAVIS; GILLON, 2004, p.107), formal theories can be grouped into reference theories, those relying on the analysis of “logical truth and falsity, entailment, presupposition, and truth conditions”; and meaning theories, those defining “analyticity, synonymy, entailment, anomaly, semantic redundancy, polysemy, antonymy, homonymy, and meaning inclusion.”

It is worth remembering that a formal language is a purely syntactic construction that ideally works without interpretation, just like programming languages, in a relationship that could be seen as referential (i.e., linguistic expressions refer to extra-linguistic entities). In an ideal formal language system, each symbol would refer to a single entity, and each entity in the world, in turn, would be the reference to a single symbol. It is even possible to build an artificial language in which this situation occurs, as in semantics for first-order logic or an assembly language command, but its application to NLP faces insurmountable difficulties. According to Anderson (2009), intrinsic characteristics of natural language are the semanticity

and arbitrariness of units, factors that make it exclusive to the human species.

These difficulties revolve around an issue already identified by Frege (1948) – the reference – and which seems to be central to the problem of semantics. Frege's theory of meaning distinguishes between sense (*sinn*) and reference (*bedeutung*), situating meaning between linguistic expressions and objects in the world. Giving meaning to a linguistic expression is not enough to relate it to its reference, an entity, or a set of entities in the world. More than that, we must associate it with another entity called sense.

Let us take, for instance, the expression "a child". It refers to certain entities or things placed in the world: the set of non-babies and non-pubertal human beings. This set of entities constitutes the reference of the expression, while the criterion used to determine this reference is the sense of the expression.

Following this, Frege carefully distinguishes the reference and the sense of an expression from the representation (*vorstellungen*) associated with it:

If the reference of a sign is a sensibly perceptible object, my representation is an internal image, emerged from the memories of past sensitive impressions and the activities, internal and external, that I performed. This inner image is often saturated with emotions; the clarity of its various parts varies and oscillates. Even in the same man, the same representation is not always associated with the same sense. The representation is subjective; one man's representation is not the same as another's. (FREGE, 1948, p.65).

Frege clearly discriminates three orders of entities at three ontological levels: (i) the physical level, from sensibly perceptible objects of the world; (ii) the mental level, which contains subjective representations, images, and memories; and (iii) the level of thoughts, where the senses, concepts, propositions, and functions are. Given the subjective nature of representations, which are absolutely unique and belong to a single individual, Frege postulates a level where objectivity and communication are possible, which is somehow universal and shared by all humans. Thus, for any given sign, different people may associate different representations, linked to their own experiences, but this does not prevent them from grasping the same sense. Since the Fregean approach to semantics covers subjective aspects and attempts a unified account, Davis and Gillon (2004) consider it as a mixed theory.

This semantic approach led to the development of intentional logic (MARTINEZ; SEQUOIAH-GRAYSON, 2023), in which semantic interpretation is derived from the Fregean distinction between sense and reference – now called intention and extension. The intention of an expression is its conceptual content, while the extension are the entities to which this

conceptual content applies. The difference with the strictly Fregean approach is that the length of an expression may vary according to the context in which it is interpreted. For this reason, semantic interpretation – called model-theoretic semantics – adds to the interpretation model a set of worlds and times. These latter build a model based on the set theory, in which correspondences are constructed with the objects, properties, and relations of the state of things.

The intention is formally defined as a function that maps language expressions (names, predicates, phrases, and sentences) to their referents in every context of worlds and times under consideration. Names and descriptions are mapped to entities, predicates to entity sets, and sentences to true values – always considering the possible worlds and times in which the interpretation is being performed.

This definition of intention adequately captures what they do but avoids the question of what their contents are. For example, an intentional function such as *the child of x* maps entities to true values for each instantiation of *x*. It identifies what the syntagma⁶ does, but leaves open the question of its content – i.e., what it means to be a son or daughter. Furthermore, this is the decisive question for the application of the function to any entity, so without this, it is not possible to decide the truth value of a particular instantiation.

From the 1950s, structural and formal linguistics would give rise to the first generation of cognitive psychology – still from the formal and objective perspectives. Indeed, Saussure's structuralism⁷ and Chomsky's generativism⁸ would leave their legacy to computer science in the definition of syntactic structures: the ground basis of programming languages, from the lowest to the highest level of abstraction. Symbolic artificial intelligence was also deeply influenced by the formal theories of language (BEZDEK, 1992; RUSSELL; NORVIG, 2010).

In linguistics, the formal-logical approaches have found their limit in the semantic treatment of natural languages, opening space for the influence of the body and the subjective experience in the formation and contextualization of meanings (pragmatics) and even in syntactic determination (CAMBRIA; WHITE, 2014; THA, 2007). Since symbolic networks are meaningless, when someone takes a step from syntax to semantics, something has to be added to this paradigm.

⁶ Syntagma is here defined as an elementary linguistic unit consisting of a set of phonemes, words, or sentences that are in a sequential relationship to one another.

⁷ Saussure (1916) stated that language is composed of signs, and those, in turn, are composed of a "signifier" (i.e., the sound, the acoustic image) and a "signified" (i.e., the concept).

⁸ Chomsky and Keyser (1987) proposed the generative grammar model. In short, it states that a set of syntactic rules generates grammatical sentences. In the generative grammar model, semantic representations are generated by the grammatical ones.

4.2.2 Cognitive Theories

This group consists of the conceptual embodiment thesis, the knowledge domains theory, the conceptual metaphor theory, and the conceptual blending theory – all of them sustained by the subjective and information processing paradigms.

Advances in cognitive theories came to show that models developed from formal-logical ideas had some limitations, especially those aiming to explain natural language and linguistic lapses (CAMBRIA; WHITE, 2014), as well as the vision process (PALMER, 1999). Since symbolic networks are meaningless, the influence of the body and the subjective experience passed to be considered in the formation and contextualization of meanings (pragmatics) and even in syntactic determination (CAMBRIA; WHITE, 2014).

George Lakoff affirmed that “the symbols used in the computation are meaningless. Thought is not meaningless, and a non-objectivist account must be given of what makes it meaningful.” (LAKOFF, 1990, p.348). He called it conceptual embodiment, claiming the importance of the human body in the formation of the concepts.

People can recognize and name known objects even in very precarious conditions (e.g., at night, in a dark place, on their backs) – which makes it hard to avoid the idea that people have some form of generic representation in mind that they apply to objects in the world to recognize and to name them. Whatever this representation is, whether an image or a symbolic scheme, it means that the sensory experience of the subject cannot be reduced to the reality mirroring, but must include the cognitive structure of the perceiving subject. Here we come to what seems to be the main issues faced by formal theories when applied to human mental phenomena, specifically the semantic attribution or the formation of concepts.

It is worth mentioning Barthes (1978) who rescued the affective and bodily status to language by stating that “language is a skin”. Further, they have pointed out the incompleteness of communication when stating that “the birth of the reader must be ransomed by the death of the author” (BARTHES, 1994), i.e., the meaning is not entirely attributed to the author, but it also depends on the interpretation of each reader.

Unlike traditional or formal semantic theories, cognitive linguistics relies on the subjective and information processing perspectives: “language provides a means of encoding and transmitting ideas.” (EVANS; GREEN, 2006, p.20). For this purpose, language has a symbolic function – which maps the objective or mental symbol to a subjective concept – and an interactive

function – which makes possible our communication.

Lakoff's conceptual embodiment thesis (LAKOFF, 1990, p.348) allowed cognitive linguists to develop other conceptualization theories, i.e., theoretical models on how perceptual elements (from the body) come to concepts or mental images. Knowledge domains theory establishes domains as cognitive structures that provide information to associate lexical content to a meaning (EVANS; GREEN, 2006, p.230). Following this, conceptual metaphor theory was developed to explain how meaning is attributed as a connection between a source domain and a target domain – a metaphor.

While domains relate to structures that coherently associate lexical elements to concepts, mental spaces “emphasizes conceptual discontinuities, the partitioning of conceptual structure into semiautonomous regions.” (LANGACKER, 2008). Later on, the conceptual blending theory was developed by Fauconnier, from where metaphors could be considered as a special case of conceptual blends (FAUCONNIER; LAKOFF, 2014). From a generic space, elements from distinct domains can connect by simultaneity, analogy, cause-effect, or identity – thus generating a new representation structure called blend (FAUCONNIER; TURNER, 2003).

Important to say that in cognitive linguistics, meaning attribution comes from a dynamic process – the conceptualization – which relates the symbol, or the objective part of language, to both internal and external subject's context information. The relevant role of context is made explicit in the following statement:

Sentences cannot be analyzed in isolation from ongoing discourse. In other words, semantics (traditionally, the context-independent meaning of a sentence) cannot be meaningfully separated from pragmatics (traditionally, the context-dependent meaning of sentences). This is because meaning construction is guided by context and is therefore subject to situation-specific information (EVANS; GREEN, 2006, p.364).

From the cognitive perspective, it becomes evident the need to explicitly include subjectivity, introduced in Subsection 4.1.2, when dealing with semantics. Kandel characterizes subjectivity as “the way each of us experiences a world of sensations that feel unique and private.” (KANDEL, 2013, p.385). In short, concepts themselves are subjective and thus inaccessible to formal-logical objectivism. The latter is only a vehicle for reference, as Frege qualified it, which can be shared objectively among the speakers of a language.

Despite the relevance of cognitive theories for semantics, Evans and Green (2006)[p.780] point to some challenges and gaps that must be adequately addressed, such as “overlapping terminology”, “lack of empirical rigor”, and divergences not clarified between cognitive and generative theories – for the latter, those generativist models that are non-objectivist

but yet supported by formal logic. We justify such challenges by the inherent multidisciplinary nature of cognitive sciences and their maturity level. Regarding the empirical rigor, it is only debatable if compared to the same paradigm, which does not apply due to the incommensurability between formal and cognitive theories.

4.3 SEMANTICS AND THE PARADIGMS OF PSYCHOLOGICAL THEORIES

In this Section, we explore the main groups of theories in psychology that seek to explain semantic attribution in humans or its related processes (e.g., vision or natural language). These theories are depicted in Figure 21, to which we associate their respective paradigms according to the symbols defined in Figure 19 and the criteria established in Table 7.

Before delving into the psychological theories, and thus assuming that semantics is also a mental phenomenon, it is essential to introduce the main theses that try to explain the mind-brain relationship: (i) localizationism, (ii) connectionism, and (iii) functionalism.

Localizationism means the perspective willing to assign capabilities and activities to specific areas of the brain, instituted from the anatomo-clinical method begun with Broca (1861)⁹.

⁹ The anatomo-clinical method consists of associating clinical observations, in life, with anatomical ones. Broca had treated Mr. Leborgne, who in life had lost his cognitive function of speech and, after his death, revealed to have a lesion in the inferior frontal gyrus, the cortical region now referred to as “Broca’s area.”

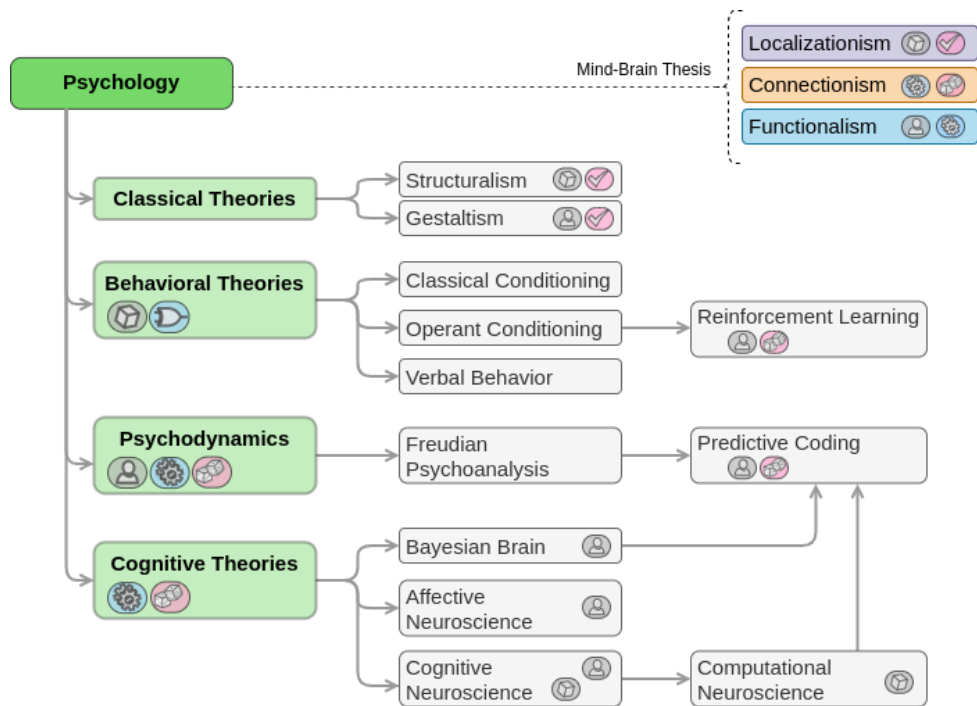


Figure 21 – Semantic-related theories in psychology and their respective paradigms.

Source: Created by the author.

From a paradigmatic point of view, localizationism is an objectivist and deterministic approach.

Connectionism emerged as a counterpart to localizationism, starting to relate cognitive processes no longer to modules or brain units but networks (HAYKIN; FUSTER, 2014). This perspective was accentuated from the 1940s onwards with the formulation of information theory and influenced by advances in computational intelligence. Therefore, connectionism is a view based on probabilistic and information processing paradigms.

The functionalist thesis – whose most contemporary definition is credited to Luria (1973) – can be understood as a reconciliation between the first two. For Luria, complex functions could not be attributed to a single cortical location but rather result from interactions and compensations of interconnected regions. Information processing and the admission of subjectivity are the central paradigms that support functionalism.

4.3.1 Classical Theories

Although without a proper definition for semantics nor supported by current neuroscientific findings, classical theories like (i) structuralism and (ii) gestaltism influenced the coming ideas for the formation of concepts.

Inspired by Saussure's structuralist linguistics (see Section 4.2), the structuralist psychological approach, developed by Edward Titchener in 1909, was an experimental method of introspection from which he sought sensory atoms: structural elements that together would compose human perception and consciousness (SCHULTZ; SCHULTZ, 2013). Even though introspective, such an approach was based on objective and deterministic paradigms.

Gestaltism, in turn, was established by Max Wertheimer in 1923, who stated that “the whole is different from the sum of its parts.” Our image perception – and so the meaning attribution – would operate through a figure-ground organization, followed by a parsing process – i.e., visual elements being divided into parts or sub-regions – and then coalesced from grouping principles. The grouping principles from Gestalt are (PALMER, 1999): (i) proximity, elements that are close to each other tend to be grouped; (ii) similarity: the most similar elements (e.g., same color, size, orientation) tend to be grouped; (iii) common fate: elements moving in the same way (e.g., direction or velocity) tend to be grouped; (iv) continuity: elements that seem to be continuations of each other tend to be grouped; (v) closure: elements or objects that constitute a closed-form also tend to be grouped; (vi) synchrony: relates to common fate and offers a dynamic aspect to visual perception; (vii) common region: relates to the closure principle but makes use

of region and sub-region definitions. Elements inside the same region are usually grouped; (viii) element connectedness: elements connected by others tend to be grouped. While the grouping principles sought to determine what constituted a visual perception, Wertheimer also considered past experiences as a vital factor in his perceptual grouping theory (PALMER, 1999), which places it in the subjective paradigm.

4.3.2 Behavioral Theories

The conditioning theory of Pavlov led to the development of behaviorism – a systematic approach mainly represented by the ideas of Watson and Skinner: the mind could not exist as an object of study since it was not observable, only behavior (SCHULTZ; SCHULTZ, 2013).

Behavioral theories enabled the development of classical and operant conditioning. These postulate that behavior is elicited in response to stimuli, either directly (stimulus-response, in classical conditioning) or in more elaborate modes. Thus, behavior can be reinforced and learned by its consequences, elicited by other behaviors, or even discriminated by context.

Behaviorists tried to explain language through “abstractions” – “the properties of stimuli which control abstract tacts” (SKINNER, 2015, p.112). *Tact* is a term coined by Skinner to define a “verbal operant in which a response of a given form is evoked (or at least strengthened) by a particular object or event or property.” (SKINNER, 2015, p.81).

Regarding semantics, Skinner (2015)[p.113] suggests that the meaning of a word, or its underlying abstract, could be discovered empirically by the following algorithm: “manipulate stimuli and, through the presence or absence of the response, identify the effective controlling properties.”. Meaning, in this case, would be the response of a controlling relationship of stimuli and tacts.

Contemporary and later scholars have severely criticized behavioral explanations for semantics (DAVIS; GILLON, 2004; CHOMSKY; KEYSER, 1987; LAKOFF, 1990). In our perspective, all criticisms are sustained since behaviorism is built on logical and objectivist formalism.

Although it has not been successful in explaining the language processes, conditioning theories brought by Skinner had an undeniable role in cognitive sciences and computing. Classical and operant conditioning are now understood as processes of associative learning that compound implicit¹⁰ long-term memory (KANDEL; SIEGELBAUM, 2013, p.1461).

¹⁰ Implicit memories are those operating unconsciously and automatically.

Reinforcement learning thus appears as a modern discipline, based on previous conditioning theories, but now established under the probabilistic and subjective paradigms (KANDEL; SIEGELBAUM, 2013). This theory inspired the development of reinforcement learning strategies in computing, which refers to “an autonomous agent [that] must learn to perform a task by trial and error, without any guidance from the human operator.” (GOODFELLOW *et al.*, 2016, p.25).

4.3.3 Psychodynamics and representations

Understanding the mind as a dynamic system was one of the main contributions of psychoanalysis, giving us tools to understand the mind mechanisms from which we give everything a meaning: the representations. Inspired by thermodynamics advances from the beginning of the 20th century, Freud (1920) postulated that there is a kind of energy processing in the mental apparatus in which it flows freely through the representations. The free energy characterizes the “primary process” of thought, typically an unconscious process. A form of bound energy is used by the “secondary process” of thought, which means that its energy is suspended until it has run many associative paths to be released.

Based on Herbart’s ideas that each representation could be quantified¹¹, Freud distinguished the mental energy from affection (affective charge). Thus, the representation has an affective charge, which gives it an affective meaning. A representation can be associated with internal or external stimuli (via the perceptual system) but can also be activated or inhibited by the flowing energy in the nervous system. Freud called this chain of activation or inhibition of representations as the “processes of thought”, resulting in actions that must be performed to discharge the excitations.

Originally defined in German as *vorstellung*, Freud conceptualized representation¹² as a complex neurological associative network from which qualitative functional differences are produced, and progressively affect the significance of mental processes, as pointed by Tha (2007). Freud also attributed a quantitative aspect to the representations that would allow the dynamic aspect of the mental processes: the psychodynamics.

Freud rejected any possibility of thinking of representation as a copy or mirroring of the perceived external object – i.e., mind representations are not homomorphic¹³ ones. In his terms,

¹¹ Johann Friedrich Herbart was a German philosopher who first named all mental contents as representations and stated that each one had an energy quantum.

¹² Representation is also known as *presentation* in the psychoanalytic jargon.

¹³ The idea of homomorphism claims there is a mapping between the objects in the environment and those

representation is the product of a successive re-transcription of sensory information in memory in a stratified way, according to complex associative principles, as depicted in Figure 22.

