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Research paper

A Fuzzy Skill Predictor for Early Childhood Educators

Moses Adah Agana[1] and Ruth Wario[2]

[1]*Department of Computer Science and Informatics, University of the Free State, South Africa*
AganaMA@ufs.ac.za – ORCID: 0000-0003-1349-5236
[2] *Department of Computer Science and Informatics, University of the Free State, South Africa*
**Corresponding author E-mail: warioRD@ufs.ac.za*

Abstract

This study presents a model of a two-input single output (TISO) Fuzzy Skill Predictor based on Howard Gardner's theory of multiple intelligences to assist early childhood educators in discovering latent skills in children of early school age as to tailor them towards professional skill development in their future lives. The skill prediction system was developed in two phases beginning with the generation of weighted fuzzy rules and then followed by the development of a fuzzy rule-based decision support system. The Mamdani Fuzzy inference model in MATLAB was used in implementing the system using weighted attributes of intelligence and ability to determine skills. The system was tested with hypothetical data based on Howard Gardner's theory of multiple intelligence and was found useful for predicting skills based on the parameters used. The system was validated using early school academic records of 7 randomly sampled undergraduates studying various courses in the university. Though limited entries were used to test the system, the model is robust and can be easily modified to accommodate more entries and rules to predict as many skills as possible.

***Keywords*:**Fuzzy, Skill, Intelligence, Ability, Inference, Prediction

1. Introduction

Skill is the exhibition of the ability that someone has and this correlates with the type of intelligence possessed by the individual too. In psychology, intelligence is believed to be both in the form of a real fact as well as a latent fact; it could equally be viewed as a process as well as a skill or capacity, or as a form and attribute for both mental and behavioral organization (Mihaela, et al., 2013). There is therefore a positive correlation between intelligence (intellectual ability) and motoric skills (e.g. combat sports) (Mihaela, et al., 2013; Evans, 2000).
The **theory of multiple intelligences** was proposed by Howard Gardner in 1983, specifying various domains of intelligence, rather than viewing intelligence as being dominated by just a single general ability (Gardner and Hatch, 1989). According to the theory, a learner cannot be associated with just a specific form of intelligence, and no learner lacks completely in intelligence. Hence, once lacking in one form of intelligence must have some other form of intelligence. This means skills too vary amongst learners; a learner lacking in one kind of skill must be endowed with some other kind of skill. What is left is how to discover the skills in each learner. Gardner therefore views intelligence as an integration of biological and psychological potentials to process information that can be utilized in a given environment to solve problems or create valuable products. This end result is skillfulness. Gardner initially identified seven types of intelligence, and letter extended it to nine (linguistic, musical, logical-mathematical, body kinesthetic, spatial, inter-personal, intra-personal, naturalistic and existential intelligence). To further buttress this, each type of sport for instance is believed to be an expression of various different requirements from intellectual abilities, creating an incentive impact on the mental coordination or mediation (Epuran and Stanescu, 2010).

Skill prediction is problematic in most early school settings. Several reasons could be responsible for this. One of the reasons is the broad curriculum the child is exposed to at the pre-primary and primary school stages, making it difficult for the teacher to figure out which talent is more pronounced in a child as to tailor the child's training towards mastering such talent. The second reason could be the process of evaluation adopted. Most tests given to learners dwell more on quantitative reasoning and cognition and cannot be articulated to figure out psychomotor skills. The incompetence of the teachers could also be another factor. There is therefore need for an automated system that can complement human efforts to predict skills in children based on their cognitive, affective and psychomotor domains of knowledge. Early childhood skill discovery and training can help in holistically molding the child for a lifelong journey.

In childhood development, the earlier the signs of the potential skills in a child is discovered, the better it is for those educating the child to tailor the child towards perfecting in such skills as the child grows; and this in turn makes the child to be more functional in the society when he is fully grown up. The discovery of the latent skills in a child is therefore a major concern in psychometrics (the study of the measurement of skills and knowledge in relation to abilities, attitudes, personality traits, and educational achievement) (Kaplan and Saccuzzo, 2010).
The concern of this study is on how metacognitive skills that are the sum of the procedural knowledge needed to actually regulate and control one's learning activities can be harnessed to predict the learner's skills as he grows up. Such skills are manifested in task analysis, planning, monitoring, checking, and recapitulation. Metacognitive skills could be interdependent, and a learner who is oriented towards a given task is likely to focus on relevant information given in the task assignment, necessary for building an adequate task representation and skill development (Brown,

1978; Brown and DeLoache, 1978; Flavell, 1992; Kluwe, 1987). A stronger relationship was discovered to exist between underlying categories of motor and cognitive skills in pre-pubertal children than in pubertal children (older than 13 years) in a study on the relationship between cognitive and motor skills in children (van der Fels et al., 2015).

Similarly, Piaget theorized that motor and cognitive skills have positive correlation. The foundation of Piaget's theory was on the idea that children learn from observable motor actions with objects (Piaget, 1952). The implication is that there is need for early child educators to design a detailed action plan reflecting goals and directions for activities; and incorporating possible process control measures during task performance to tailor a learner towards developing and practicing those skills as he grows up (Veenman et al., 2004).

These are indicators that skill detection or prediction in children depends on intermediate factors that involve reasoning with uncertainties. This is where Fuzzy Logic becomes relevant. In a Fuzzy Logic System (FLS), an acceptable and definite output is produced out of incomplete, ambiguous, distorted, or inaccurate (fuzzy) inputs. A fuzzy Logic system is programmed to reason like humans, combining intermediate possibilities between extreme (absolute) values. For instance, a statement could either be TRUE (1) or FALSE (0) in extreme or absolute cases, as is the case with a conventional logic block in the computer. In Fuzzy Logic however, there are other intermediate values (such as CERTAINLY TRUE, POSSIBLY TRUE, UNCERTAIN, POSSIBLY FALSE AND CERTAINLY FALSE) just as in human reasoning that are combined to make final decisions. These set of values are known as linguistic variables, and are combined to form a linguistic function used to derive outputs or solutions to problems that involve uncertainty. Taking musical skill for instance, the linguistic function could be expressed with respect to the linguistic variables as follows:

*Musical-skill (ms) = {*create-sound, communication-with-sound, understand-sound, understand-pitch,
understand-rhythm*}*

A person who exhibits attributes of any two of the linguistic variables in the linguistic function above can be said to possess musical skill. Fuzzy Logic thus utilizes the levels of possibilities of occurrence of the inputs to achieve a definite output. This forms the motivation for the design of a Fuzzy skill predictor for early child educators.

