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Research Article

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

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Abstract

This paper, present a fuzzy, computational model for the natural languish world 'human intelligence'. This is a mathematical model, which takes into account on different kind of understanding of the word 'intelligent' and make possible the comparison between different kind of understanding of the word 'intelligent' in case of a given IQ index. The model is a linguistic variable mathematical model, build especially for the word 'human intelligence' and is called the 'human intelligence' linguistic variable. The model is constructed systematically along the whole paper. The first step consists in the representation of the word 'human intelligence' with a fuzzy set. This step is followed by the construction of fuzzy sets corresponding to the words obtained adding different hedges to the word 'intelligent' (i.e., very intelligent, more or less intelligent etc.) The steps, which follows, use fuzzy logic operators and fuzzy sets operations in order to further expand the set of different possible understandings of the word human intelligence. Along the whole paper different example are presented in order to illustrate the new element, incorporated in the 'human intelligence' linguistic variable, and illustrate computation with the new added element.

Keywords:

IQ index; linguistique variable; fuzzy set; fuzzy logic concepts; fuzzy logic operators

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 being simultaneously, faber and sapiens, the intellectual capacity of humans, denoted by complex cognition actions and strong degree of motivation and self-consciousness, is referred to as human intelligence. Humans can learn, develop, comprehend, and use logic and reason with the help of their intelligence. Human intelligence is also believed to be their ability to recognise patterns, plan, be innovative, solve problems, make decisions, remember things and their ability to communicate using language. The term 'human intelligence' has been present since time immemorial in natural language, enshrined in literature and characterizes (from various angles) the power and function of the human mind to establish connections and make connections between connections: it is what suggests inter-legere, bringing together two meanings—to discriminate between and to bind (to gather, to put together). Of all human abilities, the most specifically human characteristic is intelligence, given that it transforms biological man into *Homo sapiens*. However, intelligence is not a material thing, but an abstract concept, being difficult to define. We can say that one analyzes the manifestations of intelligence, the faculties that define intelligence,

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but not intelligence itself. Taking into account on the above presented facts, it follows that the natural languish word 'human intelligence' is fuzzy and inappropriate for computation [1–5].

On the other hand, fuzzy set logic provides a mean for dealing with ambiguity. As it deals with imprecise objects, it has been and, for a number of scientists, remains an unacceptable tool in the precise world of science. The success of fuzzy logic surprisingly began with industrial applications including train control (Yasunobu and Miyamoto 1985), auto-focusing cameras (Shingu and Nishimori 1989) or cement kiln control (Holmblad and Ostergaard 1982). Fuzzy logic is used to describe, ambiguity and uncertainty in case of the 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 along the whole paper. The first step consists in 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 adding different hedges to the word 'intelligent' (i.e., very intelligent, more or less intelligent etc.) The steps, which follows, use fuzzy logic operators and fuzzy sets operations in order to further expand the set of different possible understandings of the word 'human intelligence'. Along the whole paper different examples are presented in order to illustrate the properties of new elements incorporated in the 'human intelligence 'linguistic variable and illustrate computation with the new added element. As far as we know for human intelligence such a mathematical construction does not exist. This is mainly the novelty in this paper.

In Section 2, the meaning of the natural languish word 'human intelligence' during history is presented. In Section 3.1, the measurement of 'human intelligence' and the meaning of IQ index during history is presented. In Section 3.2, the fuzzy set description of 'human intelligence' is presented. In Section 3.3, the effect of linguistic modifiers, in case of the natural languish 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 by each psychological school according to the general postulates of the conception of Man. 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 changed a lot. 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 about 7 million years, from the separation of the genus Pan to the emergence of behavioral modernity 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 of the evolution of human intelligence include: Robin Dunbar's Social Brain Hypothesis [2], Geoffrey Miller's sexual selection hypothesis (concerning sexual selection in human evolution) [3], The hypothesis called ecological dominance-social competition (EDSC) [4] (explained by Mark V. Flinn, David C. Geary, and Carol V. Ward, based primarily on the work of Richard D. Alexander), The intelligence hypothesis as a signal of good health and disease resistance, The hypothesis called group selection theory (this holds that organismal characteristics that benefit a group (clan, tribe, or larger population) can evolve despite individual disadvantages, such as those cited above), The hypothesis that intelligence is connected to nutrition and thus to status.[5] (this supports the idea that a higher IQ in a person could be a signal that the person comes from and lives in a physical and social environment where nutrition levels are high and vice versa).

Theories of the human intelligence include:

-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].

-There was also a proposal by Robert Sternberg that he came up with the triarchic theory of intelligence in an attempt to give a more detailed description of the intellectual competence as opposed to the traditionalized difference or cognitive theories of human ability [13–19].

-Piaget theory and Neo-Piagetian theories. The theory of cognitive development by Piaget was not centered on mental abilities but instead on mental models of the world of a child. The child also forms more and more correct representations of the world as a child grows to allow the child to interact with the world more successfully [20–24].

on the way progress could be diversified in various areas like a spatial or social one social.

-Intelligibility-Parieto-frontal integration theory. On the basis of a meta-analysis of 37 neuroimaging studies [25–27].

-Investment theory. According to the CattellHornCarroll 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 [28–32].

-Intelligence compensation theory (ICT). According to the intelligence compensation theory [33–37], 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 [38,39]. The perception of cognitive ability has been changed throughout the years and is no longer considered as a fixed property possessed by an individual.

-Process, personality, intelligence and knowledge theory (PPIK) [40–44].

-Latent inhibition. The phenomenon of familiar stimuli being associated with a delayed reaction time in comparison with unfamiliar stimuli, which is known as Latent inhibition, seems 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 model that approaches the concept of understanding intelligence in the greatest number of supporters and published research over the longest time. It is also far, far, far by far, the most popular when dealing with a practical environment. With the growth of mental testing to test adolescents and adults, however, there was need of a measure of intelligence that was independent of mental age.

In this regard, intelligence quotient (IQ) was created. 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. Part of the implications are that:

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 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, where we are simply rank-ordering 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 being measured. A dependable test has the same scores when repeated. It is the case that any given estimate of IQ comes with a standard error which quantifies the uncertainty regarding the estimate. In the case of modern tests, confidence interval may be approximated to 10 points and reported standard error of measurement may be as low as three points. The reported standard error can also be an underestimation because it does not take into consideration all sources of error. Reliability and standard errors of measurement in 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 like lack of motivation or anxiety might sometimes reduce the IQ test of an individual. In the case of those scoring very low, the 95% confidence interval can be higher than 40 points, and this might make 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, errors of measurement for scale scores will increase substantially at the extremes of the distribution. Commonly the SEM is from two to four times larger for very high scores than for scores near the mean.

