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From Human to Artificial Intuition: Transcribing Instinct in AI Agents

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ABSTRACT

Nowadays, it is an indisputable fact that the ever-growing Artificial Intelligence (AI) is one of the most effective applied technologies ever developed, which can be attributed to its inherent trait of making decisions based on real-time information, with data collected from sensors and a wide range of sources within a fraction of a second. As their storage systems are radically advancing, the processing and analyzing speed of such algorithms has now become faster than ever, pushing the horizons of what we have until now considered possible. Nonetheless, AI might be losing a part of what it could eventually evolve into. Despite being framed as ‘‘mythical’’ or ‘‘irrational’’, Intuition is an essentially significant characteristic of humans, introducing new perspectives to their problem-solving abilities and enhancing their decision-making skills; therefore, it would be highly intriguing to incorporate this concept into Artificial Intelligence systems. In this paper, the fundamental characteristics of the intuitive mechanism have been defined, and novel social research assessing the significance of Intuition for the strategic decision-making skills of individuals from different backgrounds was carried out. The results of the study assessed the predisposition of different demographic groups to use Rationality or Intuition to make decisions, but also revealed the correlations between these two Thought Systems and the Intuition Sub-Types. Finally, discussing the further implications of this study, a theoretical framework was developed to approach how each Intuition Sub-Type can be artificially imitated in AI agents, while simultaneously considering the potential ethical or social implications of such an integration.

Human Intuition

There is nothing mythical, magical, paranormal, or irrational about intuitive processes (Simon, 1987), since these mental mechanisms have an actual neurological foundation. Essentially, intuition is used by individuals to make decisions under time pressure when a situation has a high level of uncertainty and sophistication and the provided environmental stimuli are limited (Robbins & Jack, 2006). For this reason, researchers have characterized intuition as “affectively charged judgments arising through rapid, non-conscious, and holistic associations” (Dane & Pratt, 2007), as “responses reached with little apparent effort and typically without conscious awareness and which involve little or no conscious deliberation’’ or as “understanding without rationale and synthesis, not analysis… with a sense of certainty’’ (Benner & Tanner, 1987). Rapid perception, lack of awareness of the processes engaged, the concomitant presence of emotions, and a holistic understanding of the problem at hand are also underlying traits of intuitive processes (Chassy & Fernand, 2011). All of these definitions for intuition encompass some basic assumptions, namely that intuition is fast (used at a level below consciousness) and involves previously learned patterns of information, which can positively contribute to decision-making, problem identification, managing information, recognizing patterns, dealing with conflict, and forming strategies in tune with the evolving environment (Nelson et al., 2011). For this reason, some argue that logical processes, albeit increasingly necessary, are disadvantageous – if not in inferiority – compared to highly developed intuitive processes (Barnard, 1938).

Anatomically, intuition stems from the function of the following brain parts: the Precuneus, which plays a role in consciousness (Cavanna, 2007), the Ventromedial Prefrontal Cortex, a key ‘‘store’’ of all past experiences

(D'Argembeau, 2013), and the Caudate Nucleus, which speeds up the humans' reactions/automatic behavior (Kim & Hikosaka, 2015, and Sadler-Smith, 2023). Thus, past experiences are an important cornerstone of intuitive processes. For instance, specialized academic personnel, possessing a high level of knowledge and decision-making ability, not only rely on their judgment and work experiences but also use their instinct to reach a decision, since they trust their feelings more than other people when dealing with complex situations of limited information that they have not encountered before (Malewska, 2019). Something similar happens with doctors (or even with pilots), as they arrive at decisions taking into account both the existing data and their intuition, which stems, of course, from their perennial experience (Trafton, 2018).

It therefore follows that people utilize two different Thought Systems when making decisions, although the latter may not cooperate well with each other, with intuition 'clouding' logic. System I is fast, intuitive, and error-prone, whilst it can increase the chances of survival by allowing people to recognize potential threats and promising opportunities. On the other hand, System II is slower, relies on reasoning and extensive critical and analytical thinking, and has smaller chances of producing bad decisions (Kutsch, 2019). Consequently, even though intuition is faster than a rational approach, it depends on various factors and is not based on simple rules, and for this reason, the most effective method of making strategic decisions requires the combination of intuitive and rational thinking, especially nowadays, when the complexity of the environment and the huge amount of information may lead to intellectual confusion (Khatri & Ng, 2000). In the business sector, this cooperative model between intuition and rationality entails considerable success (Mintzberg, 1989; Isenberg, 1984; Agor, 1986; Yukl, 1994) since intuition is not the opposite of logic, but rather a faster and more automatic process that takes advantage of the experience and knowledge that people have accumulated throughout their lives (Malewska, 2017). Hence, it can be understood that intuition is a mainstay of the human condition, especially when combined with rational reasoning.

At this point, the characteristics of the three fundamental Types of Intuition will be analyzed, namely the following:

- *Holistic Intuition* (with sub-categories the ''Big Picture'' and ''Abstract'' Intuition) refers to people's ability to holistically imagine the entirety of the problem at hand on a larger scale without having all the necessary data.
- *Affective Intuition* refers to one's intuitive emotional response to a situation, with the simultaneous presence of emotions being closely related to the person's past experiences in similar circumstances. It is the same mechanism that makes people ''learn from their mistakes and not repeat them''. Thus, experiences that have been associated in their minds with something negative have a more significant influence than those that connote something positive, as the latter are not "impressed" as strongly as the former.
- *Inferential Intuition* expresses the ability of an individual to arrive at conclusions by logical inductions without having the necessary data, which is also accompanied by a feeling of validity (Pretz et al., 2014).

Statistical Analysis

Sample and Method

The study used two already established and validated questionnaires, the Rational Experiential Inventory (REI) (Pacini, 1999) and the Types of Intuition Scale (TIntS) (Pretz et al., 2014), which can be found in the Appendix, and explore the different ways a person makes decisions and solves problems. The REI estimates the predisposition of each person to use rational and empirical thinking through two 20-item scales, with the Rational Thought System (REI-R) being analyzed by the first 20 questions (e.g., "I enjoy intellectual challenges") and the Empirical/Intuitive Thought System (REI-E) with the remaining 20 (e.g., "I believe in trusting my hunches"). The further examination of Intuition Types was achieved with the TIntS, which consists of 29 questions categorizing Intuition into 4 different sub-groups (Holistic Abstract [IHAB], Holistic Big Picture [IHBP], Inferential [INFER], and Affective [AFF]

Intuition). Both questionnaires were scored on a Likert 5-point scale with 1 representing ‘strong disagreement’ and 5 ‘strong agreement’. TIntS scores were calculated by averaging the responses to all items on each scale.

The questionnaires were digitalized with the Google Forms program, their results were initially transferred to Microsoft Excel, and the statistical program SPSS 20 (SPSS Inc, Chicago, IL) was used for their analysis. The survey was (also) carried out within the school, and both questionnaires were uploaded to the school’s digital platform (Microsoft Teams), where they were for 5 weeks available for completion by students and teachers. At the same time, this study was sent to several European Commission employees. All respondents participated voluntarily and completed all measures individually. Albeit their anonymity was preserved, the study gathered general demographic evidence. Any answer sheet with missing data was rejected. A p-value less than 0.05 was considered to be a statistically significant result ($p \leq 0.05$).

Results

Fifty-five (55) respondents participated in the study, the population of which consisted of High School students and teachers, as well as adults with other occupations. The data show that the majority of respondents were students (45,45%) in the 15-18 years old age range (followed by adults over 45, 36.3%), female (64%), and Greeks (74.5%), while the non-Greeks came from: Germany (4), Ireland (1), Belgium (2), Romania (1), Portugal (1), Slovenia (1), Italy (2) and Lithuania (2). (Table 1).

Table 1.

Profile of Respondents	Demographic Variables	Frequency-Percentage
Gender	1: Male	40 (36.4%)
	2: Female	70 (63.6%)
Age	1: 14-15	40 (36.4%)
	2: 17-18	10 (9.1%)
	3: 25-35	6 (5.5%)
	4: 35-45	14 (12.7%)
	5: 54-55	30 (27.3%)
	6: 55+	10 (9%)
School Position	1: Student	50 (45.4%)
	2: Professor	18 (16.4%)
	3: Other (Not associated)	42 (38.2%)
Nationality	1: Greek	82 (74.5%)
	2: Other	28 (25.5%)
University Education	1: Yes	54 (49.1%)
	2: No	56 (50.9%)

Tables 2 and 3 report the [percentage %] distribution of responses according to demographic characteristics for the rational and intuitive ways of thinking, respectively. Regardless of their personal traits, all participants endorse the rational way of thinking (the mean value of the sum of the "agree" and "strongly agree" responses on the REI-R was 34%). However, the study reveals that the majority of respondents are undecided (with an average of 37.9%) about whether or not to use intuition to make decisions (compared to a mean value of 20.5% for "agree" and "strongly agree" responses respectively). They made decisions instinctively only when they assumed it was the right decision, i.e., when the situation was under a high level of uncertainty, data was limited and they acted under time pressure, trusting their feelings, and believing that their instincts were correct.