2. Related Works

Various measurement theories such as the classical test theory (CTT) and the item response theory (IRT) have been developed by psychometricians to combine attributes to determine a single outcome (Embretson and Reise, 2000; Hambleton and Swaminathan, 1985). Peculiar to attribute measurements in the physical sciences was the development of the Rash Model that has a mathematical similarity with the IRT (Rasch, 1980).

Other related measurement method for working with large matrices of correlations and covariance include factor analysis used for determining the underlying dimensions of data (Thompson, 2004), data clustering, which is a technique of finding objects that are like each other; and multidimensional scaling used for finding a simple representation of data that has a large number of latent dimensions (Davison, 1992). Structural equation modeling and path analysis are also later techniques of analyzing large covariance matrices (Kaplan, 2008).

The aforementioned instances represent various multivariate descriptive methods that are applied to attempt to distill large amounts of data into simpler structures and allow statistically sophisticated models to be fitted to data and tested to determine adequate fitness. They however appear to have a common deficiency of lacking the consensus in cutting points to ascertain the number of latent factors. IRT for instance offers a basis for obtaining an estimate of the position of a test-taker on a given potential attribute as well as the standard error of measurement of that position. For instance, a secondary school student's knowledge of biology can be deduced from his or her score on a test administered to him or her and then compared with a primary school student's knowledge of primary science deduced from a less difficult test.

Research has also been conducted on a weighted fuzzy rule-based clinical decision support system for the diagnosing heart disease by obtaining knowledge automatically from the patient's clinical data. The system phases include an automated approach to generate weighted fuzzy rules and the development of a fuzzy rule-based decision support system (Anooj, 2012). The results in risk prediction in the clinical decision support system were reported to have been better than the traditional method in use

Fuzzy logic has also been applied to model a set of machines to combine the information provided by three fuzzy systems to give a degree of risk when traveling by road, taking into account fuzzy conditions of three variables: car (age, last check, the wear on brakes and wheels, etc.); driver (tiredness, sleeping time, sight, etc.); and characteristics of the trip (day or night, weather conditions, length, urban or country road, etc). The system could predict both the degree of risk as well as the degree to which the risk could be decreased if some of the conditions change according to the advice provided by the fuzzy decision system (such as if the driver takes a rest, or if the tyres are changed) (Santos and Lopez, 2012).

In a related study, a fuzzy logic to handle the various attributes in a supplier evaluation problem has been proposed using four multi-input, single output (MISO) mamdani fuzzy inference system. The system was tested in a reputed fiber manufacturing organization in north India and found useful if applied by companies for making decisions about supplier evaluation (Kumar et al., 2013).

3. Methodology

The skill prediction system was developed in two phases beginning with the generation of weighted fuzzy rules and then followed by the development of a fuzzy rule-based decision support system. The Mamdani Fuzzy inference model in MATLAB was used in implementing the design using weighted attributes of intelligence and ability to determine skills. The method that was adopted for the design of the fuzzy skill prediction system can be summarized in seven algorithmic steps as is conventional with most other existing systems.

Algorithm: Fuzzy Skill Prediction

1. Specify linguistic variables and terms.
2. Build membership functions for them.
3. Build knowledge base of rules.
4. Perform fuzzification by converting crisp data into fuzzy data sets using membership functions.
5. Construct rules to evaluate the inference.
6. Combine results from each rule to generate inference.
7. Perform defuzzification by converting output data into non-fuzzy values.

In the design, steps 3, 5 and 6 were combined because of their close relationship.

3.1 Step 1: Specify Linguistic Variables and Terms

The simple words and sentences that form both input and output variables for the fuzzy system are generally referred to as linguistic variables and terms. Based on Howard Gardner's classification of types of intelligence and their attributes, table 1 shows the various skills that are associated with the various domains of intelligence. The linguistic variables and terms for the Fuzzy Skill Prediction System (FSPS) were drawn from this table

Table1: Knowledge Domains, Attributes and Associated Skills (Gardner and Hatch, 1989)

Intelligence	Attributes (Abilities)	Skills
Linguistic intelligence	The ability to speak, recognize, and use mechanisms of phonology (speech sounds), syntax (grammar), and semantics (meaning).	Narrators, Orators
Musical intelligence	The ability to create, communicate with, and understand meanings made of sound, understanding of pitch, rhythm.	Musicians, Singers, Composers
Logical-mathematical intelligence	The ability of use and understand relationships in the absence of action or objects. Understanding complex and abstract ideas.	Mathematicians, Scientists
Spatial intelligence	The ability to perceive visual or spatial information, change it, and re-create visual images without reference to the objects, construct 3D images, and to move and rotate them.	Map readers, Astronauts, Physicists
Bodily-Kinesthetic intelligence	The ability to use complete or part of the body to solve problems or fashion products, control over fine and coarse motor skills, and manipulate the objects.	Sportsmen (Players, Dancers)
Intra-personal intelligence	The ability to distinguish among one's own feelings, intentions, and motivations.	Disciplined leader, Counselor, Psychologist
Interpersonal intelligence	The ability to recognize and make distinctions among other people's feelings, beliefs, and intentions.	Mass Communicators, Interviewers
Naturalistic Intelligence	able to recognize flora and fauna in the natural world and use them productively	Farmer, hunter, biologist
Existential intelligence	Ability to have deep thought about one's existence (the how's and why's of life and death)	Spiritualist/ moralist

The skill variable was broken into two, such that certain linguistic variables (intelligence and ability types[i]) can be combined to arrive at a given skill. The skill variable used to represent science, technical and engineering skills (STE) could be classified as STE(i) and this depends on the intelligence and ability domains of spatial, bodily kinesthetic, logical-mathematical and naturalistic intelligence. Similarly, the skill variable used to represent general arts and humanities skills (AH), could be classified as AH(i) and this depends on the intelligence and ability domains of linguistic, musical, inter-personal, intra-personal, existential intelligence.

