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The Human Intelligence linguistic Variable Is a Potential Fuzzy Computational Model for the Natural Languish Expression Human Intelligence

Andreea V. Cojocaru[✉,*] **Stefan Balint**[✉,*]

Department of Computer Science, West University of Timisoara, 300223 Timisoara, Romania

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Abstract

This paper presents a fuzzy, computational model for the natural-language term 'human intelligence'. This mathematical model accounts for multiple interpretations of the term 'intelligent' and enables comparison of these interpretations for a given IQ score. The model is a linguistic variable–based mathematical framework specifically designed to represent human intelligence. The model is constructed systematically throughout the paper. First, the term 'human intelligence' is represented as a fuzzy set. This step is followed by the construction of fuzzy sets corresponding to the words obtained by adding different hedges to the word 'intelligent' (i.e., very intelligent, more or less intelligent, etc.) The steps that follow use fuzzy logic operators and fuzzy set operations to further expand the set of possible interpretations of the word human intelligence. Examples are provided throughout the paper to demonstrate the newly incorporated element in the 'human intelligence' linguistic variable and to illustrate computations using it.

Keywords:

IQ index; fuzzy set; fuzzy logic concepts; fuzzy logic operators; linguistic variables

1. Introduction

The natural language expression 'human intelligence' could not (even after it became an object of science) benefit from a classical definition, through delimitations of proximate gender and specific difference. Representing acts and qualities about human beings simultaneously, homo faber and homo sapiens, the intellectual capacity of humans, denoted by complex cognitive actions and a strong degree of motivation and self-consciousness, is referred to as human intelligence. Through intelligence, humans are able to learn, develop, comprehend, and apply logic and reasoning. Human intelligence is also believed to include the ability to recognize patterns, plan, innovate, solve problems, make decisions, remember information, and communicate through language. The term "human intelligence" has existed since time immemorial in natural language, has been enshrined in literature, and, from multiple perspectives, reflects the power and function of the human mind to establish connections and link relationships. It embodies the concept of inter-legere, which conveys a dual meaning: both to discern or discriminate and to bind or gather, bringing elements together. Of all human abilities, the most specifically human characteristic is intelligence, given that it transforms biological human into *Homo sapiens*. However, intelligence is not a material thing but an abstract concept, making it difficult to define. Thus, we often analyze manifestations and component faculties of intelligence rather than intelligence itself. Taking into account the above-presented facts, it follows that the natural language word 'human intelligence' is fuzzy and inappropriate for computation [1–5].

On the other hand, fuzzy set logic provides a means for dealing with ambiguity. As it deals with imprecise objects, it has been, and for many scientists remains, an unacceptable tool in the precise world of science. Fuzzy

* **Corresponding Author:**
Andreea V. Cojocaru; Stefan Balint, Department of Computer Science, West University of Timisoara, 300223 Timisoara, Romania,
candreeavalentina@gmail.com (A.V.C.); stefan.balint@e-uvt.ro (S.B.)

logic gained early traction through industrial applications, including train control (Yasunobu and Miyamoto 1985), auto-focusing cameras (Shingu and Nishimori 1989), and cement kiln control (Holmblad and Ostergaard 1982). Fuzzy logic is used to describe ambiguity and uncertainty in the case of fuzzy linguistic expressions, in a non-probabilistic (non-frequentist) framework [6–8].

In this paper, a specific linguistic variable, that of the 'human intelligence', is constructed. This linguistic variable is built up throughout the whole paper. The first step consists of the representation of the word 'human intelligence' with a numerical triangular fuzzy set. This step is followed by the construction of numerical fuzzy sets corresponding to the words obtained by adding different hedges to the word 'intelligent' (i.e., very intelligent, more or less intelligent, etc.) The following steps use fuzzy logic operators and fuzzy set operations to further expand the range of possible interpretations of the term "human intelligence.". Examples throughout the paper demonstrate the properties of the newly incorporated elements in the 'human intelligence' linguistic variable and show how computations are performed. To the best of current knowledge, no mathematical construction exists for human intelligence. This constitutes the primary novelty of the present study.

In Section 2, the historical meanings of the natural language term "human intelligence" are presented. In Section 3.1, the measurement of 'human intelligence' and the meaning of the IQ index throughout history are presented. In Section 3.2, the fuzzy set description of 'human intelligence' is presented. In Section 3.3, the effect of linguistic modifiers, in the case of the natural language expression 'human intelligence', is presented. In Section 3.4, the concept of linguistic variable 'human intelligence' is presented. In Section 3.5, extension of the kernel of 'human intelligence linguistic variable' by using fuzzy logic and fuzzy logic operators is presented. In the expanded context, the fuzzy logic operators and the fuzzy subset operations are also discussed. In Section 4, discussions are presented. In Section 5, conclusions are presented.

2. What Is the Meaning of the Natural Languish Word 'Human Intelligence'?

Intelligence has been defined and studied across psychological schools in accordance with the general postulates of its conception of human nature. The psychology of 'human intelligence' is closely related to the concept of individual differences in mental "traits" and the development of analytical tools. Throughout history, the meaning of "human intelligence" has undergone significant changes. The evolution of 'human intelligence' refers to several theories that seek to describe how 'human intelligence' evolved in relation to the evolution of the human brain and the origin of language [1]. The timeline of human evolution spans approximately 7 million years, from the divergence of the genus Pan to the emergence of behavioral modernity around 50,000 years ago. Of this timeline, the first 3 million years concern Sahelanthropus, the next 2 million concern Australopithecus, while the last 2 million cover the history of Homo Reale (Paleolithic) species. Many features of human intelligence, such as empathy, mourning, ritual, and the use of symbols and tools, are already evident in the great apes, albeit at a less sophisticated level than in humans. There is a debate between proponents of the idea of a sudden emergence of intelligence, called the "Great Leap Forward," and proponents of a "Gradual Emergence" (continuous) hypothesis of 'human intelligence'.

Theories on the evolution of human intelligence include Robin Dunbar's Social Brain Hypothesis [2], Geoffrey Miller's Sexual Selection Hypothesis, which addresses sexual selection in human evolution [3], and the Ecological Dominance–Social Competition (EDSC) hypothesis [4], proposed by Mark V. Flinn, David C. Geary, and Carol V. Ward and based primarily on the work of Richard D. Alexander. Other hypotheses include the Intelligence Hypothesis, which views intelligence as a signal of good health and disease resistance; the Group Selection Hypothesis, which proposes that organismal traits benefiting a group—such as a clan, tribe, or larger population—can evolve despite potential individual disadvantages; and the hypothesis that intelligence is linked to nutrition and, consequently, to social status. Evidence suggests that a higher IQ in an individual may indicate that the person originates from and resides in a physical and social environment with adequate nutrition, whereas lower IQ may be associated with environments where nutritional levels are insufficient [5].

2.1. Theories of Human Intelligence

- Multiple intelligences theory of Howard Gardner. This theory is rooted in the research of normal children and adults, of gifted people (so-called "savants"), of people who have been brain-damaged, of experts and virtuosos, and of people in different cultures [9–12].
- Robert Sternberg also proposed the Triarchic Theory of Intelligence in an effort to provide a more comprehensive account of intellectual competence, in contrast to traditional cognitive theories of human ability [13–23].

- Piaget theory and Neo-Piagetian theories. Piaget's theory of cognitive development was not centered on mental abilities but on children's mental models of the world. The child also forms more and more correct representations of the world as the child grows, allowing the child to interact with the world more successfully [24–31].

On the way, progress could be diversified in various areas, such as spatial or social ones.

- Intelligibility-Parieto-frontal integration theory. On the basis of a meta-analysis of 37 neuroimaging studies [32–36].
- Investment theory: According to the Cattell-Horn-Carroll theory, the most frequently deployed tests of intelligence in the related research comprise the measures of fluid ability (gf) and crystallized ability (gc), which vary in the way they evolve in individuals [37–41].
- Intelligence compensation theory (ICT): According to the intelligence compensation theory [42–47], people who are relatively less intelligent exert greater effort and labor more methodically, and become more determined and thorough (more conscientious) to get things done, to compensate the lack of intelligence, and more intelligent people do not need to have the personality factor conscientiousness in order to reach their objectives as they can count on the power of their mental capabilities instead of on structure or effort.
- Bandura's theory of self-efficacy and cognition [48, 49]: The perception of cognitive ability has evolved over time and is no longer regarded as a fixed property inherent to an individual.
- Process, personality, intelligence, and knowledge theory (PPIK) [50–55].
- Latent inhibition: The phenomenon of familiar stimuli eliciting a delayed reaction time compared with unfamiliar stimuli, known as Latent inhibition, appears to be positively correlated with creativity.

3. Methods and Results

3.1. How 'Human Intelligence' Is Measured? What Is the Meaning of the IQ Index?

Psychometric testing is the most widely used approach concept of understanding intelligence with the greatest number of supporters and published research over the longest time. It is by far the most widely used approach in practical environments. With the growth of mental testing for adolescents and adults, there arose a need for a measure of intelligence that was independent of mental age.

In this regard, the intelligence quotient (IQ) was introduced. The limited definition of IQ is a score on an intelligence test, with the average level of performance on an intelligence test being a score of 100, and other scores being assigned so that the scores are normally distributed about a mean of 100, where the standard deviation of the scores is 15. Some of the implications are:

1. About 2/3rds of all scores are in the range of 85 to 115.
2. Five per cent (1/20) of the scores are greater than 125 and one per cent (1/100) above 135.
3. Five percent are below 75, and one percent is under 65.

There are a variety of individually administered IQ tests in use

The I.Q. is essentially a rank; there are no true "units" of intellectual ability.

When we come to quantities like IQ or g, as we are presently able to measure them, we shall see later that we have an even lower level of measurement—an ordinal level. This means that the numbers we assign to individuals can only be used to rank them—the number tells us where the individual comes in the rank order and nothing else.

In the jargon of psychological measurement theory, IQ is an ordinal scale, in which we simply rank-order people. It is not even appropriate to claim that the 10-point difference between IQ scores of 110 and 100 is the same as the 10-point difference between IQs of 160 and 150. While one standard deviation is 15 points, and two SDs are 30 points, and so on, this does not imply that mental ability is linearly related to IQ, such that IQ 50 would mean half the cognitive ability of IQ 100. In particular, IQ points are not percentage points. Psychometricians generally regard IQ tests as having high statistical reliability after the age of 8–10. IQ scores remain relatively stable: the correlation between IQ scores from age 8 to 18 and IQ at age 40 is over 0.70." Reliability is the consistency of a test's scores. A dependable test has the same scores when repeated. Any given IQ estimate comes with a standard error, which quantifies the uncertainty around it. In the case of modern tests, the confidence interval may be approximated to 10 points, and the reported standard error of measurement may be as low as 3 points. The reported standard error may also be an underestimation because it does not account for all sources of error. Reliability and standard errors of measurement should be considered best-case estimates because they do not consider other major sources of error, such as transient error, administration error, or scoring error, which influence test scores in clinical assessments. Another factor that must be considered is the extent to which subtest scores reflect portions of true score variance due to a hierarchical general intelligence factor and variance due to specific group factors because these sources of true score variance are conflated."