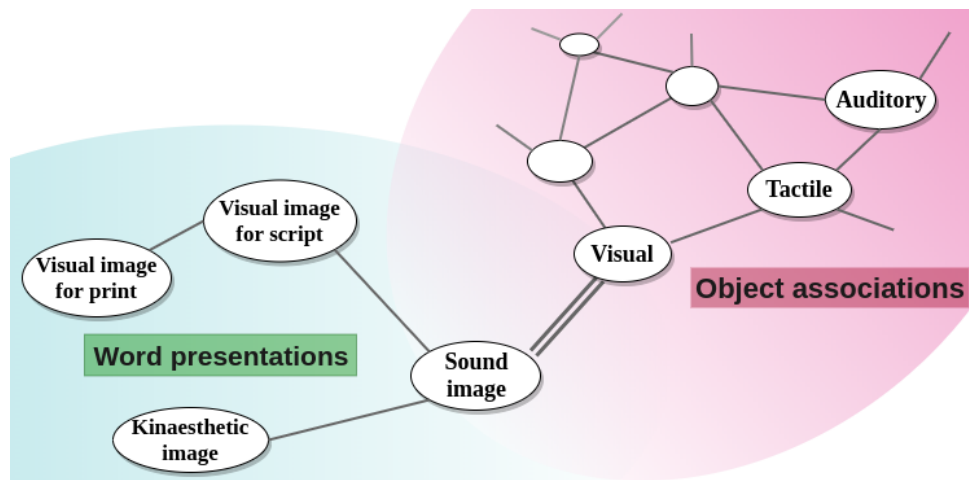


Figure 22 – Freudian representation scheme: the word presentations are associated with the object presentations through a secondary process, i.e., not directly associated with the sensory inputs.

Source: Created by the author.

What Freud called word presentation – or representation – is the unity of the language function. Like any other representation, it is a complex that is composed of acoustic, visual, and kinaesthetic elements. It acquires its meaning by attaching itself to the object association – which is also a complex with visual, tactile, and acoustic elements, among others. The connection between the word presentation and the object association is made by the most representative elements of these complexes: the sound or acoustic image, in the case of the word, and the visual image, for the object.

In the Freudian perspective, the information storage is explained by the concept of *mnemonic-trace* or *memory trace*: a special arrangement of facilitation¹⁴ so that a certain path is exploited against another (LAPLANCHE; PONTALIS, 2018). For Freud, such traces are deposited in several systems and subsist permanently, although they are reactivated only after a certain investment, called *cathexis*. The latter means the association between a particular psychic energy and a representation.

In summary, the mental representations of thing (imagery) and word (linguistic) are equivalent and consist of associative complexes of primary traits. They are secondary constructs and not primary data, i.e., not directly associated with the sensory inputs. Broadly speaking, perceptual processes provide the representational content of mental processes. The subject's

represented internally by the agent so that the corresponding relationships of the internal representations mirror the relationships between the environment and the objects.

¹⁴ Facilitation can be understood as excitatory synapses, which may happen on presynaptic or postsynaptic terms.

experience relative to that content provides its processing, i.e., the so-called thoughts. It is also worth saying that Freud considered language as an expression of thought: the thoughts proceed in non-verbal material to then be mapped into language. However, once this mapping is established, language is not only a form of thought expression but becomes part of these processes, providing indications and introducing paths to where thought processes may or may not follow.

The Freudian view is in line with modern computational neuroscience and can be understood as a rudimentary description of an information processing scheme. Recently, Solms (2020) offered a reinterpretation of the Freudian inaugural work (FREUD, 1895). In addition, there have been plenty of contributions from psychoanalysis to computational neuroscience (FRISTON, 2010; FOTOPOULOU, 2013; SOLMS; TURNBULL, 2002), affective neuroscience (PANKSEPP, 2004), and cognitive linguistics (HOPKINS, 2000; THA, 2007).

Although the model of mind proposed by Sigmund Freud predates the development of information theory, it can be understood in its entirety through the information processing paradigm. Not by chance, both Freud and Shannon have borrowed the terms free energy and entropy from thermodynamics.

4.3.4 Cognitive Theories

Cognitive psychology has shown that human functions such as vision, language, and decision-making are less related to behavior and more connected to internal processes like perception, attention, mental imagery, and representation. Additionally, it has been revealed that human decisions are generally made in a fast, emotional, and unconscious manner and are later analyzed consciously and rationally (KAHNEMAN, 2011). Moreover, cognitive neuroscience has provided evidence that human reasoning is not based on sequential algorithmic processing, but rather on imagination, previous subjective experience, and complex heuristic strategies (ANDERSON, 2009).

Computational neuroscience has served different modeling strategies to map causes and stimuli to neuronal activities (FRISTON, 2011), mostly through an objective perspective. In contrast, subjectivity finds a place in the Bayesian brain hypothesis, which considers the brain to use internal generative models to update posterior beliefs using sensory information in an approximately Bayes optimal inference machine (FRISTON, 2010).

In this context, predictive coding is a signal processing tool for representing a signal using a generative model in the way both definitions are related. Friston (2010) suggests that the

human nervous system applies the predictive coding scheme to transmit only the unpredicted part of sensory input. Doing so would allow the brain to reduce redundancy and thus use efficiently the limited neuronal capacity (HUANG; RAO, 2011).

This framework's main advantage is the allowance of multisensory integration. According to Talsma (2015), the traditional view in cognitive neuroscience is that visual and auditory signals are first processed in their respective cortices before being integrated by the temporoparietal areas. In the predictive coding scheme, this processing happens as a synchronized activity of both auditory and visual cortices. A prediction error, in this case, should enhance activation in some specific cortex. The predictive coding scheme has enabled the explanation of open problems in neuroscience, such as binocular rivalry (HOHWY *et al.*, 2008), phantom pain (De Ridder *et al.*, 2014), and the language-perception-cognition interface (LUPYAN; CLARK, 2015; FRISTON *et al.*, 2020).

Affective neuroscience, in turn, stands out for its theoretical and empirical results in demonstrating the role of interoceptive inputs in the mental constitution and functioning (HOPKINS, 2012; PANKSEPP, 2004; DAMÁSIO, 2011). Such findings open space to approximate neuroscience to linguistics through conceptual embodiment theory (see Section 4.2.2).

From the cognitive perspective, thought – and, hence, concepts – relies on perception and memory. Perception comes from a somatosensory system that encodes information provided by receptors along the human body and is classified according to its functions (GARDNER; JOHNSON, 2013): *proprioception*, the sense of oneself; *exteroception*, the sense of the external world; and *interoception*, the sense of internal state, which is mostly unconscious. Memory, in turn, is classified along (i) the storage duration, which can be *short-term* and *long-term*, and (ii) the nature of the stored information, which can be *implicit* – unconscious to the subject or agent – or *explicit* – highly flexible and available to conscious retrieval (SCHACTER; WAGNER, 2013).

According to Kandel and Siegelbaum (2013, p.1462), implicit memories are classified into priming, procedural (related to skills and habits), associative learning (classical and operant conditioning), and nonassociative learning (habituation and sensitization). Associative learning includes emotional responses and skeletal musculature. The same authors classify explicit memories into semantic (facts) and episodic (events).

Regarding the information processing scheme, memory has been analyzed through discrete operations of *encoding*, *storage*, *consolidation*, and *retrieval*. However, new studies claim that there is not a fixed and consolidated memory but a dynamic process where the information is reconsolidated and, thus, susceptible to change after any retrieval (ALBERINI;

LEDOUX, 2013). Memory reconsolidation shows that even explicit memories are not fixed or static ones but are dependent on sensory perception. Such process is succinctly described by (SCHACTER; WAGNER, 2013, p.1448):

During recall we use a variety of cognitive strategies, including comparison, inference, shrewd guessing, and supposition, to generate a memory that not only seems coherent to us but is also consistent with other memories and with our “memory of the memory.”

Solms (2014) recasts the Freudian concept of representation by stating that “cognitive representations are *mental solids*, embedded within subjective consciousness, and their tangible and visible properties are projected onto reality.” According to the author, things do not possess inherent visual quality, i.e., their visual aspect is a property of the subject.

Similarly, Damásio (2011) affirms that sensory mechanisms contribute to the construction of neural patterns that map the individual’s interaction with the object. The object representations in our minds are not copies of the real object, but images of the interactions between each of us and the object. From this concept, a question naturally arises on how we communicate our object interactions to other agents (e.g., any objective communication) if each individual creates and establishes the mental images according to their own object interactions. Damasio also argues that since humans are sufficiently similar from the biological point of view, the interactions are similar and so are the images, but in any case, they are the same in specific terms.

4.3.5 Psychometry and semantic evaluation

Once we assume semantic attribution as a cognitive process and the meaning as a mental construct, psychometry comes out as the knowledgeable area that seeks to measure mental phenomena or psychological constructs. According to Pasquali (2009), psychometry has its foundations in the theory of measurement, from mathematics and statistics, and “attempts to explain the meaning of responses given by subjects in a series of tasks typically named as items.”

Nevertheless, we must remember that measurement theory is inherently supported by the formal-logical paradigm, as discussed in Section 4.1.4.1, whose symbol manipulation is validated only by its internal consistency with the logical axioms. In other words, there is no direct connection between the measure with the phenomenon it may represent. For objective natural phenomena, this relationship can be mostly tacit. However, such an interface does not occur in the same way for mental or subjective phenomena.

As shown in Figure 23, psychometrics is an empirical area arising from psychology, mathematics, and statistics. Therefore, psychometry is, by definition, situated in the probabilistic paradigm: its claim will never be to determine the mental phenomenon, but to infer its magnitude in a valid, reliable, and theoretically consistent manner. To do so, psychometrists use different techniques and epistemological approaches to develop psychological tests or models. Figure 23 represents these approaches indicating their underlying paradigms, also according to the symbols defined in Figure 19 and the criteria established in Table 7.

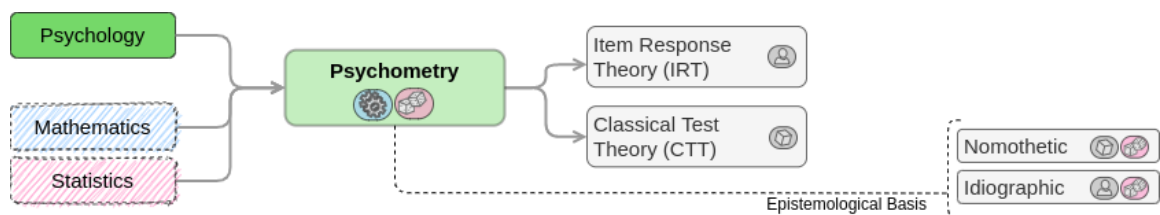


Figure 23 – Psychometry is a sub-area of psychology sustained by theories and axioms from mathematics and statistics, which settles it in the information processing and probabilistic paradigms. The main epistemological basis and theories of psychometry only differ in the ontological paradigm.

Source: Created by the author.

Epistemological bases can be nomothetic or idiographic. The first seeks to compare the assessed individual or agent with a normative standard – i.e., a probability distribution of the population to which that individual belongs. It is an objective perspective and closely related to frequentist statistics. On the other hand, the idiographic approach evaluates the individual or agent based on their history. This perspective is supported by both the frequentist and Bayesian paradigms.

Regarding psychometric techniques, the Classical Test Theory (CTT) associates the final score of a test with the phenomenon or construct evaluated. Emerging in 1904, when Charles Spearman defined the g-factor of intelligence (SPEARMAN, 1927)¹⁵, the CTT has become increasingly out of favor (PASQUALI, 2009). It is worth mentioning that, by CTT, the construct is associated with the score of the instrument or test and not with the individual itself. Therefore, it is based on the objective paradigm and the perspective of behaviorism.

The Item Response Theory (IRT), in turn, is based on a subjective perspective and built upon the idea of latent traits: mental constructs (latent variables) cannot be measured directly but are associated with observable variables through factor analysis or inferential models.

IRT has been applied in the development of tests to assess semantic memory. In Bertola and Malloy-Diniz (2018), the authors validate an instrument taking the following subtests

¹⁵ The analytical method developed by Spearman led to the statistical tool widely employed in correlation analysis (Spearman's ρ).

as factors for semantic memory assessment: verbal fluency, naming by definition, naming test, general knowledge, word definition, categorization, and similarities. Wechsler's tests, as presented in Subsection 3.2.3, also apply IRT on its development.

4.4 AN APPROPRIATE SETTING OF PARADIGMS FOR SEMANTICS

In the previous Sections, we discussed the main theories related to semantics and their respective paradigms. The observation of such paradigms associated with the historical perspective of scientific development allows us to understand, in a broader way, the constructions of a given discipline and, consequently, its limitations. Such considerations lead us to establish the following assertions:

A.1) **Semantic content will always comprise objective and subjective portions.**

In natural language, concepts have a subjective portion (inner representation on the private representational space of each agent) that is inaccessible to formal-logical objectivism (object placed on the shared environment.) However, it is undeniable that a common objective part is shared among the agents, as pointed out by Frege. If concepts were totally subjective, communication would be impossible. Following this, we can state that semantic content comprises objective (e.g., symbols) and subjective (e.g., representations) portions, each one supported by a homonymous paradigm. Therefore, both paradigms are always expected to be considered, even disproportionately¹⁶.

A.2) **Subjective semantic content is influenced by the body.**

The distinction between objectivity and subjectivity goes back to the dualist distinction between body and mind. Duality maintained from formalism and structuralism, through which it was possible to study and establish language dissociated from the agent. However, the Freudian concept of representation and, mainly, Lakkof's definition of conceptual embodiment support the increasingly evident body's role in attributing and understanding meaning. In other words, the ontological aspects of a given agent – especially the human being – determine the way they perceive information, encode representations, and decide about a meaning.

¹⁶ In natural language, metaphorical sentences are more subjective than objective, while descriptive sentences are more objective than subjective. This is not the case in many semantic gap studies (see Subsection 2.3.1) since most rely only on the objective paradigm.

A.3) Subjective semantic content is impossible to be determined, only inferred¹⁷.

There is a tacit relationship between deterministic and objective paradigms, which does not apply to subjective content. Bayesian inference thus becomes the epistemological solution to access the subjective portion of the semantic content – an argument supported by psychodynamics (SOLMS, 2020) and cognitive science (KANDEL, 2013).

A.4) Objective semantic content can be either determined or inferred.

The deterministic approach is preferable when the causes or elements of a given phenomenon are observable. In the case of semantic content, the syntagma¹⁸ is observable through its signal or symbol registration. The inferential approach, especially the frequentist one, is preferable when syntagmas are explored in the context of a population or set of syntagmas, where measures, such as variance, become relevant.

These assertions have two important implications for treating semantics: (i) the formal-logical paradigm cannot process semantic content completely; (ii) the information processing paradigm emerges as the most promising for semantic treatment and representation.

The first is precisely the limitation of formal logic due to uncertainty, which is mainly equivalent to an infinite possibility of choices. When discussing the use of symbolic logic in visual inference, Palmer (1999, p.82) points out that “if different assumptions lead to different conclusions, one cannot conclude anything using both assumptions.” Such an issue becomes evident if we consider the English language or any other spoken idiom: when treated formally (e.g., filling out a multiple-choice form), it has a finite number of entries and must obey syntactic rules. However, in spoken discourse, the possibilities for variation are immense, as well as the meaning they may carry. This is what makes their computation challenging for a Turing machine. This same issue is also addressed by Siegelmann (2013), who noticed that Turing’s model lacks an inherent ability to learn and adapt to new situations beyond those previously programmed.

The second is a consensus in cognitive theories (PALMER, 1999; ANDERSON, 2009; KANDEL, 2013) that information processing is the most appropriate paradigm for understanding mental processes, especially those related to hearing, visual perception, and language. It becomes

¹⁷ This statement becomes even more convincing if evaluated from the perspective of psychodynamic theories (FREGE, 1980; SOLMS; TURNBULL, 2002), where even the subject is unaware of his unconscious processes, which further reinforces the indeterminate character of its semantic representation.

¹⁸ Syntagma is here defined as an elementary linguistic unit consisting of a set of phonemes, words, or sentences in a sequential relationship to one another.

evident from the efforts in solving the binding problem¹⁹, which cannot be handled from the formal-logical paradigm (GARDNER; JOHNSON, 2013).

Therefore, such assertions and consequences should be considered for properly treating semantics. Figure 24 represents the semantic content in its objective, contextual, and subjective portions, showing the other appropriate paradigms for its representation. The objective portion of semantic content is supported by deterministic, frequentist, formal-logical, and information-processing paradigms. The subjective portion of semantic content is supported only by the Bayesian and information processing paradigms. The contextual portion refers to everything not inherent to the object nor part of the agent’s subjective private representations. The contextual portion derives from interrelations with the environment – any paradigms except the subjective one support it.

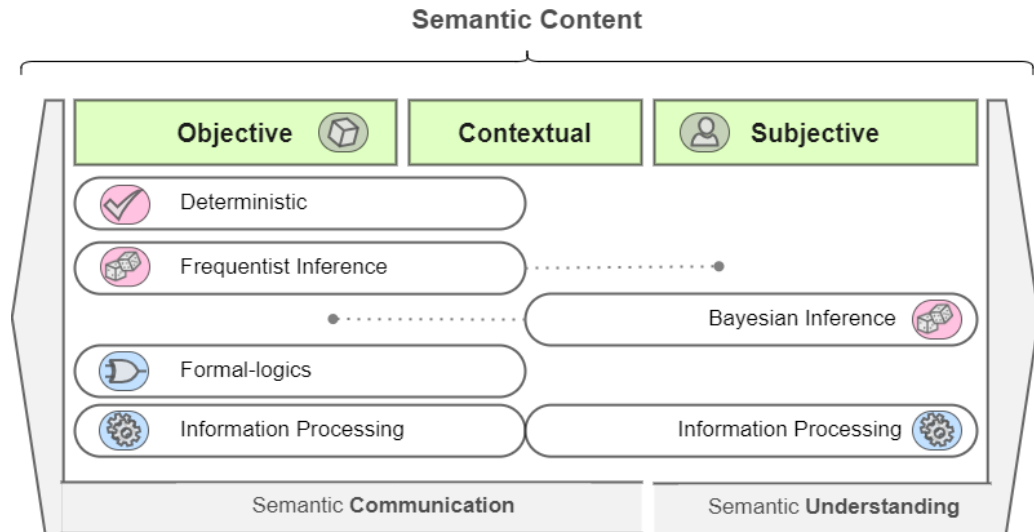


Figure 24 – Underlying paradigms for semantics: the semantic content has objective, subjective, and contextual portions, each supported by other distinct paradigms. The dashed lines indicate that the same paradigm can be applied to different ontological perspectives.

Source: Created by the author.

In Figure 24, the dashed lines indicate that the given paradigms can be applied to the other ontological approach: frequentist inference is used for subjective semantic content inference, especially in psychometric instruments. Bayesian inference can be employed for objective analysis when the distribution is not known. At the limit, if the priors are not declared (see Equation 8), the Bayesian distribution is similar to the frequentist one. It is worth noticing that the information processing paradigm pervades both ontological aspects (objective and subjective) and, thus, the three portions of semantic content. The semantic communication

¹⁹ According to Anderson (2009, p.75), the binding problem is “the question of how the brain puts together various features in the visual field.”

between agents takes place through objective and contextual portions by encoding information into objective elements shared between agents. The understanding of the meaning – i.e., the semantic attribution – happens by decoding such elements into subjective representations. In other words, through the information processing paradigm, the objective portion allows semantic communication between agents, while the subjective portion allows semantic understanding by the subject or agent itself.

4.5 CONTRIBUTIONS FROM THIS CHAPTER

This chapter consolidates the theoretical framework required for the fundamental idea of this thesis – that semantic content is given by objective, contextual, and subjective portions. Each is supported by specific paradigms, which results in incommensurability between them. For instance, subjective representations cannot be determined nor represented objectively; they can only be inferred.

This chapter, therefore, contributes by identifying the paradigms related to semantics (see Figure 19) and proposing the methodology of paradigmatic analysis according to the criteria presented in Table 7. It also contributes to the organization and categorization of knowledge in different areas related to semantics. Semantics, analyzing the theories of linguistics (see Figure 20) and psychology (see Figures 21 and 23). Finally, it discusses the appropriate paradigms for semantic representation, proposing the segmentation of semantic content into its objective, contextual, and subjective portions.