The linguistic variable and terms for STE are thus expressed as:
STE(i) = {spatial, bodily kinesthetic, logical-mathematical, naturalistic} – (1)
Each of the terms (the intelligence/ability domains) has attributes used in measuring levels of intelligence/ability which in turn determine the associated skills. These are used to build the rules and the inferences of the fuzzy system. It is therefore more suitable to represent the linguistic variable and terms reflecting the attributes of the intelligence/abilities as follows:

STE(i) = {number-use, relate-abstract-terms-with-each-other, visualize-spatial-info, re-create-images, draw-shapes/maps, move-body-parts, manipulate-objects-with-body-parts, recognize-flora/fauna, manipulate-flora/feuna} – (2)

Each of the terms in bracket in (2) is a measure of intelligence/ability, and could be generally expressed as:
STE(i) = {measure-of-intelligence/ability} – (3)
The linguistic variable AH measured on intelligence/ability i can be defined as:
AH(i) = {linguistic, musical, inter-personal, intra-personal, existential} – (4)
Each of the terms (the intelligence/ability domains) has attributes used in measuring levels of intelligence/ability which in turn determine the associated skills. These are used to build the rules and the inferences of the fuzzy system. It is therefore more suitable to represent the linguistic variable and terms reflecting the intelligence/abilities as follows:

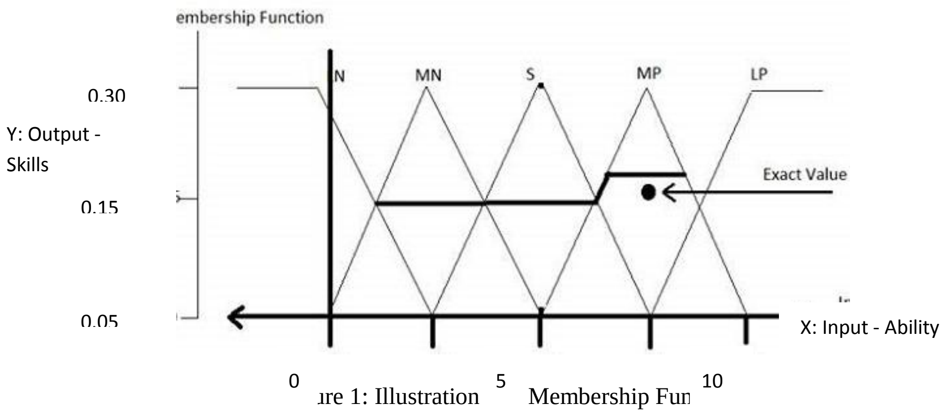
AH(i) = {speak/recognize-phonology, use/recognize-syntax/semantics, create/communicate-with- sound, understanding-pitch-rhythm, distinguish-among-one's-feelings, recognize-one's-intentions-motivations, recognize/distinguish-people's-feelings, recognize/distinguish-people's-beliefs/intentions, have- deep- thoughts-about-self-existence} – (5)

Each of the terms in bracket in (5) is a measure of intelligence/ability, and could be generally expressed as:
AH(i) = {measure-of-intelligence/ability} – (6)

3.2 Step 2: Build Membership Functions for them

Steps 2 and 4 are combined because of their relationships. A membership function is used to quantify linguistic terms (variables) and represent a fuzzy set graphically. A **membership function** for the fuzzy set STE on the universe of discourse X is defined as:
$\mu_{STE}: X \rightarrow [0,1]$.
And that for the fuzzy set AH on the universe of discourse X is defined as:
$\mu_{AH}: X \rightarrow [0,1]$.
Here, each element of *X* is mapped to a value in the y-axis between 0 and 1. It is called **membership value** or **degree of membership**. It quantifies the degree of membership of the element in *X* to the fuzzy set *STE* or *AH*. In the final outcome, we used the x-axis (ability) and y-axis (intelligence) respectively to represent the universe of discourse while the z-axis (skills) represents the degrees of membership in the [0, 1] interval. This was used to generate results as will be discussed in the results section ahead. The three-dimensional structure depicts a combination of intelligence and ability to produce skills in an individual. The centroid of the surface was taken to represent a value that measures a certain skill as the output.

Multiple membership functions were applied to fuzzify the numerical values. The numerical values at the points of intersection of the coordinates in the function could be large positive (LP), medium positive (MP), small (S), medium negative (MN) or large negative (LN) as illustrated in figure 1.



ıre 1: Illustration Membership Fun

The exact value of each fuzzy output is obtained from the midpoint of the triangles of the membership function. As the input value changes, so does the output change. In this design, each child is assumed to have a maximum of 30% of the total skills in the universe of discourse and a maximum of 10 abilities to measure intelligence, which in turn determine skill.

3.3 Step 3: Build Knowledge Base of Rules

Step 3 is combined with steps 5 and 6 to construct rules to evaluate the inference, and then combine the results from each rule to generate inference. The knowledge base of rules consists of the IF – THEN constructs that are used to determine the outcome of the combination of some linguistic terms – in this instance, the measures of ability and intelligence on which skills depend.