Extraneous factors, such as lack of motivation or anxiety, may sometimes reduce an individual's IQ score on an IQ test. In the case of those scoring very low, the 95% confidence interval can be higher than 40 points, and this might make the diagnosis of intellectual disability difficult.

The concerns associated with SEMs [standard errors of measurement] are actually substantially worse for scores at the extremes of the distribution, especially when scores approach the maximum possible on a test. when students answer most of the items correctly. In these cases, measurement errors for scale scores will increase substantially at the extremes of the distribution. Commonly, the SEM is 2 to 4 times larger for very high scores than for scores near the mean.

On the same note, high IQ scores are also much less predictive than those close to the population median. Reports of IQ scores over 160 are doubted. Curve-fitting is just one reason to be suspicious of reported IQ scores much higher than 160.

Validity refers to the extent to which a test measures what it is intended to measure. While IQ tests are generally designed to assess specific types of intelligence, they may not provide an effective measure of the broader definitions of human intelligence. It is against this reason that psychologist Wayne Weiten opines that their construct validity should be qualitatively restrained, and not overrated. Weiten further states that IQ tests are good indicators of the type of intelligence required to perform well in studies. However, when the aim is to determine intelligence in a wider context, the validity of IQ tests is doubtful. Other scientists have challenged the worth of IQ as an intelligence measure in general. Regardless of objections, in general, clinical psychologists consider IQ scores sufficiently statistically valid in many clinical applications.

3.2. What does a fuzzy set description of 'Human Intelligence' mean?

In mathematics, fuzzy sets were first introduced by Zadeh [56] in 1965 and have been applied in various fields, such as linguistics [57–59]; decision-making [60]; control [6–8]; theory of possibilities [61,62]; medicine [63–65]. Recent applications are presented in [66,67].

In the case of an ordinary set for each object, it can be decided whether it belongs to the set. A fuzzy set is a collection of objects without well-defined characteristics. In contrast with ordinary sets, a partial membership in a fuzzy set is possible.

The formal definition of a fuzzy set, according to [56], is:

Definition 1. *Let X be an ordinary set (called universe) A is called a fuzzy subset of X if A is a set of ordered pairs:* $A = \{(x, f_A(x)); x \in X, f_A(x) \in [0,\ 1]\}$.

The function $f_A : X \to [0,\ 1]$ is called the membership function of A. The membership value $f_A(x)$ is the grade of membership of x in A. The membership value $f_A(x)$ can also be regarded as the 'true value 'of the statement, 'x *belongs to* A' i.e. the closer $f_A(x)$ is to 1 the more x is considered to belong to. The closer $f_A(x)$ is to 0 less x is taken to belong to A.

In some fields, especially scientific ones, there is a tendency to define sets with sharp boundaries and to accept only 'true' or 'not true' statements.

A special case of fuzzy sets is fuzzy numbers.

Definition 2. *A fuzzy subset A of the set of real numbers R is called a fuzzy number if: there is at least one x such that $f_A(x) = 1$ (normality assumption) and for any real numbers a , b , c , with $a < b < c$ $f_A(b) > min\{f_A(a),\ f_A(c)\}$.*

The second property is the so-called convexity assumption, meaning that the membership function of a fuzzy number usually consists of an increasing and decreasing part, and possibly a flat part.

Definition 3. *A fuzzy subset A of the real numbers R is a triangular fuzzy number if there exist three real numbers $a_1, a_2,\ a_3$ such that $a_1 < a_2 < a_3$ and the membership function of A is given by : $f_A(x) = 0$ for $x \leq a_1$; $f_A(x) = \frac{x-a_1}{a_2-a_1}$ for $a_1 < x \leq a_2$; $f_A(x) = -\frac{x-a_3}{a_3-a_2}$ for $a_2 < x \leq a_3$; $f_A(x) = 0$ for $a_3 < x$. The support of the triangular fuzzy number is the interval (a_1, a_3).*

The use of triangular fuzzy numbers in the earthquake intensity description is justified by the following. Consider the measured earthquakes by the so-called body-wave technique. This technique essentially measures the amplitude of the quake as transmitted by the deep earth, rather than by the earth's surface. It is known that the measuring instruments begin to saturate at about 7.00 amplitude intensity units and that, furthermore, the measurements are by nature imprecise. In a fuzzy description, it is

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natural to take the measured value as the peak of the membership function of a fuzzy number defined on the body wave amplitude intensity scale 1 to 9. If the measured amplitude value is far enough from the saturation zone, say 6, then a symmetric triangular fuzzy number assessed subjectively by an expert may be obtained, say, with support (5.8,6.2).

A crucial point in applying fuzzy methods is the assessment of the membership functions.

A very simple way of defining a fuzzy number A with respect to a parameter x is by assessing three numbers:

1. The most credible value x^*-assigned a membership value of 1.

2. The number x^- which is almost certainly exceeded by the parameter value–assigned a membership value 0.

3. The number x^+ which is almost certainly not exceeded by the parameter value, assigned a membership value of 0.

Let the membership function be defined with 0 outside of the interval $(x^-,\ x^+)$ of possible values (support) and taken to be piecewise linear in between. The triangular fuzzy number $A_T = (x^-, x^*, x^+)$ has thus been constructed.

Note that the resulting membership function is not necessarily symmetrical. This represents a difference with respect to the usually accepted normal or at least symmetrically distributed error. Other techniques are available to assess membership functions based on the type of imprecision in a fuzzy set.

As membership functions are often related to human perception, it might be reasonable to take human responses to external stimuli into account. Once the membership function has been assessed, a sensitivity analysis may be performed to determine whether further refinement is necessary. If it is found that the model behavior is sensitive to the support or shape of the membership function, then it is possible to use artificial neural nets to improve an initial assessment.

The natural language expression "human intelligence" concerns a set of intellectual properties of humans, and it is evaluated quantitatively with the IQ index. However, the natural language expression 'human intelligence' is too vague (fuzzy) to perform computation based only on the IQ index. The word intelligent may have different meanings for different people. For example, 'intelligent' for a person may mean 'very intelligent' for a second person and may mean 'more or less intelligent' for a third person. In which kind of details are incorporated into the IQ index, which is opaque and can explain different appreciations of a person by the members of a jury in a competition? Fuzzy set model for 'human intelligence' and 'fuzzy logic' using IQ values could be a new approach that incorporates the fuzzy character of the natural language expression and transforms the expression 'human intelligence' into a computationally usable form.

To see how this can be put in practice, consider the natural language expression 'human intelligence', with the ordinary set X (the universe) represented by the set of real numbers R *and the interval of real numbers* $(40, 160)$. This is primarily because, for individuals with very low scores, the 95% confidence interval may exceed 40 IQ points, potentially complicating the accuracy of diagnoses of intellectual disability. Similarly, very high IQ scores are significantly less reliable than those near the population median, and reports of IQ scores substantially above 160 are generally considered dubious.

Definition 4. *The fuzzy subset $A_{intelligent}$ corresponding to the word 'human intelligence is the set of ordered pairs:*

$$A_{intelligent} = \{(x, f_A(x)); x \in R, f_A(x) \in [0,\ 1]\}$$

and the membership function $f_A : R \to [0,\ 1]$ is the very simple function defined by:

$$\begin{gathered} f_{A_{intelligent}}(x) = 0\ for\ x \le 40; \\ f_{A_{intelligent}}(x) = \frac{x-40}{60}\ \ for\ 40 < x \le 100; \\ f_{A_{intelligent}}(x) = -\frac{x-160}{60}\ \ for\ 100 < x \le 160 \\ f_{A_{intelligent}}(x) = 0\ for\ \ 160 < x \end{gathered} \tag{1}$$

In the above formula:

the number $x^- = 40$ which is almost certainly exceeded by the IQ index

the number $x^+ = 160$ which is almost certainly not exceeded by the IQ index

the number $x^* = 100 = the\ most\ credible\ IQ\ index)$ That is because two-thirds of the population score between an IQ index of 85 and 115.

The graphic is presented in Figure 1.

The graphic corresponds to the fuzzy logic statement $(x\ is\ A_{intelligent})$ and $f_{A_{intelligent}}(x)$ is 'the true value' or the degree of fulfillment DOF of the fuzzy logic statement $(x\ is\ A_{intelligent})$ i.e., $DOF(x\ is\ A_{intelligent}) = f_{A_{intelligent}}(x)$.

Representing the natural language expression "human intelligence" with a fuzzy subset $A_{intelligent}$ ambiguity in the interpretation of the IQ index is introduced. The 'true value'= grade of membership = the number $f_{A_{intelligent}}(x = IQ) = DOF(x = IQ\ is\ A_{intelligent})$ represent this ambiguity.

In case of a given set of IQ points, making the identification of the 'less than intelligent persons', the 'intelligent persons', and the' more than intelligent persons' using only IQ points (ignoring ambiguity), it is possible to obtain different results from those obtained using $f_{A_{intelligent}}(x = IQ)$ values. For example, in the case of the set of IQ points:

$$IQ := [71, 74, 53, 61, 41, 50, 65, 72, 119, 115, 119, 120, 125, 124, 125, 125, 129, 129, 123, 49, 50, 50, 47, 65, 132, 135, 153, 152, 42, 60, 80, 81, 95, 100, 105] \quad (2)$$

if we agree that people with IQ points less than 85 are 'less than intelligent persons, with IQ points between 85 and 115 are intelligent, and people with IQ points between 115

and 160 are more than intelligent persons,
the next results are obtained:

- less than intelligent persons

$$[71, 74, 53, 61, 41, 50, 65, 72, 49, 50, 50, 47, 65, 42, 60, 80, 81] \quad (3)$$

- intelligent persons

$$[95, 100, 105] \quad (4)$$

- more than intelligent persons

$$[119, 115, 119, 120, 125, 124, 125, 125, 129, 129, 123, 132, 135, 153, 152] \quad (5)$$

In this classification, there are 17 individuals categorized as less intelligent, 3 as intelligent, and 15 as highly intelligent.

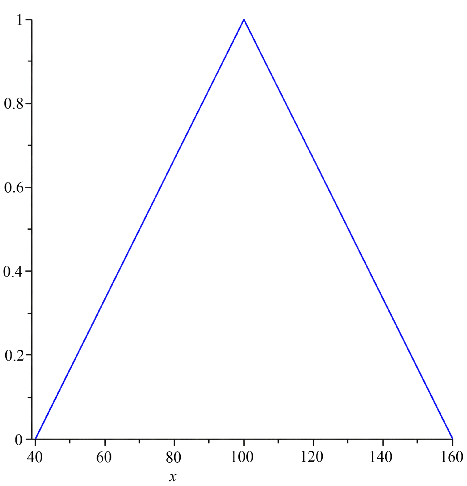

Figure 1: Fuzzy subset $A_{intelligent}$ *corresponding to the fuzzy statement* $(x \; is \; intelligent)$ in the WAIS scale.