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

Validity is the term associated with the fact that the test can measure what it is said to measure IQ tests are normally thought to measure certain types of intelligence; it might not be an effective measure of the wider definitions of human intelligence. It is against this reason that psychologist Wayne Weiten opines that their construct validity should be qualitatively restrained, and not over rated. Weiten further states that IQ tests are good indicators of a 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 Means Fuzzy Set Description of 'Human Intelligence'?

In mathematics, fuzzy sets were first introduced by Zadeh [45] in1965, have been applied in various field as: linguistics [46–48]; decision-making [49]; control [6–8]; theory of possibilities [50,51]; medicine [52–54]. Recent applications are presented in [55,56].

In case of an ordinary set for each object it can be decided whether it belongs or not to the set. A fuzzy set is a collection of objects without well-defined characteristics. In contrast with ordinary sets, a partial membership to a fuzzy set is possible.

The formal definition of a fuzzy set according to [45] is:

Definition 3.2.1. *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 ben regarded as the 'true value 'of the statement' x *belongs to* A '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.

Special case of fuzzy sets are fuzzy numbers.

Definition 3.2.2. *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 flat part.

Definition 3.2.3. *A fuzzy subset A of the real numbers R is a triangular fuzzy number if there exists 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 earthquakes intensity description is justified by the followings. 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 surface. It is known that the measuring instruments begin to saturate at about 7.00 amplitude intensity units and that by furthermore the measurements are by nature imprecise. In a fuzzy description, it is 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 from an expert may be obtained, say the 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 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 represent a difference with respect to the usually accepted normally or at least symmetrically distributed error.

Other techniques are available to assess membership functions depending on the type of imprecision described by a fuzzy set.

As membership functions are often related to the perception by humans, it might be reasonable to take the human response to outside stimuli into account.

Once the membership function has been assessed, a sensitivity analysis may be performed to find out if further refinement will be 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 expressions "human intelligence" concern a set of intellectual properties of humans and it is evaluated quantitatively with IQ index. However, the natural language expression 'human intelligence' is too vague (fuzzy) to perform computation based only on IQ index. The word intelligent may has different meanings for different persons. For example 'intelligent' for a person may be means 'very intelligent' for a second person and may be means 'more or less intelligent' for a third person. In which kind this kind of details are incorporated in IQ index is opaque, and can explain different appreciations of a person, by the members of a jury, in case of a competition. Fuzzy set model for 'human intelligence' and 'fuzzy logic' using IQ values could be a new approach which incorporate the fuzzy character of the natural languish expression and transform the expression 'human intelligence' into a computationally usable form.

In order to see how this can be put in practice consider in case of the natural language expression 'human intelligence', as ordinary set X (universe) the set of the real numbers R and the interval of real numbers $(40, 160)$.This last because for individuals with very low scores, the 95% confidence interval may be greater than 40 IQ points, potentially complicating the accuracy of diagnoses of intellectual disability. and, high IQ scores are also significantly less reliable than those near to the population median. (reports of IQ scores much higher than 160 are considered dubious.). Hence the idea that,

Definition 3.2.4. *The fuzzy subset* $A_{intelligent}$ *corresponding to the word 'human intelligence is the set of ordered pairs:*

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

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

$$\boldsymbol{f_{A_{intelligent}}(x) = 0\ for\ x \le 40; f_{A_{intelligent}}(x) = \frac{x-40}{60}\ \ for\ 40 < x \le 100;\ \ f_{A_{intelligent}}(x) = -\frac{x-160}{60}\ \ for\ 100 < x \le 160;\ f_{A_{intelligent}}(x) = 0\ for\ \ 160 < x} \tag{3.2.1}$$

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 $x^* = 100 = \boldsymbol{the\ most\ credible\ IQ\ index})$ .That is because two-thirds of the population scoring between IQ index 85 and 115.

The graphic as presented in Figure 1.

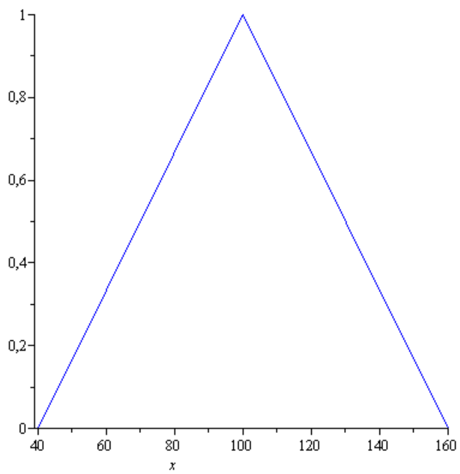

Figure 1. Fuzzy subset $A_{intelligent}\ corresponding\ to\ the\ fuzzy\ statement\ (x\ is\ intelligent)$ in WAIS scale.

The graphic describes (corresponds) 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 fuzzy subset $\boldsymbol{A_{intelligent}}$ ambiguity in the interpretation of the IQ index is introduced. The 'true value'= grade of membership = the number $\boldsymbol{f_{A_{intelligent}}(x = IQ)} = \boldsymbol{DOF(x = IQ\ is\ A_{intelligent})}$ 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 that obtained using $f_{A_{intelligent}}(x = IQ)$ values. For example in the case of the set of IQ points:

$$IQ := [71, 74, 53, 61, 41, 50, 65, 72, 119, 115, 119, 120, 125, 124, 125, 125, 129, 129, 123, 49, 50, 50, 47, 65, 132, 135, 153, 152, 42, 60, 80, 81, 95, 100, 105] \tag{3.2.2}$$

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if we agree that people with IQ points less than 85 are 'less than intelligent persons, with IQ pints between 85 and 115 are intelligent and people with IQ points between 115
and 160 are more than intelligent persons,
the next results is obtained:
-less than intelligent persons

$$[71, 74, 53, 61, 41, 50, 65, 72, 49, 50, 50, 47, 65, 42, 60, 80, 81] \quad (3.2.3)$$

-intelligent persons

$$[95, 100, 105] \quad (3.2.4)$$

-more than intelligent persons

$$[119, 115, 119, 120, 125, 124, 125, 125, 129, 129, 123, 132, 135, 153, 152] \quad (3.2.5)$$

In case of this identification there are: 17 less than intelligent persons, 3 intelligent person and 15 more than intelligent persons.