5 A PROPOSAL FOR MEASURING SEMANTICS OBJECTIVELY

Há coisas que nunca se poderão explicar por palavras.

—José Saramago, *O homem duplicado*

In this chapter, we consolidate all the theoretical arsenal and the necessary mathematical formalism to propose a metric for semantics. In Section 4.4 we explained that semantic content has objective and subjective components in addition to contextual or environmental factors, each one with a set of appropriate paradigms. Now, based on the assertions and conclusions from the former Chapter, we propose a formal model for semantics, as follows. In Section 5.1 we establish the axioms that must be fulfilled when dealing with semantics. Such formalization makes it possible to understand the semantic content in all its aspects and for any class of intelligent agents (as defined in Section 3.3.1), thus characterizing the novelty and main contribution of this work.

Then, in Section 5.2, we explore the factor structure of the semantic content by exploring the psycholinguistic dimensions, thus analyzing their subjective, objective, and contextual factors. Such dimensions allow measuring the semantic content objectively. In other words, even though subjective semantic content cannot, by definition, be objectively measured, knowing its factor load makes it possible to infer its influence and to predict its uncertainty. Following the exploration of semantic content dimensions, Section 5.3 introduces the Semantic Content Classifier, a tool developed to operationalize the measurement of semantic content. This classifier represents a practical application of our semantic model, bridging the gap between theoretical constructs and real-world semantic analysis. Based on the proposed models and measurement strategies, in Section 5.4, we offer a reinterpretation of the semantic gap problem (introduced in Section 2.3.1). In Section 5.5, we summarize the main contributions of this Chapter.

5.1 A FORMAL MODEL FOR SEMANTIC ATTRIBUTION

Based on the critical assertions established in Section 4.4 and summarized in Figure 24, we now propose the formalization of a general model for semantic attribution based on objective and subjective content. In this proposal, considering that both object and agent are situated in an environment, we also model circumstantial or contextual factors, i.e., all aspects that may influence the meaning attribution which are not inherent to the object nor produced by the agent's

subjectivity. To this end, some propositions are necessary:

Proposition 5.1 (Semantic space). *There exists a vector space S that encompasses all semantic representations and is defined as follows:*

$$S = S_O \oplus S_S \oplus \mathcal{E}, \quad (11)$$

such that:

- \mathcal{E} is the environmental subspace accounting for other factors or dimensions influencing semantic content, i.e., contextual elements, defined as:

$$\mathcal{E} = \{e(\Lambda) \mid e : \Lambda \rightarrow S\}, \quad (12)$$

where:

- $e(\Lambda)$ represents a contextual element in the environmental subspace.
- Λ is a set of parameters or variables that capture the environmental factors influencing semantic content.
- $e : \Lambda \rightarrow S$ is a function that maps the environmental parameters to elements in S .
- S_O is the objective subspace defined by:

$$S_O = \{s_o = C_O(\Theta) \mid C_O : \mathbb{R}^n \rightarrow S\}, \quad (13)$$

where:

- s_o represents an objective semantic content shared among all agents.
- Θ is the set of inherent attributes of a real-world object, defined in \mathbb{R}^n .
- $C_O : \mathbb{R}^n \rightarrow S$ is a function that maps attributes Θ to elements in S .
- S_S is the subjective subspace for a unique agent a , defined by:

$$S_S = \{s_s = C_S(C_O, e, \bar{\Omega}^A, \Psi^a) \mid C_S : S_O \times \mathcal{E} \times \Psi^a \rightarrow S\}, \quad (14)$$

where:

- s_s represents a private subjective semantic content of an agent a .

- $\bar{\Omega}^A$ represents a fixed set of ontological parameters given the agent's class A , where $A \in \{AIA, HIA, BIA\}$ (see Section 3.3.1).
- Ψ^a is the set of prior representations (i.e., memories) of an agent a .
- $C_S : S_O \times \mathcal{E} \times \Psi^a \rightarrow S$ is a function that maps representations in S_O , environmental conditions in \mathcal{E} , and prior distributions Ψ^a to elements in S .

Corollary 5.1.1 (Semantic encoding by an intelligent agent). *An agent a of class A will encode objective and contextual content into subjective content through its private mapping function:*

$$s_s = C_S|_A^a, \quad s_s = C_S(C_O, e, \bar{\Omega}^A, \Psi^a) \quad (15)$$

Corollary 5.1.2. *Semantic content s_c is defined as a non-independent relationship between the subjective semantic content s_s , the objective semantic content s_o , and the contextual elements e within the semantic space S . This relationship is expressed as:*

$$s_c = \Phi(s_s, s_o, e), \quad (16)$$

where Φ represents the class of functions $\Phi : S \rightarrow S$ that defines the interdependence between s_s , s_o , and e . The non-independence implies that the interpretation of semantic content relies on subjective, objective, and contextual aspects, reflecting the complex interplay between latent variables and observable variables within the semantic space.

Corollary 5.1.3. *There exists a class of inverse functions $\Phi^{-1} : S \rightarrow S$ which allows the decomposition of the semantic content s_c into its subjective (s_s), objective (s_o), and contextual (e) components:*

$$s_s, s_o, e \approx \Phi^{-1}(s_c). \quad (17)$$

Proposition 5.2. *An agent a engaged in the exchange of semantic content s_c , i.e., the semantic information, will encode it efficiently by the computation of Shannon information H throughout their underlying processes:*

$$H(s_c) = - \sum_i P(s_{ci}) \log_2(P(s_{ci})), \quad (18)$$

where $P(s_{ci})$ is the probability distribution of semantic content elements.

Following the Corollary 5.1.1, any agent encodes the objective semantic content s_o into a subjective representation s_s through an operator $C_S|_A^a$, which is defined accordingly to the ontology of each agent. Let us consider, for instance, two possibilities for HIA and AIA, respectively:

For HIA, and ignoring the contextual element e for simplification purposes, we assume the Bayesian brain hypothesis (see Section 4.3.4), implying that s_s is encoded as a Bayesian posterior distribution:

$$C_S|_A^a \equiv P(s_s|s_o, \Psi^a) \propto P(s_o|s_s, \Psi^a) \cdot P(s_s|\Psi^a) \quad (19)$$

where:

- The term $P(s_s|s_o, \Psi^a)$ is the posterior distribution, which means that the subjective content s_s is updated considering both prior beliefs (Ψ^a) and the objective content s_o as evidence.
- The term $P(s_o|s_s, \Psi^a)$ represents the likelihood, or the observed evidence, which quantifies how the objective content s_o aligns with the subjective content s_s within the context of prior beliefs (Ψ^a).
- The term $P(s_s|\Psi^a)$ corresponds to the prior distribution. It embodies the initial beliefs or knowledge about the subjective content s_s before the introduction of any new evidence (s_o).

In contrast, for AIA we assume a homomorphic representation, implying in $s_o \equiv s_s$ (see footnote 13 in Subsection 4.3.3). In this case, the semantic content is directly equal to both the objective and subjective content, reflecting a single interpretation of semantic information.

In this Section we have formalized an integrative model for semantic attribution, providing a comprehensive framework for understanding how agents perceive, encode, and attribute semantic content. Our model emphasizes the interplay between objective and subjective components, as well as contextual elements within the semantic space, showcasing the significance of mapping functions and private representations. With this model in place, described by the Algorithm 1, we will delve into practical applications and empirical investigations in the subsequent Sections.

Algorithm 1 – Semantic Attribution Process by an agent a .

Require: $\exists \Theta, \mathcal{E}, \Omega^A$

Ensure: $\exists \Psi^a$

- 1: Agent perceives s_o
 - 2: Agent encodes s_o into s_s through $C_S |_A^a$
 - 3: Semantic content is attributed: $s_c = \Phi(s_s, s_o, e)$
 - 4: **return** $s_c \in \mathcal{S}$
-

Source: Developed by the author.

5.2 UNPACKING THE SEMANTIC CONTENT DIMENSIONS

In the previous Section we defined an integrative model for semantics by first establishing that semantic content has an objective and a subjective portion, as shown in Figure 24, and then defining the relationship given by Equation 16, which expresses the semantic content s_c as a combination of the objective semantic content s_o , the subjective semantic content s_s , and any other environmental factor, represented by e , that may influence the semantic content s_c .

Now, the purpose is to develop a measure for such components of semantic content. A possible strategy considered in this study associates the semantic content components with psycholinguistic dimensions – the latter are associations of lexical representations (i.e., words) with psychic attributes, as detailed in Subsection 5.2.1. To do so, in Subsection 5.2.2, we employ a factor analysis over the Glasgow Norms (SCOTT *et al.*, 2019). Based on this, in Subsection 5.2.3, we propose the semantic content analysis, which we apply to sequences of words in Subsection 5.2.4.

5.2.1 Psycholinguistic dimensions

The association between linguistic aspects such as lexical representations, i.e., words, and their related psychological constructs are known as psycholinguistic variables or dimensions (DANGUECAN; BUCHANAN, 2016). The choice of psycholinguistic dimensions to access semantics is based on the arguments presented in Chapter 4, especially in Subsection 4.3.5, where we stated that semantic attribution is a cognitive process (i.e., supported by the information processing paradigm), representations are derived from bodily perception, and meaning is a mental construct, which cannot be observed directly but, among other means, through latent variables.

This is why datasets with psycholinguistic variables are created and normalized for a given population: to enable the construction of psychometric instruments. This study will employ

8 psycholinguistic dimensions available in the Glasgow Norms, a dataset compiled by Scott *et al.* (2019) providing normalized dimensions for a corpus of 5,553 words. The Glasgow Norms were built by presenting this corpus to a total of 829 participants in lists of either 101 or 150 words, asking them to rate the words in these dimensions: arousal (AROU), valence (VAL), dominance (DOM), concreteness (CNC), imageability (IMAG), familiarity (FAM), and age of acquisition (AOA). A brief description of each of these psycholinguistic dimensions and its respective scale is organized in Table 8. The descriptive statistics of the nine dimensions of the Glasgow Norms are reproduced in Table 9. Originally, the Glasgow Norms also included the gender association (GEND) dimension, measured by a 7-point scale varying from very feminine to very masculine. However, since this dimension is categorical and is low-correlated to other variables, it was removed from this analysis.

Analyzing the psycholinguistic variables that compose the Glasgow Norms, through Table 8, we can observe in the Scale column that there is no monotonicity for VAL and DOM scales. Taking, for instance, the VAL dimension, we are interested in the presence (a higher value) or absence (a minimum value) of valence, be it positive or negative. However, originally the VAL variable has maximum valence at its lowest and highest scales, for negative and positive valence, respectively. In this case, neutrality or absence of valence is centered around the value 5. For comparison, let us observe the CNC dimension for concreteness: its minimum value means the absence of concreteness, while its maximum value corresponds to the highest concreteness.

Therefore, for these two psycholinguistic dimensions (VAL and DOM), we will treat their values based on a smooth customized scaler we proposed in Equation 20:

$$y_{\text{smooth}} = \log(1 + \epsilon(x - 5)^4), \quad (20)$$

where ϵ is the smoothness parameter varying from 1.0 to 10,000. Table 10 compares the original values with the transformed ones.

Scott *et al.* (2019) verified the validity of the Glasgow Norms by correlating the ratings with different sets of English norms. The authors also employed a factor analysis for dimensionality reduction, finding a consistent structure with 4 factors they called visualization, emotion, salience, and exposure. In our study, we employ a distinct factor analysis in order to support the semantic content structure we have previously defined.

Table 8 – Psycholinguistic dimensions rated in the Glasgow Norms dataset.

Dimension	Description	Scale
Arousal (AROU)	A measure of excitement versus calmness. A word is AROUSING if it makes you feel stimulated, excited, frenzied, jittery, or wide awake. A word is UNAROUSING if it makes you feel relaxed, calm, sluggish, dull, or sleepy.	9-point scale varying from VERY UNAROUSING to VERY AROUSING.
Valence (VAL)	Valence measures value or worth. A word is POSITIVE if it represents something considered good, whereas a word is NEGATIVE if it represents something considered bad.	9-point scale varying from VERY NEGATIVE to NEUTRAL and to VERY POSITIVE.
Dominance (DOM)	A measure of the degree of control you feel. A word can make you feel DOMINANT, influential, in control, important, or autonomous. Conversely, a word can make you feel CONTROLLED, influenced, cared-for, submissive, or guided.	9-point scale varying from YOU ARE VERY CONTROLLED to YOU AVER VERY DOMINANT
Concreteness (CNC)	A measure of how concrete or abstract something is. A word is CONCRETE if it represents something that exists in a definite physical form in the real world. In contrast, a word is ABSTRACT if it represents more of a concept or idea.	7-point scale varying from VERY ABSTRACT to VERY CONCRETE
Imageability (IMAG)	A measure of how easy or difficult something is to imagine. A word is IMAGEABLE if it represents something that is very easy to imagine or picture. In contrast, a word is UNIMAGEABLE if it represents something that is very difficult to imagine or picture.	7-point scale varying from VERY UNIMAGEABLE to VERY IMAGEABLE
Familiarity (FAM)	A measure of how familiar something is. A word is very FAMILIAR if you see/hear it often and it is easily recognizable. In contrast, a word is very UNFAMILIAR if you rarely see/hear it and it is relatively unrecognizable.	7-point scale varying from VERY UNFAMILIAR to VERY FAMILIAR
Age of acquisition (AOA)	Measures the age at which that word was initially learned. Please estimate when in your life you think you first acquired or learned each word. That is, try to remember how old you were when you learned each word either in its spoken or written form (whichever came first).	7-point scale varying between 0-2, 3-4, 5-6, 7-8, 9-10, 11-12, 13+
Semantic size (SIZE)	A measure of something's dimensions, magnitude, or extent. A word represents something BIG if it refers to things or concepts that are large. A word represents something SMALL if it refers to things or concepts that are little.	7-point scale varying from VERY SMALL to VERY BIG

Source: Supplementary materials in (SCOTT *et al.*, 2019).

Table 9 – Descriptive statistics of the psycholinguistic dimensions of Glasgow Norms.

Dimension	AROU	VAL	DOM	CNC	IMAG	FAM	AOA	SIZE
Mean (M)	4.63	5.10	5.07	4.64	4.79	5.26	4.13	4.09
Std Dev (SD)	1.10	1.55	0.91	1.42	1.35	0.93	1.24	1.02

Source: (SCOTT *et al.*, 2019)

Table 10 – Distribution of VAL and DOM variables after transformation via smooth customized scaler.

	VAL_raw	VAL_smooth	DOM_raw	DOM_smooth
count	5,553	5,553	5,553	5,553
mean	5.10	3.85	5.07	2.28
std	1.55	2.93	0.91	2.23
min	1.03	0.00	1.94	0.00
max	8.65	9.43	8.37	8.77

Source: Created by the author.

5.2.2 Factor analysis of semantic dimensions

Factor Analysis is a statistical method used to explore and uncover the underlying structure (latent factors) that may exist in a set of observed variables. It aims to identify the relationships between observed variables and the latent factors that contribute to their variation. There are two main approaches: Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The first, EFA, is employed when there are no a priori hypotheses about the number of factors or how variables relate to those factors. It explores the data to identify patterns and relationships, allowing the extraction of latent factors without imposing preconceived notions. On the other hand, the second method, CFA, is employed when there are known hypotheses about the structure of the latent factors and how they relate to the observed variables. It tests and confirms whether the data supports the predefined factor structure.

In our proposal, although there are assumptions about data and their relationship to semantic components, as we discuss in Subsection 5.2.3, the fact that we do not have control over how the variables were designed and collected led us to not impose preconceived notions over the factor structure, thus choosing to implement EFA, applying the steps of Algorithm 2.

Formally, a factor analysis means associating a vector of observable variables \mathbf{X} , with dimension k , to a vector of non-observable or latent variables \mathbf{f} , with dimension q , which is given through a covariance matrix of factor loads $\mathbf{\Lambda}$, of dimension $q \times q$:

$$\mathbf{X} = \mathbf{\Lambda} \cdot \mathbf{f} + \epsilon, \quad (21)$$

where ϵ contains the errors or residuals not accounted for by the factors for each variable.

Our analysis, therefore, employs the average values of the eight psycholinguistic dimensions for each of the 5,553 words as observable variables. When applying Algorithm 2, we verified a statistically significant result for the Bartlett Sphericity Test (p-value < 0.01) and a significant result for the Kayser-Meyer-Olkin Test (KMO)¹, indicating the suitability of the factor

¹ Dataset with KMO Test values > 0.5 are recommended for factor analysis. For our data, we obtained a KMO Test value of 0.66.

Algorithm 2 – Exploratory Factor Analysis (EFA).

Require: Dataset with semantic features.

Ensure: Factor loadings Λ

- 1: Load data into a dataframe D .
 - 2: Standardize D values.
 - 3: Check adequacy through Bartlett Sphericity Test:
 - 4: **if** p-value not significant **then**
 - 5: Stop: not appropriate data.
 - 6: **end if**
 - 7: Check adequacy through Kayser-Meyer-Olkin (KMO) test:
 - 8: **if** $KMO < 0.6$ **then**
 - 9: Stop: not appropriate data.
 - 10: **end if**
 - 11: Calculate EFA estimator.
 - 12: Evaluate the scree plot or eigenvalues to determine the number of factors.
 - 13: Perform factor rotation for better interpretability:
 - 14: **if** $F_1 \perp F_2 \perp F_n$ **then**
 - 15: Apply an orthogonal method (e.g., varimax).
 - 16: **else**
 - 17: Apply an oblique method (e.g., oblimin).
 - 18: **end if**
 - 19: Calculate factor loadings Λ and communalities h^2 .
 - 20: Check EFA quality through cumulative variance (>0.6).
 - 21: Score latent variables.
 - 22: **return** Factor loadings, latent variables outputs.
-

Source: Developed by the author.

analysis for this data set. From this, the EFA estimator was calculated using the *FactorAnalysis* package in Python.

Different criteria are found in the literature for selecting the number of factors in an EFA. In our case, we used the a priori criterion of three factors in accordance with the proposed formal model. This choice is also supported by the scree plot test², shown in Figure 25, which indicates that factors with eigenvalues less or equal to 1.0 are no more informative than a single variable.

Regarding the structure of the factors, they are expected to be rotated to offer the best interpretability. As illustrated in Figure 26, rotation turns the factors' axes about the origin to find an optimal position (HAIR, 2010). When orthogonality between the factors ($F_O \perp F_S \perp F_E$) is assumed, techniques such as VARIMAX are used (the aim is to simplify the factorial matrix with factors containing the maximum load and others close to zero) or QUARTIMAX (the aim is to ensure that a variable has a maximum load on one factor and minimum on the others). When orthogonality – and, therefore, independence – between the variables is not assumed, oblique methods such as OBLIMIN are used (the aim is to minimize the obliquity between the factors). In our analysis, we employ the OBLIMIN rotation.

² A scree plot is a line plot of the eigenvalues of factors or principal components in an analysis.