The above identification uses the IQ index strictly, and the result is unique. On the other hand, according to Wayne Weiten, "IQ index is a valid measure of the kind of intelligence necessary to do well in academic work. But if the purpose is to assess intelligence in a broader sense, the validity of the IQ index is questionable."

For those persons who assess intelligence in a broader sense, maybe it is not sufficient to use the above classification, and it is necessary to use a second parameter, in which the ambiguity of the word 'human intelligence' is also incorporated. This second parameter can be '*the true value*' *of the statement* $(x = IQ \; is \; A_{intelligent}) = DOF(x = IQ \; is \; A_{intelligent}) \; value$.

In case of the of IQ indexes given by (2) the set of the $DOF(x = IQ \; is \; A_{intelligent}) \; values$ can be found using computer and the membership function of the fuzzy subset $A_{intelligent}$.

The set of $DOF(x = IQ \; is \; A_{intelligent}) \; values =$ '*the true value*' *of the statement* $(x = IQ \; is \; A_{intelligent})$ obtained in this way is:

$$DOFIIQ := [0.5166666667, 0.5666666667, 0.2166666667, 0.3500000000, 0.0166666667, 0.1666666667, 0.4166666667, 0.5333333333, 0.6833333333, 0.7500000000, 0.6833333333, 0.6666666667, 0.5833333333, 0.6000000000, 0.5833333333, 0.5833333333, 0.5166666667, 0.5166666667, 0.6166666667, 0.1500000000, 0.1666666667, 0.1666666667, 0.1166666667, 0.4166666667, 0.4666666667, 0.4166666667, 0.1166666667, 0.1333333333, 0.0333333333, 0.3333333333, 0.6666666667, 0.6833333333, 0.9166666667, 1, 0.9166666667] \quad (6)$$

The $DOFI(IQ)$ value is the membership value ('true value') of the index IQ in case of fuzzy subset $A_{intelligent}$. If in a competition, the jury decides at the start to reject those candidates whose $DOFI(IQ)$ values are low, for example, less than 0.5 points, and accept only those candidates whose $DOFI(IQ)$ is higher than 0.5 point, then it is possible, using a computer, to determine the sets of rejected and accepted candidates. The obtained result in case of the set (2) is the following:

- rejected candidates.

$$0.2166666667, 0.3500000000, 0.0166666667, 0.1666666667, 0.4166666667, 0.1500000000, 0.1166666667, 0.1666666667, 0.1166666667, 0.4166666667, 0.4666666667, 0.4166666667, 0.1166666667, 0.1333333333, 0.0333333333, 0.3333333333 \quad (7)$$

- accepted candidates.

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$$0.5166666667, 0.5666666667, 0.5333333333, 0.6833333333, 0.7500000000, 0.6833333333, 0.6666666667, 0.5833333333, 0.6000000000, 0.5883333333, 0.5833333333, 0.5166666667, 0.5166666667, 0.6166666667, 0.6666666667, 0.6833333333, 0.9166666667, 1, 0.9166666667 \quad (8)$$

According to this, among the whole set of 35 candidates, 16 are rejected at the start and only 19 are accepted to participate in the competition. The great number of candidates (16) rejected at the start shows that the $DOFI(IQ)$ = '$the\ true\ value$' $of\ the\ statement$ $(x = IQ\ is\ A_{intelligent})$ has an important influence in interpretation of the IQ index signification.

To see in detail:

- the 'less than intelligent' candidates (according to their IQ index) who are rejected because their $DOFI(IQ)$, the 'less than intelligent' candidates (according to their IQ index) who are accepted because their $DOFI(IQ)$;
- the 'intelligent' candidates' (according to their IQ index) who are rejected because their $DOFI(IQ)$, the 'intelligent' candidates (according to their IQ index) who are accepted because their $DOFI(IQ)$;
- the 'more than intelligent' candidates' (according to their IQ index) who are rejected because their $DOFI(IQ)$, the 'more than intelligent' candidates (according to their IQ index) who are accepted because their $DOFI(IQ)$;

each of the 3 groups of candidates, 'less than intelligent candidate', 'intelligent candidate', and 'more than intelligent candidates', classified according to their IQ index has to be divided into two subgroups: candidates having $DOFI(IQ)$ point less than 0.5 and candidates having $DOFI(IQ)$ point more than 0.5 points.

The obtained result is the following.

The set of $DOFLI(IQ)$ of 'less intelligent' candidates given by (3) is

$$DOFILI(IQ)\ [0.5166666667, 0.5666666667, 0.2166666667, 0.3500000000, 0.0166666667, 0.1666666667, 0.4166666667, 0.5333333333, 0.1500000000, 0.1666666667, 0.1666666667, 0.1166666667, 0.4166666667, 0.0333333333, 0.3333333333, 0.6666666667, 0.6833333333] \quad (9)$$

- candidates accepted at the outset from the group

$$[0.5166666667, 0.5666666667, 0.5333333333, 0.6666666667, 0.6833333333] \quad (10)$$

- candidates rejected at the outset from the group

$$[0.2166666667, 0.3500000000, 0.0166666667, 0.1666666667, 0.4166666667, 0.1500000000, 0.1666666667, 0.1666666667, 0.1166666667, 0.4166666667, 0.0333333333, 0.3333333333] \quad (11)$$

In the group of less-intelligent candidates, there are 17 candidates. It is interesting to note that 5 candidates from the group of 'less than intelligent persons 'are accepted at the start due to their high $DOFI(IQ)$ values and 12 candidates from the group are rejected at the start because their low $DOFI(IQ)$ values.

The set of $DOFI(IQ)$ of 'intelligent' candidates given by (4) is

$$DOFI(IQ) = DOFI := [0.9166666667,\ 1,\ 0.9166666667]; \quad (12)$$

- candidates accepted at the outset from the group

$$[0.9166666667, 1, 0.9166666667] \quad (13)$$

- candidates rejected at the outset from the group

$$[\,] \quad (14)$$

In the group of intelligent candidates, there are 3 candidates. All the 3 candidates from the group of 'intelligent' persons are accepted at the start to participate in the competition due to their high $DOFI(IQ)$ values.

The set of $DOFIMI(IQ)$ of 'more than intelligent' candidates given by (5) is

$$DOFIMI := [0.6833333333, 0.7500000000, 0.6833333333, 0.6666666667, 0.5833333333, 0.6000000000, 0.5833333333, 0.5833333333, 0.5166666667, 0.5166666667, 0.6166666667, 0.4666666667, 0.4166666667, 0.1166666667, 0.1333333333] \quad (15)$$

- candidates accepted at the outset from the group

$$[0.68333333333, 0.7500000000, 0.6833333333, 0.6666666667, 0.5833333333, 0.6000000000, 0.5833333333, 0.5833333333, 0.5166666667, 0.5166666667, 0.6166666667] \quad (16)$$

- candidates rejected at the outset from the group

$$[0.4666666667, 0.4166666667, 0.1166666667, 0.1333333333] \quad (17)$$

In the group of 'more than intelligent' candidates, there are 15 candidates. Only 11 candidates were accepted at the start due to the high value of their $DOFI(IQ)$ and 4 candidates from this group were rejected at the start due to the low value of their $DOFIMI(IQ)$. This last result can be suggestive concerning the effect of the $DOFIMI(IQ)$ use in classification.

Globally, from the set of 35 candidates, 16 were initially rejected due to the low values of their $DOFI(IQ)$ and only 19 candidates were accepted due to the high value of their $DOFI(IQ)$.

3.3. What is the Effect of Linguistic Modifiers in the case of the Natural Languish Expression 'Human Intelligence'?

In natural language, a specification of the properties is often done using linguistic modifiers (hedges) [57] These modifiers might both increase or decrease the uncertainty. Some of these phrases are: VERY, FAIRLY, MOSTLY, OFTEN, SOMEWHAT, INDEED, ROUGHLY, ALMOST, MORE OR LESS, SORT OF, PRACTICALLY, NOT, MOST OF, AT LEAST A FEW. These hedges are applied to fuzzy linguistic expressions, resulting in either a more precise or imprecise vague linguistic expression.

The effect of the linguistic modifier very. Applying the linguistic modifier very to the fuzzy statement $(x\ is\ intelligent)$, defined by (1), the fuzzy logic statement $(x\ is\ very\ intelligent)$ is obtained. It seems that the fuzzy statement $(x\ is\ very\ intelligent)$ require higher exigency in comparison with that of the fuzzy statement $(x\ is\ intelligent)$. The membership function of the fuzzy logic statement $(x\ is\ very\ intelligent)$ is the piecewise nonlinear function [57,64,65] given by:

$$f_{A_{very-intelligent}}(x) = f^2_{A_{intelligent}}(x) \tag{18}$$

The fuzzy subset $A_{very-intelligent}$, representing the fuzzy logic statement $(x\ is\ very\ intelligent)$ as presented in Figure 2.

A way to incorporate the ambiguity introduced by the fuzzy statement $(x\ is\ very\ intelligent)$ in case of the set IQ indexes (2) is by adding beside IQ indexes, a second parameter, namely the $DOFVI(IQ) = DOF$ $(x = IQ\ is\ A_{very-intelligent})\ values$ = '$the\ true\ value$' $of\ the\ statement\ (x = IQ\ is\ A_{very-intelligent})$ points.

For this purpose, the set of the $DOFVI(IQ)$ points have to be found using a computer and the membership function of the fuzzy subset $A_{very-intelligent}$.

The set of $DOFVI(IQ)$ points obtained in this way are:

$$\begin{gathered} DOFVIIO := [0.2669444444, 0.3211111111,\\ 0.0469444444, 0.1225000000, 0.0002777777778,\\ 0.0277777778, 0.1736111111, 0.2844444444,\\ 0.4669444444, 0.5625000000, 0.4669444444,\\ 0.4444444444, 0.3402777778, 0.3600000000,\\ 0.3402777778, 0.3402777778, 0.2669444444,\\ 0.2669444444, 0.3802777778, 0.0225000000,\\ 0.0277777778, 0.0277777778, 0.0136111111,\\ 0.1736111111, 0.2177777778, 0.1736111111,\\ 0.0136111111, 0.0177777778, 0.001111111111,\\ 0.001111111111, 0.4444444444, 0.4669444444,\\ 0.8402777778, 1, 0.8402777778] \end{gathered} \tag{19}$$

The $DOFVI(IQ)$ value is the membership value ('true value') of the IQ index in case of fuzzy subset $A_{very-intelligent}$. If in a competition, the jury decide at the start, to reject those candidates whose $DOFVI(IQ)$ values is low, for example less than 0.5 point, and accept only those candidates whose $DOFVI(IQ)$ is high, more than 0.5 point, then using computer it is possible to select the set of rejected candidates and the set of accepted candidates. The obtained result in case of the set (2) is the following:

- rejected candidates.

$$\begin{gathered} 0.2669444444, 0.3211111111, 0.0469444444,\\ 0.1225000000, 0.0002777777778,\\ 0.02777777778, 0.1736111111, 0.2844444444,\\ 0.4669444444, 0.4669444444, 0.4444444444,\\ 0.3402777778, 0.3600000000, 0.3402777778,\\ 0.3402777778, 0.2669444444, 0.2669444444,\\ 0.3802777778, 0.0225000000, 0.0277777778,\\ 0.0277777778, 0.0136111111, 0.1736111111,\\ 0.2177777778, 0.1736111111, 0.0136111111,\\ 0.0177777778, 0.0011111111, 0.0011111111,\\ 0.4444444444, 0.4669444444 \end{gathered} \tag{20}$$

- accepted candidates.

$$[0.5625000000, 0.8402777778, 1, 0.8402777778] \tag{21}$$

According to this, among the whole set of 35 candidates, 31 are rejected at the start, and only 4 are accepted to participate in the competition.