There are nine linguistic terms in (2), and their combinations are used to determine each skill (output). A set of rules to generate skills from the linguistic variables using the linguistic function can be built as follows:

IF STE(i) = (number-use-ability AND relate-abstract-terms-with-each-other) THEN skill is mathematician/scientist
IF STE(i) = (number-use-ability OR relate-abstract-terms-with-each-other) AND re-create-images
THEN skill is engineer
IF STE(i) = (number-use-ability OR relate-abstract-terms-with-each-other)
AND (visualize-spatial-info OR re-create-images) THEN skill is geographer/astronaut
IF STE(i) = (move-body-parts AND manipulate-objects-with-body-parts) THEN sportsman/dancer
IF STE(i) =(number-use-ability OR recognize-flora/fauna) AND (manipulate-flora/feuna)
THEN skill is farmer/hunter/biologist

The inference system for three skill domains (mathematician/scientist, engineer and geographer/astronaut) chosen from STE having four inputs is illustrated in figure 2.

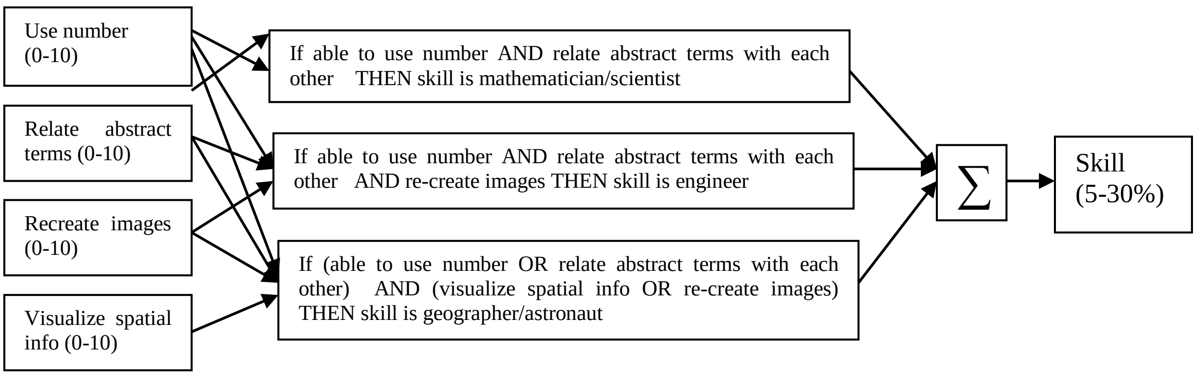


Figure 2: Data, Rules, Knowledge Base and Inference System of the Fuzzy Skill Prediction

System for STE
In figure 2 above, there are four inputs, three rules and the output summed up as the skill.

There are equally nine linguistic terms in (5), and their combinations are used to determine each skill (output). A set of rules to generate skills from the linguistic variables using the linguistic function can be built as follows:

IF AH(i) = (speak/recognize-phonology AND use/recognize-syntax/semantics) HEN skill is Narrator/orator
IF AH(i) = (create/communicate-with-sound OR understanding-pitch-rhythm)
AND (speak/recognize-phonology) THEN skill is Musician/Singer
IF AH(i) = (distinguish-among-one's-feelings OR recognize-one's-intentions-motivations)
THEN skill is Disciplined-leader/Counselor/Psychologist
IF AH(i) = (recognize/distinguish-people's-feelings OR recognize/distinguish-people's-beliefs/intentions)
AND (speak/recognize-phonology) THEN skill is Mass-Communicator/Journalist
IF AH(i) = (have- deep- thoughts-about-self-existence) THEN skill is Spiritualist/Moralist

The inference system for three skill domains (narrator/orator, musician/singe and spiritualist/moralist) chosen from AH having five inputs is illustrated in figure 3.

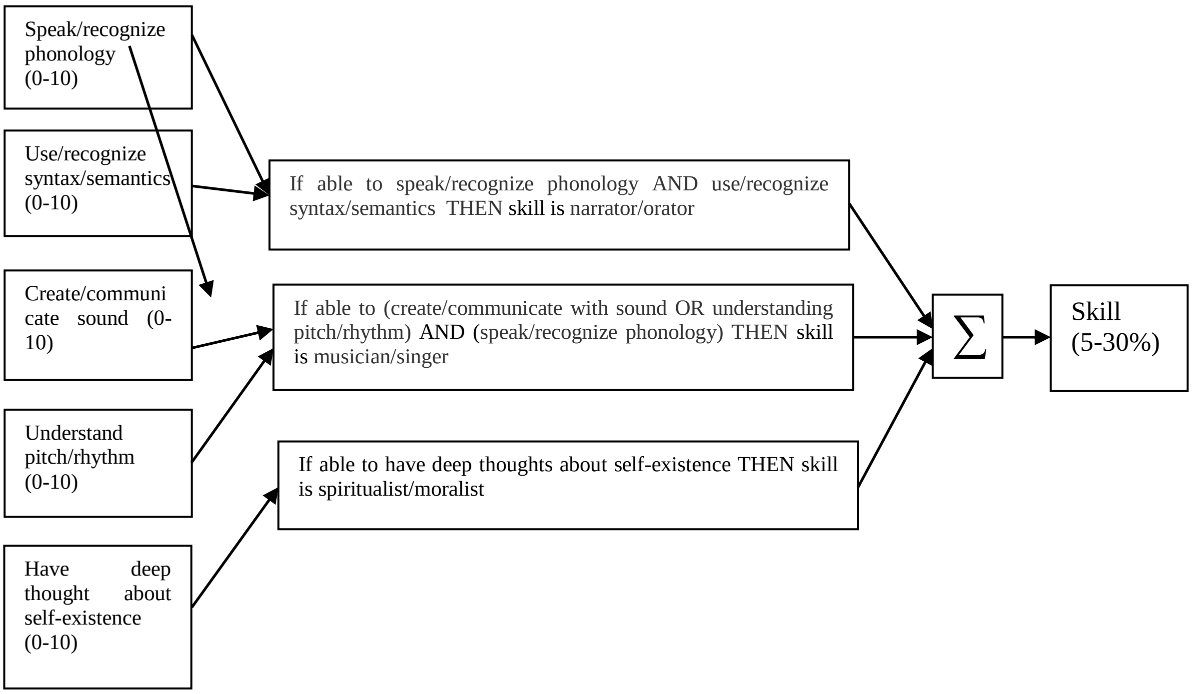


Figure 3: Data, Rules, Knowledge Base and Inference System of the Fuzzy Skill Prediction System for AH

In figure 3 above, there are four inputs, three rules yielding an output summed up as the skill. It is possible that a person could possess more than one skill. The degree of expertise amongst the skills in a person may vary, and so the skill that is reckoned with the person is that which is most pronounced (has the highest percentage).