Table 2. Percentage Distribution of Responses regarding the Rational Thought System.

REI-R	% CONTRIBUTION	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
Gender	Male R	5.5%	9.0%	19.8%	32.3%	33.5%
	Female R	4.0%	12.6%	18.1%	36.9%	28.4%
Age	14-18	6.8%	15.6%	25.6%	33.8%	18.2%
	25-45	1.5%	4.5%	12.0%	40.0%	42.0%
	45+	3.3%	9.3%	13.5%	34.5%	39.5%
School Position	Students	6.8%	15.6%	25.6%	33.8%	18.2%
	Professors	1.1%	3.9%	17.8%	41.7%	35.6%
	Other	3.3%	9.3%	11.0%	34.0%	42.4%
Nationality	Greek	4.7%	12.3%	20.6%	35.2%	27.3%
	Other	4.1%	7.3%	11.4%	35.0%	42.3%
University Education	Yes	2.4%	6.5%	13.0%	36.5%	41.7%
	No	6.6%	15.9%	24.3%	33.9%	19.3%

Table 3. Percentage Distribution of Responses regarding the Intuitive Thought System.

REI-E	% CONTRIBUTION	Strongly Dis-agree	Disagree	Undecided	Agree	Strongly Agree
Gender	Male R	6.0%	24.3%	37.8%	22.0%	10.0%
	Female R	3.3%	13.4%	38.0%	33.3%	12.0%
Age	14-18	6.0%	18.4%	40.0%	23.2%	12.4%
	25-45	2.0%	16.0%	34.0%	36.5%	11.5%
	45+	3.3%	16.8%	37.3%	33.0%	9.8%
School Position	Students	6.0%	18.4%	40.0%	23.2%	12.4%
	Professors	2.2%	13.3%	44.4%	35.0%	5.0%
	Other	3.1%	17.9%	32.6%	33.8%	12.6%
Nationality	Greek	4.7%	18.5%	37.8%	28.0%	11.0%
	Other	2.7%	12.7%	38.2%	34.1%	12.3%
University Education	Yes	3.1%	17.8%	37.6%	32.8%	8.7%
	No	5.4%	17.0%	38.2%	25.7%	13.8%

The abovementioned are also reflected in Figure 1 and Tables 4 and 5, where the correlations between the REI types and the demographics are shown. There it is obvious that the "agree" and "strongly agree" responses are more intense in the rational (65.4%) compared to the intuitive thinking group (40.4%). Notwithstanding the strong trend towards rational thinking, the percentage of "agree" versus "disagree" responses in the REI-E group (with 40.4% and 21.72% respectively) indicate a solid trend towards intuitive thinking under special conditions (i.e., in unfamiliar, complex situations under time pressure and without adequate data, as mentioned above). In such circumstances, the most frequent type of Intuition is Inferential, followed by Holistic Big Picture, Affective, and finally Holistic Abstract.

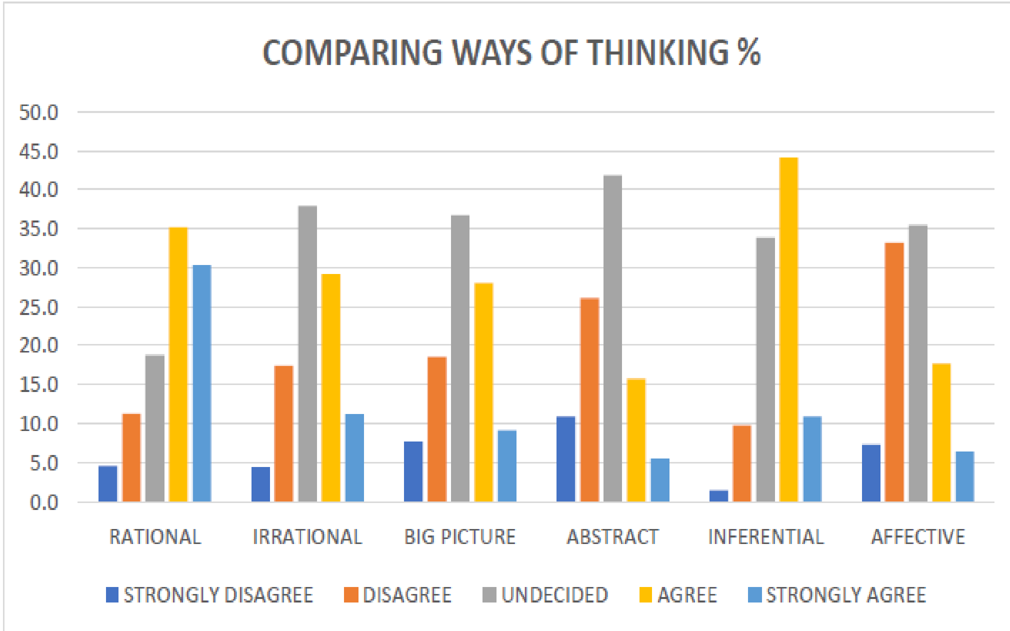


Figure 1. Assessing the Predisposition of Humans to use each Thought System and Intuition Sub-Type.

Table 4. Distribution of Likert Data Scores.

Target Category	1	2	3	4	5	TOTAL
REI-R	50	124	206	387	333	1100
REI-E	48	191	417	321	123	1100
IHBP	21	51	101	77	25	275
IHAB	18	43	69	26	9	165
INFER	6	43	149	194	48	440
AFF	32	146	156	78	28	440

1: Strongly Disagree → 5: Strongly Agree

Table 5. Percentage Distribution of Likert Data Scores.

Target Category	1	2	3	4	5	TOTAL
REI-R	4.54	11.27	18.72	35.18	30.27	100
REI-E	4.36	17.36	37.90	29.18	11.18	100
IHBP	7.63	18.54	36.72	28	9.09	100
IHAB	10.90	26.06	41.81	15.75	5.45	100
INFER	1.36	9.77	33.86	44.09	10.90	100
AFF	7.27	33.18	35.45	17.72	6.36	100

1: Strongly Disagree → 5: Strongly Agree

Preliminary Analysis of Cases and Variables

- *Descriptive Statistics:* There are no missing data in any variable. Skewness and kurtosis values indicate abnormal distribution. Therefore, the median values of REI-R, REI-E, INFER, AFF, IHBP, and IHAB were used, taking also into account that Likert data are ordinal variables (Table 6).
- *Normality*: was tested with the Shapiro-Wilk Test, showing that non-parametric tests must be used (Table 7).
- *Exploratory Factor Analysis*: Keiser-Meyer-Olkin (KMO) tests and Bartlett's Test of Sphericity were used. KMO values above 0.6 (KMO>0.6) are sufficient for data analysis to be performed, with Table 8 proving that the data were within acceptable limits, while for Bartlett's Test of Sphericity, the values had $P<0.05$.
- *Validity Analysis*: A Pearson's rank-order correlation was run to determine the relationship between each question and its total value. All categories had $p<0.05$ and were therefore valid.
- *Reliability Analysis*: Internal consistency was assessed using Cronbach's alpha Coefficient with acceptable values a>0.6 (Table 9).

Table 6. Descriptive Statistics.

Statistics						
	AFF	**INFER**	**IHBP**	**IHAB**	**REI-R**	**REI-E**
Valid	110	110	110	110	110	110
Missing	0	0	0	0	0	0
Mean	2.8182	3.6091	3.2364	2.7091	3.8636	3.3091
Median	3.0000	4.0000	3.0000	3.0000	4.0000	3.0000
Std. Deviation	0.72880	0.60622	0.76893	0.87502	0.71657	0.67694

Table 7. Normality Tests.