To see in detail:

- Who are the' less than very intelligent' candidates rejected because their low $DOFVI(IQ)$ values, and who are the 'less than very intelligent candidates' accepted because their high $DOFVI(IQ)$ values;

- Who are the 'very intelligent candidates' rejected because their low $DOFVI(IQ)$ values, and who are the 'very intelligent candidates' accepted because of their high $DOFVI(IQ)$ values;
- Who are the' more than very intelligent' candidates rejected because of their low $DOFVI(IQ)$ values, and who are the 'more than very intelligent candidates' accepted because of their high $DOFVI(IQ)$;

Each of the groups of candidates 'less than very intelligent person', 'very intelligent person', and 'more than very intelligent person', classified according to IQ points, has to be divided into two subgroups: persons having $DOFVI(IQ)$ values less than 0.5 and candidates having $DOFVI(IQ)$ values more than 0.5 points.

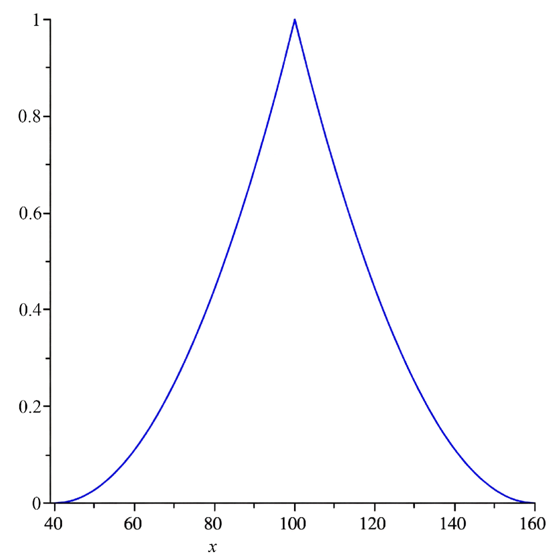

Figure 2: Fuzzy subset $A_{very-intelligent}$ representing the fuzzy statement $(x\ is\ very\ intelligent)$ in the WAIS scale.

The $DOFVI(IQ)$ of the 'less than very intelligent' candidates are the following:

$$\begin{gathered} DOFLVI := [0.26694444444, 0.32111111111, \\ 0.04694444444, 0.12250000000, 0.00277777777, \\ 0.02777777778, 0.17361111111, 0.28444444444, \\ 0.02250000000, 0.02777777778, 0.02777777778, \\ 0.01361111111, 0.17361111111, 0.00111111111, \\ 0.11111111111, 0.44444444444, 0.46694444444]; \end{gathered} \tag{22}$$

- accepted candidates at the start from the group

$$[\,]$$

- rejected candidates at the start from the group

$$\begin{gathered} 0.2669444444, 0.3211111111, 0.0469444444, \\ 0.1225000000, 0.0002777777778, 0.02777777778, \\ 0.1736111111, 0.2844444444, 0.02250000000, \\ 0.02777777778, 0.02777777778, 0.0136111111, \\ 0.1736111111, 0.001111111111, 0.1111111111, \\ 0.4444444444, 0.4669444444 \end{gathered} \tag{23}$$

In the group of 'less than very intelligent' candidates, there are 17 candidates. All 17 candidates were rejected at the start because of their low $DOFVI(IQ)$ values.

The $DOFVI(IQ)$ of the 'very intelligent' candidates is the following:

$$DOFVI := [0.8402777778, 1, 0.8402777778] \tag{24}$$

- accepted candidates at the start from the group

$$[0.8402777778, 1, 0.8402777778] \tag{25}$$

- rejected candidates at the start from the group

$$[\,] \tag{26}$$

In the group of 'very intelligent' candidates, there are 3 candidates. All the 3 candidates are accepted at the start because of their high $DOFVI(IQ)$ values.

The $DOFVI(IQ)$ of the 'more than very intelligent' candidates are the following:

$$\begin{gathered} DOFMVI := [0.4669444444, 0.5625000000, \\ 0.4669444444, 0.4444444444, 0.3402777778, \\ 0.3600000000, 0.3402777778, 0.3402777778, \\ 0.2669444444, 0.2669444444, 0.3802777778, \\ 0.2177777778, 0.1736111111, 0.0136111111, \\ 0.0177777778]; \end{gathered} \tag{27}$$

- accepted candidates at the start from the group

$$[0.5625000000] \tag{28}$$

- rejected candidates at the start from the group

$$\begin{gathered} [0.4669444444, 0.4669444444, 0.4444444444, \\ 0.3402777778, 0.3600000000, 0.3402777778, \\ 0.3402777778, 0.2669444444, 0.2669444444, \\ 0.3802777778, 0.2177777778, 0.1736111111, \\ 0.0136111111, 0.0177777778] \end{gathered} \tag{29}$$

In the group of 'more than very intelligent' candidates, there are 15 candidates. 14 candidates are rejected at the start because of their low $DOFVI(IQ)$ values. Just one of the candidates is accepted due to its high $DOFVI(IQ)$ value.

In the interpretation of the fuzzy concept 'very intelligent' globally from the set of 35 candidates, at the start 31 candidates were rejected because of the low value of their $DOFVI(IQ)$ and only 4 candidates were accepted due to the high value of their $DOFVI(IQ)$.

Comparing the rejected number 31 with the rejected number 16 obtained in the interpretation of the fuzzy concept 'intelligent', it is obvious that the exigency behind the fuzzy concept 'very intelligent' is higher than the exigency behind the fuzzy concept 'intelligent.'

The effect of the linguistic modifier MORE OR LESS. Applying the fuzzy logic statement $(x\ is\ intelligent)$, defined by (1), the linguistic modifier more or less the fuzzy logic statement $(x\ is\ more\ or\ less\ intelligent)$ is obtained. It seems that the fuzzy statement $(x\ is\ more\ or\ less\ intelligent)$ less exigent than the fuzzy statement $(x\ is\ intelligent)$. The membership function of the fuzzy logic statement $(x\ is\ more\ or\ less\ intelligent)$ is the piecewise nonlinear function [57,64,65] given by:

$$f_{A_{more\ or\ less\ intelligent}}(x) = \sqrt{f_{A_{intelligent}}}(x) \quad (30)$$

The graphic of the computed fuzzy subset $A_{more\ or\ less\ intelligent}$ representing the fuzzy logic statement (*x is more or less intelligent*), as presented in Figure 3.

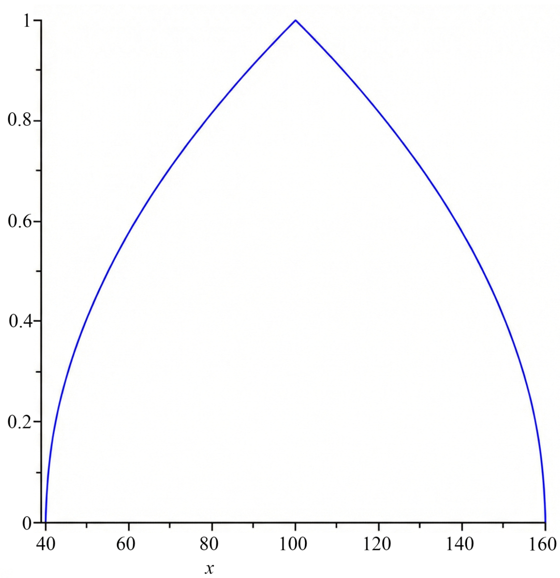

Figure 3: Graphic of the fuzzy subset $A_{more\ or\ less\ intelligent}$ representing the fuzzy statement $(x\ is\ more\ or\ less\ intelligent)$ in the WAIS scale.

A way to incorporate the ambiguity introduced by the fuzzy statement $(x\ is\ more\ or\ less\ intelligent)$ in case of IQ indexes (2) is by adding beside IQ indexes, a second parameter, namely the $DOFMLI(IQ) = DOF$ $(x = IQ\ is\ A_{more\ or\ less\ intelligent})\ value$='$the\ true\ value$' $of\ the\ statement\ (x = IQ\ is\ A_{more\ or\ less\ intelligent})$ points.

For this purpose, the set of the $DOFMLI(IQ)$ points have to be found using computer and the membership function of the fuzzy subset $A_{more\ or\ less\ intelligent}$.

The set of $DOFMLI(IQ)$ points obtained in this way is:

$$\begin{gathered} DOFMLIQ := [0.7187952883, 0.7527726526, \\ 0.4654746680, 0.5916079783, 0.1290994449, \\ 0.4082482906, 0.6454972245, 0.7302967432, \\ 0.8266397846, 0.8660254040, 0.8266397846, \\ 0.8164965809, 0.7637626160, 0.7745966692, \\ 0.7637626160, 0.7637626160, 0.7187952883, \\ 0.7187952883, 0.7852812659, 0.3872983346, \\ 0.4082482906, 0.4082482906, 0.3415650256, \\ 0.6454972245, 0.6831300514, 0.6454972245, \\ 0.3415650256, 0.3651483717, 0.1825741858, \\ 0.1825741858, 0.8164965809, 0.8266397846, \\ 0.9574271080, 1, 0.9574271080] \end{gathered} \quad (31)$$

The $DOFMLI(IQ)$ value is the membership value ('true value') of the IQ index in case of fuzzy subset $A_{more\ or\ less\ intelligent}$. If in a competition, the jury decides at the start to reject those candidates whose $DOFMLI(IQ)$ values are low, for example, less than 0.5 points, and accept only those candidates whose $DOFMLI(IQ)$ is high, more than 0.5 points, then using a computer, it is possible to select the set of rejected candidates and the set of accepted candidates at the start. The obtained result in case of the set (2) is the following:

- rejected candidates

$$\begin{gathered} [0.4654746680, 0.1290994449, 0.4082482906, \\ 0.3872983346, 0.4082482906, 0.4082482906, \\ 0.3415650256, 0.3415650256, 0.3651483717, \\ 0.1825741858, 0.1825741858] \end{gathered} \quad (32)$$

- accepted candidates

$$\begin{gathered} 0.7187952883, 0.7527726526, 0.5916079783, \\ 0.6454972245, 0.7302967432, 0.8266397846, \\ 0.8660254040, 0.8266397846, 0.8164965809, \\ 0.7637626160, 0.7745966692, 0.7637626160, \\ 0.7637626160, 0.7187952883, 0.7187952883, \\ 0.7852812659, 0.6454972245, 0.6831300514, \\ 0.6454972245, 0.8164965809, 0.8266397846, \\ 0.9574271080, 1, 0.9574271080 \end{gathered} \quad (33)$$

According to this, among the whole set of 35 candidates,11 candidates are rejected at the start, because their $DOFMLI(IQ)$ point is low, and only 24 candidates are accepted to participate at competition, because their $DOFMLI(IQ)$ point is sufficiently high.