The above identification uses strictly IQ index 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 IQ index is questionable."

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

In case of the of IQ indexes given by (3.2.2) 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 $DOF(x = IQ\ is\ A_{intelligent})\ values = 'the\ tru\ valu'\ of\ the\ statement\ (x = IQ\ is\ A_{intelligent})$ obtained in this way is:

$$\begin{aligned} DOFIIQ := [&0.5166666667, 0.5666666667, 0.2166666667, \\ &0.3500000000, 0.01666666667, 0.1666666667, 0.4166666667, \\ &0.5333333333, 0.6833333333, 0.7500000000, 0.6833333333, \\ &0.6666666667, 0.5833333333, 0.6000000000, 0.5833333333, \\ &0.5833333333, 0.5166666667, 0.5166666667, 0.6166666667, \\ &0.1500000000, 0.1666666667, 0.1666666667, 0.1166666667, \\ &0.4166666667, 0.4666666667, 0.4166666667, 0.1166666667, \\ &0.1333333333, 0.03333333333, 0.3333333333, 0.6666666667, \\ &0.6833333333, 0.9166666667, 1, 0.9166666667] \end{aligned} \quad (3.2.6)$$

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 decide at the start, to reject those candidates whose $DOFI(IQ)$ values is low, for example less than 0.5 point, and accept only those candidates whose $DOFI(IQ)$ 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 (3.2.2) is the following:

-rejected candidates.

$$\begin{aligned} &0.2166666667, 0.3500000000, 0.01666666667, 0.1666666667, \\ &0.4166666667, 0.1500000000, 0.1666666667, 0.1666666667, \\ &0.1166666667, 0.4166666667, 0.4666666667, 0.4166666667, \\ &0.1166666667, 0.1333333333, 0.03333333333, 0.3333333333 \end{aligned} \quad (3.2.7)$$

-accepted candidates.

$$0.5166666667, 0.5666666667, 0.5333333333, 0.6833333333, 0.7500000000, 0.6833333333, 0.6666666667, 0.5833333333, 0.6000000000, 0.5833333333, 0.5833333333, 0.5166666667, 0.5166666667, 0.6166666667, 0.6666666667, 0.6833333333, 0.9166666667, 1, 0.9166666667 \quad (3.2.8)$$

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

For 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 candidate' classified according to his IQ index has to be divided in two subgroups: candidates having $DOFI(IQ)$ point less than 0.5 and candidates having $DOFI(IQ)$ point more than 0.5 point.

The obtained result is the following.

The set of $DOFLI(IQ)$ of 'less intelligent' candidates given by (3.2.3) is

$$DOFILI(IQ)\ [0.5166666667, 0.5666666667, 0.2166666667, 0.3500000000, 0.01666666667, 0.1666666667, 0.4166666667, 0.5333333333, 0.1500000000, 0.1666666667, 0.1666666667, 0.1166666667, 0.4166666667, 0.03333333333, 0.3333333333, 0.6666666667, 0.6833333333] \quad (3.2.9)$$

-accepted candidates at the start from the group

$$[0.5166666667, 0.5666666667, 0.5333333333, 0.6666666667, 0.6833333333] \quad (3.2.10)$$

-rejected candidates at the start from the group

$$[0.2166666667, 0.3500000000, 0.01666666667, 0.1666666667, 0.4166666667, 0.1500000000, 0.1666666667, 0.1666666667, 0.1166666667, 0.4166666667, 0.03333333333, 0.3333333333] \quad (3.2.11)$$

In the group of less than intelligent candidates, there are 17 candidates. It is interesting to remark 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 (3.2.4) is

$$DOFI(IQ) = DOFI := [0.9166666667, 1, 0.9166666667]; \quad (3.2.12)$$

-accepted candidates at the start from the group

$$[0.9166666667, 1, 0.9166666667] \quad (3.2.13)$$

-rejected candidates at the start from the group

$$[\,] \quad (3.2.14)$$

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 at the competition due to their high $DOFI(IQ)$ values.

The set of $DOFIMI(IQ)$ of 'more than intelligent' candidates given by (3.2.5) is

$$DOFIMI := [0.6833333333, 0.7500000000, 0.6833333333, 0.6666666667, 0.5833333333, 0.6000000000, 0.5833333333, 0.5833333333, 0.5166666667, 0.5166666667, 0.6166666667, 0.4666666667, 0.4166666667, 0.1166666667, 0.1333333333]; \quad (3.2.15)$$

-accepted candidates at the start from the group

$$[0.6833333333, 0.7500000000, 0.6833333333, 0.6666666667, 0.5833333333, 0.6000000000, 0.5833333333, 0.5833333333, 0.5166666667, 0.5166666667, 0.6166666667] \quad (3.2.16)$$

-rejected candidates at the start from the group

$$[0.4666666667, 0.4166666667, 0.1166666667, 0.1333333333] \quad (3.2.17)$$

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 was 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, at the start 16 candidates were rejected because the low value 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 Case of the Natural Languish Expression 'Human Intelligence'?

In natural language frequently, a specification of the properties is often done using linguistic modifiers (hedges) [46]. These modifiers might both increase or decrease the uncertainty. Some of this hedge are: VERY, FAIRLY, MOSTLY, OFTEN, SOMEWHAT, INDEED, ROUGHLY, ALMOST, MORE OR LESS, SORT OFF, PRACTICALLY, NOT, MOST OFF, AT LEAST A FEW. These hedges are applied to fuzzy linguistic expression, 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 (3.2.1), 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,[46,53,54] given by:

$$f_{A_{very-intelligent}}(x) = f^2_{A_{intelligent}}(x) \quad (3.3.1)$$

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

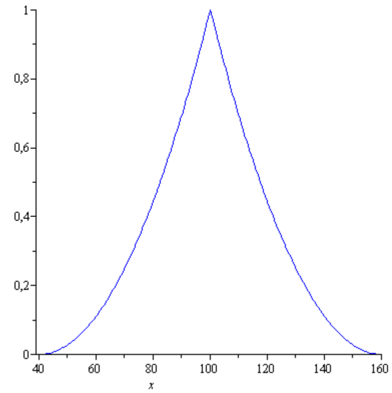

Figure 2. Fuzzy subset $A_{very-intelligent}$ representing the fuzzy statement $(x\ is\ very\ intelligent)$ in WAIS scale.

