# The Classification of Multiple Intelligences of People with Epilepsy using Fuzzy Inverse Model 

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#### Abstract

One of the most challenging problems faced by people with epilepsy (PWE) is employment. But, from human resource managers' point of view, they need reliable information before they can hire the PWE. A fuzzy model is developed to meet the need for both parties. The model is to help PWE identify their intelligence strengths and weaknesses in order to improve the probability of being employed. This paper presents a new fuzzy algorithm, namely Fuzzy Inverse ATIE (FIA) which is integrated to a crisp Logistic regression model to obtain a fuzzy model. Then based on the model, an ideal combination of eight intelligences which were based on Howard Gardner's Multiple Intelligence was determined to improve the probability of PWE to be employed. The results show that with the suggested combinations, the probability, $\mathrm{P}(\mathrm{Y}=1)$, is closed to 1 . It can be concluded that the fuzzy model developed using the FIA algorithms has successfully improved the probability of PWE to be hired based on the best parameters of the eight intelligences.


| People with Epilepsy | Multiple Intelligence Theory | Fuzzy Model |

## 1. INTRODUCTION

Regardless of the qualification and experience that they have had, many epilepsy sufferers have claimed that they are not given the same employment opportunity as what is given to other people [1,2]. Lacking of understanding and knowledge on epilepsy causes the society to be less sensitive towards the sufferers. Eventually, this leads to lack of self-acceptance and selfconfidence among the patients and thus, creates even wider gap between them.

For ages, intelligence has been considered as a matter of honour and a pre-requisite to be employed. This has caused many scholars and geniuses to dedicate their life in understanding what are intelligence and how does it affect one's life. Many definitions of Intelligence have been suggested by many outstanding scholars [3]. One of these is the Theory of Multiple Intelligences (later abbreviated as "MI") which was developed by an American Psychologist, Howard Gardner, in 1983 where he introduced seven types of intelligences; namely Linguistic, Musical, LogicalMathematical, Spatial, Bodily-Kinaesthetic, Intrapersonal and Interpersonal Intelligences. In 1993, he added two more types of intelligences, namely Naturalist and Spiritual [4].

## 2. METHODOLOGY

### 2.1 Method and instruments

A measurement tool, namely Ability Test in Epilepsy (ATIE) [5] based on Gardner's MI theory was developed to measure eight intelligence skills of PWE which are musical, kinaesthetic, math/ logic, spatial, verbal, interpersonal, intrapersonal and naturalist. The results from ATIE enable them to identify their strengths and abilities which can be highlighted in their quest seeking for jobs.

In order to suggest an ideal combination of the eight intelligence skills that the PWE should have to improve the probability of being employed, an algorithm called a Fuzzy Inversed ATIE (FIA) is created [5].

### 2.2 Fuzzy Model

In order to perform the fuzzy analysis, a fuzzy algorithm is needed. A fuzzy algorithm is a procedure like a computer program that made up of statements and control actions. Ahmad et. al [6] introduced a fuzzy algorithm that consists of nine steps to calculate time delay and characteristic impedence of strictly nonuniform coupled microstrip lines.

A fuzzy model was developed based on a fuzzy algorithm, called a Fuzzy Inverse ATIE (FIA). FIA was achieved through the adoption of the fuzzy algorithm
introduced by Ahmad et. al [6] where the algorithm was modified to suit the need of this study. A model initially obtained from the logistic regression that comprised of eight intelligence independent variables was integrated with the modified algorithm to obtain a fuzzy model.

## 3. IMPLEMENTATION AND RESULTS

### 3.1 Fuzzy Inverse ATIE (FIA)

The FIA consists of five steps as follows:

## Step I: Determination of Crisp Intelligence Parameters

The first step is to find the values of the intelligence parameters that is $\mathbf{Z}_{x}\left(\boldsymbol{x}_{1}, \boldsymbol{x}_{2}, \boldsymbol{x}_{3}, \ldots, \boldsymbol{x}_{\boldsymbol{8}}\right)$ as given by Equation (3). Based on the intelligence scores and intelligence types, a logistic regression equation for the employability based on the eight intelligences is derived from Equation (1) to obtain the Equation (2). The following delineates the process of the model development starting from the logistic regression to fuzzy approach.