More refined analysis can be made by computing the rejected or the accepted candidates at the levels: ‘less than more or less intelligent’, ‘more or less intelligent’, and ‘more than more or less intelligent’. The algorithm is similar with that presented in previous examples.

Applying the linguistic modifier INDEED to the fuzzy logic statement $(x\ is\ intelligent)$ defined by (1) the fuzzy logic statement $(x\ is\ indeed\ intelligent)$ is obtained. Apparently, the exigency of fuzzy statement $(x\ is\ indeed\ intelligent)$ is more than the exigency of fuzzy statement $(x\ is\ intelligent)$. The membership function of the fuzzy logic statement $(x\ is\ indeed\ intelligent)$ is the piecewise nonlinear function [57,64,65] given by:

$$\begin{aligned} f_{A_{indeed\ intelligent}}(x) &= 2 \times f^2_{A_{intelligent}}(x) \\ &for\ f_{A_{intelligent}}(x) \le 0.5 \\ &and\ f_{A_{indeed\ intelligent}}(x) \\ &= 1 - 2 \times \left(1 - f_{A_{intelligent}}(x)\right)^2 \\ &for\ \ 0.5 < \ f_{A_{intelligent}}(x) \end{aligned} \tag{34}$$

The graphic of the computed fuzzy subset $A_{indeed\ intelligent}$ representing the fuzzy logic statement $(x\ is\ indeed\ intelligent)$, as presented in Figure 4.

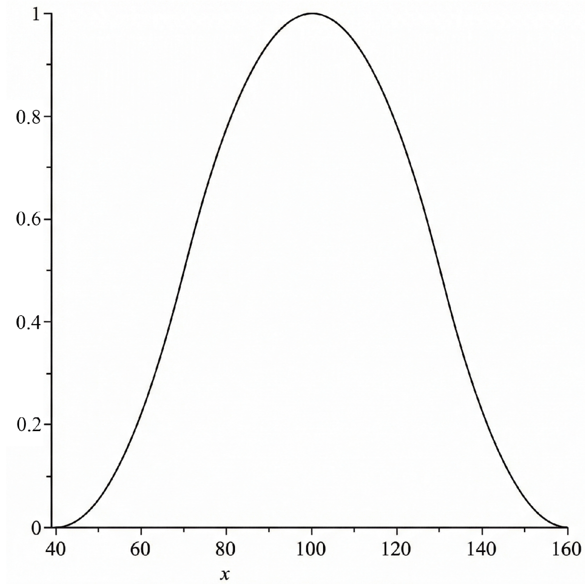

Figure 4: Graphic of the fuzzy subset $A_{indeed\ intelligent}$ representing the fuzzy statement $(x\ is\ indeed\ intelligent)$ in the WAIS scale.

A way to incorporate the ambiguity introduced by the fuzzy statement $(x\ is\ indeed\ intelligent)$, in case of IQ indexes (2), is by adding beside IQ indexes, a second parameter, namely the $DOFII(IQ) = DOF$ $(x = IQ\ is\ A_{indeed\ intelligent})\ value =$ ‘$the\ true\ value$’ $of\ the\ statement\ (x = IQ\ is\ A_{indeed\ intelligent})$ points.

For this purpose, the set of the $DOFII(IQ)$ points have to be found using a computer and the membership function of the fuzzy subset $A_{indeed\ intelligent}$.

The set of $DOFII(IQ)$ points obtained in this way are:

$$\begin{gathered} DOFIIIQ := [0.5327777778, 0.6244444444, \\ 0.0938888889, 0.2450000000, 0.0005555555556, \\ 0.0555555556, 0.3472222222, 0.5644444444, \\ 0.7994444444, 0.5625000000, 0.4669444444, \\ 0.7777777778, 0.6527777778, 0.6800000000, \\ 0.6527777778, 0.3402777778, 0.5327777778, \\ 0.5327777778, 0.3802777778, 0.04500000000, \\ 0.05555555556, 0.05555555556, 0.02722222222, \\ 0.3472222222, 0.4311111111, 0.3194444444, \\ 0.02722222222, 0.03555555556, 0.002222222222, \\ 0.002222222222, 0.7777777778, 0.7994444444, \\ 0.9861111111, 1, 0.9861111111]; \end{gathered} \tag{35}$$

The $DOFII(IQ)$ value is the membership value (‘true value’) of the IQ index in case of fuzzy subset $A_{indeed\ intelligent}$. If in a competition, the jury decides at the start to reject those candidates whose $DOFII(IQ)$ values are low, for example, less than 0.5 points, and accept only those candidates whose $DOFII(IQ)$ is high, more than 0.5 points, then using a computer, it is possible to select the set of rejected candidates and the set of accepted candidates at the start. The obtained result in case of the set (2) is the following:

- rejected candidates

$$\begin{gathered} 0.09388888889, 0.2450000009, 0.0005555555556, \\ 0.05555555556, 0.3472222222, 0.4669444444, \\ 0.3402777778, 0.3802777778, 0.04500000000, \\ 0.05555555556, 0.05555555556, 0.02722222222, \\ 0.3472222222, 0.4311111111, 0.3194444444, \\ 0.02722222222, 0.03555555556, 0.002222222222, \\ 0.002222222222 \end{gathered} \tag{36}$$

- accepted candidates

$$\begin{gathered} [0.5327777778, 0.6244444444, 0.5644444444, \\ 0.7994444444, 0.5625000000, 0.7777777778, \\ 0.6527777778, 0.6800000000, 0.6527777778, \\ 0.5327777778, 0.5327777778, 0.7777777778, \\ 0.7994444444, 0.9861111111, 1, 0.9861111111] \end{gathered} \tag{37}$$

According to this, among the whole set of 35 candidates,19 candidates are rejected at the start, because their $DOFII(IQ)$ point is low, and only 16 candidates are accepted to participate at competition, because their $DOFII(IQ)$ point is sufficiently high.

More refined analysis can be made by computing the rejected or the accepted candidates at the levels: 'less than more or less intelligent', 'more or less intelligent', and 'more than more or less intelligent'. The algorithm is similar to that presented in previous examples.

A rough representation of the difference between the fuzzy subsets $A_{intelligent}$, $A_{very\ intelligent}$, $A_{more\ or\ less\ intelligent}$, $A_{indeed\ intelligent}$ corresponding to the fuzzy logic statements $(x\ is\ intelligent)$, $(x\ is\ very\ intelligent)$, $(x\ is\ more\ or\ less\ intelligent)$ $(x\ is\ indeed\ intelligent)$ respectively can be seen in the next Figure 5, where $A_{intelligent}$, $A_{very\ intelligent}$, $A_{more\ or\ less\ intelligent}$, $A_{indeed\ intelligent}$ are represented with colors red, blue, green, and black, respectively.

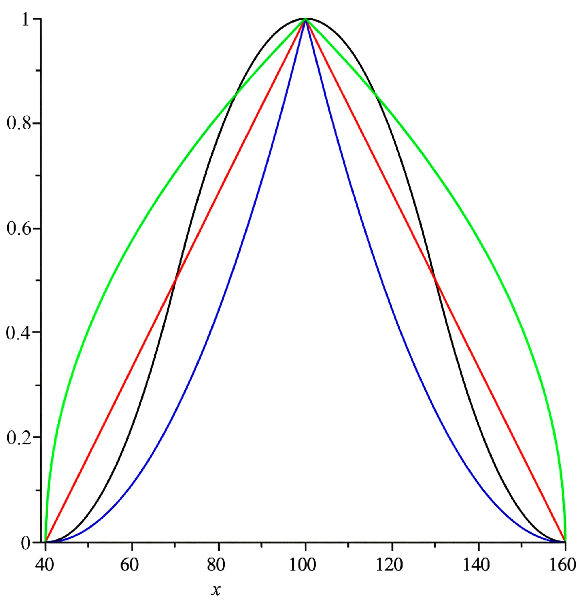

Figure 5: Fuzzy sets corresponding to the fuzzy logic statements: $(x\ is\ intelligent)$ color red; $(x\ is\ very\ intelligent)$ color blue; $(x\ is\ more\ or\ less\ intelligent)$ color green, $(x\ is\ indeed\ intelligent)$ color black.

It can be seen that:

- in case of the fuzzy logic statement $(x\ is\ very\ intelligent)$ the membership value of all the uncertain elements is less than in the case of the fuzzy logic statement $(x\ is\ intelligent)$;
- in case of the fuzzy logic statement $(x\ is\ more\ or\ less\ intelligent)$ the membership of all the uncertain elements is more than in the case of the fuzzy logic statement $(x\ is\ intelligent)$;
- in case of the fuzzy logic statement $(x\ is\ indeed\ intelligent)$ the membership value of uncertain elements x for which $DOFI(x\ is\ A_{intelligent}) \leq 0.5\ implies\ DOFII(x\ is\ A_{indeed\ intelligent}) \leq DOFI(x\ is\ A_{intelligent}) \leq 0.5$ and for those x for which $DOFI\ (x\ is\ A_{intelligent}) > 0.5$ inequality $DOFII\ (x\ is\ A_{indeed\ intelligent}) > DOFI\ (x\ is\ A_{intelligent})$.

Mathematically, these differences are generated by the choice of interpolation of the values $0\ at\ x^- = 40$; $1\ at\ x^* = 100$; $and\ 0\ at\ x^+ = 160$. In case of $A_{intelligent}$ the interpolation is piecewise linear; in the case of $A_{very\ intelligent}$, $A_{more\ or\ less\ intelligent}$ and $A_{indeed\ intelligent}$) is nonlinear.

If $A_{intelligent}$ describes the understanding of general intelligence, then $A_{very\ intelligent}$ describes a more exigent understanding of the general intelligence; $A_{more\ or\ less\ intelligent}$ describes a less exigent understanding of the general intelligence; $A_{indeed\ intelligent}$ represent a more exigent understanding of the general intelligence for the $IQ\ values\ in\ the\ intervals\ [40,\ 70]$ and $[130,\ 160]$ and $A_{indeed\ intelligent}$ represent a less exigent understanding of the general intelligence for the $IQ\ values\ in\ the\ interval\ [70,\ 130]$.

3.4. What Is the Linguistic Variable 'Human Intelligence'?

The formal definition of a linguistic variable Y is:

Definition 5.
$Y\ is\ a\ 4-tuple\ Y = (T,\ X,\ G,\ M)\ where:$
$T\ is\ a\ set\ of\ natural\ language\ terms\ from\ which\ t\ cantake\ on\ its\ values,\ X\ is\ a\ univers,$
$on\ which\ the\ fuzzy\ sets\ corresponding\ to\ the\ linguistic\ variable\ are\ defined,$
$G\ is\ a\ context\ free\ grammar\ used\ to\ generate\ the\ elements\ of\ T, and\ M\ is\ a\ mapping\ from\ T\ to\ the\ fuzzy\ subsets\ of\ X,\ M: T \rightarrow F$ see [58,64,65].

