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Research article

Decoding career success: A personality-based analysis of data science Professional based on ANFIS modeling

Ali Rezaiee Fard [a], Babak Amiri [b,*]

[a] School of Management, Economics and Progress Engineering, Iran University of Science and Technology, Iran
[b] School of Industrial Engineering, Iran University of Science and Technology, Iran

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ABSTRACT

Career selection is one of the most important decisions every person faces in their life. Finding the right career path can be a complicated task, particularly in choosing careers with similarly required proficiencies. One of the critical factors affecting a person's career success is their personality, and taking account of this factor is of paramount importance. This study uses the NEO-FFI questionnaire to find personality patterns of software engineering and data science experts based on the Big Five personality traits: Neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. Afterward, an ANFIS (Adaptive Network-Based Inference System) is conducted using the experts' personality data to match the participants of these fields with their corresponding choices. This study demonstrated that data scientists and software engineers score higher in conscientiousness and agreeableness, respectively. Also, data experts have higher scores in all traits overall. In the end, the ANFIS is tested with another similar dataset and the prediction accuracy of the model is measured.

1. Introduction

Choosing a career path is one of the essential decisions every student must make in their life. Given the variety and complexity of the jobs, it might be an overwhelming process that might require some facilitators. Pursuing the trending professions and jobs is always a priority in students' career planning. At the age of digitalization, pursuing IT careers is a popular choice: two of the highest required jobs in this area are data science and software engineering [1].

There has been a growing, popular business and academic attention to data science, predictive analytics, and big data fields in the last years [2]. Companies across industries start to identify their need in order to hire more data scientists, and accordingly, educational institutions have launched new courses to train data scientists [3]. As the data science is called the "sexiest job of 21st century" [4], many students are interested in this field. Apart from the data scientist job, according to the US Bureau of Labor Statistics [5], the software engineering career is also a well-known job, the number of which is likely to grow by 24 % rate between 2019 and 2029. There are many technical skills required in being a data scientist, such as programming with various languages, database programming, data architecture, machine learning, data visualization, communication skills, etc. [6–8]. Like various programming languages, data structures, and database concepts, some of these skills are in common with the technical skills required to be a software engineer [9]. Therefore, people qualified for these skills and interested in both careers might face a dilemma of choosing one of the two paths; addressing the factors affecting this choice can make it easier. One of these contributing factors is personality since many studies have

* Corresponding author.
E-mail address: babakamiri@iust.ac.ir (B. Amiri).

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examined and validated personality's effect on career success and performance. Therefore, when choosing a career path or selecting an appropriate workforce to be recruited, personality should be taken into consideration [10–30].

Several studies focus on the relationship between the workforce personality and their jobs. Some of these studies analyzed how personality traits influence their vocational specialty, such as Lysack et al. [31] comparing the occupational and physical therapists. Also, Buddeberg-Fischer et al. [32], Woods et al. [33], McLarnon et al. [34], Mullola et al. [35] and Nawaiseh et al. [36] investigated how personality affected specialty choice among medical graduates and Holt et al. [37] did a similar study for accounting students. Another portion of the related works examined personality's role in the students' major or field selection. Larson et al. [38], Chen and Simpson [39], Kemboi et al. [40], and Alkhelil [41] are the most recent examples of those studies. Apart from statistical methods, some used fuzzy systems, like Martinez et al. [42,43] using ANFIS to extract the personality patterns of students in different fields. In addition to analyzing the relationship between personality traits and career selection, some studies developed career recommendations or prediction systems based on personality traits. Todd and Zhang [44] implemented a discrete choice dynamic programming (DCDP) model of decision-making. Similarly, Krishnamurthi and Goyal [45] used fuzzy logic to develop a career selection model. There are also some other studies introducing career prediction systems using fuzzy methods, such as Fuzzy AHPs [46,47], Fuzzy expert systems [48,49], and Neuro-Fuzzy models [50,51]. However, personality traits have not been taken into consideration in their investigations.

Using an automated self-learning prediction model can be a very useful tool for career selection. However, it seems that there is a gap in self-learning prediction approaches for career selection based on personality traits. Therefore, this paper introduces an approach using the Neuro-Fuzzy model for predicting which of the two data scientist or software engineering careers is suitable for an individual based on their personality by extracting the personality patterns of experts using the Big Five personality model. This study provides some insights for students interested in these careers to determine whether they would find success in these occupations based on the personality factor and whether they should consider these fields and make a better choice for their future career. This study has potential practical utility for career counseling, talent management, and organizational decision-making, and the HR departments could also use it for better recruitments based on the personality of the applicants.

This research consists of four sections. Section One was this introduction. Section Two provides some background knowledge, describing the Big Five personality model and its five traits and the basics of Neural networks and fuzzy logic. Section Three describes the methodology, the collected data, and the proposed Neuro-Fuzzy Model. Finally, Section Four presents the analysis, data training, the study results, and conclusion.