Following this, the calculated factor loadings Λ are transcribed in Table 11. The suffix $_M$ in each variable indicates that EFA considered its average for each word. The interpretation of these factors is consistent with the theoretical discussion from the Chapter 4:

- Factor 1 \implies **F_Objectivity**: It is strongly related to how one perceives concreteness and imageability, i.e., how one can easily imagine or picture a given concept. In other words, it relates mostly to the object's inherent attributes shared among all agents.
- Factor 2 \implies **F_Subjectivity**: It is strongly influenced by arousal, valence, dominance,

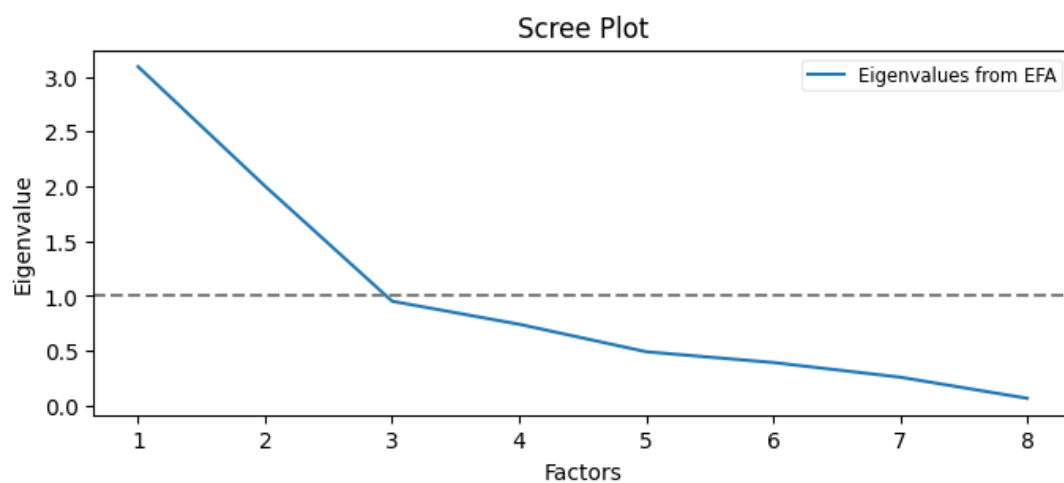


Figure 25 – Scree plot for the exploratory factor analysis with 8 psycholinguistic dimensions. Factors with eigenvalues lower than 1.0 are not recommended for selection.

Source: Created by the author.

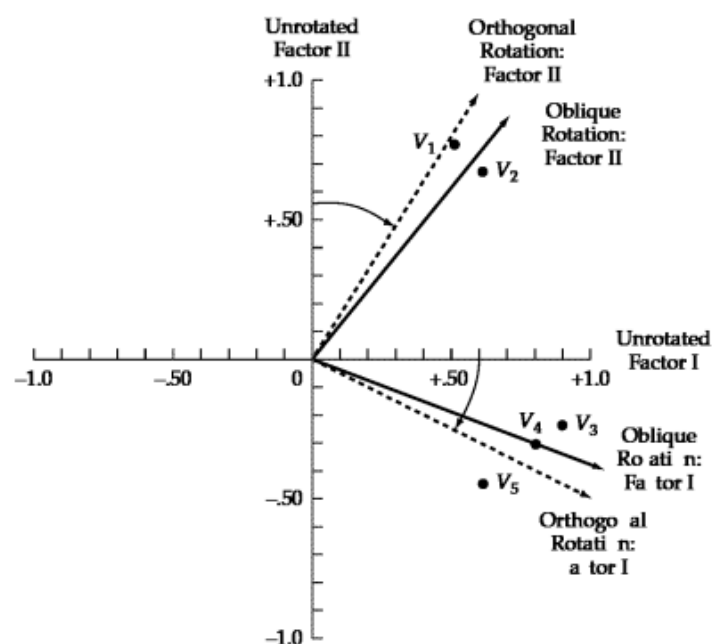


Figure 26 – Orthogonal and oblique factor rotation for exploratory factor analysis.

Source: (HAIR, 2010)

and semantic size. In other words, it relates to the affection load one attributes to a given concept, as discussed in Sections 4.3.3 and 4.3.4.

- Factor 3 \implies **F_Context**: It is inversely related to familiarity and influenced by the age of acquisition. This factor is theoretically associated with context or environmental aspects, i.e., elements that are not intrinsic to the object nor a private representation of the agent but influence the meaning attribution.

Table 11 – Factor loadings for EFA. Values > 0.5 highlighted in orange, values < -0.5 highlighted in red.

	Factor 1	Factor 2	Factor 3
AROU_M	0.100534	0.766473	-0.000532
VAL_M	-0.056289	0.717348	-0.031101
DOM_M	-0.141356	0.513557	-0.038233
CNC_M	0.889828	-0.144661	0.033229
IMAG_M	1.010328	0.091591	-0.039095
FAM_M	-0.043042	0.188115	-0.703989
AOA_M	-0.028245	0.074148	0.985521
SIZE_M	-0.102300	0.590176	0.132671

Source: Created by the author.

The significance of this EFA can be assessed through its overall fit, as the factor variances presented in Table 12. The factors are now labeled as **F_Objectivity**, **F_Subjectivity**, and **F_Context**. The *SumSquared Loadings* row quantifies the proportion of variance explained by the latent constructs. In the *Proportional Var* row, the values indicate the proportion of total variance attributed to each factor, offering insights into their individual contributions to the overall variability in the observed variables. The *Cumulative Var* row shows the cumulative proportion of variance explained by the factors, demonstrating their combined explanatory power. From this analysis, about 64% of the variance of the data is explained by these three factors – an acceptable result for this type of analysis.

Table 12 – Calculated factor variance for EFA.

	F_Objectivity	F_Subjectivity	F_Context
SumSquared Loadings	1.858929	1.784319	1.489516
Proportional Var	0.232366	0.22304	0.186189
Cumulative Var	0.232366	0.455406	0.641596

Source: Created by the author.

Finally, the last step consists of scoring the latent variables where, in practical terms, each word will have a value assigned to each factor. Figure 27 shows the first 50 words with the highest score for each factor. Appendix B lists the top 50 words with the highest values for **F_Objectivity**, **F_Subjectivity**, and **F_Context** in Tables 19, 20, and 21, respectively, and the

bottom 50 words with the lowest values for the same factors in Tables 22, 23, and 24, respectively. A discussion of these results will be elaborated in the following section.

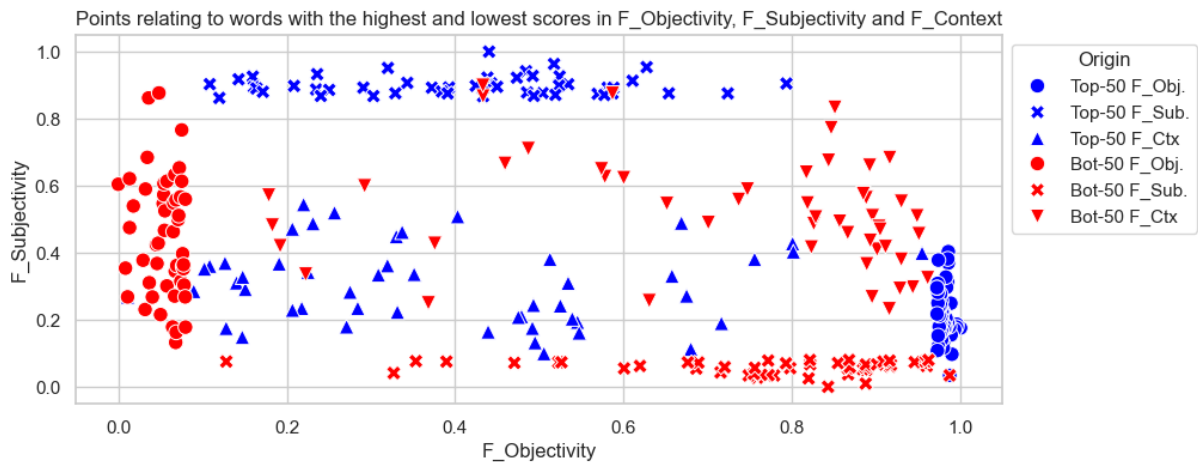


Figure 27 – Points relating to the top-50 and bottom-50 words with the highest and lowest scores in F_Objectivity, F_Subjectivity, and F_Context factors, respectively.

Source: Created by the author.

5.2.3 Semantic Component Analysis (SCA)

In this study, the contextual factor has its factorial load determined by the variables of familiarity with the concept (FAM) and the age of acquisition of the term (AOA). Tables 21 and 24 in Appendix B are used for reference in this study. The words with the highest score in F_Context are those with adult content (i.e., not learned in childhood) or professional jargon (i.e., with little familiarity to the general public). Although coherent, in our interpretation this factor is biased towards the age of acquisition. However, according to the model formalized in Section 5.1, the contextual factor must encompass any aspect other than the objective or subjective ones. Therefore, we do not discard the validity of the F_Context factor of semantic content but suggest future works – as improving the number of psycholinguistic dimensions – to guarantee its suitability.

Our second observation concerns the arrangement of words based on objective and subjective factors. When observing Figure 28, where the entire corpus is projected onto the factors F_Subjectivity and F_Objectivity, with intervals between $[0,1]$, at first sight, we tend to assume a central value of 0.5. If we analyze the distribution of these factors, however, we see that they do not meet normality – a finding verified by the Shapiro-Wilk normality test for both factors. Therefore, it is recommended that the following medians give the centrality of each factor:

$$\begin{aligned}\tilde{X}_{F_{\text{Objectivity}}} &= 0.565 \\ \tilde{X}_{F_{\text{Subjectivity}}} &= 0.392\end{aligned}\quad (22)$$

Semantic Components Analysis

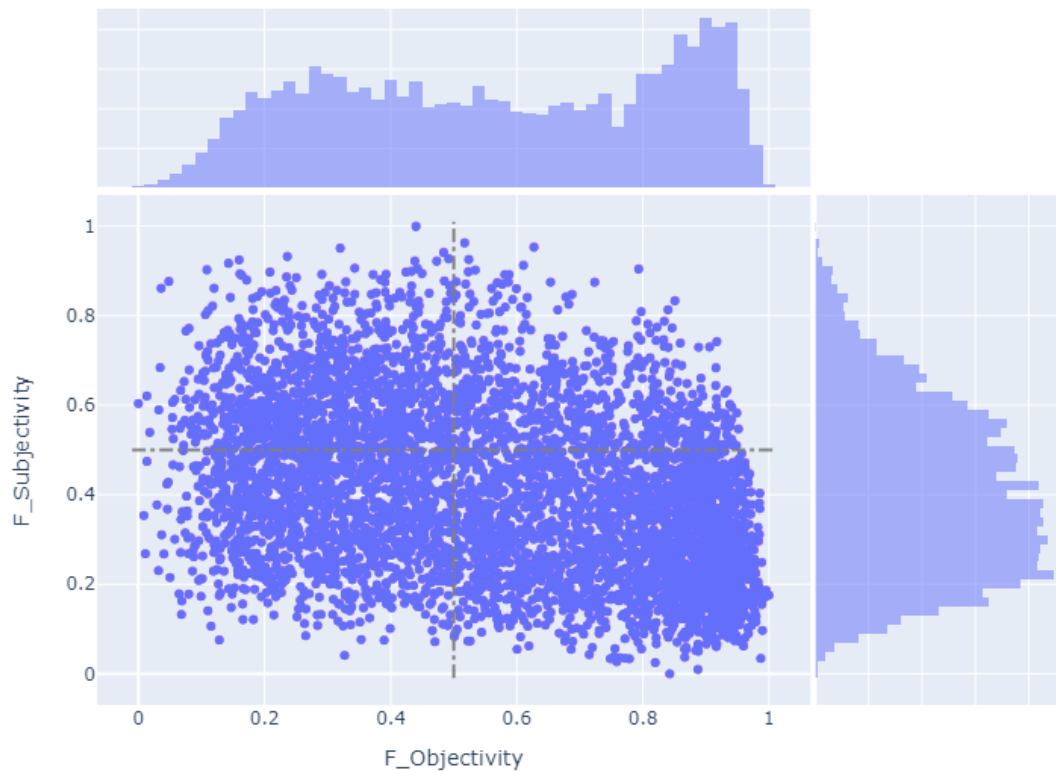


Figure 28 – Distribution of F_Objectivity and F_Subjectivity for the Glasgow Norms corpus.

Source: Created by the author.

Once we have defined these parameters, we can now interpret the plane generated by the factors F_Objectivity and F_Subjectivity, represented in Figure 29, which we divided into four quadrants given their medians. Inspired by the work of Tha (2007), who proposed a conceptual categorization of subjectivity through the conceptual blending theory (see Subsection 4.2.2), we offer the categorization of quadrants resulting from the crossing between the medians of each factor, as represented in Figure 29, which we called Semantic Component Analysis (SCA).

The quadrant determined by a higher significant subjective load and a lower objective load represents the latent content, i.e., the content placed in the agent's private space that can only be inferred. In contrast, the quadrant determined by a higher significant objective load and a lower subjective load represents manifest content, i.e., objects and concepts placed in the physical world. The quadrant determined by both high objective and subjective load is classified

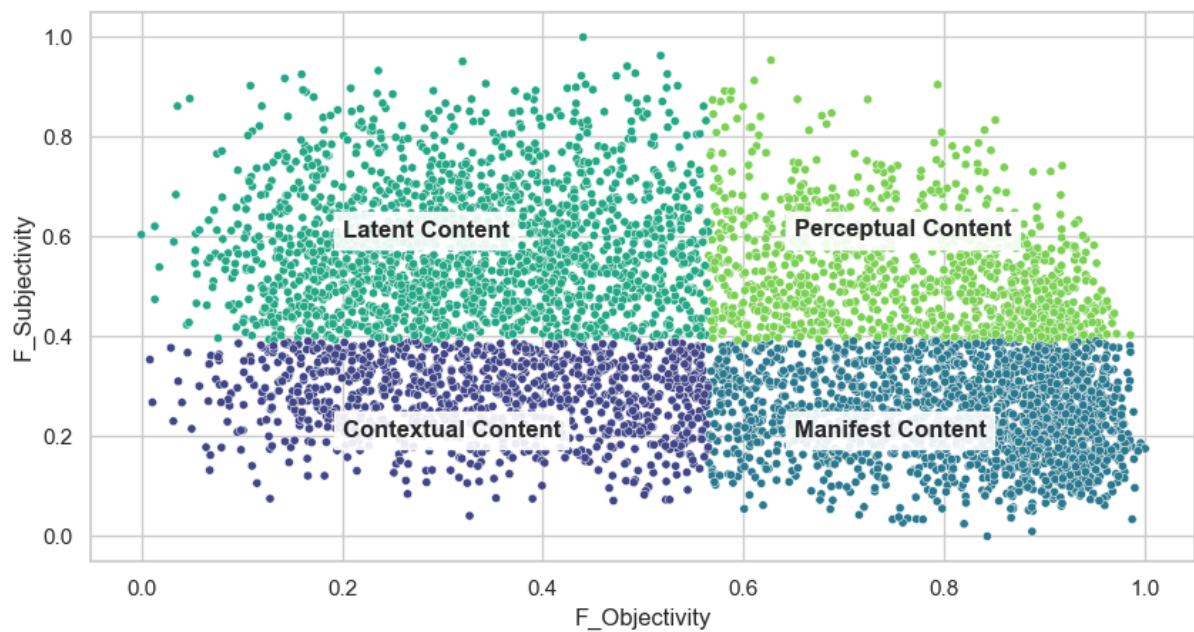


Figure 29 – Semantic Component Analysis: classification of semantic content in quadrants generated by the medians of the plane formed by F_Objectivity and F_Subjectivity.

Source: Created by the author.

as perceptual content: the interface between objects in the world and meanings in the private space, modulated by the agent's perception. Finally, the quadrant determined by low objective and subjective load is defined as contextual content, which is formed by concepts that do not depend on the object or the agent.

5.2.4 Applying SCA to sequences of words

Let us now explore how a set of words behaves through the SCA. The first set relates to *child* (a term discussed in Subsection 4.2.1 through the perspective of formal linguistics) and is given by the words *child*, *Mom*, *Dad*, *toy*, *doll*, *monster*, *fear*, *play*, *protection*, *care* and *imagination*, as represented in Figure 30. The concepts of child, toy, and doll are the most manifest ones in this case. Through the perspective of psychodynamic representations (see Subsection 4.3.3), the entities represented by *monster*, *Mom*, and *Dad* are interfaces between the manifest world and private representations, somehow modulating affection. All these already mentioned terms are related to *imagination*, *care*, *fear*, *play* and *protection*, which are latent content of private or subjective representations.

In this analysis, we should notice that we are not interested – and are not even capable of – in defining the individual meaning of these concepts. The meaning of these words is singular to each agent. However, observing the method in which such factors were developed,

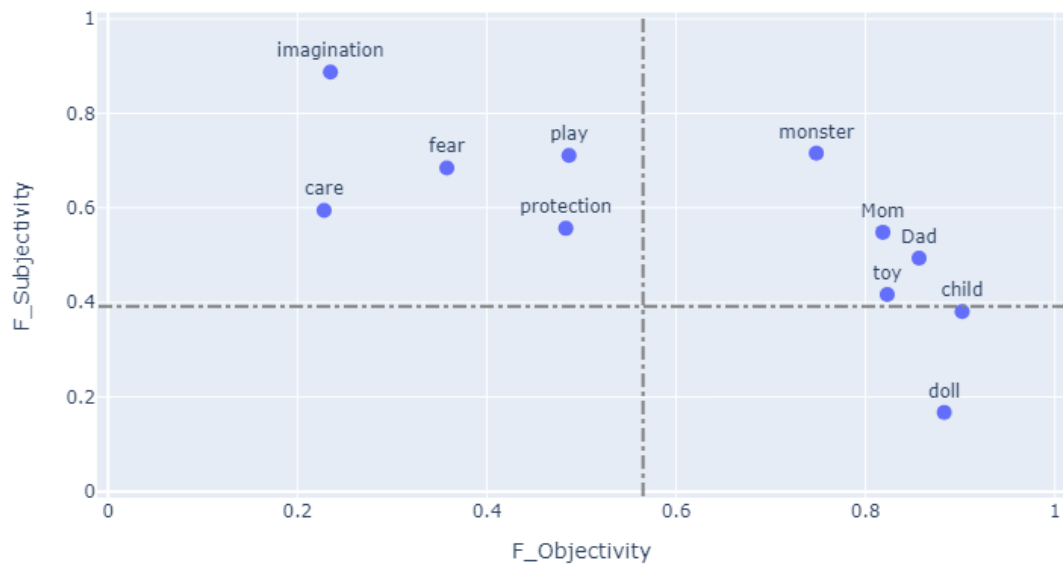


Figure 30 – Semantic component analysis of words related to child and childhood activities.

Source: Created by the author.

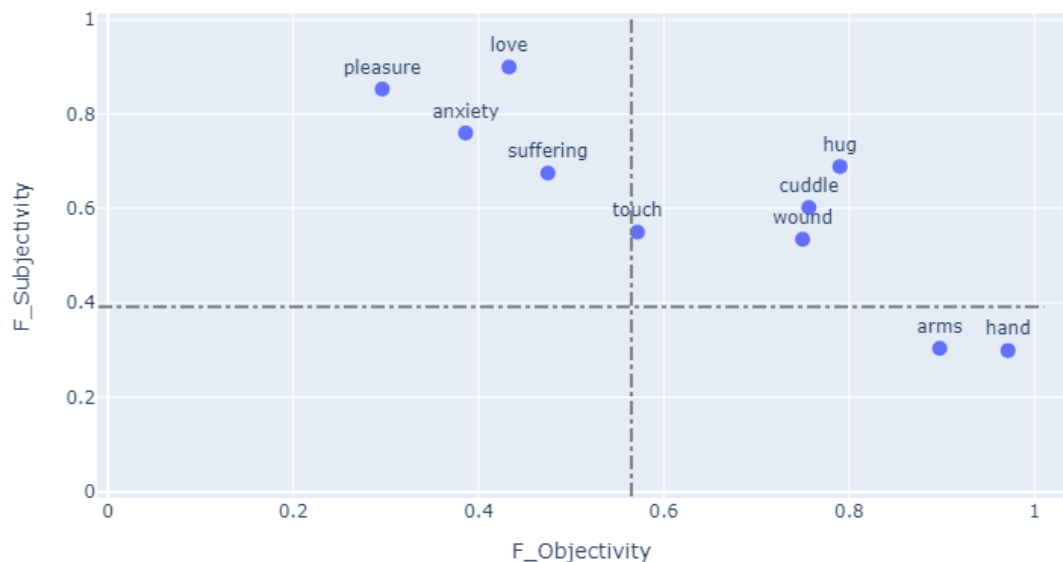


Figure 31 – Semantic component analysis of words related to suffering-pleasure in bodily and psychic aspects.