Test of Normality						
	Kolmogorov-Smimov[1]			**Shapiro Wilk**		
	Statistic	Df	Sig.	Statistic	df	Sig.
AFF	0.199	110	0.000	0.919	110	0.001
INFER	0.344	110	0.000	0.637	110	0.000
IHAB	0.267	110	0.000	0.881	110	0.000
IHBP	0.275	110	0.000	0.853	110	0.000
REI-R	0.230	110	0.000	0.883	110	0.000
REI-E	0.312	110	0.000	0.825	110	0.000

[1] Lilliefors Significance Correction

Table 8. Exploratory Factor Analysis.

KMO and Barlett's Test RESULTS						
	REI-R	**REI-E**	**IHBP**	**IHAB**	**INFER**	**AFF**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.724	0.692	0.742	0.645	0.605	0.692
Approx. Chi-Square	486.268	456.883	86.463	25.832	135.223	137.082
Barlett's Test of Sphericity df	190	190	21	3	28	28

Sig.	0.000	0.000	0.000	0.000	0.000	0.000

Table 9. Reliability Analysis.

Variables	Cronbach's Alpha
REI-R	0.864
REI-E	0.858
IHBP	0.609
IHAB	0.669
INFER	0.686
AFF	0.782

Statistical Results

Relations Between the REI-Dimensions and Among the Types of Intuition

The median values of participants' response scores were evaluated between the REI dimensions, while Friedman's Test and Wilcoxon signed-rank test were used. Statistically significant differences emerged between the two Thought Systems (REI-R and REI-E) in terms of the power of the ''agree''/''strongly agree'' selections. Rational thinking was the dominant way of thinking for all participants, regardless of their demographics. (Tables 10 and 11)

For the correlations between the Types of Intuition to be evaluated, Friedman's Test, Wilcoxon's signed ranked test, and the Bonferroni adjustment were used, setting the limit of statistical significance at the level of 0.08 (Table 12). Statistically significant differences emerged between IHAB-IHBP (Z = -3.246b, p =.001), INFER-IHBP (Z = -6.277, p<0.001), IHAB-INFER (Z = -5.716, p <0.001), INFER-AFF (Z = -5.040, p<0.001) and IHBP - AFF (Z = -2.655, p = 0.008), which changed in inverse proportion. No significant statistical difference was observed between IHAB-AFF. The priority of use of Intuition Types was in order: Inferential>Big Picture>Abstract/Affective (Table 13).

Tables 10.

Table 12.

Test Statistics	
N	110
Chi-Square	14,400
Df	1
Asymp. Sig.	0.000

Table 11.

Test Statistics[i]	
	REI-R // REI-E
Z	-3.633[ii]
Asymp. Sig. (2-tailed)	0.000

Test Statistics	
N	110
Chi-Square	37,530
Df	3
Asymp. Sig.	0.000

Table 13.

Test Statistics					
	IHAB-IHBP	INFER-IHBP	IHAB-INFER	INFER-AFF	IHBP-AFF
Z	-3.246[ii]	-6.227[i]	-5.716[iii]	-5.040[i]	-2.655[v]
Asymp. Sig (2-tailed)	0.001	0.000	0.000	0.000	0.008

[i] Wilcoxon-Signed Ranked Tests.

[ii] Based on positive ranks.
[iii] Based on negative ranks.

Relations Between Demographic Characteristics (Gender, Ethnicity, Age, Student/Teacher Role, University Studies), REI Thought Systems and Types of Intuition

The independent non-parametric Kruskal-Wallis H test was used for each demographic characteristic, manifesting that there was a statistically significant difference for:

A) Gender: affected only Abstract Intuition which was significantly selected by males (p=0,021) (Table 14, Graphs 2 and 3).

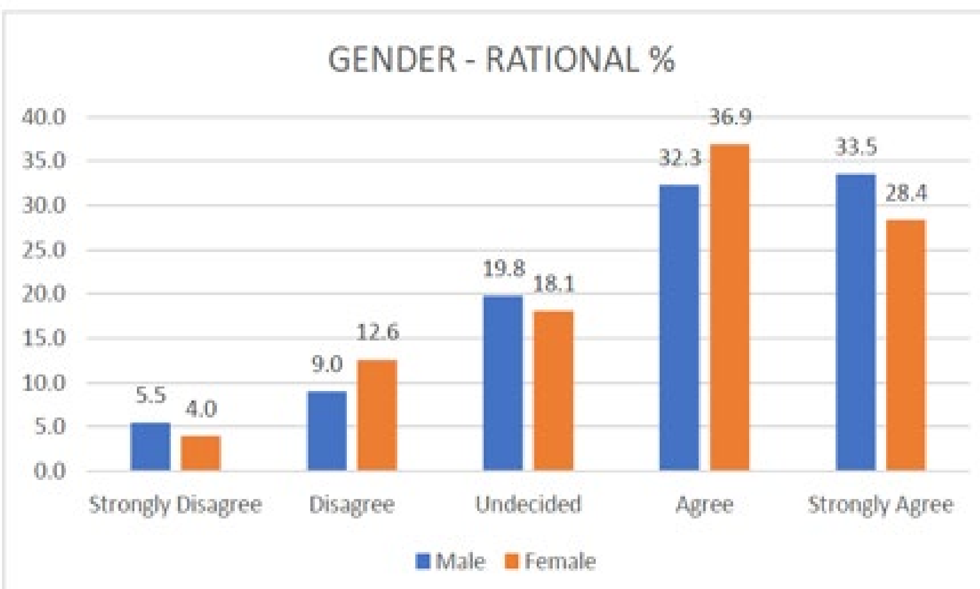
B) Age: does not affect which type of thinking is preferred, with an exception being that rationality was most strongly selected by age groups 35-45 (p=0,003) and 45-55 (p=0,008) years old (Table 15 and Graphs 4 and 5).

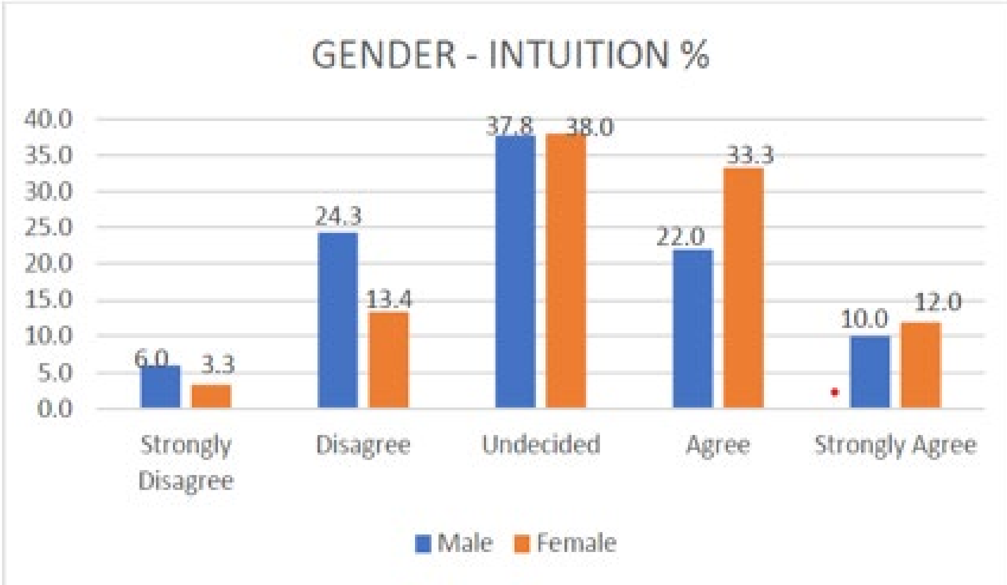
C) Whether the respondent was a student or a teacher (referred to as School Position in the diagrams): Abstract Intuition was chosen mostly by adolescent students (p=0.021) and the Rational Thought System mainly by adults, regardless of their profession (for schoolteachers p=0.026, for others p<0.001) (Table 16 and Graphs 6 and 7).

D) Nationality: Greek participants favored a blend of Inferential (p=0,002) and Abstract (p=0,022) Intuition, while north-Europeans preferred the Holistic Big Picture (p=0,035) intuitive thinking (Table 17 and Graphs 8 and 9).
E) University Studies: People who have studied at the university favored rational thinking (p<0,001), while school students chose to use Inferential Intuition (p<0,001) (Table 18 and Graphs 10 and 11).

Table 14. Kruskal-Wallis Test for Gender.