2. Literature review

2.1. Personality and personality traits

Personality theory provides mental processes and structures regulating how people adjust their behavior and emotions to their environment [52]. Personality is the pattern of distinctive characteristic thoughts, feelings, and behaviors that are steady over different times and situations, determining the individual's responses to their environment [53]. The personality traits are tendencies to behave or react in a specific way under certain circumstances [54]. Personality traits have been subject to a series of changes and evolution; today, two general approaches are the most popular: The Big Five Personality Model (the Five-Factor model) and Eysenck Personality Questionnaire (EPQ) [55–60].

The Big Five model, mostly used today and implemented in this study, was developed by McCrae and Costa [61,62] by introducing different versions of the revised NEO personality inventory.

The five dimensions of the "Big Five" model are indicated as follows: Neuroticism (N), Extraversion (E), Openness to experience (O), Agreeableness (A), and Conscientiousness (C) [63].

Neuroticism demonstrates an individual's tendency to experience psychological distress [63] and measures how emotionally stable an individual is. Individuals with low neuroticism levels are more confident, experiencing less nervousness. On the other hand, individuals with high Neuroticism are more susceptible to negative emotions like worry and anger [54].

The Extraversion dimension defines traits, *e.g.*, sociability and activity. Extraverts tend to be more outgoing, warmer, and talkative, embracing pleasures more actively. However, introverts tend to be quiet, not call for company and avoid social activities [63,64].

Openness to experience describes how much a person is enthusiastic about new experiences and innovation. People with high openness levels are appreciative of art, more emotional and imaginative, comfortable with changes and new values, and considered liberal. In contrast, individuals with a low level of openness tend to be more conservative and dogmatic, seek familiarity, and do not pay much attention to emotions [63,64].

Agreeableness can be described as a measure of altruism or hostility [40]. Individuals with low agreeableness are subject to being cynical and competitive and prioritize their own needs and desires before others. On the contrary, an agreeable person is more likely to show sympathy and willingness to help others [63].

Conscientiousness is about how many goals a person focuses on. People with a high level of conscientiousness, called *Focused,* concentrate on few goals and are more disciplined, steady, and resistant to distractions. On the other hand, *Flexible* people are more impulsive, less organized, mostly unreliable, and focused on many goals. Still, while being less effective than the focused ones, this trait helps them be creative [64].

2.2. Fuzzy models, artificial neural networks and neuro-fuzzy systems

One way to make a computer think and solve a problem more like a human is using fuzzy logic [49]. Zadeh introduced fuzzy logic as a mathematical solution in 1965 for dealing with complex or uncertain problems or those with multiple solutions or values, using fuzzy sets [65]. Later, Mamdani and Assilian [66] and Takagi and Sugeno [67] used fuzzy logic to develop Fuzzy control systems.

Fuzzy systems use IF-THEN rules, expressions like *if A, then B,* in which both A and B are a fuzzy set, described by a Membership Function (MF). A and B variables can be linguistic values helping use imprecise and vague human language labels, such as great or low, to create uncertain models [65,68]. An expert's knowledge provides the fuzzy rules. However, if an expert's knowledge is not available, rules could be obtained from data by training data and implementing machine learning methods [69].

Also, unlike Classis logic, Fuzzy logic does not describe each set's elements as a Boolean value, *True* or *False* or 0 or 1, but as a membership value in an interval of 0–1 [49,68].

An artificial intelligence network is a multilayer perception model including layers (and hidden layers) of interconnected units called nodes, inspired by the biological neural system of the living. ANN helps with forecasting or decision-making by integrating the inputs and creating an output that will be used as an input for the next layer of nodes until the final output completes the task. The nodes have certain connections biased and controlled by an expert or adjusted by training data [70–72].

The integration of ANN and Fuzzy logic IF-THEN rules led to the introduction of ANFIS or an Adaptive network-based fuzzy inference system by Jang [68], which is the used method in this research. It will be discussed in the methodology section.

2.3. *Related research*

Many studies have focused on the effect of personality on career success and performance or job satisfaction based on these traits.

Two separate studies in 1991 investigated the relationship between personality and career success by Barrick and Mount [10] and Tett et al. [11]. In their meta-analysis, Barrick and Mount [10] found consciousness as a valid predictor among different careers and extraversion, emotional stability (Neuroticism), and agreeableness as predicting factors for certain occupations. On the other hand, Tett et al. [11] found all the traits as valid predictors. However, they found extraversion, openness, and agreeableness to be the more valid traits. Salgado [12] did similar studies in Europe. The results showed that, followed by Neuroticism, consciousness has the most validity across the traits among all investigated occupations.