A way to incorporate the ambiguity introduced by the fuzzy statement $(x\ is\ very\ intelligent)$ in case of the set IQ indexes (3.2.2) is by adding beside IQ indexes, a second parameter, namely the $DOFVI(IQ) = DOF\left(x = IQ\ is\ A_{very-intelligent}\right)\ values = 'the\ tru\ valu'\ of\ the\ statement\ \left(x = IQ\ is\ A_{very-intelligent}\right)$ points.

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

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

$$\begin{aligned} DOFVIIQ := [&0.2669444444, 0.3211111111, 0.04694444444,\\ &0.1225000000, 0.0002777777778, 0.02777777778, 0.1736111111,\\ &0.2844444444, 0.4669444444, 0.5625000000, 0.4669444444,\\ &0.4444444444, 0.3402777778, 0.3600000000, 0.3402777778,\\ &0.3402777778, 0.2669444444, 0.2669444444, 0.3802777778,\\ &0.02250000000, 0.02777777778, 0.02777777778, 0.01361111111,\\ &0.1736111111, 0.2177777778, 0.1736111111, 0.01361111111,\\ &0.01777777778, 0.001111111111, 0.001111111111, 0.4444444444,\\ &0.4669444444, 0.8402777778, 1, 0.8402777778] \end{aligned} \tag{3.3.2}$$

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 (3.2.2) is the following:

-rejected candidates.

$$\begin{aligned} &0.2669444444, 0.3211111111, 0.04694444444, 0.1225000000,\\ &0.0002777777778, 0.02777777778, 0.1736111111, 0.2844444444,\\ &0.4669444444, 0.4669444444, 0.4444444444, 0.3402777778,\\ &0.3600000000, 0.3402777778, 0.3402777778, 0.2669444444,\\ &0.2669444444, 0.3802777778, 0.02250000000, 0.02777777778,\\ &0.02777777778, 0.01361111111, 0.1736111111, 0.2177777778,\\ &0.1736111111, 0.01361111111, 0.01777777778, 0.001111111111,\\ &0.001111111111, 0.4444444444, 0.4669444444 \end{aligned} \tag{3.3.3}$$

-accepted candidates.

$$[0.5625000000, 0.8402777778, 1, 0.8402777778] \quad (3.3.4)$$

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

For 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 their high $DOFVI(IQ)$ values;

-who are the' more than very intelligent' candidates rejected because their low $DOFVI(IQ)$ values,and who are the 'more than very intelligent candidates' accepted because 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 in two subgroups: persons having $DOFVI(IQ)$ values less than 0.5 and candidates having $DOFVI(IQ)$ values more than 0.5 point.

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

$$DOFLVI := [0.2669444444, 0.3211111111, 0.04694444444, 0.1225000000, 0.0002777777778, 0.02777777778, 0.1736111111, 0.2844444444, 0.02250000000, 0.02777777778, 0.02777777778, 0.01361111111, 0.1736111111, 0.001111111111, 0.1111111111, 0.4444444444, 0.4669444444]; \quad (3.3.5)$$

-accepted candidates at the start from the group

$$[\ ]$$

-rejected candidates at the start from the group

$$0.2669444444, 0.3211111111, 0.04694444444, 0.1225000000, 0.0002777777778, 0.02777777778, 0.1736111111, 0.2844444444, 0.02250000000, 0.02777777778, 0.02777777778, 0.01361111111, 0.1736111111, 0.001111111111, 0.1111111111, 0.4444444444, 0.4669444444 \quad (3.3.6)$$

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

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

$$DOFVI := [0.8402777778, 1, 0.8402777778] \quad (3.3.7)$$

-accepted candidates at the start from the group

$$[0.8402777778, 1, 0.8402777778] \quad (3.3.8)$$

-rejected candidates at the start from the group

$$[\ ] \quad (3.3.9)$$

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 is the following:

$$DOFMVI := [0.4669444444, 0.5625000000, 0.4669444444, 0.4444444444, 0.3402777778, 0.3600000000, 0.3402777778, 0.3402777778, 0.2669444444, 0.2669444444, 0.3802777778, 0.2177777778, 0.1736111111, 0.01361111111, 0.01777777778]; \quad (3.3.10)$$

-accepted candidates at the start from the group

$$[0.5625000000] \quad (3.3.11)$$

-rejected candidates at the start from the group

$$[0.4669444444, 0.4669444444, 0.4444444444, 0.3402777778, 0.3600000000, 0.3402777778, 0.3402777778, 0.2669444444, 0.2669444444, 0.3802777778, 0.2177777778, 0.1736111111, 0.01361111111, 0.01777777778] \quad (3.3.12)$$

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 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 to the fuzzy logic statement $(x\ is\ intelligent)$, defined by (3.2.1), 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 [46,53,54] given by:

$$f_{A_{more\ or\ less\ intelligent}}(x) = \sqrt{f_{A_{intelligent}}}(x) \quad (3.3.13)$$

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

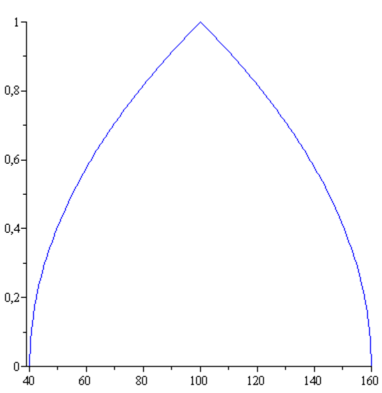

Figure 3. Graphic of the fuzzy subset $A_{more\ or\ less\ intelligent}$ representing the fuzzy statement $(x\ is\ more\ or\ less\ intelligent)$ in WAIS scale.

A way to incorporate the ambiguity introduced by the fuzzy statement $(x\ is\ more\ or\ less\ intelligent)$ in case of IQ indexes (3.3.2) is by adding beside IQ indexes, a second parameter, namely the $DOFMLI(IQ)$ = $DOF\left(x = IQ\ is\ A_{more\ or\ less\ intelligent}\right)\ value = 'the\ tru\ valu'\ of\ the\ statement\ \left(x = IQ\ is\ A_{more\ or\ less\ intelligent}\right)$ points.