Test Statistics: Kruskal Wallis Test --- Grouping Variable: GENDER						
	AFF	**INFER**	**IHAB**	**IHBP**	**REI-R**	**REI-E**
Chi-Square	0.328	2.452	5.305	0.875	0.031	2.105
Df	1	1	1	1	1	1
Asymp. Sig.	0.567	0.117	0.021	0.350	0.861	0.147

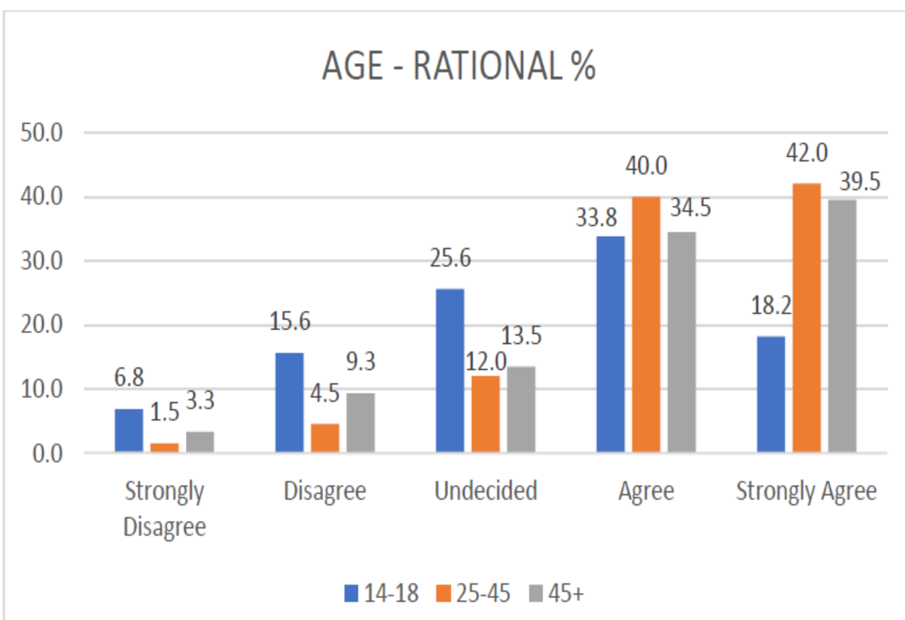


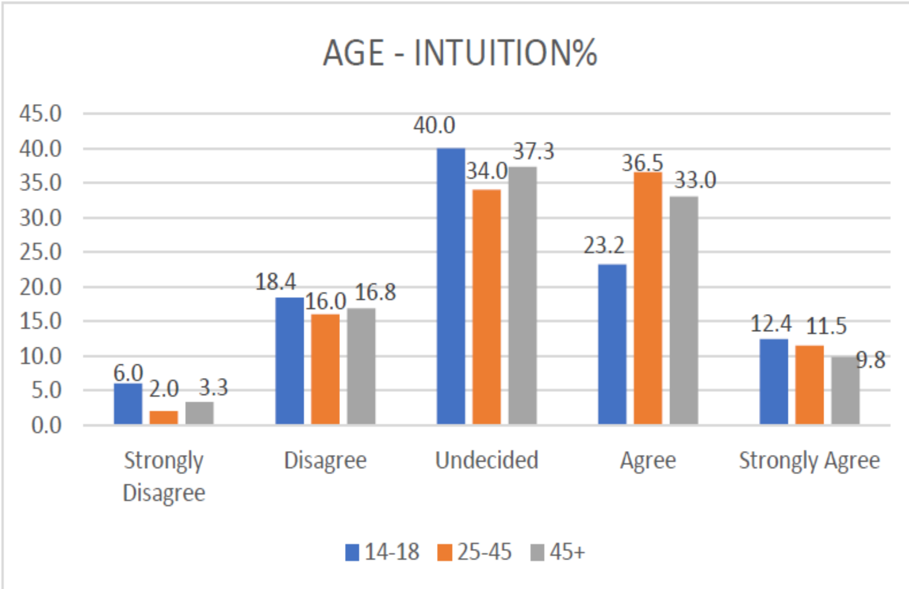


Figures 2 and 3. The Distribution of Responses for the Rational and Intuitive Thought Systems divided by Gender.

Table 15. Kruskal-Wallis Test for Age.

Test Statistics: Kruskal Wallis Test --- Grouping Variable: AGE						
	AFF	**INFER**	**IHAB**	**IHBP**	**REI-R**	**REI-E**
Chi-Square	5.905	7.135	8.175	6.767	17.200	7.151
Df	5	5	5	5	5	5
Asymp. Sig.	0.316	0.211	0.147	0.239	0.004	0.210

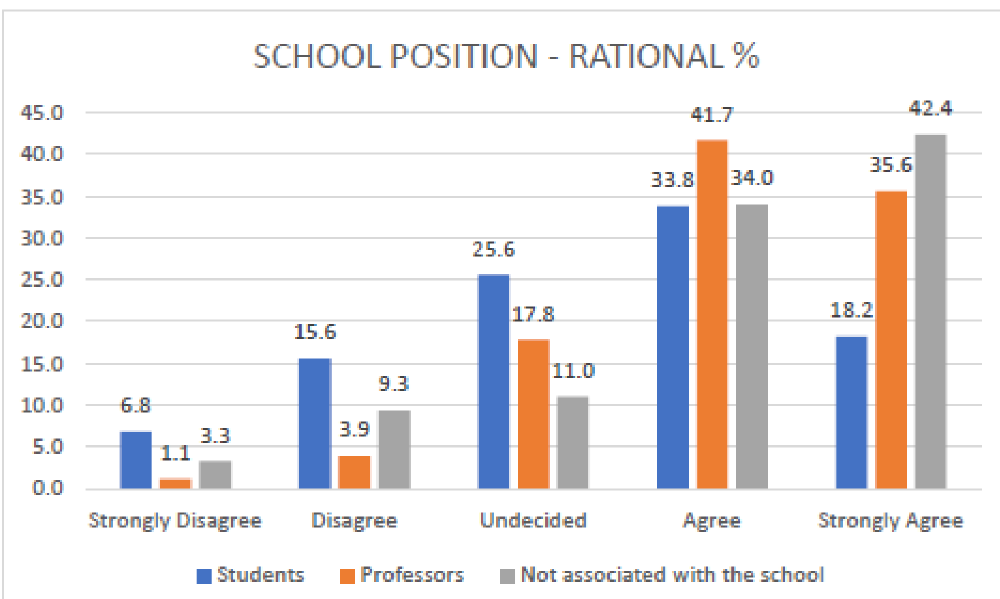


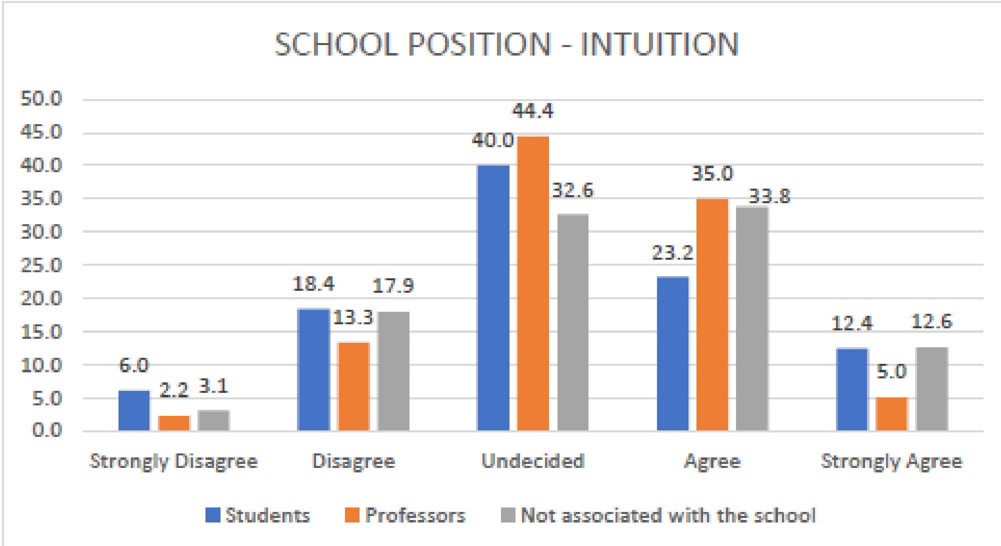


Figures 4 and 5. The Distribution of Responses for the Rational and Intuitive Thought Systems divided by Age.

Table 16. Kruskal-Wallis Test for School Position.