Linguistic variables enable natural language computation [58,64,65]. Sometimes there is no set X that can be naturally associated to the linguistic expression. This is because no objective measure exists for such expressions. For example, consider the linguistic terms good, pain, happy, joy, excellent, acceptable, and so on.

Definition 6.
We take the natural language term 'intelligent', adding the terms obtained with the 14 linguistic modifiers, obtaining a set T of 15 natural language terms T = {'intelligent

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',’very intelligent’,…}. For universe X *we take the set of real numbers*. The elements of the set F are the fuzzy subsets $A_{intelligent}$, $A_{very\ intelligent}$, $A_{more\ or\ less\ intelligent}$, $A_{indeed\ intelligent}$, *etc* $F = \{A_{intelligent}, A_{very\ intelligent}, A_{more\ or\ less\ intelligent}, A_{indeed\ intelligent}, \ldots\}$ corresponding to the elements of T and M *is the mapping from the set* T *to the set* F which associate to the elements of T the corresponding fuzzy subset from F. In this way, the kernel of a linguistic variable is obtained, which we will call ‘human intelligence’ linguistic variable.

In the next section, this kernel of the ‘human intelligence’ linguistic variable, which contains 15 elements, is expanded. This means that the sets T *and* F *are expanded*. The new terms which are added to T are generated by the fuzzy logic operators while the new fuzzy subsets added to the set F are the fuzzy subsets corresponding to the new terms added to T.

3.5. Extension of the Kernel of ‘Human Intelligence’ Linguistic Variable by Using Fuzzy Logic and Fuzzy Logic Operators [58,64,65]

In classic logic, a statement is true or false. For this reason, in Boolean mathematical logic two values 0 (false) and 1 (true) are assigned to any statement. In Table 1, the true values are given in case of the application of different logical operators.

Table 1: ‘Truth values resulting from the application of different logical operators in Boolean logic, where 0 represents false and 1 represents true’.

A	B	Not A	A (AND) B		A (XOR) B	A (IMPLY) B
1	1	0	1	1	0	1
1	0	0	0	1	1	0
0	1	1	0	1	1	1
0	0	1	0	0	0	1

where XOR stands for “either…, or,….”.

In fuzzy logic, no explicit functional form is assumed. Binary logic is replaced by fuzzy logic, in which a statement and its opposite can both be “true” to a certain degree. For example, both “severe” and “moderate” pathology may be partially true for a given patient. For fuzzy statements A and B, the “true value” can vary between 0 and 1. The Boolean table must be extended to handle such situations in a plausible manner.

The fuzzy logic operator *NOT* [59,64,65] In fuzzy logic, the fuzzy statement $(x\ is\ A)$ by the fuzzy logic operator NOT, is transformed into the fuzzy logic statement $(x\ is\ not\ A)$. The new fuzzy statement is usually denoted by $NOT(x\ is\ A)$ or $(x\ is\ not\ A)$. The fuzzy statement $(x\ is\ not\ A)$ is represented by the fuzzy subset usually denoted by $C = A^C$ and called the fuzzy complement of A. The membership function f_C of the fuzzy subset C representing the fuzzy statement $(x\ is\ not\ A)$ is by definition

$$f_C(x) = 1 - f_A(x) \tag{38}$$

Notation $f_{NOT\,A}$ *for the fuzzy complement of* A *is also usual*.

It can be seen that the following equalities hold:

$$DOF[NOT(xisA)] = f_{NOT\,A}(x) = 1 - f_A(x) = f_C(x)$$

Starting with the fuzzy logic statement $(x\ is\ intelligent)$ and its representation by the fuzzy subset $A_{intelligent,}$ then using the fuzzy logic operator NOT the fuzzy logic statement $(x\ is\ not\ intelligent)$ and its fuzzy set representative, the fuzzy complement *of* $A_{intelligent}$ *can be constructed*.

Namely the fuzzy subset $C_{not\ intelligent} = A^C_{intelligent}$.

In this way, the existing kernel of the human intelligence linguistic variable can be expanded with the new linguistic expression *not intelligent*, and the corresponding fuzzy subset $A^C_{intelligent}$

The fuzzy subset $A^C_{intelligent}$ as presented in Figure 6.

The above-described procedure can be repeated for all elements of the kernel of the human intelligence linguistic variable.

The fuzzy subsets $A^C_{very\ intelligent}$, $A^C_{more\ or\ less\ intelligent}$, $A^C_{indeed\ intelligent}$ are represented in the following Figures 7–9:

In this way, the existing kernel of the human intelligence linguistic variable, having 15 elements, is expanded with another 15 new elements.

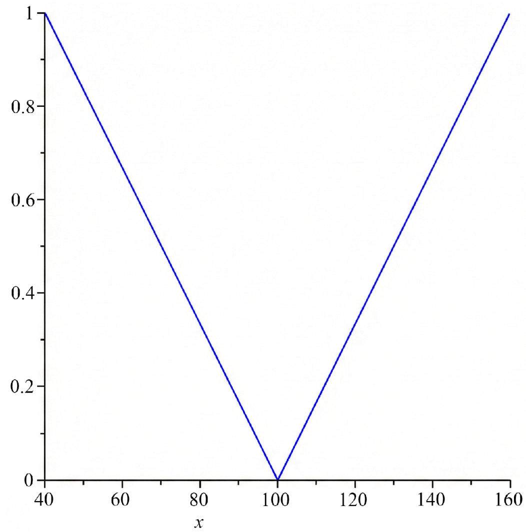

Figure 6: Fuzzy subset $A^C_{intelligent}$ representing the linguistic expression *not intelligent*.

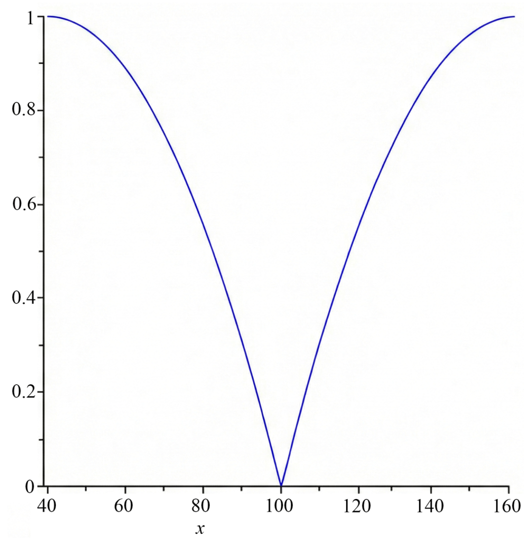

Figure 7: Fuzzy subset $A^C_{very\ intelligent}$ representing the linguistic variable very intelligent.

The fuzzy logic operator *AND*. According to [59, 64,65], in fuzzy logic, two types of ***AND*** fuzzy logic operators are used: the so-called 'minimum fuzzy logic operator ***AND*** 'and the so-called 'product fuzzy logic operator ***AND***'.

The 'minimum fuzzy logic operator *AND*'. [59, 64,65] In the case of two fuzzy statements $(x\ is\ A_1)$, $(x\ is\ A_2)$ the 'minimum fuzzy logic operator ***AND***' transform these statements in the fuzzy statement $\underline{(x\ is\ A_1)\boldsymbol{AND}(x\ is\ A_2)}$ denoted usually by' $\underline{minimum(x\ is\ A_1)\boldsymbol{AND}(x\ is\ A_2)}$ 'The fuzzy statement ' $\underline{minimum(x\ is\ A_1)\boldsymbol{AND}(x\ is\ A_2)}$' is described by the fuzzy subset $C_{minimum\ intersection}$ which membership function is

$$f_{C_{minimum\ intersection}}(x) = minimum\{f_{A_1}(x), f_{A_2}(x)\} \quad (39)$$

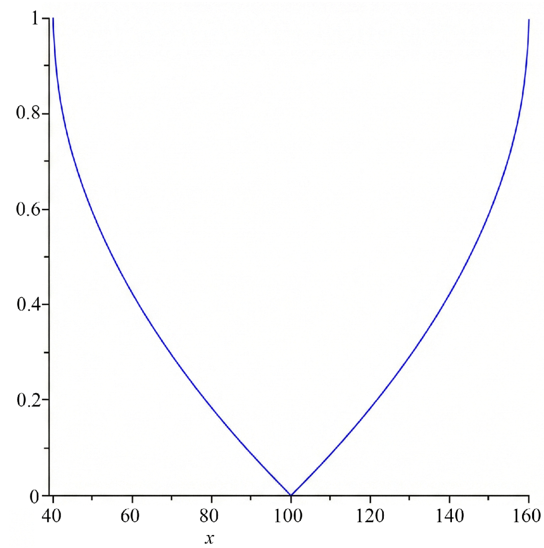

Figure 8: Fuzzy subset $A^C_{more\ or\ less\ intelligent}$ representing the linguistic variable more or less intelligent.

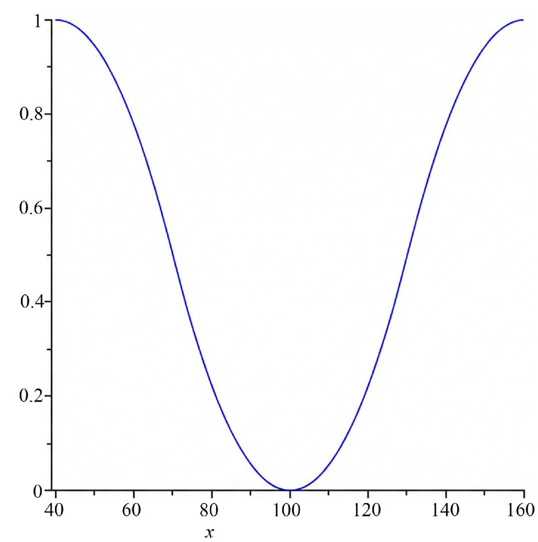

Figure 9: Fuzzy subset $A^C_{indeed\ intelligent}$ representing the linguistic variable indeed.

This fuzzy subset is usually denoted by $C_{minimum\ intersection} = minimum\ (A_1 \cap A_2)$ and is called the "minimum fuzzy intersection" of fuzzy subsets A_1 and A_2.

According to this definition, and Figure 5 is easy to see that the 'minimum fuzzy intersection' for some of the

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elements of the 'human intelligence linguistic variable', the following equalities hold:

$minimum(A_{intelligent} \cap A_{very\ intelligent} = A_{very\ intelligent}$; $minimum(A_{intelligent} \cap A_{more\ or\ less intelligent} = A_{intelligent}$;$minimum(A_{very intelligent} \cap A_{more\ or\ less\ intelligent} = A_{very\ intelligent}$;$minimum(A_{very\ intelligent} \cap A_{indeed\ intelligent} = A_{very\ intelligent}$ However, in general, the "minimum fuzzy intersection" for other elements of the 'human intelligence linguistic variable' requires a more complex computation of the membership function.