The logistic regression model includes all the eight independent variables which are music ( $x_{1}$ ), kinesthetic ( $x_{2}$ ), math-logic ( $x_{3}$ ), spatial $\left(x_{4}\right)$, verbal $\left(x_{5}\right)$, interpersonal $\left(x_{6}\right)$, intrapersonal ( $x_{7}$ ) and naturalist ( $x_{8}$ ) with the employability as the binary dependent variable. The model was developed based on the data of 147 patients who are employed and unemployed as described in Table 1.

Table 1. Descriptive statistics of the logistic categorical variables

| Variable | Frequency | Percentage | Cumulative <br> Percentage |
| :--- | :---: | :---: | :---: |
| (Dependent) |  |  |  |
| Employment Status | 40 | 27.2 | 27.2 |
| $0=$ Unemployed | 107 | 72.8 | 100.0 |
| Employed |  |  |  |

The estimated logistic regression model for the study is written as:

$$
\begin{equation*}
P(Y=1)=\frac{1}{1+e^{-z}} \tag{1}
\end{equation*}
$$

such that

$$
\begin{align*}
\mathrm{z}= & -.879-.094 \text { music }+.497 \text { kinaesthetic }+.256 \text { math- } \\
& \text { logic }+.121 \text { spatial }-.180 \text { verbal }-.086 \text { interpersonal } \\
& +.308 \text { intrapersonal }-.154 \text { naturalist } \tag{2}
\end{align*}
$$

This equation is then incorporated into a fuzzy model to determine the most suitable parameters to produce optimum probability.

$$
\begin{align*}
Z_{x}\left(x_{1}, x_{2}, x_{3}, \ldots, x_{8}\right)= & c_{0}+c_{1} x_{1}+c_{2} x_{2}+c_{3} x_{3}+c_{4} x_{4}+c_{5} x_{5} \\
& +c_{6} x_{6}+c_{7} x_{7}+c_{8} x_{8} \tag{3}
\end{align*}
$$

## Step II: Fuzzification process

This second algorithm contains the process of obtaining the input parameters and the $\alpha$-cut values. From the values, the combinations of the input parameters with respect to each $\alpha$-cut value will be determined. At the end of this process, minimum and maximum values are calculated.

The domain has two limits, namely, the lowest and highest fuzzy values as shown in Table 2. For example, in Figure 1, 1 is the lowest and 5 the highest fuzzy value for the musical skill. The values which are shown in the Figure 1 represent the means (suggested values) of each skill based on the actual mean scores ( 3.55 for music, 4.2 for kinaesthetic, 3.7 for math-logic and so forth). The mean score value is designated as the highest fuzzy value.

Table 2. Input parameters for Patient $A$

| Parameters | Domain | Suggested <br> (Mean Score) |
| :--- | :---: | :---: |
| Music | $1-5$ | 3.55 |
| Kinaesthetic | $1-5$ | 4.20 |
| Math-logic | $1-5$ | 3.70 |
| Spatial | $1-5$ | 3.10 |
| Verbal | $1-5$ | 3.90 |
| Interpersonal | $1-5$ | 4.80 |
| Intrapersonal | $1-5$ | 3.70 |
| Naturalist | $1-5$ | 3.60 |



Fig. 1. Input parameters Patient $A\left(\right.$ music $\left.-x_{1}\right)$

In this study, the value of the $\alpha$-cut starts from 0 , increasing by intervals of 0.1 , and ends with 1.0 , giving a total of eleven $\alpha$-cuts for each intelligence skill. This will generate $11\left(2^{n}\right)$ combinations of $\alpha$-cut values in total per subject, eventually producing a total of $2,816\left(11^{*} 2^{8}\right)$ combinations. The $\alpha$-cut values for Patient A are presented in Table 4.