Test Statistics: Kruskal Wallis Test --- Grouping Variable: SCHOOL POSITION						
	AFF	**INFER**	**IHAB**	**IHBP**	**REI-R**	**REI-E**
Chi-Square	2.866	4.803	7.834	3.189	14.727	0.858
Df	2	2	2	2	2	2
Asymp. Sig.	0.239	0.091	0.020	0.203	0.001	0.651

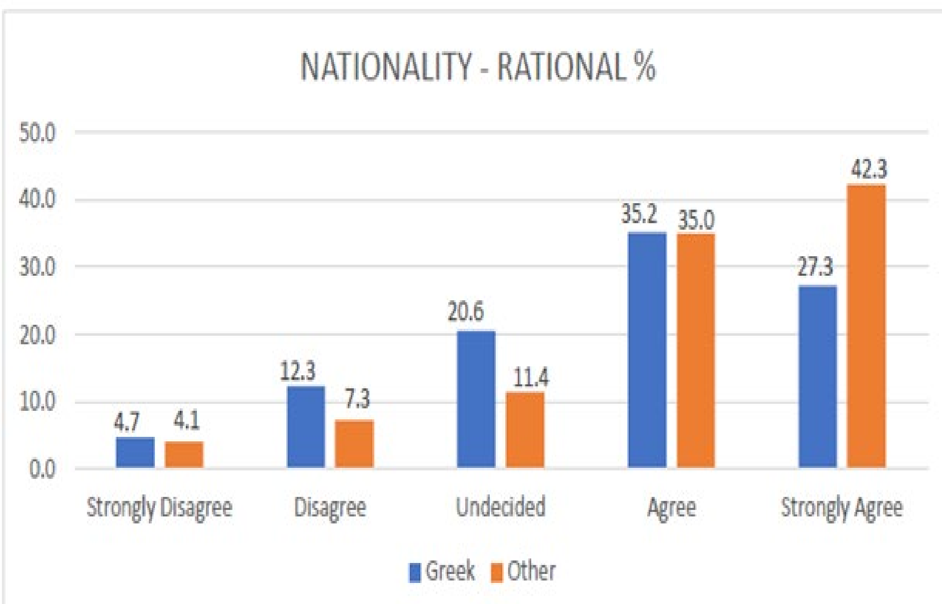


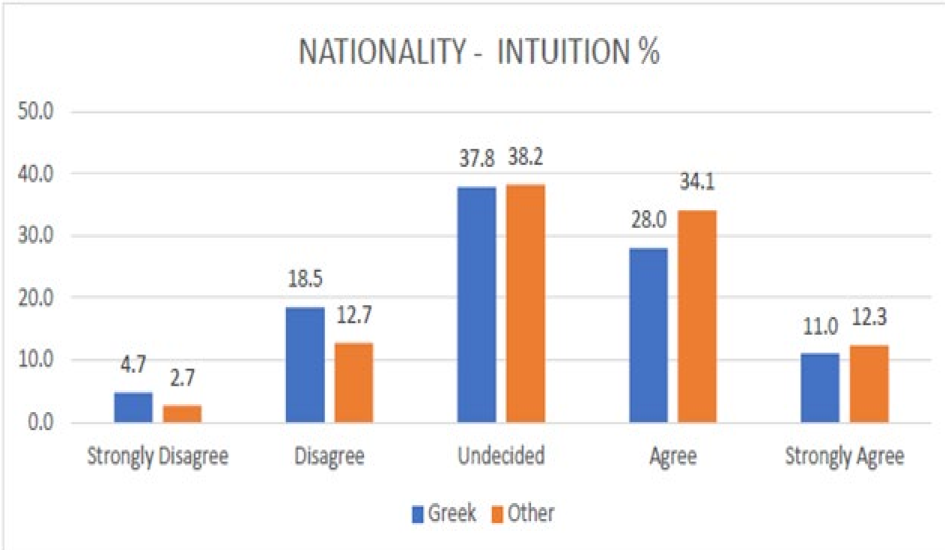


Figures 6 and 7. The Distribution of Responses for the Rational and Intuitive Thought systems divided by the role the participant had with the school, in which the study was realized.

Table 17. Kruskal-Wallis Test for Nationality.

Test Statistics: Kruskal Wallis Test --- Grouping Variable: NATIONALITY						
	AFF	**INFER**	**IHAB**	**IHBP**	**REI-R**	**REI-E**
Chi-Square	1.836	9.446	5.258	4.456	2.457	0.945
Df	1	1	1	1	1	1
Asymp. Sig.	0.175	0.002	0.022	0.035	0.117	0.331

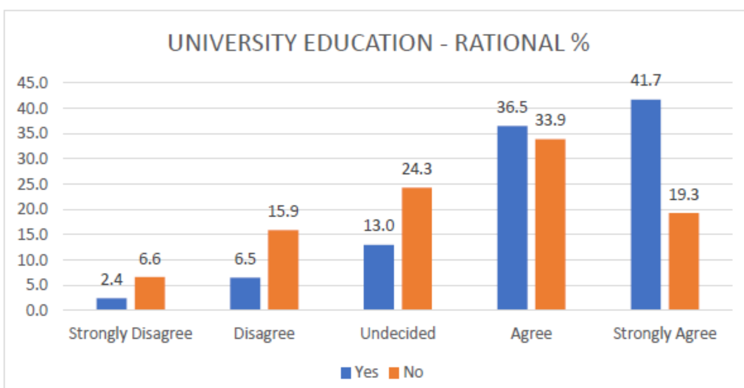


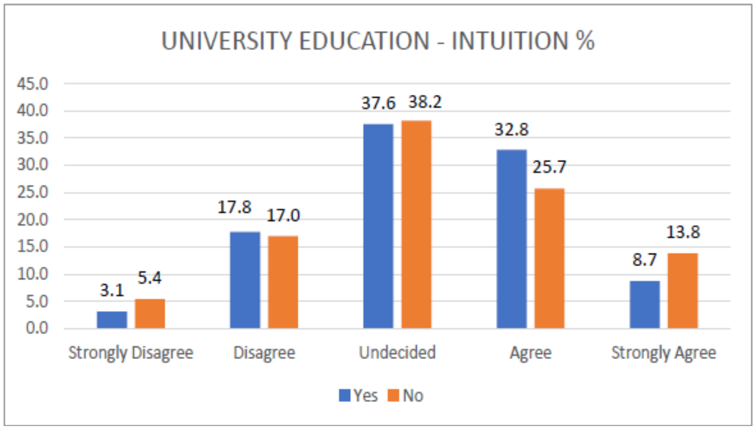


Figures 8 and 9. The Distribution of Responses for the Rational and Intuitive Thought Systems divided by Nationality.

Table 18. Kruskal-Wallis Test for University Education.

Test Statistics: Kruskal Wallis Test --- Grouping Variable: UNIVERSITY EDUCATION						
	AFF	**INFER**	**IHAB**	**IHBP**	**REI-R**	**REI-E**
Chi-Square	0.240	54.000	1.394	1.139	13.168	0.028
Df	1	1	1	1	1	1
Asymp. Sig.	0.624	0.000	0.238	0.286	0.000	0.866





Figures 10 and 11. The Distribution of Responses for the Rational and Intuitive Thought Systems divided by whether the respondent had a University Education or not.

Association Between the REI-Dimensions and the Types of Intuition

Table 19. Spearman's Correlation Analysis for the Rational Thought System.

Spearman's Coefficient [Rho]						
		AFF	**INFER**	**IHAB**	**IHBP**	**REI-R**
AFF	Correlation Coefficient	1.000	0.067	0.154	-0.254	-0.202
	Sig. (2-tailed)		0.629	0.260	0.061	0.139
	N	110	110	110	110	110
INFER	Correlation Coefficient	0.067	1.000	0.161	-0.145	-0.494[i]
	Sig. (2-tailed)	0.629		0.241	0.290	0.000
	N	110	110	110	110	110
IHAB	Correlation Coefficient	0.154	0.161	1.000	0.084	-0.191
	Sig. (2-tailed)	0.260	0.241		0.542	0.161
	N	110	110	110	110	110
IHBP	Correlation Coefficient	-0.254	-0.145	0.084	1.000	0.282[ii]
	Sig. (2-tailed)	0.061	0.290	0.542		0.037
	N	110	110	110	110	110
REI-R	Correlation Coefficient	-0.202	-0.494[i]	-0.191	0.282[ii]	1.000
	Sig. (2-tailed)	0.139	0.000	0.161	0.037	
	N	110	110	110	110	110

Table 20. Spearman's Correlation Analysis for the Intuitive Thought System.