For this purpose, the set of the $DOFMLI(IQ)$ points has 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:

$$DOFMLIQ := [0.7187952883, 0.7527726526, 0.4654746680, 0.5916079783, 0.1290994449, 0.4082482906, 0.6454972245, 0.7302967432, 0.8266397846, 0.8660254040, 0.8266397846, 0.8164965809, 0.7637626160, 0.7745966692, 0.7637626160, 0.7637626160, 0.7187952883, 0.7187952883, 0.7852812659, 0.3872983346, 0.4082482906, 0.4082482906, 0.3415650256, 0.6454972245, 0.6831300514, 0.6454972245, 0.3415650256, 0.3651483717, 0.1825741858, 0.1825741858, 0.8164965809, 0.8266397846, 0.9574271080, 1 , 0.9574271080]; \quad (3.3.14)$$

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 decide at the start, to reject those candidates whose $DOFMLI(IQ)$ values is low, for example less than 0.5 point, and accept only those candidates whose $DOFMLI(IQ)$ 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 at the start. The obtained result in case of the set (3.2.2) is the following:

-rejected candidates

$$[0.4654746680, 0.1290994449, 0.4082482906, 0.3872983346, 0.4082482906, 0.4082482906, 0.3415650256, 0.3415650256, 0.3651483717, 0.1825741858, 0.1825741858] \quad (3.3.15)$$

-accepted candidates

$$0.7187952883, 0.7527726526, 0.5916079783, 0.6454972245, 0.7302967432, 0.8266397846, 0.8660254040, 0.8266397846, 0.8164965809, 0.7637626160, 0.7745966692, 0.7637626160, 0.7637626160, 0.7187952883, 0.7187952883, 0.7852812659, 0.6454972245, 0.6831300514, 0.6454972245, 0.8164965809, 0.8266397846, 0.9574271080, 1, 0.9574271080 \quad (3.3.16)$$

According to this, criteria 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 for participate at competition, because their $DOFMLI(IQ)$ point is sufficiently high.

More refined analysis can be made 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 (3.2.1) 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 [46,53,54] given by:

$$f_{A_{indeed\ intelligent}}(x) = 2 \times f^2_{A_{intelligent}}(x)\ \ for\ f_{A_{intelligent}}(x) \leq 0.5\ \ and\ f_{A_{indeed\ intelligent}}(x) = 1 - 2 \times \left(1 - f_{A_{intelligent}}(x)\right)^2\ \ for\ \ 0.5 < f_{A_{intelligent}}(x) \quad (3.3.17)$$

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

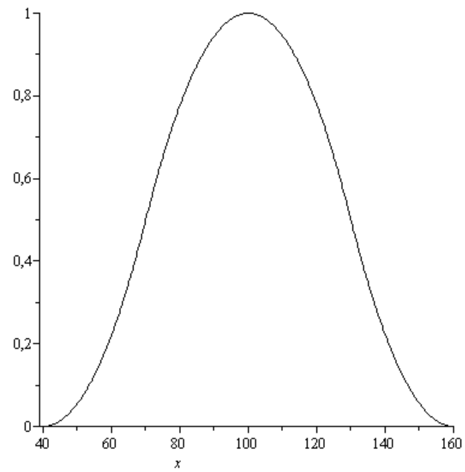

Figure 4. Graphic of the fuzzy subset $A_{indeed\ intelligent}$ representing the fuzzy statement $(x\ is\ indeed\ intelligent$ in WAIS scale.

A way to incorporate the ambiguity introduced by the fuzzy statement $(x\ is\ indeed\ intelligent$, in case of IQ indexes (3.3.2), is by adding beside IQ indexes, a second parameter, namely the $DOFII(IQ) = DOF\left(x = IQ\ is\ A_{indeed\ intelligent}\right)\ value = 'the\ tru\ valu'\ of\ the\ statement\ \left(x = IQ\ is\ A_{indeed\ intelligent}\right)$ points.

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

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

$$DOFIIIQ := [0.5327777778, 0.6244444444, 0.09388888889, 0.2450000000, 0.0005555555556, 0.05555555556, 0.3472222222, 0.5644444444, 0.7994444444, 0.5625000000, 0.4669444444, 0.7777777778, 0.6527777778, 0.6800000000, 0.6527777778, 0.3402777778, 0.5327777778, 0.5327777778, 0.3802777778, 0.04500000000, 0.05555555556, 0.05555555556, 0.02722222222, 0.3472222222, 0.4311111111, 0.3194444444, 0.02722222222, 0.03555555556, 0.002222222222, 0.002222222222, 0.7777777778, 0.7994444444, 0.9861111111, 1, 0.9861111111]; \quad (3.3.18)$$

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 decide at the start, to reject those candidates whose $DOFII(IQ)$ values is low, for example less than 0.5 point, and accept only those candidates whose $DOFII(IQ)$ 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 at the start. The obtained result in case of the set (3.2.2) is the following:

-rejected candidates

$$\begin{gathered}0.09388888889, 0.2450000000, 0.0005555555556, 0.05555555556, \\ 0.3472222222, 0.4669444444, 0.3402777778, 0.3802777778, \\ 0.04500000000, 0.05555555556, 0.05555555556, 0.02722222222, \\ 0.3472222222, 0.4311111111, 0.3194444444, 0.02722222222, \\ 0.03555555556, 0.002222222222, 0.002222222222\end{gathered} \tag{3.3.19}$$

-accepted candidates

$$\begin{gathered}[0.5327777778, 0.6244444444, 0.5644444444, 0.7994444444, \\ 0.5625000000, 0.7777777778, 0.6527777778, 0.6800000000, \\ 0.6527777778, 0.5327777778, 0.5327777778, 0.7777777778, \\ 0.7994444444, 0.9861111111, 1, 0.9861111111]\end{gathered} \tag{3.3.20}$$

According to this, criteria 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 for participate at competition, because their $DOFII(IQ)$ point is sufficiently high.

More refined analysis can be made 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.

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.

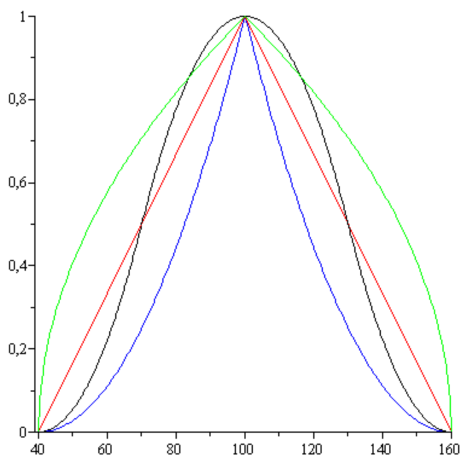

Figure 5. Fuzzy sets corresponding to the fuzzy logic statements: $(x\ is\ intelligent\ )$ color red; $(x\ is\ very\ intelligent)$ color blue; $(x\ is\ more\ or\ less\ intelligent)$ color green, $(x\ is\ indeed\ intelligent)$ color black.