Using the values in Table 3, the minimum and the maximum values of the intelligence parameters were obtained by substituting these values and the fuzzy values into Equation (3), which then produced the normal and convex fuzzy intelligence parameters of induced graph. The results obtained were then used for the next step.

Table 4 summarizes the fuzzy induced parameters resulting from all the $\alpha$-cut values when substituted into Equation (3). These values are needed in the next step.

Table 3. The $\alpha$-cut values for Patient $A$

|  | Input Parameters |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\alpha_{i}$-cut |  |  |  |  | $\begin{aligned} & \pi \\ & 0 \\ & 0 \\ & \hline 10 \end{aligned}$ |  |  |  |
| 0.0 | $\begin{aligned} & {[1.00,} \\ & 5.00] \end{aligned}$ | $\begin{gathered} \hline[1.00, \\ 5.00] \end{gathered}$ | $\begin{gathered} \hline[1.00, \\ 5.00] \end{gathered}$ | $\begin{aligned} & \hline[1.00, \\ & 5.00] \end{aligned}$ | $\begin{gathered} \hline[1.00, \\ 5.00] \end{gathered}$ | $\begin{aligned} & \hline[1.00, \\ & 5.00] \end{aligned}$ | $\begin{gathered} \hline[1.00, \\ 5.00] \end{gathered}$ | $\begin{aligned} & \hline[1.00, \\ & 5.00] \end{aligned}$ |
| 0.1 | $\begin{aligned} & \hline[1.26, \\ & 4.86] \end{aligned}$ | $\begin{aligned} & \hline[1.32, \\ & 4.92] \end{aligned}$ | $\begin{aligned} & \hline[1.27, \\ & 4.87] \end{aligned}$ | $\begin{aligned} & \hline[1.21, \\ & 4.81] \end{aligned}$ | $\begin{aligned} & \hline[1.29, \\ & 4.89] \end{aligned}$ | $\begin{aligned} & \hline[1.38, \\ & 4.98] \end{aligned}$ | $\begin{gathered} \hline[1.27, \\ 4.87] \end{gathered}$ | $\begin{aligned} & \hline[1.26, \\ & 4.86] \end{aligned}$ |
| 0.2 | $\begin{aligned} & \hline[1.51, \\ & 4.71] \end{aligned}$ | $\begin{aligned} & \hline[1.64, \\ & 4.84] \end{aligned}$ | $\begin{aligned} & \hline[1.54, \\ & 4.74] \end{aligned}$ | $\begin{aligned} & \hline[1.42, \\ & 4.62] \end{aligned}$ | $\begin{gathered} \hline[1.58, \\ 4.78] \end{gathered}$ | $\begin{aligned} & \hline[1.76, \\ & 4.96] \end{aligned}$ | $\begin{aligned} & \hline[1.54, \\ & 4.74] \end{aligned}$ | $\begin{aligned} & \hline \text { [1.52, } \\ & 4.72] \end{aligned}$ |
| 0.3 | $\begin{gathered} \hline[1.77, \\ 4.57] \end{gathered}$ | $\begin{aligned} & \hline[1.96, \\ & 4.76] \end{aligned}$ | $\begin{gathered} \hline[1.81, \\ 4.61] \end{gathered}$ | $\begin{aligned} & \hline[1.63, \\ & 4.43] \end{aligned}$ | $\begin{aligned} & \hline[1.87, \\ & 4.67] \end{aligned}$ | $\begin{gathered} \hline[2.14, \\ 4.94] \end{gathered}$ | $\begin{aligned} & \hline[1.81, \\ & 4.61] \end{aligned}$ | $\begin{gathered} \hline[1.78, \\ 4.58] \end{gathered}$ |
| 0.4 | $\begin{aligned} & {[2.02,} \\ & 4.42] \end{aligned}$ | $\begin{aligned} & \hline[2.28, \\ & 4.68] \end{aligned}$ | $\begin{aligned} & \hline[2.08, \\ & 4.48] \end{aligned}$ | $\begin{gathered} \hline[1.84, \\ 4.24] \end{gathered}$ | $\begin{aligned} & {[2.16,} \\ & 4.56] \end{aligned}$ | $\begin{aligned} & \hline[2.52, \\ & 4.92] \end{aligned}$ | $\begin{aligned} & \hline[2.08, \\ & 4.48] \end{aligned}$ | $\begin{gathered} \hline[2.04, \\ 4.44] \end{gathered}$ |