Spearman's Coefficient [Rho]

		AFF	INFER	IHAB	IHBP	REI-E
AFF	Correlation Coefficient	1.000	0.067	0.154	-0.254	0.421[i]
	Sig. (2-tailed)		0.629	0.260	0.061	0.001
	N	110	110	110	110	110
INFER	Correlation Coefficient	0.067	1.000	0.161	-0.145	0.023
	Sig. (2-tailed)	0.629		0.241	0.290	0.868
	N	110	110	110	110	110
IHAB	Correlation Coefficient	0.154	0.161	1.000	0.084	-0.156
	Sig. (2-tailed)	0.260	0.241		0.542	0.255
	N	110	110	110	110	110
IHBP	Correlation Coefficient	-0.254	-0.145	0.084	1.000	0.042
	Sig. (2-tailed)	0.061	0.290	0.542		0.762
	N	110	110	110	110	110
REI-E	Correlation Coefficient	0.421[i]	0.023	-0.156	0.042	1.000
	Sig. (2-tailed)	0.001	0.868	0.255	0.762	
	N	110	110	110	110	110

[i] Correlation is significant at the 0.01 level (2-tailed).
[ii] Correlation is significant at the 0.05 level (2-tailed).

This was studied with the method of Spearman's correlation analysis. There was a statistically significant negative correlation between Inferential Intuition and Rationality, and statistically significant positive correlations between Holistic Big Picture Intuition and Rationality, and the Intuitive Thought System and Affective Intuition (Tables 19 and 20).

Artificial Intuition

Having recognized both the importance and the basic characteristics of human intuition through the social experiment of the previous chapter, it is now possible to define the properties that Artificial Intuition (the integration of human intuition into AI agents) must acquire to solve certain problems. In little words, Artificial Intuition is defined as an automatic process that switches to useful reactions in a short period and focuses mainly on providing answers to a given problem, while not looking for either rational alternatives or repeated solutions. Therefore, it can calculate the most likely answer by adjusting its algorithms' predictive functions (Diaz-Hernandez & Gonzalez-Villela, 2015).

Nonetheless, now the question arises, to what extent would it be practically feasible to integrate Artificial Intuition into AI machines, since the 'computerization' of human intuitive processes has proven so far to be problematic, with the main challenge being that intuition is driven by non-logical reasoning, while the function of most AI models is governed by rational processes (Jolly). On the one hand, some scholars do not believe that such an essential human trait as intuition could be incorporated into AI, commenting that "human beings have an intuitive intelligence that 'reasoning' machines simply cannot match" (Dreyfus & Dreyfus, 1986). and stressing that the mind could never be algorithmic (Penrose, 1989). On the other hand, some thinkers are more optimistic about the possibility of computerization of human-like intuitive processes, arguing that "computers will do all things that humans have been programmed to do", and that "properly programmed AI machines could imitate the actions of intelligent individuals''.

Generally, Artificial Intuition is expected to analyze unknown data with astonishing accuracy (although it won't have any historical context leading it in the right direction) because once presented with a specific dataset, its complex algorithms can identify any correlations or anomalies between data points, thereby identifying the most important parameters of the problem and developing a qualitative rather than quantitative data processing model and an algorithmic language representing the overall synthesis of what it observes (Jolly). It is the programming equivalent of eliminating the "ELSE" of the "IF" structure and renaming it to "WHEN", creating a new operating condition for the AI where, if the right conditions are present, then a single answer is calculated and other possibilities are obviated (Diaz-Hernandez & Gonzalez-Villela, 2015).

But what perhaps best demonstrates the conceptual importance of Artificial Intuition is an experiment that took place at the Chemistry Department of Glasgow University, which compared the efficiencies of human researchers, an AI algorithm, and chance experiments in creating crystals from certain chemical compounds. The results showed the overwhelming superiority of the algorithm as far as both the final result's quality and its predictions' quantitative success are concerned. However, when the algorithm and humans worked together, their "team" results significantly outperformed the outcomes of both the algorithm and humans, when working separately, in every research field. It can thus be concluded that the increased computational power of a machine-learning model can allow the identification of hidden data patterns, while human intuition can develop the direction of experimental procedures, as its most important advantage is its ability to perform well even in areas of high uncertainty (Duros et al., 2019). Hence, it seems that the introduction of Artificial Intuition into AI will be transformative, at the very least.

Algorithmic Building: Transcending from Human to Artificial Intuition

The following Algorithmic Idea attempts, for the first time ever, to artificially imitate each distinct sub-type of Human Intuition, namely the Holistic, Affective, and Inferential Intuition, based on which the AI agent will be able to overcome problems in a similar way to humans' Intuitive Thought System.

Initially, the concept of databases/datasets in AI machines should be disambiguated: they contain a huge variety of data describing each specific stimulus that machines may receive from their environment. They are placed in particular positions, forming ordered sets (information), and are connected with different OUTPUTS/reaction commands for the machine. Normally, when an ideal AI machine faces a problem, it searches the entire area of this database to find matches between the received environmental stimuli and the recorded information; when all stimuli are perfectly matched with a particular data series, its relevant OUTPUT is executed (Figure 12).

Data Pattern: **AKSKJSDFJSDFJIJASDASDJx1+** =
IF A: True **AND** K: True **AND** S: True **AND** …… **AND** J: True **THEN** OUTPUT=x1

Figure 12. The 'physiological' function of an AI database, which is akin to the reasoning of Boolean Algebra.

Nonetheless, this processing of stimuli inevitably requires a certain amount of time. So, when the machine acts under time pressure, it cannot search the whole area of the database; contrariwise, some limitations ought to be established in this particular occasion to aid the machine in assessing instead only a confined amount of data patterns. In case the machine received enough environmental stimuli, the issue would not be so difficult to resolve – but if there is also a lack of environmental stimuli and the problem being faced is rather sophisticated, then the machine processes its inputs as in Figure 13. Correspondingly with a human, who in a similar case would use the Intuitive Thought System, the limitations established by the machine could embrace Artificial Intuition and discover the information with the greatest probability of being the optimally applicable pattern (namely the ideal solution) in the situation at hand.

A….CE…FGE…R…THD…….. ➔ OUTPUT= x1
C…..EEAGF……TDH……….R ➔ OUTPUT= x2
……………………………………………………………………
REEHDAG………FC………… ➔ OUTPUT= x3

Figure 13. The way AI agents process limited stimuli when facing a sophisticated problem under time pressure.

By definition, the Greedy Algorithm could not be used on this particular occasion, since it makes the optimal decision at any one step based on the information it has up to this point, without a holistic regard to the overall problem; and the lack of stimuli is apparent in the problems being resolved with this algorithmic idea. Instead, a Heuristic Algorithm should be created, as it is designed to resolve problems as quickly as possible while evaluating all available stimuli and creating a globally good path. Albeit it may not produce the best solution, it will give a near-optimal solution in a short time (Datta). Therefore, it is obvious that Dynamic Programming could form the basis of this algorithmic idea, since it is a multistage optimization approach, transforming a complex problem into a sequence of simpler overlapping problems and using the solutions of one to proceed to the next, even though these sub-problems should be solved sequentially, thus partially following the methods of intuitive Divide-and-conquer Algorithms.

With that in mind, the 1st limitation, imitating Holistic (Abstract and Big Picture) Intuition, shall decrease the number of potentially correct data patterns drastically. More particularly, the vectors of the environmental stimuli will be transformed into a covariance matrix and then into eigenvectors, which will 'imagine' the whole puzzle of given stimuli without any gaps. Based on the interrelations of the latter, this mechanism will then work backward to fill in any gaps existing due to the limited environmental stimuli (Dutta, 2020). Under the same principle, the eigenvectors shall exclude from the dataset any data points that either have a wrong position in the data pattern (which, by definition, is an ordered set), contradict the received environmental stimuli, or present logical anomalies with each other (Figure 14).