Source: Created by the author.

we are interested in identifying how subjective (and therefore indeterminable) or objective (and consequently determinable) each term can be.

The second set of words relates to suffering and pleasure in bodily and psychic aspects,

as represented in Figure 31. Let us consider *arms* and *hand*, body parts that *touch* or can be *wounded*, *hugged*, or *cuddled*. They all lead to subjective sensations – and thus representations – of *love*, *pleasure*, *anxiety*, or *suffering*. Again, our discussion point is not on the meaning itself that each term carries but on its possibilities to be publicly determined or privately experienced.

We recognize possible limitations of these analyses – inherent to any attempts to objectify subjectivity. On the other hand, it is precisely through the use of normalized variables (i.e., the Glasgow Norms are standardized for a specific population) and the assumption that the subjective space cannot be directly accessed, if not recognized, that we believe this to be a significant contribution to research on semantics in the areas of CI, psychology, and linguistics.

5.3 A SEMANTIC CONTENT CLASSIFIER

As discussed in the previous Section, the SCA is limited to the 5,553 words available in the reference corpus. To overcome this, we propose training a classifier from the vectorial representation of these words by using pre-trained word embedding³, as presented in Subsection 5.3.1. A generalization of these models is provided in Subsection 5.3.2. For last, in Subsection 5.3.3, we verify the consistency of our hypothesis and the provided method by comparing them to the SICK database (MARELLI *et al.*, 2014). The source code for any model in this Section is available in a public GitHub repository⁴ to ensure reproducibility and facilitate further analysis by the research community.

5.3.1 Word embedding-based classifier

The model development followed the four steps of the machine learning pipeline represented in Figure 4. In the first (pre-processing), we loaded the dataset resulting from SCA, where for each word there was attributed a value for objectivity and subjectivity. Since the Glasgow Norms differentiated some words from their homonymous – such as “charge” and “club”, whose distinct values are represented in Table 13 – we input to all those words their mean value. For example, all six occurrences of the word “charge” were replaced by a unique occurrence with the mean values $F_{\text{Objectivity}} = 0.4077$ and $F_{\text{Subjectivity}} = 0.3522$. For the word “club” the mean values were $F_{\text{Objectivity}} = 0.7830$ and $F_{\text{Subjectivity}} = 0.3943$. This step concluded

³ Word embeddings were introduced in Subsection 2.2.2.

⁴ Semantic Content Classifier is available at https://github.com/tbnsilveira/semantic_classifier.

with a dataset with 4,683 unique words, split into train and test portions with 3,512 and 1,171, respectively.

In the second step (feature extraction), we made use of *en_core_web_lg* model from SpaCy⁵, a comprehensive NLP library. This large-scale English model features an extensive vocabulary of over 500,000 tokens, including words, punctuation, and symbols, and is trained on a broad web corpus. It is particularly noted for its inclusion of 300-dimensional word vectors (i.e., embeddings). The choice of *en_core_web_lg* was driven by its ability to provide rich linguistic representations.

Table 13 – Analysis of F_Objectivity and F_Subjectivity scores for polysemous words 'charge' and 'club' with their contextual distinctions. SCA_id refers to the word index in the SCA dataset.

SCA_id	Word	F_Objectivity	F_Subjectivity	Distinction
819	charge	0.340881	0.330534	None
820	charge (card)	0.477083	0.293352	card
821	charge (dependent)	0.256759	0.164572	dependent
822	charge (electric)	0.391504	0.413080	electric
823	charge (price)	0.428509	0.353942	price
824	charge (rush)	0.551191	0.557549	rush
942	club	0.774815	0.476734	None
943	club (card suit)	0.773094	0.187918	card suit
944	club (disco)	0.863845	0.547812	disco
945	club (hit)	0.725571	0.435103	hit
946	club (organisation)	0.699817	0.428406	organisation
947	club (tool)	0.860703	0.289625	tool

Source: Created by the author.

In the development of our semantic content classifier, we adopted varied data preparation approaches to train models under different conditions and objectives. These approaches are delineated as follows:

- (A) Multi-output continuous variables: The first approach involved preparing data for a multi-output regression model, where continuous values for F_Objectivity and F_Subjectivity were retained. This method allows the model to predict the degree of objectivity and subjectivity of words as continuous variables, providing nuanced insights into their semantic content.
- (B) Multi-labeled single output: Building on the SCA criteria, this approach consolidated the objectivity and subjectivity measures into a single output with multiple labels: latent, contextual, manifest, or perceptual. Each word was assigned one of these labels based

⁵ SpaCy is publicly available in <https://spacy.io/>.

on its F_Objectivity and F_Subjectivity scores, offering a more compact yet expressive representation of semantic content.

Furthermore, in recognizing the limitations of mean-based measures in capturing the central tendency of skewed data, we incorporated the Median Absolute Deviation (MAD) as a robust measure of variability. The MAD is less influenced by outliers and provides a clearer distinction between central and distant data points:

$$\text{MAD} = \text{median}(|x_i - \text{median}(X)|), \quad (23)$$

where x_i represents each data point in the dataset X .

Leveraging MAD, we refined our dataset to focus on words significantly divergent from the median values of objectivity and subjectivity, using a predefined threshold. This led to the generation of two additional datasets:

- (C) MAD selection for regression: This dataset comprises words whose objectivity or subjectivity scores deviate beyond a specified threshold from the median, tailored for regression models that predict continuous outputs.
- (D) MAD data for multiclass training: Analogous to the multi-labeled single output data, this dataset excludes words with scores close to the median, thereby eliminating potentially ambiguous cases and enhancing the classifier's ability to discern distinct semantic categories.

Continuing from the diverse data preparation methods, we moved to the third step (NLP modeling phase), an essential part of the machine learning pipeline. This step involved training two types of models tailored to the specific characteristics of the numerical and categorical data sets prepared earlier.

- **Model 01 – Multilayer Perceptron for Continuous Output:** The first model, a MLP, was designed with two continuous outputs ranging from 0 to 1, using sigmoid activation functions, targeting the prediction of objectivity and subjectivity scores. This model's structure is detailed in Section C and was trained on data sets (A) and (C), which included continuous values for the full SCA data and MAD-filtered data, respectively.
- **Model 02 – Multilayer Perceptron for Categorical Output:** The second model, another MLP, was set up to handle a single multiclass output through a softmax activation function.

This setup aimed to classify words into one of four semantic categories: Latent, Manifest, Perceptual, and Contextual, as defined by the SCA framework. The architecture of this model is detailed in Section C, and it was trained using data sets (B) and (D), which comprised categorical values for the full SCA data and MAD-filtered data, respectively.

The results from the final stage of the machine learning pipeline, focusing on model evaluation, are detailed in Table 14. This phase assesses the models' performance through metrics such as training and test accuracies.

Table 14 – Model performance summary of the Semantic Content Classifier.

Model	Training Data	Training Accuracy	Test Accuracy
Model 01	A	98.22%	88.38%
Model 01	C	98.23%	90.36%
Model 02	B	100.00%	70.09%
Model 02	D	100.00%	75.20%

Source: Created by the author.

For Model 01, the training accuracy remains consistent across different datasets (A and C), with a slight increase in test accuracy when trained on Dataset C (90.36%), indicating effective generalization. However, Model 02, despite achieving 100% training accuracy on Datasets B and D, exhibits significantly lower test accuracies (70.09% and 75.20%, respectively), suggesting overfitting issues where the model captures noise or irrelevant patterns in the training data, impairing its performance on new data.

On the other hand, Model 02 provides a useful categorical result, labeling any word from the pre-trained embedding accordingly to the SCA. For this reason, we choose for the Semantic Component Classifier (SCC) the models 01 and 02 trained over C and D data, respectively.

5.3.2 General classifier based on Universal Sentence Encoder

The approach delineated in the preceding section, while effective for word-level semantic analysis, encounters notable limitations when extended to sentence-level classification. Primarily, it is constrained to the semantic scope of individual words, thereby lacking the capacity to fully capture the nuanced semantic content inherent in sentences. Moreover, its applicability is confined to the 400,000-word vocabulary of the pre-trained embeddings utilized, further restricting its breadth of semantic understanding.

To address these limitations, we employ the Universal Sentence Encoder (USE), as proposed by Cer *et al.* (2018), to retrain our models. The USE, designed for higher-order

language understanding, converts sentences into dense vector representations. Unlike word-level embeddings, the USE captures the overall semantic meaning of sentences, making it suitable for comprehensive semantic content analysis. It led us to develop other two models:

- **Model 03 – Multilayer Perceptron for Continuous Output:** A very equivalent version of Model 01, except for applying USE as encoder and distinct optimization parameters, as detailed in Section C. This model was only trained on dataset (C), with MAD-filtered data.
- **Model 04 – Multilayer Perceptron for Categorical Output:** Also a very equivalent version of Model 02, except for applying USE as encoder and distinct optimization parameters, as detailed in Section C. This model was only trained on dataset (D), with categorical MAD-filtered data.

The performance results for the models trained using USE as feature generation are detailed in Table 15. By integrating the USE into our semantic content classification framework, we achieve a dual-fold enhancement. Firstly, we extend our model’s capability to encompass sentence-level semantic analysis, thereby addressing the intrinsic limitation of word-based approaches. Secondly, we leverage the expansive linguistic understanding derived from its training on a diverse and extensive text corpus, thereby mitigating the vocabulary constraints of our initial method.

Table 15 – Model performance summary of the enhanced Semantic Content Classifier.

Model	Training Data	Training Accuracy	Test Accuracy
Model 03	C	96.03%	91.39%
Model 04	D	99.76%	79.79%

Source: Created by the author.

5.3.3 Consistency of the Semantic Content Classifier

To validate the SCC, we conducted a rigorous test against the SICK (Sentences Involving Compositional Knowledge) dataset, as presented by Marelli *et al.* (2014), which comprises of 9,840 English sentence pairs with annotations for meaning relatedness and entailment relations. This dataset was instrumental in assessing the SCC’s capacity to gauge semantic content beyond mere word-level analysis, aligning with our objective to comprehend the causes of the semantic gap.

The relatedness scores provided by SICK were normalized using the min-max method, allowing for a direct comparison with the similarity metrics derived from SpaCy's standard models, as depicted in Figure 32.

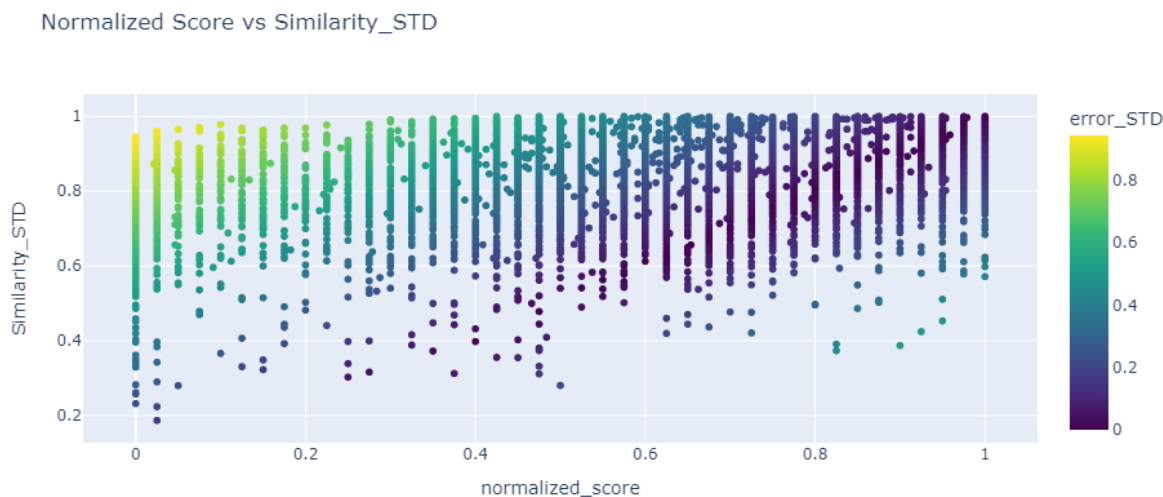


Figure 32 – Error between relatedness score (normalized_score) from SICK database and similarity score calculated via SpaCy (similarity_STD).

Source: Created by the author.

Additionally, we augmented the SICK dataset with numerical features generated by our SCC framework, focusing on objective and subjective dimensions of semantic content for each sentence pair. Our analysis revealed a nuanced relationship between the semantic content categories (i.e., latent, manifest, perceptual, contextual) of sentence pairs and their relatedness scores. Particularly, the grouping of SCA categories and the subsequent aggregation of the other dimensions by their average – as shown in Table 16 – shed light on how subjective and objective dimensions influence semantic understanding. For instance, pairs categorized under 'Manifest' and 'Latent' content showed a notable discrepancy in their error rates and normalized scores.

To bring more consistent evidence, we trained a multivariate linear regression to explore the influence of objective and subjective deltas on the standard error, as detailed in Section C, resulting in a significant model with an R-squared value of 0.904. This high level of model fit indicates a strong relationship between the chosen variables and the error rate, underscoring the predictive power of objective and subjective semantic dimensions on semantic interpretation accuracy.

A critical analysis of the regression results, particularly the coefficient δ_{Subj} , calculated by the absolute difference of F_Subjectivity in the sentences, suggests a pronounced impact of subjective semantic differences on the error rates. The positive coefficient for δ_{-

Table 16 – Analysis of semantic content categories and their impact on error rates and similarity scores.

A_SCA	B_SCA	error_STD	normalized_score	Similarity_STD	delta_Obj	delta_Subj
Manifest	Latent	0.384953	0.460303	0.833844	0.160983	0.187113
Perceptual	Contextual	0.371159	0.516071	0.887230	0.181462	0.080537
Perceptual	Latent	0.349466	0.533908	0.873375	0.178577	0.100616
Latent	Manifest	0.340848	0.523667	0.840012	0.163346	0.163928
Perceptual	Manifest	0.320876	0.543179	0.853130	0.056119	0.148418
Manifest	Perceptual	0.309785	0.558708	0.848757	0.050877	0.147896
Manifest	Contextual	0.270469	0.610127	0.867162	0.144316	0.064421
Contextual	Perceptual	0.253672	0.581369	0.830866	0.169390	0.194301
Manifest	Manifest	0.244538	0.656499	0.877018	0.039695	0.064407
Perceptual	Perceptual	0.227100	0.678191	0.877065	0.046313	0.077131
Latent	Perceptual	0.225987	0.680128	0.884240	0.152483	0.093327
Contextual	Latent	0.225921	0.729896	0.934469	0.076636	0.152314
Contextual	Manifest	0.205565	0.685354	0.864511	0.164877	0.065869
Contextual	Contextual	0.204428	0.776445	0.948173	0.070615	0.047662
Latent	Contextual	0.202585	0.693333	0.821898	0.078642	0.087234
Latent	Latent	0.184961	0.769428	0.933588	0.088105	0.059057

Source: Created by the author.

Subj implies that greater subjective semantic discrepancies between sentence pairs correlate with higher error rates in semantic similarity assessments, reinforcing our hypothesis that subjective content significantly contributes to the semantic gap.

This consistency check with the SICK database not only underscores the SCC's efficacy in capturing nuanced semantic variations but also highlights the pivotal role of subjective semantics in understanding and bridging the semantic gap.

5.4 A REINTERPRETATION OF THE SEMANTIC GAP

Once we have covered the theories related to semantics and defined a formal model for the attribution of meaning, we will now turn our attention to one of the main challenges related to semantics in CI. For this purpose, in Subsection 5.4.1, we will apply the paradigmatic analysis methodology proposed in Subsection 4.1.5 to evaluate the studies on the semantic gap initially listed in Table 1. Then, in Subsection 5.4.2, based on the phenomenon known as pareidolia, we explore a particular case of a semantic gap that brings evidence to the ontological component defined in the model proposed in Section 5.1. Finally, in Subsection 5.4.3, we consolidate these perspectives by offering a new definition of the semantic gap.

5.4.1 Paradigmatic analysis of the semantic gap studies

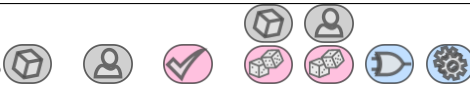
Making use of the paradigmatic analysis criteria, available in Table 7, we review the surveyed literature that explores the semantic gap and other semantic-related issues, first listed in Table 1, thus categorizing them according to the semantic-related paradigms shown in Figure 19. The result is presented in Table 17, where we indicate those studies that bring definitions of semantics (SD), empirical comparisons (EC) between different methods, also indicating their main application field: Decision-Making (DM), CV, and NLP. Finally, we categorize each study according to the influence of different paradigms: the number accompanying each study presented in the table corresponds to the categorization in the respective paradigm in one of the four levels, according to the criteria shown in Table 7.

By observing Table 17, we can assume that (i) the research topic remains current, and (ii) there is no apparent change in the choice of paradigms that support these works. Of the 40 surveyed studies, only 23 present a definition for semantics. Considering the inherent subjective aspect of the semantic content, as discussed in Chapter 4, it is intriguing to observe that the subjective paradigm is predominant in only four of the evaluated studies (10%) and that nine studies (22.5%) do not even consider subjective aspects of the meaning. At some level, the frequentist inference paradigm is applied in all but one of the studies considered. The Bayesian inference paradigm, in turn, is applied in less than half of the studies evaluated (47.5%), being predominant in only four (12.5%). Such data evidence the research opportunity to represent subjective semantic content through the Bayesian approach. Lastly, one can observe the correlation between the objective and the formal-logical paradigms and, also, between the subjective and the information processing paradigms.

Another conclusion from Table 17 is that many studies offer strategies to overcome the semantic gap, but none of them present a comprehensive definition or understanding of the problem. Even more critical, many of the semantic definitions presented in the surveyed studies are limited to an objective perspective of semantics – that is, neglecting the subjective aspect of any attribution of meaning.

Based on the assertions given in Section 4.4, we can state that the semantic gap is caused by the limitations of the objective, deterministic, and formal-logical paradigms, which are not affordable for representing the subjective portion of semantics. It follows that the semantic gap only arises when the meaning attribution process is being considered under ontological

Table 17 – Categorization of the main paradigms underlying each reviewed study, ordered by publication year. The acronyms stand for (SD) semantic definition; (EC) empirical comparison; (DM) decision-making; (CV) computer vision; (NLP) natural language processing; (O) objective paradigm; (S) subjective paradigm; (D) deterministic paradigm; (FI) frequentist inference paradigm; (BI) Bayesian inference paradigm; (FL) formal-logical paradigm; (IP) information processing paradigm. The adherence of each study to a given paradigm is indicated on a scale from 0 to 4, according to the criteria presented in Table 7.