For example, in the case of the minimum intersection, $minimum\left(A_{intelligent} \cap A^C_{intelligent}\right)$ the following membership function is found:

$f_{minimum(A_{intelligent} \cap\ A^C_{intelligent})}(x) = 0\ for\ x \le 40$; $f_{minimum(A_{intelligent} \cap\ A^C_{intelligent})}(x) = \frac{x-40}{60}\ for\ 40 < x \le 70$;

$f_{minimum(A_{intelligent} \cap\ A^C_{intelligent})}(x) = 1 - \frac{x-40}{60}\ for\ 70 < x \le 100$; $f_{minimum(A_{intelligent} \cap\ A^C_{intelligent})}(x) = 1 - \frac{160-x}{60}\ for\ 100 < x \le 130$;

$f_{minimum(A_{intelligent} \cap\ A^C_{intelligent})}(x) = \frac{160-x}{60}\ for\ 130 < x \le 160$; $f_{minimum(A_{intelligent} \cap\ A^C_{intelligent})}(x) = 0\ for\ 160 < x$.

The fuzzy subset $minimum(A_{intelligent} \cap A^C_{intelligent})$ as presented in Figure 10.

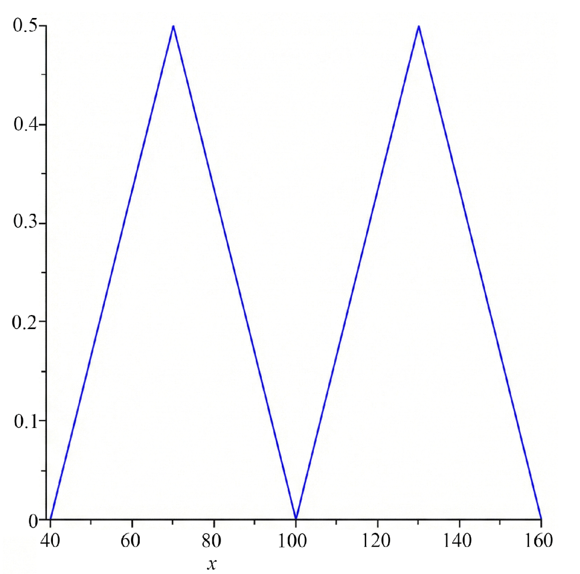

Figure 10: Fuzzy subset $minimum\ intersection\left(A_{intelligent} \cap A^C_{intelligent}\right)$.

We emphasize that

$$DOF[\left(x\ is\ minimum\left(A_{intelligent} \cap A^C_{intelligent}\right)\right)] = f_{minimum(A_{intelligent} \cap\ A^C_{intelligent})}(x)$$

for $x = 70\ and\ x = 130\ is\ equal\ to\ 0.50$. This situation is similar to the one already mentioned, in which both "severe" and "moderate" pathology may be true for a given patient.

Representing the fuzzy statement '$intelligent\ and\ non\ intelligent$' $with\ the\ fuzzy\ subset\ minimum\left(A_{intelligent} \cap A^C_{intelligent}\right)$ permits the introduction of the fuzzy statement '$intelligent\ and\ non\ intelligent$' together with the $fuzzy\ subset\ minimum(A_{intelligent} \cap A^C_{intelligent}$ as a novel element of the human intelligence linguistic variable. According to this new linguistic variable, the $DOF[\left(x\,is\,minimum\left(A_{intelligent} \cap A^C_{intelligent}\right)\right)]$ is less than or equal to 0.5 for every IQ index from the data set (2).

In case of the minimum intersection, $minimum(A_{intelligent} \cap A_{indeed\ intelligent})$ the following membership function is found:

$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = 0\ for\ x \le 40$; $f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = 2 \times \left(\frac{x-40}{60}\right)^2\ for\ 40 < x \le 70$

$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = \frac{100-x}{60}\ for\ 70 < x \le 100$; $f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = \frac{x-100}{60}\ for\ 100 < x \le 130$

$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = 2 \times \left(\frac{160-x}{60}\right)^2\ for\ 130 < x \le 160$; $f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = 0\ for\ 160 < x$

We emphasize that

$$DOF[(x\ is\ minimum(A_{intelligent} \cap A_{indeed\ intelligent}))] = f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x)$$

Representing the fuzzy statement (Figure 11) '*intelligent and indeed intelligent*' *with the fuzzy subset minimum* $(A_{intelligent} \cap A_{indeed\ intelligent})$

a novel element of the human intelligence linguistic variable, is constructed.

Product fuzzy logic operator AND [59,64,65] The **'product fuzzy logic operator *AND*'** transform two fuzzy statements $(x\ is\ A_1)$, $(x\ is\ A_2)$ in the fuzzy statement $(x\ is\ A_1)$ $\boldsymbol{AND}(x\ is\ A_2)$ denoted usually by '$product(x\ is\ A_1)$ $\boldsymbol{AND}(x\ is\ A_2)$'. The fuzzy statement ' $product(x\ is\ A_1)\boldsymbol{AND}(x\ is\ A_2)$ 'is described by the fuzzy subset $C_{product\ intersection}$ which membership function is

$$f_{C_{product\ intersection}}(x) = f_{A_1}(x) \times f_{A_2}(x) \tag{40}$$

This fuzzy subset usually is denoted by $C_{product\ intersection} = product\ (A_1 \cap\ A_2)$ and is called the 'product fuzzy intersection' of fuzzy subsets A_1 and A_2.

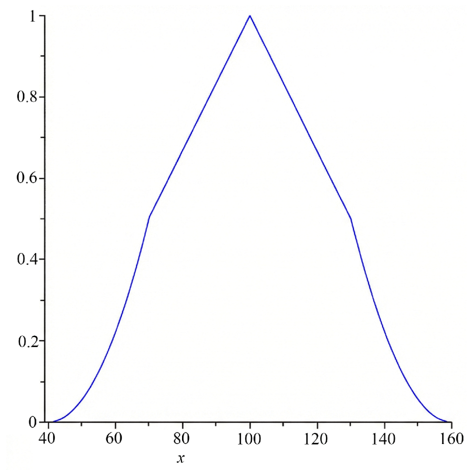

Figure 11: Fuzzy subset, $minimum\ intersection(A_{intelligent} \cap A_{indeed\ intelligent})$.

In general, the 'product fuzzy intersection' for the elements of the 'human intelligence linguistic variable' require the computation of the membership function using (40). For example if A_1 is the fuzzy subset $A_{intelligent}$ and A_2 is the fuzzy subset $A_{very\ intelligent}$ then their "prod fuzzy intersection" computed with (40) as presented in Figure 12.

Representing the fuzzy statement '*intelligent and very intelligent*' *with the fuzzy subset product* $(A_{intelligent} \cap A_{very\ intelligent})$ a novel element of the human intelligence linguistic variable, is constructed.

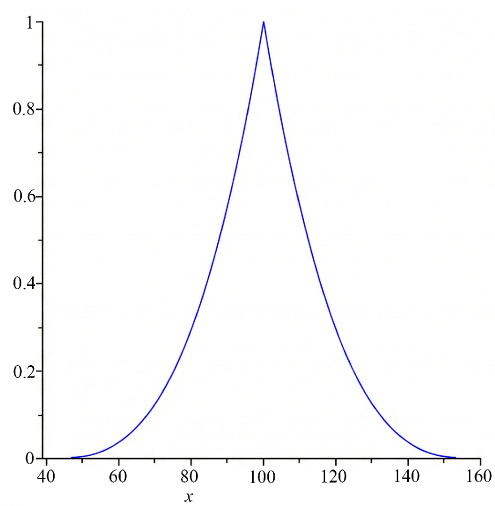

Figure 12: Fuzzy subset, $product\ intersection(A_{intelligent} \cap A_{very\ intelligent})$.

We emphasize that $DOF[(x\ is\ product(A_{intelligent} \cap A_{very\ intelligent})) = f_{A_{intelligent}}(x) \times f_{A_{very\ intelligent}}(x)$

Fuzzy logic operator *OR*. According to [59,64,65] in fuzzy logic, two types of fuzzy logic operators ***OR*** are used: the so-called 'maximum fuzzy logic operator ***OR***' and a so-called 'product fuzzy logic operator ***OR***'

Maximum fuzzy logic operator *OR*. [59,64,65] The 'maximum fuzzy logic operator ***OR'*** transforms two fuzzy statements $(x\ is\ A_1)$, $(x\ is\ A_2)$ in the fuzzy statement

$(x\ is\ A_1)\boldsymbol{OR}$, $(x\ is\ A_2)$ denoted usually with '$maximum(x\ is\ A_1)\boldsymbol{OR}(x\ is\ A_2)$'. The fuzzy statement ' $maximum(x\ is\ A_1)\boldsymbol{AND}(x\ is\ A_2)$' is described by the fuzzy subset

$C_{maximum\ union}$ which membership function is

$$f_{C_{maximum\ union}}(x) = maximum\{f_{A_1}(x), f_{A_2}(x)\} \tag{41}$$

This fuzzy subset is usually denoted by $C_{maximum\ union} = maximum\ (A_1 \cup\ A_2)$ and is called the 'maximum fuzzy union' of fuzzy subsets A_1 and A_2.

In general, the 'maximum fuzzy union' for the elements of the 'human intelligence linguistic variable' requires the computation of the membership function using (41). For example if A_1 is the fuzzy subset $A_{intelligent}$ and A_2 is the fuzzy subset $A_{indeed\ intelligent}$ then their "maximum fuzzy union" is computed with (3.5.4) as presented in Figure 13.

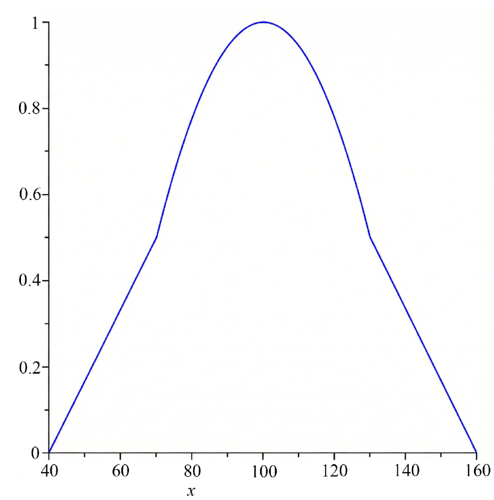

Figure 13: $Maximum\ union\ (A_{intelligent} \cup A_{indeed\ intelligent})$.

Representing the fuzzy statement *'intelligent or indeed intelligent' with the fuzzy subset maximum* $(A_{intelligent} \cup A_{indeed\ intelligent})$ a novel element of the human intelligence linguistic variable, is constructed.

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We emphasize that $DOF[(x \; is \; maximum \; (A_{intelligent} \cup A_{indeed \; intelligent}))$ = $maximum \; \{f_{\; A_{intelligent}}(x), f_{A_{indeed \; intelligent}}(x)\}$.