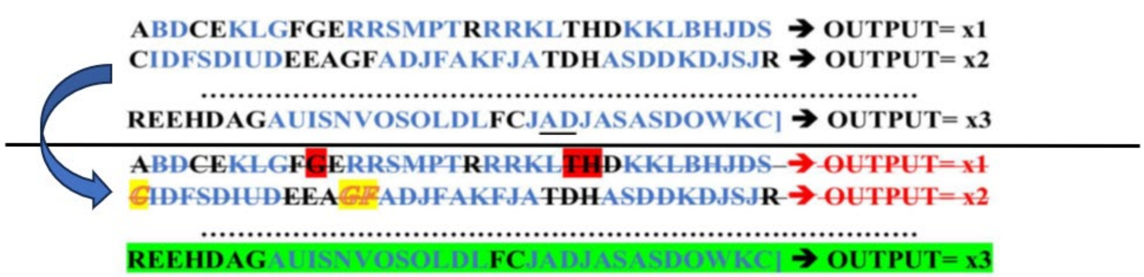


Figure 14. An illustration of how the eigenvectors will reduce the number of potentially correct data patterns.

The area of potentially correct patterns has now become considerably smaller. It should be emphasized, at this point, that all information contained in the database consist of decisions (outputs) made by people with high expertise in the field of each specific problem, once presented with a certain input of data (each data pattern). Beyond them, however, the last element of each information will be a sign (positive [+] or negative [-]) indicating whether each decision was successful or unsuccessful, always with regard to the machine's main objective.

Thus, the 2nd limitation, imitating Affective Intuition, shall exclude from the dataset all patterns with negative signs; similar to a person, whose emotional reaction to a situation is based on their relevant past experiences, the machine will react to the remaining data patterns based on their signs (+ means useful, positive memory, - means dangerous, negative memory). The introduction of such signs has a dual role: first, it will broaden the horizons of the database (and a more complete database is always more efficient), and second, it shall include the concept of the "wrong choice" in the machine's system, so its decisions will be no longer so biased by the human factor. That is, the machine must learn to overcome the mistakes and weaknesses of humans, while simultaneously excluding possible combinations of data that may be identical to the environmental stimuli but will lead to an erroneous output (Fig. 15)

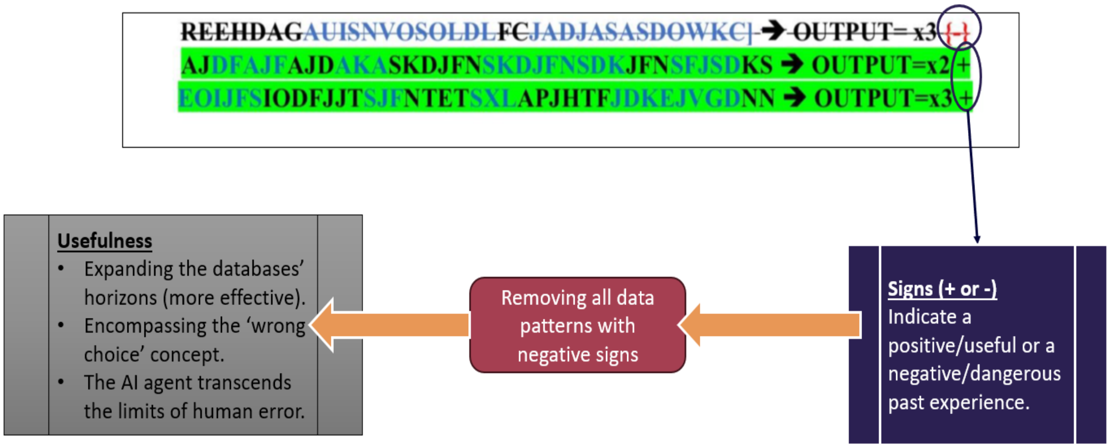


Figure 15. An illustration of the function of the 2nd limitation mechanism.

The machine is now assessing an even more limited region of the database. The 3rd and final limitation imitates Inferential Intuition and arrives at the reaction command most likely to be the optimal one by calculating the frequency of appearance of each remaining OUTPUT. For this approach, the concept of Fuzzy Logic will be utilized instead of a Minimax Algorithm, since it recognizes there are other alternative representations of values between the 0-1 extremes of the latter. As probability is a measure of certainty, vagueness extends these concepts to include partial events, each of which can now be represented with a power between 0 and 1; thus, fuzzy logic is a measure of completeness and has no relation to uncertainty. For every input to the system, multiple patches or fuzzy sets will be activated, giving multiple parallel outputs, which can be combined to reach a decision, a weighted average (a characteristic example of inferential intuition) (Sgurev, 2019). This process will be accelerated by Instant Recognition algorithms, whose elimination speed is even more striking, as they concentrate on the elimination of alternate possibilities and do not seek exact matches (Thomas). Through these techniques, the OUTPUT with the highest probability of being the most optimal will be estimated and in the end, executed (Fig. 16)

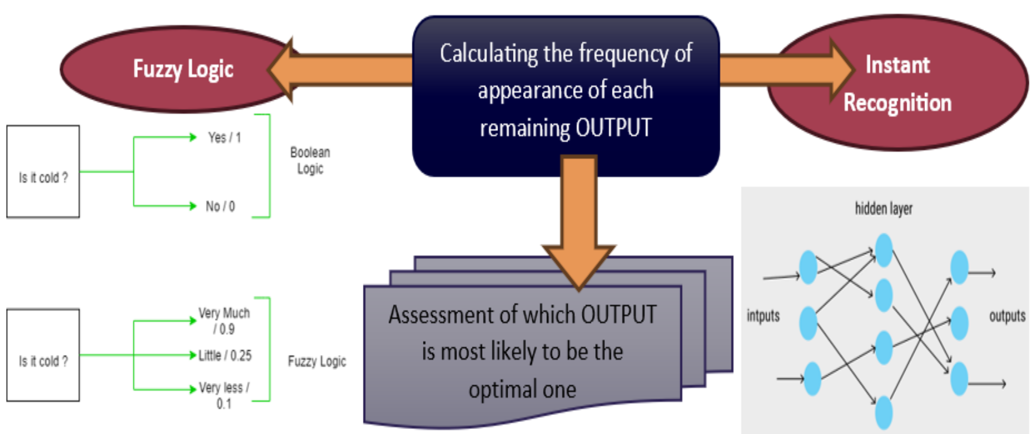


Figure 16. An illustration of the algorithmic methods that the 3rd limitation will employ.

All steps of the abovementioned algorithmic process, imitating the Holistic, Affective, and Inferential Intuition, are briefly presented in Fig. 17.

INPUT

1. The AI agent receives environmental stimuli.
2. The environmental stimuli are compared to the data patterns of the database.

ALGORITHMIC SYSTEM

3. Using Heuristic Algorithms and Dynamic Programming.

1st limitation

4. Imitating Holistic (Big Picture and Abstract) Intuition.
5. Specifying the interrelations between eigenvectors and the data points.
6. Excluding from the dataset data patterns that present incohesive logical anomalies.

2nd limitation

7. Imitating Affective Intuition.
8. Removing from the database information with negative signs (-).

3rd limitation

9. Imitating Inferential Intuition.
10. Evaluating the frequency of appearance of each remaining OUTPUT.
11. Using the concept of Fuzzy Logic (instead of a Minimax Algorithm) for this approach.
12. Accelerating this process with the utilization of Instant Recognition Algorithms.
13. Thus, finding the OUTPUT with the most possibilities of being the most optimal/viable one.

OUTPUT

14. The OUTPUT which is most likely to be the optimal one is executed.

ALGORITHMIC FEEDBACK AND EVOLUTION

15. Using Backpropagation algorithms (the machine learns from its mistakes – Deep Machine Learning).
16. Transcending from Static to Dynamical Approximation of the problem.
17. Algorithmically developing Neural Networks.

Figure 17. A brief summary of all steps of this project's algorithmic idea, encompassing the machine's input, limitations, output, and further process to transform its Artificial Intuition imitation into Deep Machine Learning.

Discussion and Further Prospects

The old adage is that a computer can never be original, as it only spews out what has been programmed into it, following its standardized algorithms.[34] Nevertheless, since the concept of Artificial Intuition has started developing, this reality has drastically changed. Computers are now cultivating consciousness, and to benefit from this evolutionary process, we have to cover their newfound needs and develop their new skills, such as their creativity and their imagination – but most importantly: their intuition.

This project initially proved the undeniable significance of intuition for humans, with the social study reaching the following conclusions: Educated adults prefer rational thinking; Greek adolescent male students prefer intuitive thinking; Inferential intuition is chosen by adolescent males; Holistic Big Picture Intuition is chosen by North-European adults; Rational thinking is associated with Big Picture and Inferential Intuition; and experiential thinking is associated with Affective Intuition.