Ref.	SD	EC	DM	CV	NLP							
						O	S	D	FI	BI	FL	IP
(CHEN <i>et al.</i> , 2022)	-	✓	✓	✓	✓	3	1	1	3	1	1	3
(HAQUE <i>et al.</i> , 2021)	✓	✓	-	✓	✓	3	1	3	2	0	1	2
(LI <i>et al.</i> , 2021)	-	✓	-	✓	✓	2	1	1	3	1	1	1
(XU <i>et al.</i> , 2021)	✓	✓	-	✓	✓	4	1	3	2	0	4	1
(SONG <i>et al.</i> , 2020)	-	✓	✓	✓	✓	4	1	2	1	0	1	1
(XU <i>et al.</i> , 2020)	-	-	✓	✓	✓	4	1	3	3	1	2	2
(WIYATNO <i>et al.</i> , 2019)	-	-	✓	✓	✓	3	1	2	1	2	3	3
(ZHANG <i>et al.</i> , 2019)	-	✓	-	✓	✓	3	0	2	2	0	2	2
(LI <i>et al.</i> , 2019)	-	✓	-	✓	✓	4	0	3	2	1	1	3
(ZHANG <i>et al.</i> , 2019)	✓	✓	-	✓	✓	3	1	3	1	0	1	2
(FINLAYSON <i>et al.</i> , 2019)	-	-	✓	✓	✓	2	1	1	1	0	1	3
(YUAN <i>et al.</i> , 2019)	-	-	✓	✓	✓	3	1	2	1	2	3	2
(VADUVA <i>et al.</i> , 2018)	✓	✓	✓	✓	✓	2	4	2	2	1	1	4
(BAÂZAOUI <i>et al.</i> , 2018)	✓	✓	✓	✓	-	4	0	3	2	0	4	2
(AYTAR <i>et al.</i> , 2018)	-	✓	✓	✓	✓	3	1	2	3	0	2	1
(EYKHOLT <i>et al.</i> , 2018)	-	✓	✓	✓	-	3	2	3	1	0	3	1
(TU <i>et al.</i> , 2017)	✓	✓	-	✓	✓	2	2	1	2	3	2	2
(ZHANG <i>et al.</i> , 2017)	✓	✓	-	✓	✓	2	0	0	2	0	2	2
(CAI <i>et al.</i> , 2016)	-	-	✓	-	✓	4	1	3	2	1	4	2
(CALUMBY <i>et al.</i> , 2016)	✓	-	✓	✓	✓	2	2	1	3	1	0	2
(GUO <i>et al.</i> , 2016)	-	✓	-	✓	✓	3	1	2	2	0	1	3
(PANDEY <i>et al.</i> , 2016)	✓	✓	-	✓	✓	3	1	1	3	1	2	3
(ZHANG <i>et al.</i> , 2016)	✓	✓	✓	✓	✓	1	3	2	4	0	0	4
(GOODFELLOW <i>et al.</i> , 2016)	✓	✓	✓	✓	✓	3	2	2	3	3	3	3
(KUMAR; RAVI, 2016)	-	-	✓	-	✓	3	1	2	3	2	2	2
(JAIN <i>et al.</i> , 2015)	-	-	✓	-	✓	2	0	1	1	0	4	1
(BAHMANYAR <i>et al.</i> , 2015)	✓	-	✓	✓	✓	2	2	2	1	0	2	2
(SHAO <i>et al.</i> , 2015)	✓	✓	✓	✓	-	3	0	2	3	2	2	2
(CAMBRIA; WHITE, 2014)	✓	-	✓	-	✓	1	4	0	3	3	4	3
(KURTZ <i>et al.</i> , 2014)	✓	✓	✓	✓	✓	4	2	3	2	0	4	1
(BASTINOS; KRISPER, 2013)	-	-	✓	-	✓	4	0	3	0	0	4	0
(ANDREOPOULOS; TSOTSOS, 2013)	✓	-	✓	✓	✓	3	2	2	2	3	2	3
(SZEGEDY <i>et al.</i> , 2013)	✓	✓	✓	✓	-	4	0	2	3	0	3	1
(MIKOLOV <i>et al.</i> , 2013b)	✓	✓	-	-	✓	4	0	1	4	0	2	2
(TANG <i>et al.</i> , 2012)	✓	✓	✓	✓	✓	1	4	1	2	3	0	4
(TOUSCH <i>et al.</i> , 2012)	✓	-	✓	✓	✓	2	2	1	2	1	3	2
(LANG <i>et al.</i> , 2012)	✓	-	-	✓	✓	3	1	2	2	0	3	1
(HEIN, 2010)	✓	-	✓	-	-	2	2	1	1	0	1	1
(PAN; YANG, 2010)	-	✓	-	✓	✓	2	1	2	2	2	1	3
(DENG <i>et al.</i> , 2009)	✓	✓	-	✓	✓	3	1	2	1	0	3	1

Source: Created by the author.

objectivity – i.e., the idea that there must be a true, real, and inherent meaning for the things. Following this view, the meaning could be determined when all the variables would be known or inferred by the number of times they appear (i.e., inferred by their frequency), which still carries out the idea of certainty.

The gap ceases to exist when the ontological paradigm changes: meaning is a real-time production attributed subjectively – in the human case, there is evidence it comes from the embodied experience (LAKOFF, 1990; KANDEL, 2013) – as presented in Subsection 4.2.2 and Subsection 4.3.4 – and thus can only be measured by credibility levels (e.g., through Bayesian factor, latent factor analysis, etc.).

Strictly speaking, considering that the semantic gap arises from the impasses found by relational semantics (adopted by formal languages) when applied to human cognition, it cannot be argued that humans also suffer its effects. A similar understanding is defended by Hui (2015), Tousch *et al.* (2012), and Guo *et al.* (2016), who claim that humans are not affected by it. It does not mean that there is no ambiguity in human semantic production, as evidenced by Quine (1969) when defining the indeterminacy of translation, as presented in Section 1.1.

More broadly, the semantic gap can be considered as the result of the interaction between humans and artificial agents (e.g., human-computer interfaces), or even in human communication itself when established within a formal system distinct from the natural one (e.g., filling in forms or objective psychometric tests). Addressing the semantic gap as a communication issue between agents naturally establishes it in the information processing paradigm, as described in Subsection 4.1.4.2.

Moving away from the formal logic toward information processing does not extinguish the problem of semantic attribution that we must, in fact, elaborate for computational agents. The information processing approach, associated with subjective Bayesianism, seems to be a promising computational paradigm as it is able to represent the subjective portion of semantic content. Such a framework relates to predictive coding, introduced in Subsection 4.3.4 and explored in-depth by Friston (2010), through the free-energy principle and by Lupyan and Clark (2015), with a language-perception-cognition explanation. Although theoretically satisfactory, such a proposal presents a practical challenge to computationally simulate multivariate distributions, which will demand much more research to be deployed.

5.4.2 Observing the semantic gap through pareidolia

Throughout this thesis, we argue about the role of an ontological component in both intelligence (see Section 3.3 and Definition 3.1) and semantic attribution (see Sections 4.1 and 4.4). In our model proposed in Section 5.1, ontology plays a vital role in defining the subjective semantic content, as explained by Equation 14, where $\bar{\Omega}^A$ represents the ontological parameters of a given class of agents.

In this Section, to bring evidence on the impact of this ontological parameter on semantic attribution, we propose a simple experiment based on pareidolia – a phenomenon by which humans recognize illusory faces on objects (VARELLA, 2018; CARLSON *et al.*, 2018).

Regarding pareidolia, Wardle *et al.* (2020) were interested in the dynamic processing of face in the human brain, finding out that “the representation of illusory faces is confined to occipital-temporal face-selective visual cortex” – i.e., a specific phylogenetic characteristic of human beings that we consider as part of the ontological parameters set. In their experiment, they employed 32 examples of illusory faces in inanimate objects matched to 32 nonface objects. In our proposal, we randomly selected 6 pairs of those images, as depicted in Figure 33. We then selected three volunteers (i.e., HIA agents) to describe what they see in each image, followed by a question if they see any face. We applied the same set of images in three instances of Azure AI Services⁶ – specifically the modules *detect faces in an image*, *add captions to images*, and *add dense captions to images*, which are AIA agents. The results of our experiment are synthesized in Table 18 and detailed in Appendix D.

Table 18 – Experiment with pareidolia: number of faces and objects detected by HIA and AIA on illusory and matched objects images, respectively. Data synthesized from Appendix D.

Agent ID	Agent Type	Faces detected in illusory images	Objects detected in matched objects
Volunteer 1	HIA	6	6
Volunteer 2	HIA	6	6
Volunteer 3	HIA	6	6
Azure VS ACI	AIA	0	6
Azure VS ADCI	AIA	1	6
Azure VS DFI	AIA	0	6

Source: Created by the author.

Suppose a person is trying to communicate to another agent (human or artificial) about a face found in one of these images through the effect of pareidolia. Assuming that the meaning attributed by intelligent agents is also related to parameters inherent to the constitution of a given agent – as is the case of pareidolia in humans – we hypothesize that this communication

⁶ Services available at <https://portal.vision.cognitive.azure.com/gallery/featured>.



Figure 33 – Randomly selected pairs of images from the original dataset with illusory faces through pareidolia (images *a, c, e, g, i, k*) and their corresponding matched objects (images *b, d, f, h, j, l*).

Source: Adapted from (WARDLE *et al.*, 2020).

will be more efficient for agents of the same category. In other words, agents will communicate more efficiently (with lower entropy, as in Proposition 5.2) if they share the same ontological parameters.

To demonstrate this hypothesis, we can use the concept of Shannon entropy (see Subsection 4.1.4.2). Let us denote the semantic content exchanged between two agents as s_c and the ontological parameters of the agents as Ω^A and Ω^B , respectively. We want to demonstrate that $H(s_c|\Omega^A = \Omega^B)$ is lower than $H(s_c|\Omega^A \neq \Omega^B)$, indicating that having the same ontological parameters reduces the uncertainty (entropy) in the exchanged semantic content.

We can apply this analysis to the data represented in Table 18, considering the semantic content s_c as the identification of a face in an illusory image:

A) When the agents have the same ontological parameters, $H(s_c|\Omega^A = \Omega^B)$, we can have:

– Entropy for only HIA agents:

$$\begin{aligned}
 P(s_c|\bar{\Omega}^{\text{HIA}}) &= 18/18 = 1 \\
 H(s_c|\bar{\Omega}^{\text{HIA}}) &= - \left(P(s_c|\bar{\Omega}^{\text{HIA}}) \log_2 P(s_c|\bar{\Omega}^{\text{HIA}}) \right) \\
 &= - (1 \log_2 1) \\
 &= 0
 \end{aligned} \tag{24}$$

– Entropy for only AIA agents:

$$\begin{aligned}
 P(s_c|\bar{\Omega}^{\text{AIA}}) &= 1/18 = 0.0556 \\
 H(s_c|\bar{\Omega}^{\text{AIA}}) &= - \left(P(s_c|\bar{\Omega}^{\text{AIA}}) \log_2 P(s_c|\bar{\Omega}^{\text{AIA}}) \right) \\
 &= - (0.0556 \log_2 0.0556) \\
 &= 0.2316
 \end{aligned} \tag{25}$$

B) When the agents have distinct ontological parameters and they attribute semantics independently, $H(s_c|\bar{\Omega}^{\text{HIA}}, \bar{\Omega}^{\text{AIA}})$:

$$\begin{aligned}
 P(s_c|\bar{\Omega}^{\text{HIA}}, \bar{\Omega}^{\text{AIA}}) &= P(s_c|\bar{\Omega}^{\text{HIA}}) \times P(s_c|\bar{\Omega}^{\text{AIA}}) \\
 &= 1 \times 0.0556 \\
 &= 0.0556 \\
 H(s_c|\bar{\Omega}^{\text{HIA}}, \bar{\Omega}^{\text{AIA}}) &= H(s_c|\bar{\Omega}^{\text{HIA}}) + H(s_c|\bar{\Omega}^{\text{AIA}}) \\
 &= 0.2316
 \end{aligned} \tag{26}$$

C) When the agent's ontological parameters are not considered, $H(s_c)$:

$$\begin{aligned}
 P(s_c) &= 19/36 = 0.5277 \\
 H(s_c) &= - (P(s_c) \log_2 P(s_c)) \\
 &= - (0.5277 \log_2 0.5277) \\
 &= 0.4866
 \end{aligned} \tag{27}$$

Based on these results, we can state that:

$$H(s_c|\bar{\Omega}^{\text{HIA}}) < H(s_c|\bar{\Omega}^{\text{AIA}}) \leq H(s_c|\bar{\Omega}^{\text{HIA}}, \bar{\Omega}^{\text{AIA}}) < H(s_c), \tag{28}$$

which aligns with the expectation that when agents share ontological parameters ($\Omega^A = \Omega^B$), communication tends to be more efficient or predictable, resulting in lower entropy. In contrast, when ontological parameters differ, communication may involve more varied interpretations, leading to higher entropy. This becomes specifically important when agents have some ontological property that enables them to attribute meaning in a particular way, as is the case of pareidolia for HIA. Although the consistency of this demonstration, we suggest future works to assess the significance of these differences through statistical tests applied to larger datasets.

5.4.3 Proposing a new definition for the semantic gap

In Section 5.4.1, we pointed out that many studies offer strategies to overcome the semantic gap, but none of the surveyed ones present a comprehensive definition of the problem. To overcome it, we finish this thesis by proposing a definition, sustained by the formal model for semantic attribution we proposed in Section 5.1:

Definition 5.1 (Semantic Gap). The semantic content residual arising from its representation through different agents due to a communication process. The semantic gap δ for the content s_c between agents a and b is given by:

$$\delta_c^{a,b} = |s_c^a - s_c^b|. \quad (29)$$

Following this, the semantic gap will be minimal if the semantic content contains only objective components. On the other hand, the semantic gap will be greater the greater (i) the magnitude of the subjective component, (ii) the noise in the environmental component, and (iii) the difference in ontological parameters between the agents.

5.5 CONTRIBUTIONS FROM THIS CHAPTER

This chapter made essential contributions to the topic. Initially, we consolidated the theoretical aspects of semantics in a formal model, from which all the analyses and proposals in this chapter were derived.

In the proposed model, semantic content is given by objective, subjective, and contextual components. As evidence of the validity of this proposal, we developed a factor analysis of the Glasgow Norms, a corpus with 5,553 words from which eight psycholinguistic variables were

used. From this analysis, we were able to measure the factors that make up semantic content – hence the title of the chapter as a proposal for measuring semantics objectively.

Then, reducing our analysis only to the plane formed by objective and subjective factors, we proposed semantic content analysis (SCA), a strategy in which we categorize content as latent, manifest, perceptual, or contextual according to the load of each factor in a respective word.

Our examination also extends to the practical application of these concepts through the Semantic Content Classifier. Tested against the SICK database, the classifier underscored our hypothesis that subjective semantic elements predominantly contribute to the semantic gap. This finding not only validates our semantic model but also emphasizes the intricate role of subjectivity in semantic analysis.

Finally, based on this model, we reinterpret the semantic gap. First, we applied the paradigmatic analysis proposed in Chapter 4 to classify and discuss the related studies presented in Chapter 2. Again, based on the proposed formal model, we observe the role of ontological parameters through pareidolia. The chapter ends with our proposal to define the semantic gap, which can now be treated as the residual content between semantic representations.

6 CONTRIBUTIONS AND FUTURE WORK

The study of semantics is a critical aspect of understanding how symbols, such as words and images, convey meaning. Its study, initiated in linguistics and later explored in psychology through psychodynamics and cognitive sciences, becomes a requirement for the area of computational intelligence given the growing number of applications – and the challenges that arise from them – that seek to emulate human abilities of perception and language, especially in natural language processing and computer vision.

There is an intricate relationship between semantics and different areas of knowledge – areas that are based on other epistemological bases, making challenging knowledge exchange efforts. Keeping this in mind, in this thesis we sought to define and equalize concepts and tools between different areas to enable a transdisciplinary study of this common phenomenon of interest to all of them. Therefore, Section 6.1 highlights this research’s main contributions and lists the publications made during this research. Finally, Section 6.2 points to future research that will bring new answers and confirmations to this study.

6.1 RESEARCH CONTRIBUTIONS

In general, it can be stated that the objectives originally proposed in this thesis were achieved. This thesis conveys a body of transdisciplinary knowledge related to semantics and its attribution by intelligent agents. Specifically, we report the contributions of this thesis based on the initial objectives declared in Section 1.2:

1.2.1 Conduct a critical analysis of the main issues and challenges related to semantic attribution in CI:

The treatment of semantics is a task already consolidated in artificial intelligence, with numerous strategies, methods, and algorithms applied to natural language processing and computer vision. However, as explored in Chapter 2, even with the recent advances in LLM research and the development of applications such as ChatGPT, there are persistent semantic-related challenges, consolidated in Table 1. In this aspect, the main contribution of this research was to elucidate the subjective role in semantic content and the impossibility of its determination.

- 1.2.2 Offer a global definition for intelligence based on bibliometric analysis and corresponding theoretical articulation.

Our investigation revealed a lack of consensus on intelligence, even within the same field. To address this issue, we introduced a comprehensive definition of intelligence: the capacity of an autonomous agent to process external and internal information for optimal environmental adaptation. This definition encompasses human, artificial, and biological intelligent agents. While the CHC model is recognized as a gold standard in psychological studies, however, its application to computing is still challenging. We also provided the visual interpretation of the CHC model through Figure 16. Additionally, in Section 3.3, we proposed a categorization of its 83 factors into five intelligence aspects: formal, semantic, contextual, social or affective, and processing resources.

- 1.2.3 Identify the epistemological divergences when dealing with the semantic attribution process, thus understanding the causes of the semantic gap problem in CI and figuring out possible solutions.

We took a transdisciplinary approach to semantic intelligence, acknowledging the challenge of different epistemic bases across various domains. To address this, we introduced paradigmatic analysis by categorizing studies and theories into three paradigm groups related to semantics: ontological (exploring the nature of meaning, whether objective or subjective); measurement (focusing on observation of meaning, whether deterministic or inferential); and computational (centered on the decision or attribution of meaning, whether formal-logical or based on information processing). Using this framework, we extensively examined and classified semantics-related theories from linguistics and psychology. This organizational approach contributes significantly to the integration of knowledge across these fields, with these perspectives summarized through Figures 20, 21, and 23. Such stratification of semantic-related paradigms led us to attribute as the cause of the semantic gap, the limitation of formal-logic (paradigm on which Turing machines are built), and the deterministic perspective in the attribution of meaning (paradigm by which databases are labeled). Finally, our contribution to this aspect occurs with the reinterpretation of the semantic gap, offered in Section 5.4.

- 1.2.4 Investigate and validate the underlying (latent) factors of the semantic content.

Our theoretical articulation led us to propose a formal model for semantic attribution in Section 5.1. It breaks down the semantic content into objective, subjective, and contextual

components. We conducted an exploratory factor analysis of the Glasgow Norms, in Subsection 5.2.2, to verify our proposed model and to gather evidence for supporting our findings.

1.2.5 Develop methods to quantify the semantic content experimentally, validating the proposed approaches using publicly available datasets.

Based on the proposed semantic factors, we put forward a proposal for a semantic content analysis, as detailed in Subsection 5.2.3. Ultimately, we provided a simple experiment to demonstrate the effect of ontological parameters on semantic attribution by exploring an illusory image dataset created over the pareidolia phenomenon, as detailed in Subsection 5.4.2.

During the development of this thesis, the following publications were produced:

- In (SILVEIRA; LOPES, 2023), we elaborate an interdisciplinary study between computing and psychology, offering a joint perspective on intelligence, as discussed in Section 3.2.
- In (THA *et al.*, 2021), we offer an articulation of the Freudian theory and the Bayesian account based on the aspects introduced in Chapter 4.
- In (CONTI *et al.*, 2017), we propose a crowd-counting strategy through machine learning. Although not directly related to this thesis, the publication consolidates methods developed during the research period.
- In (SILVEIRA *et al.*, 2019), we discuss the concept formation in natural language through an interdisciplinary approach.
- In (SILVEIRA *et al.*, 2018), we proposed a method for context classification based on *word2vec* and *k-means* algorithms, as introduced in Chapter 2.
- In (SILVEIRA, 2023), we provide the code and data necessary for the factor analysis and semantic components analysis, presented in Section 5.2.