In the fuzzy logic system, rules flow in parallel and rather than sharp switching between modes based on breakpoints, the logic flow is smooth from regions where one rule or another dominates.

3.4 Step 7: Perform Defuzzification by Converting Output Data into non-fuzzy Values

The fuzzy set constitutes the input for the defuzzification process, and the fuzzy set is usually an aggregate of the output, represented by a single number, in this instance, a value representing the percentage of the skill obtained from the combination of some fuzzy sets in a membership function. The decisions are based on testing all the rules in Fuzzy inference system. Aggregation is achieved by combining the fuzzy sets that represent the outputs of each rule into a single fuzzy set, and this occurs only once for each output variable, which is before the final defuzzification step. The list of truncated output functions returned by the implication process for each rule constitutes the input of the aggregation process and the output one fuzzy set for each output variable. The methods used to achieve aggregation include *maximum*, *probor* (probabilistic OR) and *sum* (sum of the rule output sets).

The parameter for measuring the level and type of intelligence/ability required for a certain skill should be determined by educational measurement and evaluation standards. Hypothetical values were used to test the system. The output of the single number forms the final desired output for the variable under consideration and is derived from a range of output values either by taking the centroid, by bisection, average of the maximum value of the output set, largest of maximum, or the smallest of maximum. The defizzication method that was applied in this design is the centroid calculation, which returns the center of area under the curve, as illustrated in figure 4

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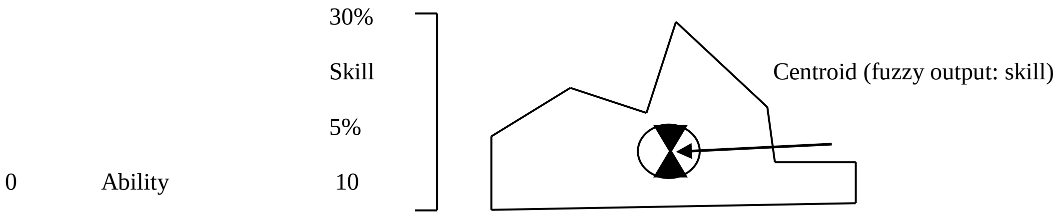

Figure 4: Illustration of Defuzzification

The graphical user interface of the skill prediction Fuzzy system is illustrated in figure 5.

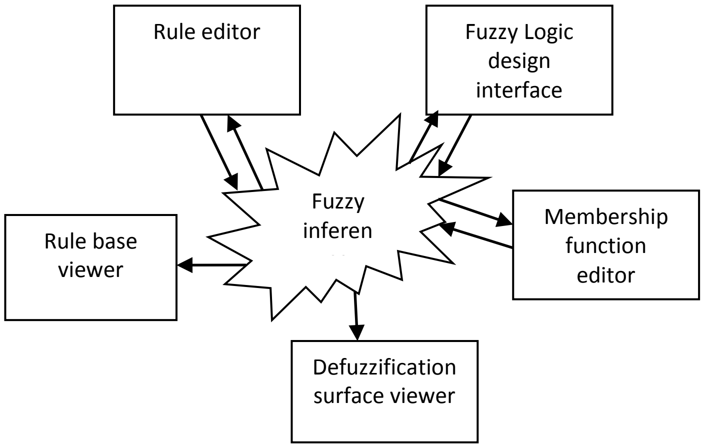

Figure 5: The Fuzzy Skill Prediction Graphical User Interface

As illustrated in figure 5 above, the Fuzzy logic design interface is the region for specifying the input and output variables. For efficiency, the number of inputs should be minimal according to the memory capacity of the system used. The membership functions are specified in the membership function editor, while the rule editor is used to edit the list of rules that defines the behavior of the system. The inference is viewed at the rule base viewer while the surface viewer is where the final output is displayed. The components are dynamically linked and a variation in one of them affects the output on the surface viewer. The general architecture of the skill prediction fuzzy system is illustrated in figure 6.

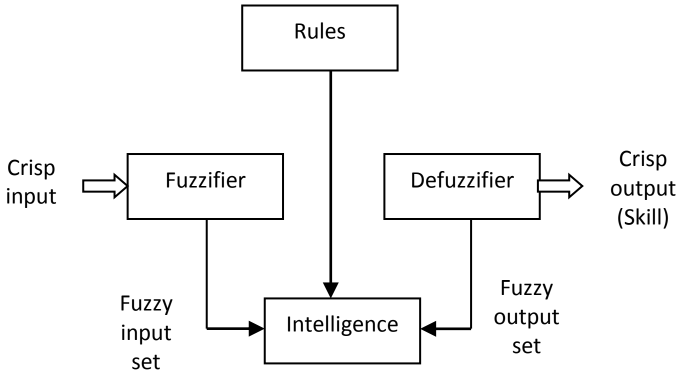

Figure 6: General Architecture of the Fuzzy Skill Prediction System

As illustrated in figure 6, the transformation of the system inputs (crisp numbers) into fuzzy sets is performed by the fuzzifier and their conversion into output crisps is handled by the defuzzifier. These are achieved by the rules built into the intelligence system where inferences are drawn from a combination of rules based on the inputs.

4. Results/Discusion

The results obtained are presented and discussed in this section. The linguistic terms for the science, technical and engineering skills were used to test the system. These were used to create membership functions for intelligence and ability. A combination of some intelligence and ability yields a certain skill. Figure 7 illustrates the two input variables (ability and intelligence) and output variable (skill) that were used to test-run the Fuzzy skill predictor.