| 0.5 | $\begin{gathered} \hline[2.28, \\ 4.28] \end{gathered}$ | $\begin{gathered} \hline[2.60, \\ 4.60] \end{gathered}$ | $\begin{gathered} \hline[2.35, \\ 4.35] \end{gathered}$ | $\begin{gathered} \hline[2.05, \\ 4.05] \end{gathered}$ | $\begin{gathered} \hline[2.45, \\ 4.45] \end{gathered}$ | $\begin{aligned} & \hline[2.90, \\ & 4.90] \end{aligned}$ | $\begin{gathered} \hline[2.35, \\ 4.35] \end{gathered}$ | $\begin{aligned} & \hline[2.30, \\ & 4.30] \end{aligned}$ |
| 0.6 | $\begin{gathered} \hline[2.53, \\ 4.13] \end{gathered}$ | $\begin{aligned} & \hline[2.92, \\ & 4.52] \end{aligned}$ | $\begin{aligned} & \hline[2.62, \\ & 4.22] \end{aligned}$ | $\begin{aligned} & \hline[2.26, \\ & 3.86] \end{aligned}$ | $\begin{gathered} {[2.74,} \\ 4.34] \end{gathered}$ | $\begin{aligned} & \hline[3.28, \\ & 4.88] \end{aligned}$ | $\begin{aligned} & \hline[2.62, \\ & 4.22] \end{aligned}$ | $\begin{aligned} & \hline[2.56 \\ & 4.16] \end{aligned}$ |
| 0.7 | $\begin{gathered} \hline[2.79, \\ 3.99] \end{gathered}$ | $\begin{gathered} \hline[3.24, \\ 4.44] \end{gathered}$ | $\begin{gathered} \hline[2.89, \\ 4.09] \end{gathered}$ | $\begin{gathered} \hline[2.47, \\ 3.67] \end{gathered}$ | $\begin{gathered} \hline[3.03, \\ 4.23] \end{gathered}$ | $\begin{aligned} & \hline \text { [3.66, } \\ & 4.86] \end{aligned}$ | $\begin{gathered} \hline[2.89, \\ 4.09] \end{gathered}$ | $\begin{aligned} & \hline[2.82, \\ & 4.02] \end{aligned}$ |
| 0.8 | $\begin{gathered} \hline[3.04, \\ 3.84] \end{gathered}$ | $\begin{aligned} & \hline[3.56, \\ & 4.36] \end{aligned}$ | $\begin{aligned} & \hline[3.16, \\ & 3.96] \end{aligned}$ | $\begin{gathered} \hline[2.68, \\ 3.48] \end{gathered}$ | $\begin{gathered} \hline[3.32, \\ 4.12] \end{gathered}$ | $\begin{gathered} \hline[4.04, \\ 4.84] \end{gathered}$ | $\begin{gathered} \hline[3.16, \\ 3.96] \end{gathered}$ | $\begin{gathered} \hline[3.08, \\ 3.88] \end{gathered}$ |
| 0.9 | $\begin{gathered} \hline[3.30, \\ 2.70] \end{gathered}$ | $\begin{gathered} \hline[3.88, \\ 4.28] \end{gathered}$ | $\begin{gathered} \hline[3.43, \\ 3.83] \end{gathered}$ | $\begin{gathered} \hline[2.89, \\ 3.29] \end{gathered}$ | $\begin{gathered} \hline[3.61, \\ 4.01] \end{gathered}$ | $\begin{aligned} & \hline[4.42, \\ & 4.82] \end{aligned}$ | $\begin{gathered} \hline \text { [3.43, } \\ 3.83] \end{gathered}$ | $\begin{gathered} \hline[3.34, \\ 3.74] \end{gathered}$ |
| 1.0 | $\begin{gathered} {[3.55,} \\ 3.55] \end{gathered}$ | $\begin{gathered} {[4.20,} \\ 4.20] \end{gathered}$ | $\begin{gathered} \hline[3.70, \\ 3.70] \end{gathered}$ | $\begin{gathered} \hline[3.10, \\ 3.10] \end{gathered}$ | $\begin{gathered} {[3.90,} \\ 3.90] \end{gathered}$ | $\begin{aligned} & \hline[4.80, \\ & 4.80] \end{aligned}$ | $\begin{gathered} \hline[3.70, \\ 3.70] \end{gathered}$ | $\begin{gathered} \hline[3.60, \\ 3.60] \end{gathered}$ |