6.2 FUTURE WORKS

Building upon the foundational research presented in this thesis, future directions are both abundant and critical. The paradigmatic analysis and the formal semantic model

established thus far serve as a robust framework for addressing numerous semantic-related issues in computational intelligence, linguistics, and psychology. To that end, the following key areas have been identified for subsequent investigation:

1. **Interdisciplinary Application:** The paradigmatic analysis and the formal semantic model, while primarily applied to the semantic gap in this thesis, should be tested against other semantic-related challenges, such as those in the translation problem and the binding problem. This entails demonstrating the applicability of the current models to these problems and exploring their computational equivalence [Chapters 1, 4, and 5].
2. **Psychometric Evaluation:** The proposed aspects of intelligence within this thesis warrant further validation. Future work should focus on a comprehensive psychometric evaluation to ensure construct, criterion, and content validity, especially across different classes of intelligent agents [Chapter 3].
3. **Quantitative Paradigm Assessment:** Though qualitative methods were developed to assess six scientific paradigms, future research should aim to develop quantitative methods to identify and assess the underlying paradigms in semantic-related challenges found in scientific publications [Chapter 4].
4. **Expansion of Semantic Component Analysis:** The semantic model proposed, formalized through algebraic axioms, would benefit from the incorporation of category theory to model the morphisms between semantic components. This theoretical framework allows for a deeper exploration of the interconnectedness and structure of semantic spaces. Moreover, extending the semantic component analysis to more psycholinguistic dimensions and the measurement of contextual aspects of semantics will enhance the robustness of this model. This includes a quantitative and qualitative expansion of the analysis to a broader array of word strings [Chapters 5].
5. **Operationalization of the Semantic Gap Analysis:** The qualitative interpretation of the semantic gap's magnitude, as per the definition provided in this study, calls for the development of experimental methods to quantitatively validate the definition provided and measure the semantic gap [Chapter 5].

In addition to these points, the study of semantic components should be broadened from the initial NLP approach to enhance its applicability to CV problems. The exploration

of subjective, objective, and contextual factors in image datasets will also contribute to the understanding of semantics in computational contexts.

Furthermore, the impact of ontological parameters on meaning attribution, as observed through pareidolia, has been a pivotal aspect of understanding the semantic gap. Future studies should aim to validate these observations with an increased number of tests and participating agents, supported by statistical tests with larger sample sizes.

In essence, the quest to minimize the semantic gap is ongoing, and this thesis lays the groundwork for more quantitative explorations. Subsequent research should strive to estimate and evaluate the magnitude of the semantic gap using the mathematical formalization provided, thereby yielding insights into the conditions that minimize or exacerbate this gap.

The endeavors outlined above not only strive to minimize the semantic gap but also pave the way for significant transdisciplinary contributions. The integration of computing, linguistics, and psychology, facilitated by the methodologies and theories posited in this thesis, is poised to foster a collaborative academic milieu to develop a comprehensive understanding of semantic phenomena – propelling forward the frontiers of research in artificial intelligence, human cognition, and language processing.

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APPENDIX

APPENDIX A – CHATGPT-3.5 PROMPT

This supplementary material contains the complete transcription of a conversation between a human user and the ChatGPT prompt. Each section is a question asked by the human user. The content of each section is the response given by the artificial agent. The conversation was recorded on the author's OpenAI account, registered under the code *cd5546d7-1ed8-4bcf-b4b6-29922f7a4239*.

WHAT IS INTELLIGENCE?

Intelligence is a multifaceted and complex construct that can be defined in different ways. At its core, intelligence refers to the ability to learn, understand, reason, and adapt to new situations and challenges. It involves a combination of cognitive abilities such as problem-solving, critical thinking, memory, language, and spatial skills, as well as social and emotional skills such as empathy, self-awareness, and emotional regulation.

There are many different theories of intelligence, including the well-known "g factor" theory, which posits that intelligence can be measured by a single general factor, and the multiple intelligence theory, which suggests that intelligence can be divided into several distinct types, such as linguistic, logical-mathematical, musical, spatial, bodily-kinesthetic, interpersonal, and intrapersonal.

Intelligence is also influenced by a variety of factors, including genetics, environment, education, and culture. It is a dynamic and malleable trait that can be developed and improved through practice, learning, and experience.

WHAT IS THE DIFFERENCE FROM HUMAN INTELLIGENCE AND ARTIFICIAL INTELLIGENCE?

Human intelligence and artificial intelligence (AI) are fundamentally different in several ways. Human intelligence is the product of the complex interactions between the brain's neurons and the environment, resulting in the ability to learn, reason, and solve problems. On the other hand, AI refers to the ability of machines or computer systems to perform tasks that typically require human-like intelligence, such as language processing, visual perception, decision making, and problem-solving.

One of the main differences between human intelligence and AI is their underlying mechanisms. Human intelligence is based on the processing of information through neural networks in the brain, whereas AI relies on algorithms and computer programs that process data and perform operations based on pre-defined rules and decision trees.

Another key difference is that human intelligence is characterized by its flexibility and adaptability, allowing individuals to learn and adjust to new situations and challenges. In contrast, AI is generally designed to perform specific tasks or solve particular problems, and its abilities are limited to the scope of its programming.

Finally, human intelligence is influenced by factors such as emotion, motivation, and context, whereas AI is typically designed to operate in a context-free environment and lacks emotional awareness or subjective experience.

WOULD YOU BE ABLE TO TRY A WAIS ASSESSMENT?

As an AI language model, I am not able to administer a Wechsler Adult Intelligence Scale (WAIS) assessment, as this requires a trained professional with specific qualifications and expertise in psychological assessment. The WAIS is a standardized assessment tool that requires a specific set of instructions and guidelines to be followed to ensure its accuracy and reliability. It also requires a human administrator to interpret the results and provide appropriate feedback and recommendations.

However, I can provide you with general information about the WAIS, its components, and its use in psychological assessment. The WAIS is a widely used intelligence test designed to measure cognitive abilities in adults. It assesses several key areas of intelligence, including verbal comprehension, perceptual reasoning, working memory, and processing speed. The test consists of several subtests that measure specific abilities, such as vocabulary, arithmetic, block design, and digit span.

The results of the WAIS assessment can provide valuable information about an individual's cognitive strengths and weaknesses, as well as their overall intellectual functioning. However, it is important to note that the results of the WAIS should not be used in isolation to make important decisions about an individual's abilities, as other factors such as motivation, education, and experience can also influence performance on the test.

COULD SOMEONE APPLY A WAIS OR WISC ASSESSMENT ON YOU?

As an AI language model, I am not capable of being assessed using the Wechsler Adult Intelligence Scale (WAIS) or the Wechsler Intelligence Scale for Children (WISC). These tests are designed to measure human cognitive abilities and are administered by trained professionals to individuals who are capable of providing verbal and nonverbal responses to the test items.

As an artificial intelligence, I am not capable of experiencing emotions or responding to test items in the same way that a human would. My responses are generated based on statistical patterns in large datasets and are not reflective of a cognitive profile that could be assessed using standardized testing.

It is important to note that the use of psychological tests on artificial intelligence systems is not currently a recognized practice within the field of psychology, as these systems do not possess the same cognitive abilities or experiential factors as humans.

HOW COULD YOU CATEGORIZE ARTIFICIAL INTELLIGENCE OR COMPUTATIONAL INTELLIGENCE BASED ON THE CHC THEORY OF INTELLIGENCE?

The Cattell-Horn-Carroll (CHC) theory of intelligence is a comprehensive model of cognitive abilities that organizes them into three broad strata: narrow abilities, broad abilities, and a general factor (g). While this theory was originally developed to describe human intelligence, it has also been applied to the evaluation of artificial intelligence and computational intelligence.

Here are some examples of how different aspects of artificial intelligence or computational intelligence might be categorized based on the CHC theory of intelligence:

- **Narrow Abilities:** These are specific cognitive skills that are involved in particular tasks or domains. For example, in artificial intelligence, narrow abilities might include natural language processing, image recognition, speech synthesis, or game playing. These abilities might be further subcategorized based on their specific characteristics or demands.

- **Broad Abilities:** These are higher-order cognitive abilities that involve the integration and coordination of multiple narrow abilities. For example, in artificial intelligence, broad abilities might include problem solving, reasoning, decision-making, or learning. These abilities might be evaluated by assessing performance across multiple narrow abilities or tasks.

- **General Factor (g):** This is the overarching construct that reflects an individual's overall cognitive ability. In artificial intelligence or computational intelligence, this might be

reflected in the ability of a system to perform well across a wide range of tasks or domains. However, it is important to note that the concept of *g* may not be directly applicable to artificial intelligence or computational intelligence, as these systems do not possess the same type of cognitive profile as humans.

Overall, the CHC theory of intelligence provides a useful framework for understanding the cognitive abilities that are involved in artificial intelligence and computational intelligence, and how these abilities can be evaluated and measured.

WHAT IS THE BEST WAY TO MEASURE INTELLIGENCE FROM MACHINES AND HUMANS?

Measuring intelligence in both machines and humans can be challenging and involves different approaches and methodologies. Here are some commonly used methods for measuring intelligence in both machines and humans:

For humans: - **Intelligence Tests:** Standardized intelligence tests, such as the Wechsler Adult Intelligence Scale (WAIS) or the Stanford-Binet Intelligence Scale, are widely used to measure human intelligence. These tests assess a range of cognitive abilities, including verbal and nonverbal reasoning, problem-solving, and memory.

- **Cognitive Tasks:** These are specific tasks that are designed to measure different aspects of cognitive ability, such as working memory, attention, or decision-making. Cognitive tasks can range from simple tasks like digit span to more complex tasks like the Wisconsin Card Sorting Test.

- **Behavioral Observations:** Observing an individual's behavior in real-world situations can provide insight into their cognitive abilities. For example, monitoring a person's ability to navigate a complex environment or make decisions under time pressure can provide information about their cognitive abilities.

For machines: - **Performance on Specific Tasks:** In artificial intelligence, machine intelligence is often evaluated based on performance on specific tasks, such as natural language processing, image recognition, or game playing. The accuracy and speed with which a machine can complete these tasks can be used as a measure of its intelligence.

- **Learning Curves:** In machine learning, learning curves can be used to evaluate the performance of an AI system as it is trained on a particular task or dataset. A system that shows rapid improvement and reaches high levels of performance may be considered more intelligent

than one that shows slower improvement or lower overall performance.

- **Human Evaluation:** In some cases, human evaluators may be used to assess the intelligence of a machine system. For example, in the Turing Test, human judges interact with a machine and a human through a text-based interface and attempt to determine which is which based on their responses.

It is important to note that intelligence is a complex and multi-faceted construct, and no single measure or method can fully capture all aspects of intelligence in either machines or humans. Multiple measures and methods are often used in combination to provide a more comprehensive understanding of intelligence in both domains.

CONSIDERING THESE DIFFERENCES BETWEEN HUMANS AND MACHINES, WHAT ARE THE COMMON ASPECTS OF THEIR INTELLIGENCE? HOW TO MEASURE THEM?

While humans and machines have different types of intelligence, there are some common aspects of intelligence that can be measured in both. Here are some examples of these common aspects of intelligence and how they can be measured:

1. **Problem Solving:** Both humans and machines can demonstrate their intelligence through their ability to solve problems. In humans, problem-solving ability is often measured using standardized intelligence tests, such as the Wechsler Adult Intelligence Scale (WAIS). In machines, problem-solving ability can be measured by evaluating their performance on specific tasks or problems, such as solving puzzles or playing games.

2. **Learning:** Both humans and machines can learn from experience and adapt to new situations. In humans, learning ability is often assessed through cognitive tasks or by observing behavior in real-world situations. In machines, learning ability can be measured by evaluating their performance on specific tasks as they are trained on larger and more complex datasets.

3. **Language and Communication:** Both humans and machines can use language and communication to express ideas and interact with others. In humans, language ability is often measured using standardized language tests, such as the Peabody Picture Vocabulary Test (PPVT). In machines, language and communication ability can be measured by evaluating their performance on tasks such as natural language processing, speech recognition, and speech synthesis.

4. **Perception and Recognition:** Both humans and machines can perceive and recognize objects, patterns, and other stimuli in their environment. In humans, perception and recognition

ability are often assessed using cognitive tasks or by observing behavior in real-world situations. In machines, perception and recognition ability can be measured by evaluating their performance on specific tasks, such as image or speech recognition.

5. Decision Making: Both humans and machines can make decisions based on available information and evaluate potential outcomes. In humans, decision-making ability is often measured using cognitive tasks or by observing behavior in real-world situations. In machines, decision-making ability can be measured by evaluating their performance on specific tasks, such as decision-making in game playing or problem solving.

Measuring these aspects of intelligence in both humans and machines often involves using different methods and techniques, depending on the specific task or domain. However, standardized tests, cognitive tasks, and real-world observations are commonly used to assess these common aspects of intelligence in both humans and machines.

APPENDIX B – WORDS WITH HIGHEST FACTOR SCORES

Table 19 – Top 50 words with the highest score in F_Objectivity factor.

Word	F_Objectivity	F_Subjectivity	F_Context
loaf (bread)	1.0000	0.1756	0.3444
carrot	0.9955	0.1868	0.2392
cow	0.9953	0.1781	0.1162
padlock	0.9930	0.1706	0.5431
toes	0.9897	0.0971	0.1069
chihuahua	0.9888	0.1548	0.6414
lorry	0.9885	0.2493	0.2279
snail	0.9871	0.0341	0.2413
bee	0.9869	0.1796	0.1910
pyramid	0.9855	0.4032	0.4223
pint (beer)	0.9854	0.3691	0.6943
notepad	0.9849	0.1925	0.4470
giraffe	0.9848	0.3816	0.2180
gorilla	0.9848	0.3114	0.2957
rhino	0.9835	0.2965	0.2723
mushroom	0.9828	0.2047	0.3187
fridge	0.9826	0.3274	0.2315
fingers	0.9825	0.1788	0.1644
fox	0.9816	0.1749	0.1930
pepper (vegetable)	0.9800	0.1862	0.4556
tank (fish)	0.9798	0.1718	0.3488
ear	0.9796	0.1288	0.1354
lettuce	0.9795	0.1163	0.3553
screwdriver	0.9790	0.2250	0.4282
toaster	0.9780	0.2238	0.2992
nose	0.9775	0.1406	0.1622
frog	0.9774	0.2047	0.2041
caterpillar	0.9774	0.1660	0.2445
pencil	0.9772	0.2561	0.2192
bat (animal)	0.9771	0.1692	0.3045
duck (bird)	0.9771	0.1673	0.1398
pumpkin	0.9764	0.2395	0.2743
table	0.9764	0.1974	0.2163
hippo	0.9764	0.2767	0.2416
sheep	0.9762	0.2437	0.1512
desks	0.9754	0.1860	0.3281
pen	0.9754	0.1570	0.1999
fork (cutlery)	0.9746	0.1792	0.1748
building	0.9744	0.2125	0.2748
canoe	0.9740	0.2359	0.6141
hippopotamus	0.9736	0.3780	0.3093
toe	0.9735	0.1206	0.1461
hairdryer	0.9734	0.1524	0.3649
football	0.9731	0.2498	0.2609
arm (limb)	0.9731	0.2817	0.1290
trumpet	0.9729	0.3085	0.3933
foot (body)	0.9725	0.1082	0.1315
walrus	0.9721	0.2954	0.4228
ass (donkey)	0.9721	0.2172	0.5325
pineapple	0.9720	0.2957	0.2590

Source: Created by the author.

Table 20 – Top 50 words with the highest score in F_Subjectivity factor.

Word	F_Objectivity	F_Subjectivity	F_Context
passionate	0.4402	1.0000	0.6571
ecstatic	0.5174	0.9632	0.6978
sexy	0.6273	0.9537	0.6617
euphoria	0.3200	0.9513	0.8360
adventure	0.4840	0.9417	0.2548
freedom	0.2361	0.9329	0.4281
loving	0.4921	0.9276	0.2459
excitement	0.5240	0.9262	0.2784
spectacular	0.1597	0.9254	0.6152
excited	0.4383	0.9226	0.2035
enthusiastic	0.4732	0.9223	0.5879
independence	0.1428	0.9175	0.5958
beautiful	0.6106	0.9131	0.1991
magnificent	0.3431	0.9069	0.5629
victory	0.4426	0.9054	0.5218
fuck (sex)	0.7933	0.9048	0.7802
inspiration	0.1086	0.9029	0.5681
gorgeous	0.5343	0.9027	0.4424
love	0.4330	0.8995	0.0965
paradise	0.5232	0.8985	0.4868
enjoyment	0.4244	0.8980	0.4348
brilliant (great)	0.2086	0.8977	0.2914
successful	0.4498	0.8950	0.5439
optimism	0.1610	0.8942	0.6792
magical	0.3927	0.8931	0.2551
courage	0.2910	0.8926	0.4008
fantasy	0.3723	0.8925	0.4888
cheer (happiness)	0.5811	0.8922	0.2945
happiness	0.5879	0.8921	0.2363
determination	0.1640	0.8902	0.6192
imagination	0.2349	0.8872	0.2795
ambition	0.2504	0.8858	0.6127
success	0.3843	0.8810	0.4813
phenomenal	0.1717	0.8801	0.6765
content (happy)	0.4853	0.8782	0.5632
incredible	0.0483	0.8768	0.4910
attractive	0.5039	0.8763	0.5512
optimist	0.3290	0.8758	0.7172
fun	0.5868	0.8757	0.0686
laugh	0.6536	0.8757	0.1672
celebration	0.7236	0.8754	0.3732
enthusiasm	0.3911	0.8753	0.5701
hero	0.5692	0.8741	0.2217
erotic	0.5190	0.8710	0.8420
hell	0.5771	0.8707	0.3754
explore	0.4934	0.8679	0.3309
optimistic	0.2404	0.8677	0.6950
passion	0.3030	0.8674	0.6649
happy	0.4331	0.8672	0.0904
knowledge	0.1200	0.8619	0.4774

Source: Created by the author.

Table 21 – Top 50 words with the highest score in F_Context factor.

Word	F_Objectivity	F_Subjectivity	F_Context
Twitter	0.7555	0.3805	1.0000
cortex	0.4929	0.2436	0.9855
dildo	0.9544	0.3985	0.9838
tweet (Twitter)	0.6574	0.3304	0.9786
zephyr	0.3314	0.2230	0.9708
convener	0.4391	0.1641	0.9705
traction (medical)	0.4948	0.1318	0.9692
dissident	0.1910	0.3669	0.9651
imam	0.5452	0.1931	0.9619
abattoir	0.5125	0.3806	0.9605
theologian	0.5390	0.2028	0.9575
temerity	0.1404	0.3104	0.9533
head (semen)	0.6748	0.2713	0.9507
citation	0.4788	0.2099	0.9493
proxy	0.1281	0.1749	0.9473
impotent	0.3302	0.4484	0.9462
belfry	0.5054	0.0992	0.9461
neurotic	0.2200	0.5440	0.9449
edifice	0.4750	0.2078	0.9444
doctrine	0.2252	0.3421	0.9435
savant	0.2567	0.5194	0.9427
latent	0.2178	0.2345	0.9388
socialist	0.3196	0.3617	0.9385
quiescent	0.0110	0.2683	0.9381
hooker (rugby)	0.7161	0.1895	0.9375
banal	0.0896	0.2849	0.9358
emancipation	0.1267	0.3689	0.9354
defame	0.1085	0.3602	0.9350
charlatan	0.3371	0.4616	0.9346
inebriated	0.4029	0.5081	0.9343
syphilis	0.2067	0.4710	0.9331
trellis	0.6798	0.1124	0.9331
legislator	0.5249	0.2417	0.9319
embezzle	0.2311	0.4872	0.9299
collate	0.2068	0.2290	0.9287
bondage	0.6686	0.4887	0.9276
anthropology	0.1508	0.2908	0.9275
proprietor	0.5472	0.1610	0.9271
foible	0.1477	0.3276	0.9261
deluge	0.3513	0.3358	0.9238
neutron	0.4917	0.1751	0.9227
evangelist	0.3088	0.3340	0.9225
nuptials	0.5342	0.3094	0.9224
cite	0.2710	0.1792	0.9219
pot (drugs)	0.8006	0.4275	0.9207
interim	0.1472	0.1481	0.9206
paradox	0.1022	0.3517	0.9205
franchise	0.2843	0.2342	0.9193
pussy (vagina)	0.8015	0.4028	0.9187
neural	0.2751	0.2828	0.9186

Source: Created by the author.