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 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 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 3.4.1.
$\boldsymbol{Y\ is\ a\ 4 - tuple\ Y = (T, X, G, M)\ where}$:
$\boldsymbol{T\ is\ a\ set\ of\ natural\ language\ terms\ from\ which\ t\ can\ take\ on\ its\ values, X\ is\ a\ univers,}$
$\boldsymbol{on\ which\ the\ fuzzy\ sets\ corresponding\ to\ the\ linguistic\ variable\ are\ defined,}$
$\boldsymbol{G\ is\ a\ context\ free\ grammar\ used\ to\ generate\ the\ elements\ of\ T, and\ M\ is\ a\ mapping}$
$\boldsymbol{from\ T\ to\ the}$
$\boldsymbol{fuzzy\ subsets\ of\ X, M: T \rightarrow F}$ **[47,53,54].**

Linguistic variables make the natural language computation possible [47,53,54].

Sometimes there is no set X that can be naturally associated to the linguistic expression. That is because there is no measure for them. Consider for example the linguistic expression; good, pain, happy, joy, excellent, acceptable, etc.

Definition 3.4.2.

Following definition 6.1. we take the natural language term ‘intelligent’ adding the terms obtained with the 14 linguistic modifiers obtaining a set $\boldsymbol{T}$ of 15 natural language terms $\boldsymbol{T}$ ={ ‘intelligent ‘,’very intelligent’,…}. For universe $\boldsymbol{X\ we\ take\ the\ set\ of\ real\ numbers}$. The elements of the set $\boldsymbol{F}$ are the fuzzy subsets $\boldsymbol{A_{intelligent}, A_{very\ intelligent}, A_{more\ or\ less\ intelligent}, A_{indeed\ intelligent}, etc\ F = \{A_{intelligent}, A_{very\ intelligent}, A_{more\ or\ less\ intelligent}, A_{indeed\ intelligent}, \dots\}}$ corresponding to the elements of $\boldsymbol{T}$ and $\boldsymbol{M\ is\ the\ mapping\ from\ the\ set\ T\ to\ the\ set\ F}$ which associate to the elements of $\boldsymbol{T}$ the corresponding fuzzy subset from $\boldsymbol{F}$. In this way the kernel of a linguistic variable is obtained what 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.

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3.5. Extension of the Kernel of 'Human Intelligence' Linguistic Variable by Using Fuzzy Logic and Fuzzy Logic Operators [47,53,54]

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	$A(AND)\,B$	$A(OR)\,B$	$A(XOR)\,B$	$A(implyB)$
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 where a statement and its opposite may both be "true" to a certain degree. For example, "severe" and "moderate" pathology may be both be "true "for a given patient. For fuzzy statements A, B the "true value" can vary between 0 and 1. The Boolean table has to be extended to cope with such situations in a plausible manner.

The fuzzy logic operator $\boldsymbol{NOT}$ [48,53,54] In the fuzzy logic, the fuzzy statement $(x\ is\ A)$ by the fuzzy logic operator NOT,is transformed in the fuzzy logic statement $(x\ is\ not\ A)$.The new fuzzy statement usually is 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

$$f_C(x) = 1 - f_A(x) \tag{3.5.1}$$

Notation $f_{NOTA}\ for\ the\ fuzzy\ complement\ of\ A\ is\ also\ usual.$
It can be seen that the following equalities hold:

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

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 is 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.

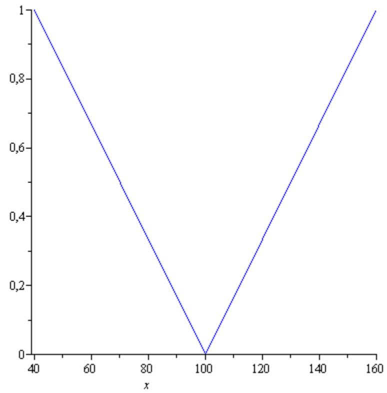

Figure 6. Fuzzy subset $A^{C}_{intelligent}$ representing the linguistic expression $not\ intelligent$.

The above-described procedure can be repeated for all elements of the kernel of 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:

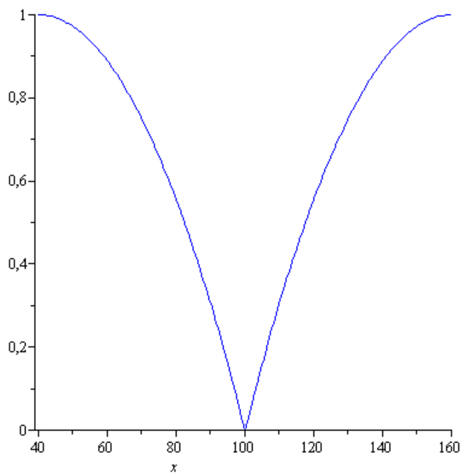

Figure 7. $A^{C}_{very\ intelligent}$.

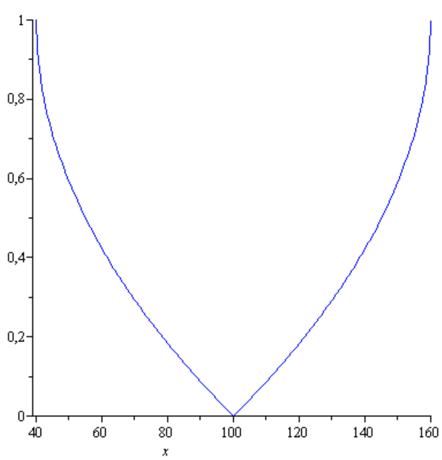

Figure 8. $A^{C}_{more\ or\ less\ intelligent}$.

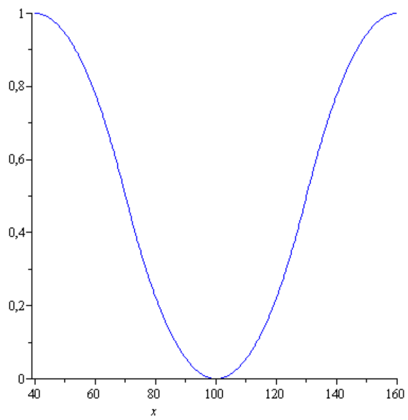

Figure 9. $A^{C}_{indeed\ intelligent}$.