Table 4. The minimum and the maximum values of the intelligence parameters (Patient A)

| $\alpha$-cut <br> values | [a,b] | Min Combination | $Z_{\text {minimum }}$ | Max Combination | $Z_{\text {maximum }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0.0 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | -2.27 | $\left\{x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a\right.$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 4.52 |
| 0.1 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | -1.87 | $x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 4.23 |
| 0.2 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | -1.48 | $x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 3.95 |
| 0.3 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | -1.09 | $\left\{x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a\right.$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 3.66 |
| 0.4 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | -0.69 | $\left\{\begin{array}{c}x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a, \\ \left.x_{6} a, x_{7} b, x_{8} a\right\}\end{array}\right.$ | 3.38 |
| 0.5 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | -0.30 | $\left\{\begin{array}{c}x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a, \\ \left.x_{6} a, x_{7} b, x_{8} a\right\}\end{array}\right.$ | 3.09 |


| 0.6 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | 0.09 | $\left\{x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a\right.$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 2.81 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0.7 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | 0.49 | $x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 2.52 |
| 0.8 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | 0.88 | $\left\{x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a\right.$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 2.24 |
| 0.9 | $[1,5]$ | $\left\{x_{1} b, x_{2} a, x_{3} a, x_{4} a, x_{5} b\right.$, <br> $\left.x_{6} b, x_{7} a, x_{8} b\right\}$ | 1.27 | $x_{1} a, x_{2} b, x_{3} b, x_{4} b, x_{5} a$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 1.95 |
| 1.0 | $[1,5]$ | $\left\{x_{1} a, x_{2} a, x_{3} a, x_{4} a, x_{5} a\right.$, <br> $\left.x_{6} a, x_{7} a, x_{8} a\right\}$ | 1.67 | $x_{1} a, x_{2} a, x_{3} b, x_{4} a, x_{5} b$, <br> $\left.x_{6} a, x_{7} b, x_{8} a\right\}$ | 1.67 |

## Step III: The Determination of Optimised Fuzzy Value $f^{*}$

The process of defuzzification starts with the determination of $f^{*}$ and $Z_{x}{ }^{*}$, the intersection of preferred and induced graphs, obtained as the result of the Algorithm II. $f^{*}$ is the fuzzy induced value obtained from the intersection. The results derived from this process were then analysed to obtain the ideal parameters for each intelligence skill.

The mean score of 4 ( $80 \%$ ) is the score that is needed as a person with such a score is deemed to have that particular skill. Figure 2 illustrates the process for Patient A. In this figure, the blue triangle on the right represents the preferred graph and the black triangle on the left represents the induced graph. From the intersection, the $f^{*}$ value is 0.6012. Different patients may have different $f^{*}$ values. These values were used to determine the optimum values in the next step.


Fig. 2. Intersection of Induced and Preferred Graphs $\left(f^{*}\right)$ for Patient A

## Step IV: Defuzzification

Once the value of $f^{*}$ is obtained, it is used as the new $\alpha$-cut value to determine the optimised input parameters of every intelligence parameters as illustrated in Figure 3 for Patient A using $f^{*}=0.6012$.

The complete results for Patient A for all eight intelligences are summarised in Table 5. Once these values were obtained, they were substituted into Equation (1) as in Algorithm 2. There would be $2^{8}$ combinations for the simulation to determine the best value that is nearest to the $Z_{i j}$ value.