Table 22 – Bottom 50 words with the lowest score in F_Objectivity factor.

Word	F_Objectivity	F_Subjectivity	F_Context
atrocious	0.0000	0.6043	0.7791
ever	0.0085	0.3540	0.1715
quiescent	0.0110	0.2683	0.9381
infinite	0.0134	0.6211	0.6747
misconception	0.0135	0.4749	0.8672
become	0.0179	0.5395	0.4103
vague	0.0294	0.3776	0.6733
habituate	0.0318	0.2306	0.9119
dogma	0.0323	0.5900	0.8872
personality	0.0344	0.6845	0.5535
inspire	0.0360	0.8619	0.5988
elude	0.0368	0.3105	0.8277
aspect	0.0405	0.2679	0.8276
aptitude	0.0452	0.4238	0.8788
theoretical	0.0460	0.3678	0.8892
conceptual	0.0474	0.4284	0.8607
incredible	0.0483	0.8768	0.4910
occur	0.0501	0.2154	0.6392
economy	0.0533	0.5469	0.7753
believe	0.0539	0.5729	0.3274
ideal	0.0542	0.6063	0.5877
thoughtless	0.0548	0.4668	0.6064
fortuitous	0.0553	0.5251	0.8976
gist	0.0577	0.3009	0.7838
troubling	0.0578	0.6135	0.5763
particular	0.0645	0.1784	0.6946
disparity	0.0652	0.4628	0.8877
insincere	0.0658	0.5486	0.7707
might (possibly)	0.0669	0.2706	0.3026
virtue	0.0671	0.6332	0.6856
inane	0.0676	0.3449	0.8215
other	0.0681	0.1324	0.2382
unbelievable	0.0685	0.5577	0.5286
namesake	0.0687	0.1626	0.8677
impropriety	0.0694	0.3619	0.9001
sublime	0.0711	0.4989	0.8067
philosophy	0.0717	0.5111	0.7630
mind	0.0725	0.6532	0.3465
profound	0.0738	0.5666	0.8499
actually	0.0743	0.3148	0.4569
tragic	0.0753	0.7664	0.5455
know	0.0753	0.6132	0.1496
notion	0.0764	0.3970	0.7441
quantum	0.0765	0.3592	0.9102
applied	0.0774	0.3524	0.7308
abstract	0.0774	0.3642	0.7949
affect	0.0781	0.3036	0.5686
rather	0.0794	0.2683	0.4341
sense (common)	0.0796	0.5598	0.4968
instance	0.0798	0.1780	0.6706

Source: Created by the author.

Table 23 – Bottom 50 words with the lowest score in F_Subjectivity factor.

Word	F_Objectivity	F_Subjectivity	F_Context
vole	0.8427	0.0000	0.6426
cornflour	0.8874	0.0097	0.6955
barley	0.8196	0.0250	0.5986
pail	0.7585	0.0271	0.5676
yarn (fabric)	0.7787	0.0337	0.6548
carp	0.7484	0.0339	0.7484
snail	0.9871	0.0341	0.2413
bit (horse bridal)	0.7721	0.0347	0.7164
kipper	0.7634	0.0358	0.5872
peg	0.8665	0.0372	0.3712
pecan	0.7546	0.0384	0.7334
over (cricket)	0.3270	0.0411	0.8866
yarn	0.7151	0.0429	0.5685
mole	0.8879	0.0505	0.4243
nut (bolt)	0.8837	0.0524	0.5275
bugle	0.6863	0.0543	0.8049
lapel	0.6006	0.0550	0.8403
pin	0.8684	0.0550	0.3210
prune (fruit)	0.8662	0.0553	0.5022
cod	0.7979	0.0555	0.4995
sole (fish)	0.7558	0.0566	0.7945
straw	0.8871	0.0583	0.2328
lid	0.8686	0.0585	0.2350
hanky	0.7200	0.0588	0.4016
pea	0.9165	0.0608	0.2221
paperclip	0.9597	0.0621	0.4240
pickle (preserve)	0.6194	0.0621	0.6115
stool	0.9174	0.0660	0.3473
squash (vegetable)	0.8876	0.0664	0.6192
bonnet	0.9008	0.0667	0.6045
thimble	0.8215	0.0670	0.5682
slip (notepaper)	0.7927	0.0701	0.5242
scale (fish)	0.8544	0.0708	0.4809
unit (measure)	0.4703	0.0714	0.6413
shrimp	0.9543	0.0714	0.4736
bridge (card game)	0.6888	0.0724	0.8715
flint	0.6761	0.0729	0.6750
beet	0.5225	0.0732	0.7051
sediment	0.5262	0.0732	0.8951
raisin	0.9455	0.0736	0.2451
ounce	0.3897	0.0752	0.6108
beak	0.9084	0.0752	0.3354
adage	0.1282	0.0754	0.8672
handkerchief	0.9586	0.0759	0.3842
unit	0.3533	0.0764	0.5397
rice	0.9157	0.0781	0.2263
moss	0.7716	0.0782	0.5161
ant	0.9620	0.0799	0.1762
case (container)	0.8211	0.0800	0.4003
plug	0.8676	0.0800	0.2957

Source: Created by the author.

Table 24 – Bottom 50 words with the lowest score in F_Context factor.

Word	F_Objectivity	F_Subjectivity	F_Context
Mum	0.8880	0.5643	0.0000
Dad	0.8565	0.4938	0.0161
Mom	0.8183	0.5485	0.0289
head	0.8887	0.3667	0.0401
red	0.8955	0.5104	0.0405
up	0.6513	0.5470	0.0415
yellow	0.9296	0.3806	0.0466
father (dad)	0.8661	0.4597	0.0479
Christmas	0.8508	0.8339	0.0479
goodbye	0.3757	0.4280	0.0500
water	0.9484	0.5101	0.0519
sky	0.9159	0.6839	0.0546
please	0.1829	0.4824	0.0557
bad	0.2924	0.5997	0.0562
grandma	0.9009	0.4104	0.0570
cry	0.7365	0.5591	0.0576
have	0.1922	0.4208	0.0596
toy	0.8229	0.4168	0.0601
colour	0.8170	0.6402	0.0621
sun	0.8921	0.6609	0.0622
boy	0.8949	0.2685	0.0627
arm	0.9154	0.2327	0.0643
name	0.3682	0.2504	0.0675
fun	0.5868	0.8757	0.0686
bed	0.9032	0.4787	0.0700
birthday	0.5777	0.6274	0.0717
sad	0.5737	0.6502	0.0738
play (game)	0.6001	0.6238	0.0748
eat	0.7006	0.4901	0.0760
mother	0.8846	0.5764	0.0767
man	0.9045	0.4701	0.0772
toys	0.8257	0.4873	0.0796
head (body)	0.9109	0.4183	0.0812
sleep	0.7470	0.5899	0.0820
apple	0.9610	0.3255	0.0830
smile	0.8464	0.7732	0.0840
dinner	0.8280	0.5065	0.0843
small	0.6304	0.2571	0.0860
play	0.4868	0.7108	0.0870
food	0.8433	0.6758	0.0884
happy	0.4331	0.8672	0.0904
thanks	0.1787	0.5719	0.0915
brother	0.8928	0.4370	0.0922
apple (fruit)	0.9433	0.2976	0.0953
love	0.4330	0.8995	0.0965
dog	0.9297	0.5535	0.0974
green (colour)	0.9506	0.4567	0.0976
leg	0.9280	0.2936	0.0984
all	0.2225	0.3363	0.0985
open	0.4592	0.6665	0.0986

Source: Created by the author.

APPENDIX C – SEMANTIC CONTENT CLASSIFIER MODELS

This Appendix complements Chapter 5 by describing the deep learning models discussed in our research. For each model, we outline its architecture and key features. For those interested in a deeper dive, the complete codebase, along with extensive comments, is available in a GitHub repository at https://github.com/tbnsilveira/semantic_classifier.

MODEL 01

"Model_01" - Available as:

/model/model_01_A.h5

/model/model_01_C.h5

Modeling parameters:

```
optimizer = 'adam',
loss = 'mean_squared_error',
metrics = ['accuracy']
```

Training parameters:

```
epochs = 50,
batch_size = 16,
validation_split = 0.2
```

Layer (type)	Output Shape	Param #
dense_5 (Dense) -> ReLu	(None, 256)	77056
dense_6 (Dense) -> ReLu	(None, 128)	32896
dense_7 (Dense) -> ReLu	(None, 64)	8256
dense_8 (Dense) -> ReLu	(None, 32)	2080
dense_9 (Dense) -> Sigmoid	(None, 2)	66

MODEL 02

"Model_02" - Available as:

```

/model/model_02_B.h5
/model/model_02_D.h5
/model/encoder_oneHot_B.pickle
/model/encoder_oneHot_D.pickle

```

Modeling parameters:

```

optimizer = 'adam',
loss = 'categorical_crossentropy',
metrics = ['accuracy']

```

Training parameters:

```

epochs = 50,
batch_size = 16,
validation_split = 0.2

```

Layer (type)	Output Shape	Param #
dense_20 (Dense) -> ReLu	(None, 300)	90300
dense_21 (Dense) -> ReLu	(None, 150)	45150
dense_22 (Dense) -> ReLu	(None, 100)	15100
dense_23 (Dense) -> ReLu	(None, 64)	6464
dense_24 (Dense) -> ReLu	(None, 32)	2080
dense_25 (Dense) -> SoftMax	(None, 4)	132

MODEL 03

"Model_03" - Available as:

/model/model_03_C.h5

Modeling parameters:

optimizer = 'adam', # Learning rate of 0.0005

loss = 'mean_squared_error',

metrics = ['accuracy']

Training parameters:

epochs = 100,

batch_size = 16,

validation_split = 0.2

callbacks = early_stopping; reduce_lr

Layer (type)	Output Shape	Param #
dense_48 (Dense)	(None, 256)	131328
dropout_27 (Dropout)	(None, 256)	0
dense_49 (Dense)	(None, 128)	32896
dropout_28 (Dropout)	(None, 128)	0
dense_50 (Dense)	(None, 64)	8256
dropout_29 (Dropout)	(None, 64)	0
dense_51 (Dense)	(None, 32)	2080
dropout_30 (Dropout)	(None, 32)	0
dense_52 (Dense)	(None, 2)	66

MODEL 04

"Model_04" - Available as:

/model/model_04_D.h5

/model/encoder_oneHot_D.pickle

Modeling parameters:

optimizer = 'adam', # Learning rate of 0.0005

loss = 'categorical_crossentropy',

metrics = ['accuracy']

Training parameters:

epochs = 100,

batch_size = 16,

validation_split = 0.2

callbacks = early_stopping; reduce_lr

Layer (type)	Output Shape	Param #
dense_42 (Dense)	(None, 512)	262656
dropout_22 (Dropout)	(None, 512)	0
dense_43 (Dense)	(None, 256)	131328
dropout_23 (Dropout)	(None, 256)	0
dense_44 (Dense)	(None, 128)	32896
dropout_24 (Dropout)	(None, 128)	0
dense_45 (Dense)	(None, 64)	8256
dropout_25 (Dropout)	(None, 64)	0
dense_46 (Dense)	(None, 32)	2080
dropout_26 (Dropout)	(None, 32)	0
dense_47 (Dense)	(None, 4)	132

MULTIVARIATE MODEL FOR SCC RESULTS

OLS Regression Results						
Dep. Variable:	error_STD	R-squared:	0.904			
Model:	OLS	Adj. R-squared:	0.794			
Method:	Least Squares	F-statistic:	8.222			
Date:	Wed, 14 Feb 2024	Prob (F-statistic):	0.00587			
Time:	00:04:31	Log-Likelihood:	39.977			
No. Observations:	16	AIC:	-61.95			
Df Residuals:	7	BIC:	-55.00			
Df Model:	8					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	0.0904	0.016	5.591	0.001	0.052	0.129
delta_Obj	0.4519	0.154	2.932	0.022	0.087	0.816
delta_Subj	0.7666	0.192	3.985	0.005	0.312	1.221
A_SCA_Contextual	-0.0332	0.014	-2.355	0.051	-0.066	0.000
A_SCA_Latent	-0.0062	0.014	-0.458	0.661	-0.039	0.026
A_SCA_Manifest	0.0558	0.014	4.008	0.005	0.023	0.089
A_SCA_Perceptual	0.0740	0.013	5.482	0.001	0.042	0.106
B_SCA_Contextual	0.0419	0.014	2.902	0.023	0.008	0.076
B_SCA_Latent	0.0207	0.015	1.398	0.205	-0.014	0.056
B_SCA_Manifest	0.0322	0.014	2.367	0.050	3.44e-05	0.064
B_SCA_Perceptual	-0.0044	0.015	-0.299	0.773	-0.040	0.031
Omnibus:	0.661	Durbin-Watson:	2.595			
Prob(Omnibus):	0.719	Jarque-Bera (JB):	0.678			
Skew:	0.282	Prob(JB):	0.713			
Kurtosis:	2.165	Cond. No.	3.10e+16			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The smallest eigenvalue is 2.54e-32. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

APPENDIX D – RESULTS OF THE EXPERIMENT WITH PAREIDOLIA

Table 25 – Responses and face detection by intelligent agents for the illusory images set. The Image ID corresponds to those of Figure 33. VS stands for Vision Studio.

Agent Description	Agent Type	Image ID	Responses (in Portuguese or English)	Found a face?
Volunteer 01	HIA	(a)	Um boneco olhando para uma panela.	Yes
Volunteer 01	HIA	(c)	A imagem de um peixe. Um peixe de boca aberta.	Yes
Volunteer 01	HIA	(e)	Pimentões apavorados.	Yes
Volunteer 01	HIA	(g)	Um aspirador mal-encarado.	Yes
Volunteer 01	HIA	(i)	Uma careta vermelha.	Yes
Volunteer 01	HIA	(k)	Uma máquina mostrando a língua.	Yes
Volunteer 02	HIA	(a)	Um objeto com cara de bobo.	Yes
Volunteer 02	HIA	(c)	Um peixe safado.	Yes
Volunteer 02	HIA	(e)	Pimentões gritando por terem sido cortados.	Yes
Volunteer 02	HIA	(g)	Uma bruxa de vassoura que está zangada.	Yes
Volunteer 02	HIA	(i)	Um aviãozinho feliz.	Yes
Volunteer 02	HIA	(k)	Uma máquina de lavar maluca.	Yes
Volunteer 03	HIA	(a)	Uma cara admirada.	Yes
Volunteer 03	HIA	(c)	Um peixe sorrindo.	Yes
Volunteer 03	HIA	(e)	Pimentões assustados.	Yes
Volunteer 03	HIA	(g)	Um babuíno.	Yes
Volunteer 03	HIA	(i)	Eu escuto até a voz dele.	Yes
Volunteer 03	HIA	(k)	Alguém fazendo "blergh".	Yes
Azure VS: "Add captions to images"	AIA	(a)	A red and silver blender.	No
Azure VS: "Add captions to images"	AIA	(c)	A close up of a metal scissors.	No
Azure VS: "Add captions to images"	AIA	(e)	A green bell pepper cut in half.	No
Azure VS: "Add captions to images"	AIA	(g)	A mop head with a blue handle.	No
Azure VS: "Add captions to images"	AIA	(i)	A close-up of a red airplane.	No
Azure VS: "Add captions to images"	AIA	(k)	A clothes in a washing machine.	No
Azure VS: "Add dense captions to images"	AIA	(a)	A red and silver blender. A red object with three eyes.	Yes
Azure VS: "Add dense captions to images"	AIA	(c)	A close up of a crack in a bowl. A close up of a metal scissors.	No
Azure VS: "Add dense captions to images"	AIA	(e)	A green bell pepper cut in half.	No
Azure VS: "Add dense captions to images"	AIA	(g)	A mop head with a blue handle. A mop head with a green mop.	No
Azure VS: "Add dense captions to images"	AIA	(i)	The nose of a red plane.	No
Azure VS: "Add dense captions to images"	AIA	(k)	A clothes in a washing machine.	No
Azure VS: "Detect faces in an image"	AIA	(a)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(c)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(e)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(g)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(i)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(k)	No face detected.	No

Source: Created by the author.

Table 26 – Responses and face detection by intelligent agents for the matched objects set. The Image ID corresponds to those of Figure 33. VS stands for Vision Studio.

Agent Description	Agent Type	Image ID	Responses (in Portuguese or English)	Found a face?
Volunteer 01	HIA	(b)	Uma batedeira profissional.	No
Volunteer 01	HIA	(d)	Uma faca. Uma tesoura de poda.	No
Volunteer 01	HIA	(f)	Pimentões sem semente.	No
Volunteer 01	HIA	(h)	Uma vassoura de pano.	No
Volunteer 01	HIA	(j)	Um avião de brinquedo.	No
Volunteer 01	HIA	(l)	Uma máquina de lavar.	No
Volunteer 02	HIA	(b)	Uma batedeira vermelha.	No
Volunteer 02	HIA	(d)	Um canivete.	No
Volunteer 02	HIA	(f)	Pimentões verdes.	No
Volunteer 02	HIA	(h)	Uma vassoura.	No
Volunteer 02	HIA	(j)	Um avião mono-hélice.	No
Volunteer 02	HIA	(l)	Uma máquina de lavar.	No
Volunteer 03	HIA	(b)	Uma batedeira.	No
Volunteer 03	HIA	(d)	Metade de uma tesoura.	No
Volunteer 03	HIA	(f)	Pimentões.	No
Volunteer 03	HIA	(h)	Uma vassoura.	No
Volunteer 03	HIA	(j)	A hélice de um avião.	No
Volunteer 03	HIA	(l)	Uma máquina de lavar.	No
Azure VS: "Add captions to images"	AIA	(b)	A red mixer with a bowl.	No
Azure VS: "Add captions to images"	AIA	(d)	A metal object on a brick surface.	No
Azure VS: "Add captions to images"	AIA	(f)	A green bell pepper cut in half.	No
Azure VS: "Add captions to images"	AIA	(h)	A mop with a handle.	No
Azure VS: "Add captions to images"	AIA	(j)	A propeller on a plane.	No
Azure VS: "Add captions to images"	AIA	(l)	A white washinh machine with a round door.	No
Azure VS: "Add dense captions to images"	AIA	(b)	A red mixer with a bowl. A close-up of a mixer.	No
Azure VS: "Add dense captions to images"	AIA	(d)	A metal knife on a brick surface.	No
Azure VS: "Add dense captions to images"	AIA	(f)	A green pepper with a hole in it.	No
Azure VS: "Add dense captions to images"	AIA	(h)	A mop with a handle.	No
Azure VS: "Add dense captions to images"	AIA	(j)	A propeller on a plane.	No
Azure VS: "Add dense captions to images"	AIA	(l)	A white washing machine with a round door. A white sky with clouds.	No
Azure VS: "Detect faces in an image"	AIA	(b)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(d)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(f)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(h)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(j)	No face detected.	No
Azure VS: "Detect faces in an image"	AIA	(l)	No face detected.	No

Source: Created by the author.