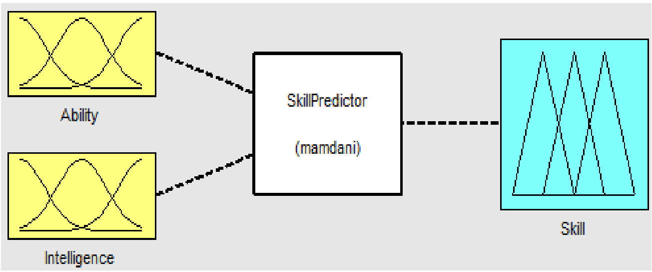

Figure 7: Fuzzy Input and Output Variables for the Fuzzy Skill Predictor

Four membership functions (draw shapes/maps, relate abstract terms with each other, move body with objects and use numbers) were derived to test the ability variable input as illustrated in figure 8.

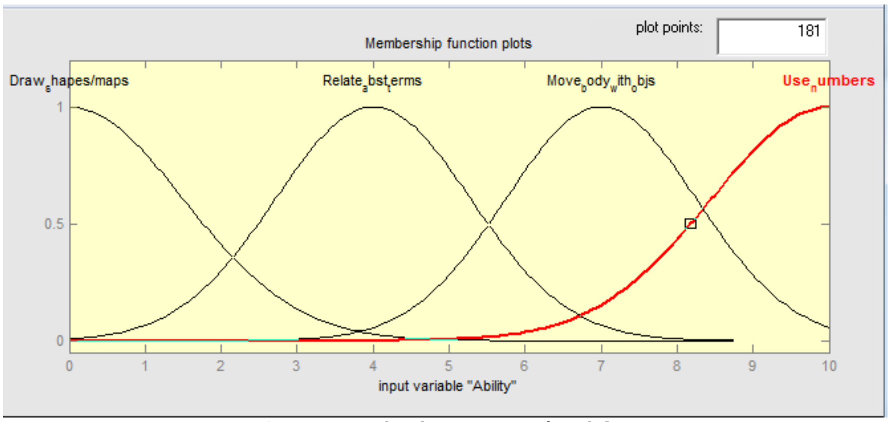

Figure 8: Membership Functions for Ability

Three membership functions (use numbers, visualize spatial information and move objects with body parts) were derived to test the intelligence input variable as illustrated in figure 9.

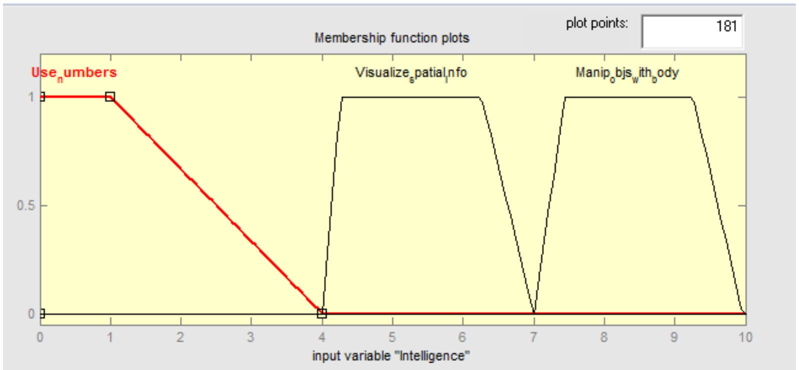

Figure 9: Membership Functions for Intelligence

The system was tested for four different types of skills using rules to combine ability types with intelligence types. The four types of skills (sportsman/dancer, geographer/astronaut, engineer and mathematician/scientist) constitute the membership functions for the skill variable as illustrated in figure 10.

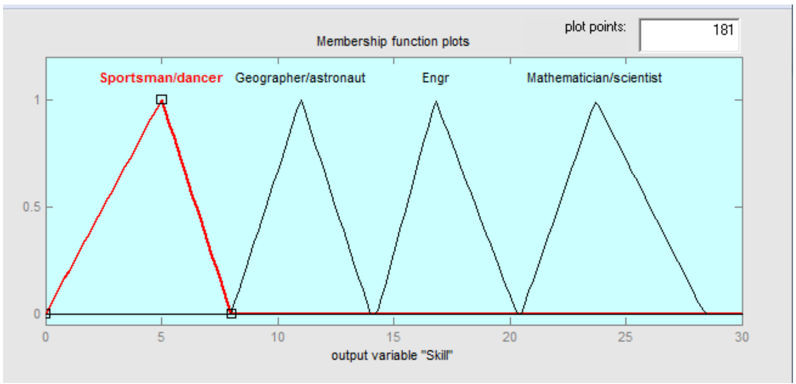

Figure 10: Membership Functions for Skill

Six rules were modeled to test the system, each having an associated but adjustable weight (the weights should be chosen by the educational evaluators based on laid down grading systems). The rules were drawn from the membership functions of the two input variables (ability and intelligence. The rules and their associated weights are:

1. If (ability is draw shape/maps) and (intelligence is use numbers) then (skill is geographer/astronaut) [0.7]
2. If (ability is relate abstract terms with each other) or (intelligence is visualize spatial information) then (skill is geographer/astronaut) [0.6]
3. If (ability is move body parts with objects) and (intelligent is manipulate objects with body parts) then (skill is sportsman/dancer) [0.8]
4. If (ability is use numbers) and (intelligence is use numbers) then (skill is mathematician/scientist) [1]
5. If (ability is relate abstract terms with each other) and (intelligence is use numbers) then (skill is engineer) [1]
6. If (ability is relate abstract terms with each other) and (intelligence is visualize spatial information) the (skill is geographer/astronaut) [0.8]

A range of test values were assigned to each of the membership functions of the skill variable as follows:

Sportsman/dancer 0-8

Geographer/astronaut 8-14
Engineer 14-20
Mathematician/scientist 20-28

When the aggregated value of rules falls within any of the given ranges, the learner's skill is predicted to be the skill having such range of values.

The rule editor is illustrated in figure 11. More rules can be added to the rules editor, or existing rules can be deleted or modified in the rules editor. The consequence (result) of each rule has a weighted value which is used to judge the outcome when the input values are changed.