Fig. 3. Fuzzified Input Parameters for $f=.6012$ by intelligence Math-logic ( $x_{3}$ )

Table 5. Minimum and maximum values of eight intelligence for Patient A for $f^{*}=0.6012$

| Intelligence | $\boldsymbol{a}$ | $\boldsymbol{b}$ |
| :---: | :---: | :---: |
| 1. Music | 2.53 | 4.13 |
| 2. Kinaesthetic | 2.92 | 4.52 |
| 3. Math-logic | 2.62 | 4.22 |
| 4. Spatial | 2.26 | 3.86 |
| 5. Verbal | 2.74 | 4.34 |
| 6. Interpersonal | 3.28 | 4.88 |
| 7. Intrapersonal | 2.62 | 4.22 |
| 8. Naturalist | 2.56 | 4.16 |

For example, the best combination of the eight intelligences obtained from the simulation is $\left\{x_{1} a, x_{2} b, x_{3} b\right.$, $\left.x_{4} b, x_{5} a, x_{6} a, x_{7} b, x_{8} a\right\}$ and using Equation (3),

$$
\begin{aligned}
\mathrm{z}= & -0.879-0.094 \text { music }+0.497 \text { kinaesthetic }+0.256 \\
& \text { math-logic }+0.121 \text { spatial }-0.180 \text { verbal }-0.086 \\
& \text { interpersonal }+0.308 \text { intrapersonal }-0.154 \\
& \text { naturalist } \\
=\quad & -0.879-0.094(2.53)+0.497(4.52)+0.256(4.22) \\
& +0.121(3.86)-0.180(2.74)-0.086(3.28)+ \\
& 0.308(4.22)-0.154(2.56) \\
= & 2.804
\end{aligned}
$$

## Step V: Recalculate the Logistic Regression Performance Parameters

The last algorithm is to recalculate the logistic regression parameters, $\mathrm{P}_{i}(Y=1)$. Table 6 shows the actual and optimized scores for the intelligence parameters.

For Patient A the ideal combination of intelligence levels to ensure high probability of employment is: \{music $=2.53$, kinaesthetic $=4.52$, math-logic $=4.22$, spatial $=$ 3.86 , verbal $=2.74$, interpersonal $=3.28$, intrapersonal $=$ 4.22, naturalist $=2.56\}$.

In order to find the probability of employment, the logit values ( $z$ ) must be calculated and substituted into Equation (3) as follows.

$$
\begin{aligned}
z_{\text {actual }}= & -.879-.094 \text { music }+.497 \text { kinaesthetic }+ \\
& .256 \text { math-logic }+.121 \text { spatial }-.180 \\
& \text { verbal }-.086 \text { interpersonal }+. .308 \\
& \text { intrapersonal }-.154 \text { naturalist }
\end{aligned}
$$

$$
\begin{aligned}
&=-.879-.094(3.55)+.497(4.20)+.256 \\
&(3.70)+.121(3.10)-.180(3.90)-.086 \\
&(4.80)+.308(3.70)-.154(3.60) \\
&= 1.667 \\
& Z_{\text {optimized }}=\quad-0.879-0.094 \text { music }+0.497 \text { kinaesthetic } \\
&+0.256 \text { math-logic }+0.121 \text { spatial }-0.180 \\
& \quad \text { verbal }-0.086 \text { interpersonal }+0.308 \\
& \quad \text { intrapersonal }-0.154 \text { naturalist } \\
&=-0.879-0.094(2.53)+0.497(4.52)+0.256 \\
&(4.22)+0.121(3.86)-0.180(2.74)- \\
& 0.086(3.28)+0.308(4.22)-0.154(2.56)
\end{aligned}
$$

Table 6. Actual and optimized value: Patient A

| Parameters | Actual Mean <br> Score | Optimized <br> Value |
| :--- | :---: | :---: |
| 1. Music | 3.55 | 2.53 |
| 2. Kinaesthetic | 4.20 | 4.52 |
| 3. Math-Logic | 3.70 | 4.22 |
| 4. Spatial | 3.10 | 3.86 |
| 5. Verbal | 3.90 | 2.74 |
| 6. Interpersonal | 4.80 | 3.28 |
| 7. Intrapersonal | 3.70 | 4.22 |
| 8. Naturalist | 3.60 | 2.56 |