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

The fuzzy logic operator $\boldsymbol{AND}$. According to [48,53,54] in fuzzy logic two type of $\boldsymbol{AND}$ fuzzy logic operator are used: the so called 'minimum fuzzy logic operator $\boldsymbol{AND}$ 'and the so called 'product fuzzy logic operator $\boldsymbol{AND}$'.

The 'minimum fuzzy logic operator $\boldsymbol{AND'}$.[48,53,54] In case of two fuzzy statements $(x\ is\ A_1)$, $(x\ is\ A_2)$ the 'minimum fuzzy logic operator $\boldsymbol{AND'}$ 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

$$f_{C_{minimum\ intersection}}(x) = minimum\{f_{A_1}(x), f_{A_2}(x)\} \tag{3.5.2}$$

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

According to this definition and Figure 5 is easy to see that the 'minimum fuzzy intersection' for some of the 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' require a more complex computation of the membership function.

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

$f_{\ minimum\left(A_{intelligent} \cap A^{C}_{intelligent}\right)}(x) = 0\ for\ x \leq 40$; $f_{\ minimum\left(A_{intelligent} \cap A^{C}_{intelligent}\right)}(x) = \frac{x-40}{60}\ for\ 40 < x \leq 70$;

$f_{\ minimum\left(A_{intelligent} \cap A^{C}_{intelligent}\right)}(x) = 1 - \frac{x-40}{60}\ for\ 70 < x \leq 100$;

$f_{\ minimum\left(A_{intelligent} \cap A^{C}_{intelligent}\right)}(x) = 1 - \frac{160-x}{60}\ for\ 100 < x \leq 130$;

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

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

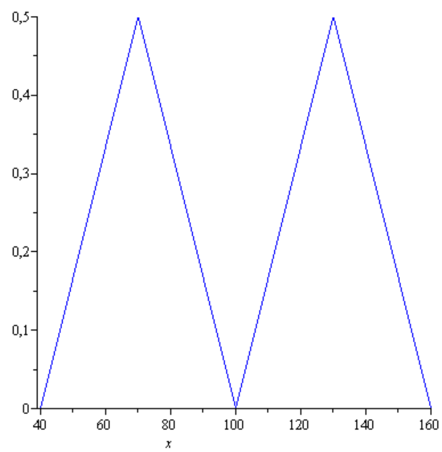

Figure 10. Fuzzy subset $minimum\ intersection(A_{intelligent} \cap A^C_{intelligent})$.

We emphasize that

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

for $x = 70\ and\ x = 130\ is\ equal\ to\ 0.5$0.This situation is similar with that already mentioned : "severe" and "moderate" pathology may be both be "true "for a given patient.

Representing the fuzzy statement $'intelligent\ and\ non\ intelligent'\ with\ the\ fuzzy\ subset\ minimum(A_{intelligent} \cap A^C_{intelligent})$ 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 $DOF[(x\ is\ minimum(A_{intelligent} \cap A^C_{intelligent}))]$ is less or is equal than 0.5 for every IQ index from the data set (3.2.2).

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

$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = 0\ for\ x \leq 40;$
$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = 2 \times (\frac{x-40}{60})^2\ for\ 40 < x \leq 70$
$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = \frac{100-x}{60}\ for\ 70 < x \leq 100;$
$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = \frac{x-100}{60}\ for\ 100 < x \leq 130$
$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = 2 \times (\frac{160-x}{60})^2\ for\ 130 < x \leq 160;$
$f_{minimum(A_{intelligent} \cap A_{indeed\ intelligent})}(x) = 0\ for\ 160 < x$

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.

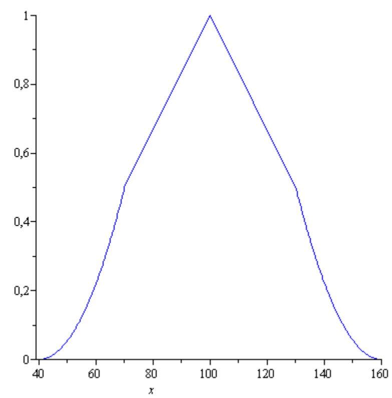

Figure 11. Fuzzy subset, $minimum\ intersection(A_{intelligent} \cap A_{indeed\ intelligent}$.

Product fuzzy logic operator AND [48,53,54] 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 '$\underline{product(x\ is\ A_1)\boldsymbol{AND}(x\ is\ A_2)}$ 'is described by the fuzzy subset $C_{product\ intersection}$ which membership function is

$$f_{C_{product\ intersection}}(x) = f_{A_1}(x) \times f_{A_2}(x) \quad (3.5.3)$$

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.

In general the 'product fuzzy intersection' for the elements of the 'human intelligence linguistic variable' require the computation of the membership function using (3.5.3)

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 (3.5.3) as presented in Figure 12.

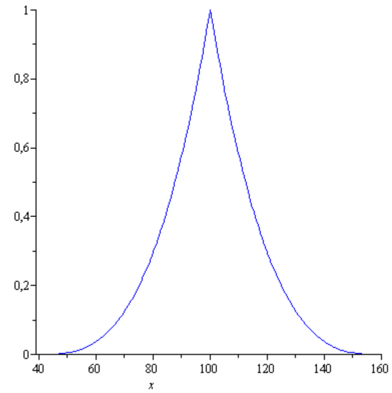

Figure 12. Fuzzy subset, $product\ intersection(A_{intelligent} \cap A_{very\ intelligent}$.

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

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

Fuzzy logic operator $\boldsymbol{OR}$. According to [48,53,54] in fuzzy logic, two type of fuzzy logic operator $\boldsymbol{OR}$ are used: the so called 'maximum fuzzy logic operator $\boldsymbol{OR}$' and a so called 'product fuzzy logic operator $\boldsymbol{OR}$'

Maximum fuzzy logic operator$\boldsymbol{OR}$. [48,53,54] The 'maximum fuzzy logic operator $\boldsymbol{OR'}$ 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 '$\underline{maximum(x\ is\ A_1)\boldsymbol{AND}(x\ is\ A_2)}$' is described by the fuzzy subset

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

$$f_{C_{maximum\ union}}(x) = maximum\{f_{A_1}(x), f_{A_2}(x)\} \tag{3.5.4}$$

This fuzzy subset usually is denoted by $C_{maximum\ union} = maximum\ (A_1 \cup A_2)$ and is called the 'maximum fuzzy union' of fuzzy subsets A_1 andA_2.