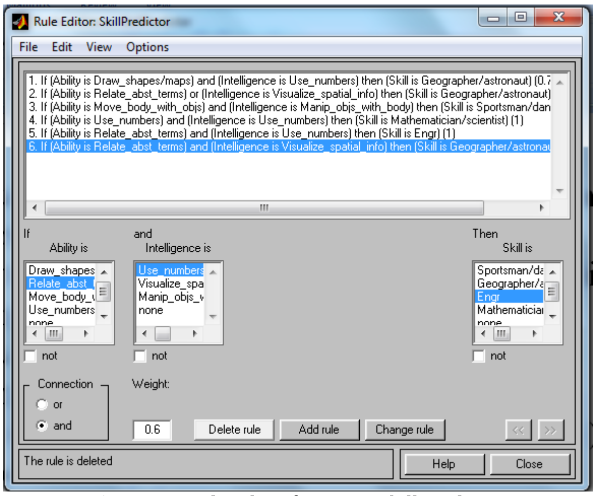

Figure 11: Rule Editor for Fuzzy Skill Predictor

The rule viewer is the component of the system where the outcomes of the rules are displayed. A single numerical value is computed for each of the variables in the Fuzzy skill predictor during fuzzification as illustrated in figure 12.

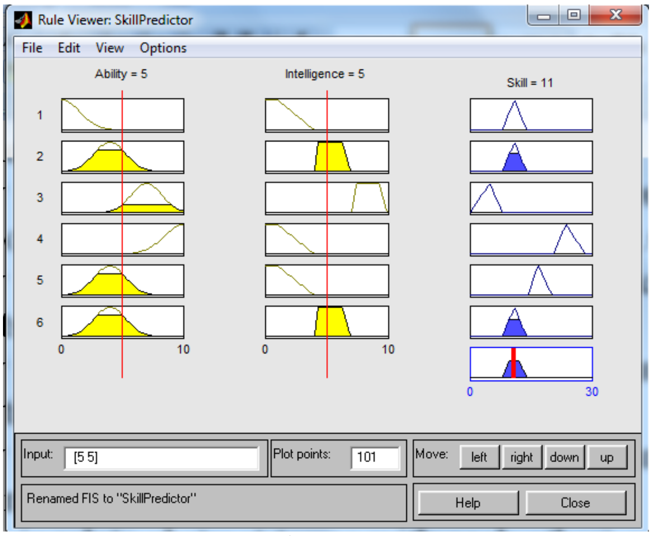

Figure 12: Rule Viewer of the Fuzzy Skill Prediction System

In the figure, the values of the variables ability, intelligence and skill are displayed on the top as 5, 5 and 11 respectively. The evaluation standard based on the pre-assigned range of test values for skills has for instance the skill for geographer/astronaut to be in the range 8-14, therefore the predicted skill indicated in figure 12 is ***geographer/astronaut.***

As illustrated in figure 12, the rule viewer displays a roadmap of the whole fuzzy inference process and is derived from the fuzzy inference. The rule viewer for the Fuzzy skill predictor has 19 plots in a single window, with the three plots across the top of the figure representing the antecedent and consequent of the first rule. A row of plots represents each rule while each column represents a variable. The left of each row has the rule number displayed there. To view a rule on the status line, the user can click on a rule number.

The six yellow plots in the first two columns represent the membership functions referenced by the antecedent, or the if-part of each rule, while the third column of plots shows three shaded blue plots representing the membership functions referenced by the consequent, or the then-part of each rule. The aggregate weighted decision for the given inference system is represented by the seventh plot in the third column, and the decision depends on the input values for the system. The bold vertical line on this plot represents the defuzzified output.

The text field labeled **Input** at the lower left of the rule viewer is where values of the input vector can be adjusted to show various outputs. The user can key in the values and press **Enter**. The values can also be adjusted by clicking on or clicking and dragging any of the six plots for each input, causing the red index line to move horizontally to the point where the user has clicked. This causes a new calculation to be performed, and the value of the output changes. A region shaded yellow under any membership function curve is used to make the fuzzy membership value visually apparent.

The entire fuzzy inference process can be interpreted by the user at once in the rule viewer; and it as well illustrates how the shape of certain membership functions influences the overall result, by showing one calculation at a time. To get an entire output service of the Fuzzy skill prediction system requires the surface view as illustrated in figure 13.

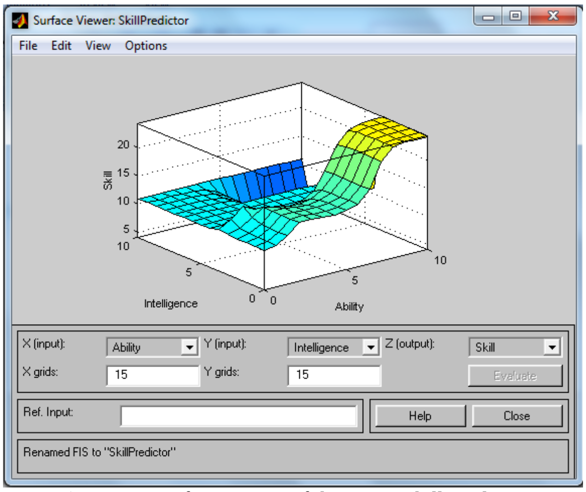

Figure 13: Surface Viewer of the Fuzzy Skill Predictor

The defuzzification was achieved by taking the centroid of the surface under the curve. In figure 13 above, the centroid shows the unit value for skill = 11. Varying the values of the rules generates different outputs for the rule viewer as shown in figures 14 and 15 respectively with their corresponding surface viewers.