### 3.2 Optimisation

The optimisation which is the probability of employment can be obtained the by substituting the optimized values into Equation (1).

$$
\begin{aligned}
P(\text { Actual }=1) & = \\
& =\quad \frac{1}{1+e^{-1.67}} \\
& \mathbf{0 . 8 4 1}
\end{aligned}
$$

For the fuzzy optimized value,

$$
\begin{array}{lll}
P(\text { Optimized }=1) & = & \frac{1}{1+e^{-2.80}} \\
& = & \mathbf{0 . 9 4 3}
\end{array}
$$

Thus, it can be concluded that through this combination, Patient $A$ is capable of increasing the employment probability from 0.841 to 0.943 by working on optimised intelligence values.

For further illustrations, Table 7 presents four more examples of patients with different employability status, fuzzified values, employment probability and skills that need improvement. The results are sorted by the value of the original probability in ascending order. Two subjects (ID: 95 and 99) needed to improve their kinaesthetic, mathlogic, spatial and intrapersonal skills in order to enhance their chances of being employed, while one subject (ID 03) required the four skills as well as the interpersonal skill.

Table 7. Results of the model application for 4 patients

| ID | Employability <br> Status | $\boldsymbol{f}^{*}$ | Actual <br> $\boldsymbol{P ( \boldsymbol { X } )}$ | Targeted <br> $\boldsymbol{P ( \boldsymbol { X } )}$ | Skills need <br> improvement |
| :---: | :---: | :---: | :---: | :---: | :--- |
| 03 | Unemployed | 0.643 | 0.683 | 0.928 | Kinaesthetic <br> Math-logic <br> Spatial <br> Interpersonal <br> Intrapersonal |
| 99 | Unemployed | 0.604 | 0.845 | 0.943 | Math-logic <br> Spatial <br> Intrapersonal |
| 02 | Employed | 0.632 | 0.876 | 0.943 | Math-logic <br> Spatial <br> Einaesthetic |
| 95 | Employed | 0.515 | 0.665 | 0.927 | Intrapersonal |
|  |  |  | Math-logic <br> Spatial <br> Intrapersonal |  |  |

The skills identified above could be enhanced by practice and training and by specific activities as suggested by Gardner in his MI theory $[7,8,9]$. For example, the kinaesthetic intelligence can be improved if a person interact with space, process knowledge through bodily sensations and communicate ideas through gestures more often. Meanwhile, in order to improve the math-logic intelligence, a person needs to practice working with patterns and relationships, playing with numbers and classifying things.

### 3.3 Flexibility of the Model

This method is also flexible that it can accommodate changes in the probability $P(Y=1)$ and recalculate the intelligence parameters. This feature is formally presented by the following lemmas and theorems.

## LEMMA 3.1:

The probability of FIA of a patient being reduced by reducing the intersection at the minimum side of induced and preferred fuzzy values (Figure 4).

## Proof:

Given $\mathrm{P}^{*}\left(\mathrm{Y}_{\mathrm{i}}\right)=\frac{1}{1+e^{-z_{i}}}$ is the probability of an arbitrary patient $i$.
Now,

$$
\mathrm{P}_{i}=\frac{1}{1+e^{-z_{i}^{*}}}=\frac{1}{1+\frac{1}{e^{z_{i}^{*}}}}>0 \text { since } e^{z_{i}}>0
$$

Therefore, if $\mathrm{P}_{j}<\mathrm{P}_{i}$ is needed, then

$$
\begin{aligned}
\frac{1}{1+\frac{1}{e^{z_{j}^{*}}}}<\frac{1}{1+\frac{1}{e^{z_{i}^{*}}}} \Rightarrow \quad & \frac{1}{e^{z_{j}^{*}}}>\frac{1}{e^{z_{i}^{*}}} \\
& \Rightarrow \quad e^{z_{j}^{*}}<e^{z_{i}^{*}} \\
& \Rightarrow z_{j}^{*}<z_{i}^{*} \\
& \Rightarrow f_{j}^{*}<f_{i}^{*}
\end{aligned}
$$

since the fuzzy membership value is ordered and intersects on the minimum side.