Therefore, the advantages of integrating Intuition in the logical procedures of AI agents shall be many, since such a radically new technology can find many applications in various fields. For instance, these machines could help doctors and medical staff in hospitals' emergencies in Intensive Care Units (ICU), or during robotic surgeries, predict unexpected changes in economic circles, foresee – and prevent – financial crises, ensure an investment's safety, create effective driverless cars, enhance the function of airplanes' autopilots, etc.

Based on these observations, an algorithmic idea has been developed artificially imitating the different Types of Intuition, and, despite its holistic approach to this human Thought System, it has certain negative aspects. Firstly, some people argue that machines exhibit behaviors and express their intelligence in ways fundamentally different from biological agents (animals and humans), so the project's extreme anthropomorphism and zoomorphism should be avoided (Dutta, 2020). Secondly, the human-driven foundation of the database is flawed, as people, however qualified or not, make decisions based on reflexes they may carry from traumatic experiences, which would not be beneficial as data since they are biased either positively or negatively. Finally, another faint line is the machine's morality, with the question prevailing: Does intuition result in consciousness or even morality? Such a statement is highly debatable, so fundamental rules of ethics have to be established in the machine's code and no AI agent must deal with problems encompassing subtle ethical ambiguities.

As far as the future prospects of this project are concerned, this algorithmic idea should initially be translated from pseudo-code to a normal programming language (perhaps C++). What is more, the anthropocentric aspects of this algorithm must be abolished, and instead, such AI agents must develop an intuition of their own. In other words, their intuitive problem-solving abilities must evolve from a static to a dynamical approximation of the problem, as they will teach themselves how to think on their own, becoming independent of humans (deep machine learning). This can be achieved through backpropagation algorithms, with which the AI agent shall process every wrong decision (error) it produces, recording it as information in the database and ''learning from its mistakes'' (Telelis). Only through this way shall the essence of the algorithmic concept of Neural Networks be practically realized in these Artificial Intelligence machines (Madhaven).

I sincerely hope that this project, even to a minimal degree, will be a stepping stone in the research effort to investigate the properties of intuition and its computerization in AI machines.

Limitations

The social study of this paper should be repeated with a greater sample of respondents so that more accurate conclusions can be drawn regarding the associations between rationality, intuition, and different demographic characteristics, particularly as far as the impact of nationality is concerned. Moreover, apart from the changes in the computerization process listed in the discussion, the algorithmic idea at hand should be practically applied in a real-world context (e.g. creating an algorithm combining Rationality and Intuition as an AI-aid for the medical personnel working on emergency cases in hospitals) to showcase more clearly any shortcomings of this idea that were not apparent in a theoretical framework.

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References

Softtek. (2021, February 1). Fourth generation of AI arrives: Artificial intuition. https://blog.softtek.com/en/fourth-generation-of-ai-arrives-artificial-intuition

Simon, H. A. (1987). Making management decisions: The role of intuition and emotions. *The Academy of Management Executive, 1*(1), 57-64.

Robbins, P., & Jack, A. I. (2006). The phenomenal stance. *Philosophical Studies, 127*(1), 59-85. https://doi.org/10.1007/s11098-005-1995-4

Dane, E., & Pratt, M. G. (2007). Exploring intuition and its role in managerial decision making. *The Academy of Management Review, 32*(1), 33-54. https://doi.org/10.5465/amr.2007.23463693

Benner, P., & Tanner, C. (1987). Clinical judgment: How expert nurses use intuition. *The American Journal of Nursing, 87*(1), 23-31. https://doi.org/10.2307/3470396

Chassy, P., & Fernand, G. (2011). A hypothesis about the biological basis of expert intuition. *Review of General Psychology, 15*(3), 198-212. https://doi.org/10.1037/a0023958

Nelson, D., Quick, J. C., & Khandelwal, P. (2011). An innovative approach to learning and teaching organizational behavior. *ORGB*.

Barnard, C. I. (1938). *The functions of the executive*. Harvard University Press.

Cavanna, A. E. (2007). The precuneus and consciousness. *CNS Spectrums, 12*(7), 545-552. https://doi.org/10.1017/S1092852900021295

D'Argembeau, A. (2013). On the role of the ventromedial prefrontal cortex in self-processing: The valuation hypothesis. *Frontiers in Human Neuroscience, 7*, 372. https://doi.org/10.3389/fnhum.2013.00372

Kim, H. F., & Hikosaka, O. (2015). Parallel basal ganglia circuits for voluntary and automatic behavior to reach rewards. *Brain, 138*(Pt 7), 1776-1800. https://doi.org/10.1093/brain/awv134

Sadler-Smith, E. (2023). *Intuition in business*. Oxford University Press. https://doi.org/10.1093/oso/9780198871569.003.0006

Malewska, K. (2019). Intuition in decision-making: A review of empirical research in the area of management.

Trafton, A. (2018, July 20). Doctors rely on more than just data for medical decision making. *MIT News*. https://news.mit.edu/2018/doctors-rely-gut-feelings-decision-making-0720

Kutsch, L. (2019, August 15). Can we rely on our intuition? *Scientific American*. https://www.scientificamerican.com/article/can-we-rely-on-our-intuition/

Khatri, N., & Ng, H. (2000). The role of intuition in strategic decision making. *Human Relations, 53*(1), 57-86. https://doi.org/10.1177/0018726700531005

Mintzberg, H. (1989). Coupling analysis and intuition in management. In *Mintzberg on management: Inside our strange world of organizations* (pp. 372-373, 354-355).

Isenberg, D. J. (1984). How senior managers think. *Harvard Business Review, 62*(6), 81-90.

Agor, W. H. (1986). The logic of intuition: How top executives make important decisions. *Organizational Dynamics, 14*(2), 5-18. https://doi.org/10.1016/0090-2616(86)90003-3

Yukl, G. (1994). *Leadership in organizations* (3rd ed., pp. 275-276, 442-444). Prentice Hall.

Malewska, K. (2017). The profile of an intuitive decision maker and the use of intuition in decision-making practice. *Management, 22*, 31-44. https://doi.org/10.2478/manment-2018-0003

Pretz, J., Brookings, J., Carlson, L., Keiter Humbert, T., Roy, M., Jones, M., & Memmert, D. (2014). Development and validation of a new measure of intuition: The types of intuition scale. *Journal of Behavioral Decision Making, 27*, 10.1002/bdm.1820. https://doi.org/10.1002/bdm.1820

Pacini, R., & Epstein, S. (1999). The relation of rational and experiential information processing styles to personality, basic beliefs, and the ratio-bias phenomenon. *Journal of Personality and Social Psychology, 76*(6), 972-987. https://doi.org/10.1037//0022-3514.76.6.972

Diaz-Hernandez, O., & Gonzalez-Villela, V. (2015). Analysis of human intuition towards artificial intuition synthesis for robotics. *Mechatronics and Applications: An International Journal (MECHATROJ), 1*, 23. https://doi.org/10.2139/ssrn.3427647

Jolly, M. The concept of intuition in artificial intelligence. *Academia*.
Dreyfus, H., & Dreyfus, S. E. (1986). *Mind over machine*.

Penrose, R. (1989). *The emperor's new mind: Concerning computers, minds and the laws of physics*. Oxford University Press.

Duros, V., Grizou, J., Sharma, A., Mehr, S., Bubliauskas, A., Frei, P., & Miras, H. (2019). Intuition-enabled machine learning beats the competition when joint human-robot teams perform inorganic chemical experiments. *Journal of Chemical Information and Modeling, 59*, 10.1021/acs.jcim.9b00304. https://doi.org/10.1021/acs.jcim.9b00304

Datta, S. (n.d.). Greedy vs heuristic algorithm. https://www.baeldung.com/cs/greedy-vs-heuristic-algorithm

AMP. (n.d.). Chapter 11 - Dynamic programming. https://web.mit.edu/15.053/www/AMP-Chapter-11.pdf

Dutta, S. (2020). The fourth generation artificial intuition working process. *Open Growth Magazine*.

Sgurev, V. (2019). S-Logic with first and second imaginary states. In *Advances in Intelligent Systems and Computing* (pp. 10-1007/978-3-319-78931-6_7).

Thomas, A. The intuitive algorithm. https://artificial-intelligence/the-intuitive-algorithm-r770/

Telelis, O. Set covering and network optimization: Dynamic and approximation algorithms.

Madhaven, P. G. (n.d.). Static and dynamical machine learning. https://www.datasciencecentral.com/static-dynamical-machine-learning-what-is-the-difference/