Product fuzzy logic operator [59,64,65]. The 'product fuzzy logic operator ***OR'*** transforms two fuzzy statements $(x \; is \; A_1), (x \; is \; A_2)$ in the fuzzy statement

$(x \; is \; A_1)\boldsymbol{OR}$, $(x \; is \; A_2)$ denoted usually with '$product(x \; is \; A_1)\boldsymbol{OR}(x \; is \; A_2)$'. The fuzzy statement ' $product(x \; is \; A_1)\boldsymbol{OR}(x \; is \; A_2)$ 'is described by the fuzzy subset

$C_{product \; union}$ which membership function is

$$f_{C_{product \; union}}(x) = f_{A_1}(x) + f_{A_2}(x) - f_{A_1}(x) \times f_{A_2}(x) \tag{42}$$

This fuzzy subset is usually denoted by $C_{product \; union} = product(A_1 \cup A_2)$ and is called the 'product fuzzy union' of fuzzy subsets A_1 and A_2.

In general, the 'product fuzzy union' for the elements of the 'human intelligence linguistic variable' requires the computation of the membership function using (42). For example if A_1 is the fuzzy subset $A_{intelligent}$ and A_2 is the fuzzy subset $A_{indeed \; intelligent}$ then their "maximum fuzzy union" is computed with (42) as presented in Figure 14.

Representing the fuzzy statement *'intelligent or indeed intelligent' with the fuzzy subset product union* $(A_{intelligent} \cup A_{indeed \; intelligent})$ a novel element of the human intelligence linguistic variable, is constructed.

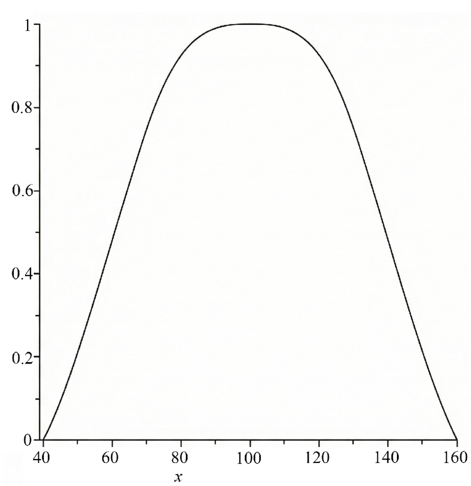

Figure 14: Fuzzy subset '$product \; union \; (A_{intelligent} \cup A_{indeed \; intelligent})$.

We emphasize that $DOF[(x \; is \; product \; union \; (A_{intelligent} \cup A_{indeed \; intelligent})) = f_{A_{intelligent}}(x) + f_{A_{indeed \; intelligent}}(x) - f_{A_{intelligent}}(x) \times f_{A_{indeed \; intelligent}}(x)$.

Fuzzy logic operator *XOR*. According to [59,64,65] in fuzzy logic, two kinds of XOR operator is used in the so-called **'product fuzzy logic operator *XOR*** 'and a so-called **'min-max fuzzy logic operator *XOR*'**.

Product fuzzy logic operator *XOR*. [59,64,65] The **'product fuzzy logic operator *XOR'*** transforms two fuzzy statements $(x \; is \; A_1)$, $(x \; is \; A_2)$ in the fuzzy statement

$(x \; is \; A_1)\boldsymbol{XOR}(x \; is \; A_2)$ denoted usually with '$product(x \; is \; A_1)\boldsymbol{XOR}(x \; is \; A_2)$'. The fuzzy statement ' $product(x \; is \; A_1)XOR(x \; is \; A_2)$' is described by the fuzzy subset

$C_{product \; XOR \; union}$ which membership function is

$$f_{C_{product \; XOR \; union}}(x) = f_{A_1}(x) + f_{A_2}(x) - 2 \times f_{A_1}(x) \times f_{A_2}(x) \tag{43}$$

This fuzzy subset is usually denoted by $C_{product \; XOR \; union} = product \; XOR \, union \; (A_1 \cup \; A_2)$ and is called the 'product fuzzy XOR union of fuzzy subsets A_1 and A_2.

In general, the 'product fuzzy XOR union' for the elements of the 'human intelligence linguistic variable' requires the computation of the membership function using (43). For example if A_1 is the fuzzy subset $A_{intelligent}$ and A_2 is the fuzzy subset $A_{indeed \; intelligent}$ then their 'product fuzzy XOR union computed with (43) as presented in Figure 15.

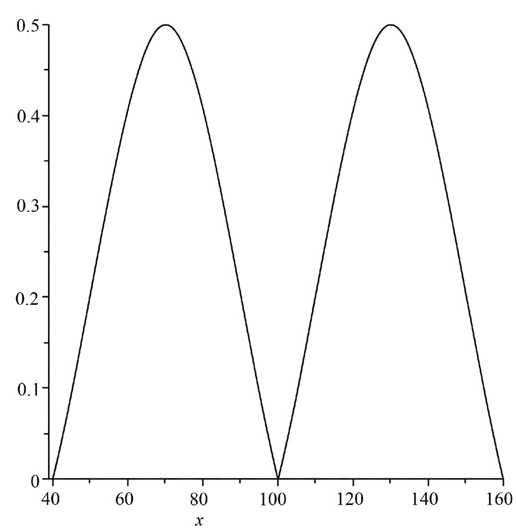

Figure 15: $Product \; fuzzy \; XOR \; union \; (A_{intelligent} \cup A_{indeed \; intelligent})$.

Representing the fuzzy statement *'intelligent XOR indeed intelligent' with the fuzzy subset product fuzzy XOR union* $(A_{intelligent} \cup A_{indeed \; intelligent})$ a novel element of the human intelligence linguistic variable, is constructed.

We emphasize that $DOF[(x\ is\ product\ XOR\ union\ (A_{intelligent} \cup A_{indeed\ intelligent}))] = f_{A_{intelligent}}(x) + f_{A_{indeed\ intelligent}}(x) - 2 \times f_{A_{intelligent}}(x) \times f_{A_{indeed\ intelligent}}(x)$.

Min-Max fuzzy logic operator *XOR*. [59,64,65] 'Minimum-Maximum fuzzy logic operator ***XOR'*** transforms two fuzzy statements $(x\ is\ A_1)$, $(x\ is\ A_2)$ in the fuzzy statement

$(x\ is\ A_1)$***XOR***, $(x\ is\ A_2)$ denoted usually with

'$minimum{-}maximum(x\ is\ A_1)\boldsymbol{XOR}(x\ is\ A_2)$'.

The fuzzy statement '$minimum - maximum\ (x\ is\ A_1)\boldsymbol{XOR}(x\ is\ A_2)$' is described by the fuzzy subset $C_{minimum-maximum\ XOR\ union}$ which membership function is

$$f_{C_{minimum-maximum\ XOR\ union}}(x) = maximum\{minimum[1 - f_{A_1}(x), f_{A_2}(x)],\ minimum[1 - f_{A_2}(x), f_{A_1}(x)]\} \quad (44)$$

This fuzzy subset usually is denoted by $C_{minimum\ maximum\ XOR\ union} = minimum\ maximum\ XOR\ union\ (A_1 \cup A_2)$ and is called the 'minimum maximum fuzzy XOR union' of fuzzy subsets A_1 and A_2.

In general, the 'minimum maximum fuzzy XOR union' for the elements of the 'human intelligence linguistic variable' require the computation of the membership function using (44).

For example, if A_1 is the fuzzy subset $A_{intelligent}$ and A_2 is the fuzzy subset $A_{indeed\ intelligent}$ then for $IQ = x = 71$ the following equalities hold:

$$f_{A_{intelligent}}(x) = 0.5166666667;$$
$$f_{A_{indeed\ intelligent}}(x) = 0.5327777778;$$
$$1 - f_{A_{intelligent}}(x) = 0.4833333333;$$
$$1 - f_{A_{indeed\ intelligent}}(x) = 0.467222222;$$

$$minimum[1 - f_{A_1}(x), f_{A_2}(x)] = minimum[0.4833333333, 0.5327777778] = 0.4833333333;\ minimum[1 - f_{A_2}(x), f_{A_1}(x)] = minimum[0.467222222, 0.5166666667] = 0.467222222$$

Therefore $DOF[(x = 71\ is\ minimum\ maximum\ XOR\ union\ (A_{intelligent} \cup A_{indeed\ intelligent})) = 0.4833333333$

Representing the fuzzy statement '$intelligent\ XOR\ indeed\ intelligent$' with the fuzzy set minimum maximum fuzzy $XOR\ union\ (A_{intelligent} \cup A_{indeed\ intelligent})$ a novel element of the human intelligence linguistic variable, is constructed.

4. Discussions

A computational model is constructed, which is called the 'human intelligence' linguistic variable. This model makes possible a new quantitative evaluation of an IQ index, depending on how "human intelligence" is understood. The new quantitative evaluation index is the 'true value of IQ '=DOF(IQ)=' degree of membership of IQ'. Computations are presented within this framework, and significant differences are revealed with respect to, for example, the computational identification of groups of individuals with IQ indices within a given range, the interpretation of fuzzy logic concepts, the meaning of operations on fuzzy sets, and the interpretation of fuzzy logic operators. This constitutes the main contribution of the paper. To the best of our knowledge, a comparable computational model for the linguistic variable 'human intelligence' has not been reported. The study has limited applications, and further research is needed on reasoning rules, rule systems, and modeling real-world phenomena using the constructed computational model of the linguistic variable "human intelligence.".

Nowadays, it is common to classify scientific journals, universities, researchers, and individuals based on numerical parameters obtained by aggregating measured parameters. IQ scores are an example of numerical outcomes obtained from psychometric tests. Classifying individuals based solely on IQ scores yields an unambiguous numerical categorization. However, this result raises a relevant question for those who use IQ scores for classification: does the term "intelligent" carry the same meaning for everyone? This question is natural, given that intelligence does not have a universally accepted definition.

The term 'intelligent' is an ambiguous word. For this reason, an individual IQ number must be accompanied by a second number called the degree of fulfillment of the individual IQ number, which reflects a certain degree of ambiguity in the interpretation of the word intelligent. This second number is calculated using the fuzzy set attached to a concrete understanding of the word intelligent and represents the confidence value (true value) of that IQ index.

5. Conclusions

A computational model was constructed, which is called the 'human intelligence' linguistic variable. This model en-

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ables a new quantitative evaluation of an IQ index, depending on how "human intelligence" is defined and understood. The new quantitative evaluation index is the 'true value of IQ '=DOF(IQ)='degree of membership of IQ'

Author Contributions

Both authors were equally involved in conceptualization, methodology, software development, validation, formal analysis, investigation, data curation, manuscript preparation (original draft), manuscript revision, editing, visualization, and project administration. All authors have read and agreed to the final version of the manuscript.

Availability of Data and Materials

The data supporting the findings of this study are included within the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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AI Declaration

The authors confirm that no AI tools were used to generate any content of this manuscript.

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