Fig. 4. Intersection at the Minimum Side of Induced Value

Hence, by reducing the intersection of induced fuzzy preferred value, the probability can be set to be smaller as described formally by the following lemma.

## LEMMA 3.2:

If the intersection of the induced and preferred fuzzy values occurs at the minimum side of induced value (Figure 5), then $f_{j}^{*}<f_{i}^{*} \Rightarrow \mathrm{P}_{j}<\mathrm{P}_{i}$.

## Proof:

$$
\begin{aligned}
f_{j}^{*}<f_{i}^{*} \Longrightarrow \quad & z_{j}^{*}<z_{i}^{*} \\
& \Rightarrow \quad e^{z_{j}^{*}}<e^{z_{i}^{*}} \\
& \Rightarrow \quad \frac{1}{e^{z_{j}^{*}}}>\frac{1}{e^{z_{i}^{*}}} \\
& \Rightarrow \quad 1+\frac{1}{e^{z_{j}^{*}}}>1+\frac{1}{e^{z_{i}^{*}}} \\
& \Rightarrow \frac{1}{1+\frac{1}{e^{z_{j}^{*}}}}<\frac{1}{1+\frac{1}{e^{z_{i}^{*}}}}
\end{aligned}
$$

$$
\Rightarrow \mathrm{P}_{j}<\mathrm{P}_{i}
$$

Consequently, the following theorem is deduced when the intersection occurs at minimum side of the induced value.

## THEOREM 3.3:

$f_{j}^{*}<f_{i}^{*}$ iff $\mathrm{P}_{j}<\mathrm{P}_{i}$

## Proof:

$(\Leftarrow)$ By Lemma 3.1
$(\Rightarrow)$ By Lemma 3.2
On the other hand, if the intersection occurs at the maximum side of induced value, the following theorem is easily deduced.

## THEOREM 3.4:

$f_{j}^{*}<f_{i}^{*}$ iff $\mathrm{P}_{j}>\mathrm{P}_{i}$

## Proof:

$(\Leftrightarrow)$

$$
\text { Let } \begin{aligned}
f_{j}^{*}< & f_{i}^{*} \quad \Leftrightarrow \quad z_{j}^{*}>z_{i}^{*} \\
& \Leftrightarrow \quad e^{z_{j}^{*}}>e^{z_{i}^{*}} \\
& \Leftrightarrow \quad \frac{1}{e^{z_{j}^{*}}}<\frac{1}{e^{z_{i}^{*}}} \\
& \Leftrightarrow \frac{1}{1+\frac{1}{z^{*}}}>\frac{1}{e^{z_{j}^{*}}}<1+\frac{1}{1+\frac{1}{e^{z_{i}^{*}}}} \\
& \Leftrightarrow \mathrm{e}_{j}>\mathrm{P}_{i}
\end{aligned}
$$



Fig. 5. Intersection at the Maximum Side of Induced Value

## 4. CONCLUSION

Fuzzy algorithms, FIA are introduced in this paper in order to determine how the chances of PWE getting hired could be improved. According to Gardner, a person's intelligence can be enhanced if the person focuses and practices regularly [7] PWE need to undergo ATIE ${ }^{\ominus}$, have the result analysed using the Fuzzy Inverse ATIE (FIA), and their weaknesses identified. Based on this diagnosis, the PWE concerned could then embark on specific remedial actions to overcome their weaknesses and improve their chances of being hired.

The process of developing an employability model for PWE has been demonstrated and discussed. Based on the results of the logistic regression and the fuzzy model, the optimal combination of the eight intelligences was derived. Since the probability of employability, $P(Y=1)$ was close to 1 , one may conclude that the approach adopted by this study would help to enhance the likelihood of a PWE being employed.

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