In general the 'maximum fuzzy union' for the elements of the 'human intelligence linguistic variable' require the computation of the membership function using (3.5.4)

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" computed with (3.5.4) as presented in Figure 13.

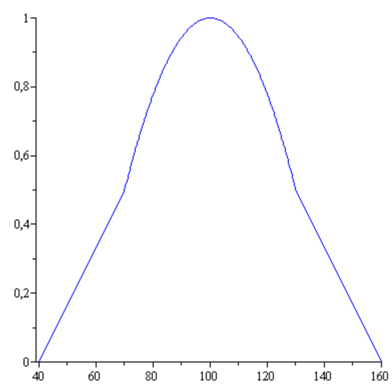

Figure 13. $Maximum\ union(A_{intelligent} \cup\ A_{indeed\ intelligent})$".

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

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

Product fuzzy logic operator [48,53,54]. The 'product fuzzy logic operator $\boldsymbol{OR'}$ 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 '$\underline{product(x\ is\ A_1)\boldsymbol{OR}(x\ is\ A_2)}$ 'is described by the fuzzy subset

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

$$f_{C_{product\ union}}(x) = f_{A_1}(x) + f_{A_2}(x) - f_{A_1}(x) \times f_{A_2}(x) \quad (3.5.5)$$

This fuzzy subset usually is 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' require the computation of the membership function using (3.5.5)

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" computed with (3.5.5) as presented in Figure 14.

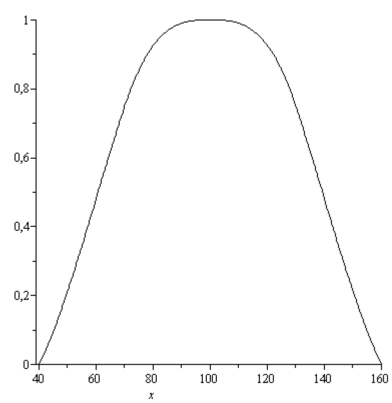

Figure 14. Fuzzy subset $'product\ union(A_{intelligent} \cup\ A_{indeed\ intelligent})$'.

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

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

Fuzzy logic operator XOR. According to [48,53,54] in fuzzy logic, two kind of XOR operator are used the so called 'product fuzzy logic operator XOR 'and a so called 'min-max fuzzy logic operator XOR'.

Product fuzzy logic operator $\boldsymbol{XOR}$. [48,53,54] The 'product fuzzy logic operator $\boldsymbol{XOR}'$ 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 '$product(x\ is\ A_1)\boldsymbol{XOR}(x\ is\ A_2)$' is described by the fuzzy subset

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

$$f_{C_{product\ XOR\ union}}(x) = f_{A_1}(x) + f_{A_2}(x) - 2 \times f_{A_1}(x) \times f_{A_2}(x) \tag{3.5.6}$$

This fuzzy subset usually is 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' require the computation of the membership function using (3.5.6)

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 (3.5.6) as presented in Figure 15.

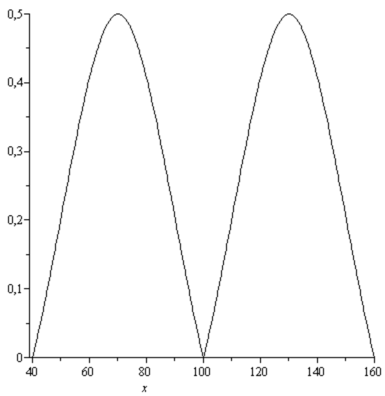

Figure 15. $Product\ fuzzy\ XOR\ union\ (A_{intelligent} \cup\ A_{indeed\ intelligent})$'.

Representing the fuzzy statement $'intelligent\ XOR\ indeed\ intelligent'\ with\ the\ fuzzy\ subset\ product\ fuzzy\ XOR\ union\ \left(A_{intelligent} \cup A_{indeed\ intelligent}\right)$ 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. [48,53,54] 'Minimum-Maximum fuzzy logic operator $\boldsymbol{XOR}'$ 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

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

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

$$f_{C_{minimum-maximum\ XOR\ union}}(x) = maximum\{minimum[1 - f_{A_1}(x), f_{A_2}(x)], minimum[1 - f_{A_2}(x), f_{A_1}(x)]\} \tag{3.5.7}$$

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 (3.5.7)

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 'human intelligence' linguistic variable. This model makes possible a new quantitative evaluation of one IQ index, depending on the kind of understanding of what means 'human intelligence' The new quantitative evaluation index is the 'true value of IQ'=DOF(IQ)='degree of membership of IQ'. Computations are presented in this framework and significant differences are revealed concerning for example: computational identification of group of persons having IQ index in a given range, meaning of fuzzy logic concepts, meaning of operations with fuzzy sets and meaning of fuzzy logic operators. This is the main novelty in this paper. As far as we know this kind of computational model for 'human intelligence' linguistic variable never been constructed. The paper is limited in application. Further research needed concerning: rules (reasoning), rule systems, and modelling real word phenomena in the framework of the constructed computational model 'human intelligence' linguistic variable.

Nowadays, it is common to classify scientific journals, universities, researchers, individuals based on numerical parameters, obtained by aggregating some measured parameters. Individual IQ performance indices are an example of such a numerical parameter obtained after a psychological test. Classifying a group of people based on the results of IQ number gives a precise and unequivocal result. However, there is a question related to such a result. It is concern those who use IQ numbers for classification. The question is: does the word intelligent have the same meaning for all of us? This question is natural because intelligence does not have a classic definition.

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 reflect 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 the word intelligent and represent the confidence value (true value) of that IQ index.

5. Conclusions

A computational model was constructed which is called ‘human intelligence’ linguistic variable**.** This model makes possible a new quantitative evaluation of one IQ index, depending on the kind of understanding of what means ‘human intelligence’ The new quantitative evaluation index is the ‘true value of IQ‘=DOF(IQ)=’degree of membership of IQ’

Author Contributions

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

Availability of Data and Materials

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

Consent for Publication

No consent for publication is required, as the manuscript does not involve any individual personal data, images, videos, or other materials that would necessitate consent.

Conflicts of Interest

The authors declare no conflicts of interest regarding this manuscript.

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The authors confirm that all content of the manuscript (including figures), was developed without the use of artificial intelligence or AI-assisted technologies.

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