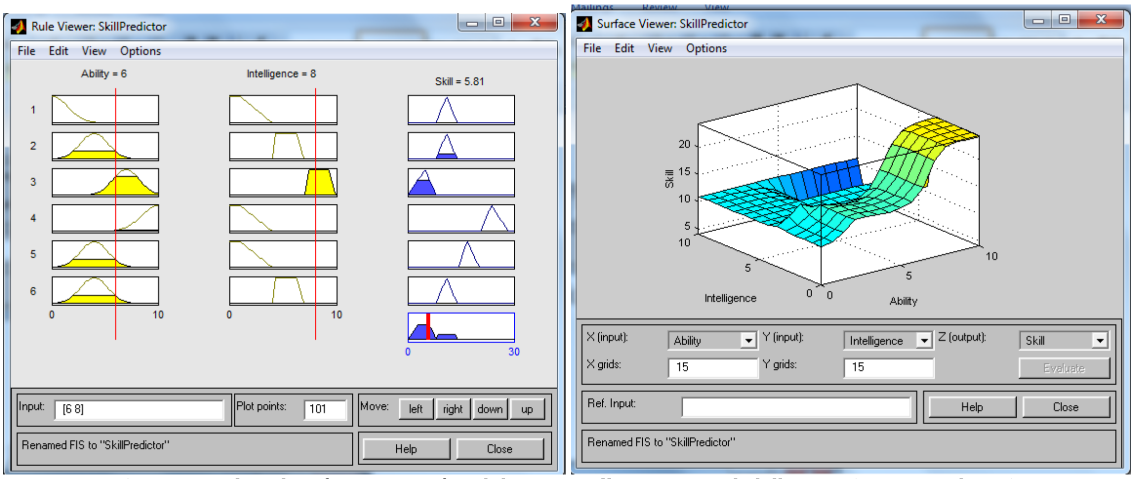

Figure 14: Rule and Surface Viewers for Ability= 6, Intelligence = 8 and Skill = 5.81 (Sportsman/dancer)

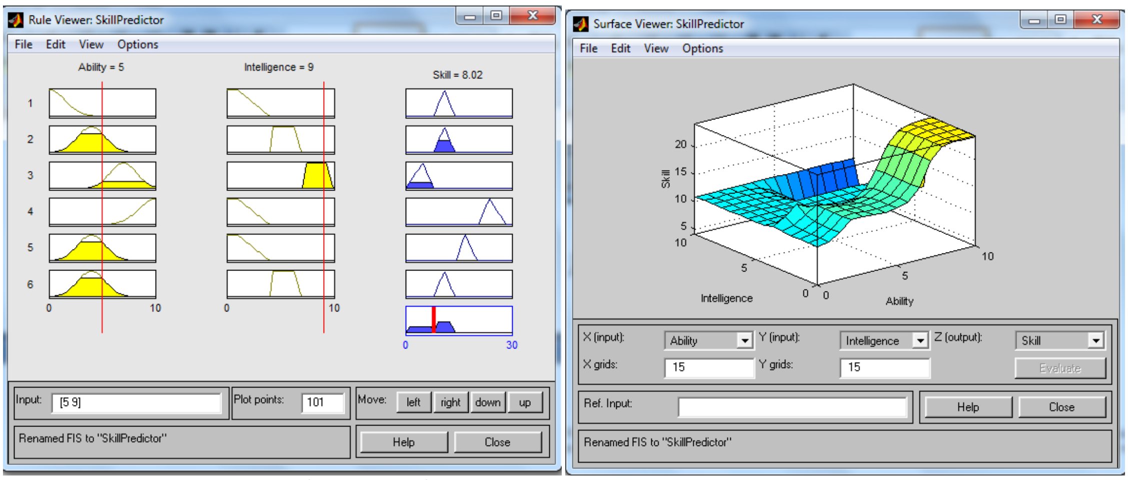

Figure 14: Rule and Surface Viewers for Ability= 5, Intelligence = 9 and Skill = 8.02 (Geographer/astronaut)

5. System Validity

Seven undergraduate students excelling in various departments were sampled at random and their average performances in various subjects in their early school days were collected to verify how they correlate with their present skills. Face validity was adopted, by inspecting their previous performances in early school and their respective cumulative grade point average (CGPA) in their undergraduate courses. The results showed that early school knowledge and ability in various domains manifest in the skills exhibited in later school activities as illustrated in table 2.

Table 2: Validity test result

Students	Undergraduate courses	Early school subjects/ average scores						Early school averages	Undergraduate CGPAs (5-points scale)
		Maths	English language	Physical/health education	Quantitative reasoning	Social studies	General science		
1	Geography/Regional planning	63	72	62	74	80	67	69.7	3.87
2	Civil engineering	82	68	66	79	62	85	73.7	4.10
3	Computer Science	84	70	61	85	66	83	74.8	4.31
4	Games/athletics	67	68	86	82	68	64	72.5	3.95
5	Physics	83	67	61	84	63	84	73.7	3.97
6	Electrical/electronics engineering	86	63	64	88	65	86	75.5	4.41
7	Biochemistry	80	61	63	72	67	81	70.7	3.88

The results shown in table 2 confirm that those who exhibited high ability in certain knowledge domains exhibit high skills in domains related to such knowledge and abilities. For instance, all those who had high average scores in mathematics and general science were found to do well in science and engineering course, likewise the student who had high average in physical and health education was found doing well in games and athletics, etc.

6 Conclusion

Two multi-input single output (MISO) Fuzzy Skill Predictor has been designed and tested based on Howard Gardner's theory of multiple intelligences. The Mamdani Fuzzy inference model in MATLAB was used in implementing the system. The Fuzzy Skill Predictor will be a useful tool in discovering latent skills in children of early school age and would contribute to training them to develop such skills for functional living at adulthood if adopted and utilized. Though limited entries were used to test the system, the model is robust and can be easily modified to accommodate more entries and rules to predict as many skills as possible. This can be achieved by adding more input variables as well as membership functions. The limitation of the system is the difficulty in extracting all attributes that contribute to skills development into the rule base. Secondly, the interwoven nature of some skills may make it difficult to distinguish clearly some closely related skills. These limitations do not however apply to the skills within the Howard Gardner's theory of multiple intelligences confines used in the system.

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