Judge et al. [13] categorized career success into two dimensions: intrinsic success (job satisfaction) and extrinsic success (income and occupational status). They examined the effect of personality traits on these two dimensions. Their research provided evidence of a stable relationship between personality traits, general mental ability, and career success. High consciousness was accompanied by extrinsic career success; Neuroticism and extraversion did not predict intrinsic success, and agreeableness negatively affected extrinsic success.

Barrick et al. [12] conducted a second study on the matter in 2001 and found out that conscientiousness and Neuroticism were valid predictors of job performance for all job groups. They also found that the other three personality dimensions were valid predictors of some occupations and criteria.

In another study, Seibert and Kraimer [14] examined the relationship between personality and career success. They found out that a positive relationship between extraversion and salary level, promotions, and career satisfaction and Neuroticism negatively impacted career satisfaction. They also found a negative relationship between agreeableness and career satisfaction and between openness and salary level.

A study carried out by Rothmann and Coetzer [15] proved that Neuroticism, extraversion, openness to experience, and conscientiousness were related to task performance and creativity, and Neuroticism, openness, and agreeableness brought about 28 % of the variance in participants' management performance.

On their study on the relationships between personality traits and job performance, Le et al. [18] found that Conscientiousness and Neuroticism are beneficial for high complexity jobs.

De Haro et al. [19] concluded that three of the Big Five Personality traits, including conscientiousness, Neuroticism, and openness combined with general mental abilities, have a noticeable association with early career success.

Salgado and Tauriz [20] reviewed and confirmed the validity of Big Five personality traits on academic and occupational performance with a meta-analysis study.

On their study on the relationships between personality traits, job performance and job satisfaction, Yang and Hwang [21] found that all personality traits have significant impact job performance, especially Agreeableness and Extraversion.

Garbarino et al. [73] found Neuroticism and Agreeableness associated with stress levels and stress reactivity in special force police officers.

Ongore [74] surveyed university academic and administrative personnel and found that Extraversion, Agreeableness, Conscientiousness and Openness to Experience were positively related to job engagement, while Neuroticism showed a negative relation.

Barnett et al. [75] explored the predictive power of FFM traits on perceived and actual technology usage. Conscientiousness was positively associated, and neuroticism was negatively associated with both perceived and actual use, while extraversion showed a negative association with actual usage. This is of particular interest to our study due to the nature of the careers being investigated.

Binti Rusbadrol et al. [22] Demonstrated a positive association between Openness to experience and Agreeableness and job performance, and a negative association with Neuroticism, among secondary school teachers.

Wiersma and Kappe [23] investigated the effect of extroversion and conscientiousness on career success, finding conscientiousness significantly related to salary growth and extroversion to starting salary among freshmen college students.

Van Aarde et al. [76] did a meta-analysis of South African studies. The results were comparable to previous studies, such as Barrick and Mount [10], highlighting conscientiousness and Neuroticism, to a lesser degree, the strongest predictors of technical performance. They also found extraversion as an effective factor for training.

Lado and Alonso [24] carried out four studies to investigate how FFM can predict performance in low complexity jobs in terms of overall job performance, task performance, and contextual performance measures. The results demonstrated Conscientiousness and Neuroticism as predictors of all three of them, while extraversion was a predictor of overall job performance and task performance, and Agreeableness was a predictor of contextual performance.

Bui [77] showed Neuroticism, Conscientiousness, Openness to experience, and Agreeableness as important predictors of job satisfaction among a UK national sample of over 7000 respondents.

De Jong et al. [78] studied the relationships between personality traits, career role preferences and career role enactment. Their results demonstrated that Extraversion, Conscientiousness and Openness to experience influence various career role preferences.

Rubenstein et al. [79] examined the link between Five Factor model traits and job characteristics, such as satisfaction and commitment, illustrating how individuals perceive their jobs positively or negatively due to their personality trait levels.

Gridwichai et al. [27] provided empirical evidence for the influence of FFM personality traits on job performance among the employees of the pharmaceutical industry in Thailand.

Babar and Tahir [25] studied FFM and job performance relationship among university teaching staff and found openness to experience, conscientiousness, and agreeableness to have positive and significant effects on employee job performance.

Yao and Li [29] examined the correlation between FFM traits and employee creativity in probation and formal employment periods. Openness to experience and conscientiousness correlated with creativity in both job stages, while agreeableness correlated in probation periods and extraversion in formal employment periods.

In a meta-analysis study, Zell and Lesick [28] found correlations between each Big Five trait and performance, highlighting the Five Factor Model as a useful framework for performance prediction in school and work settings.

Schoeman & Kotzee [30] examined the relationship between the big five traits and academic performance within MBA graduates, demonstrating Openness to Experience, Agreeableness, Conscientiousness and Neuroticism as valid predictors of performance.

According to these studies, it can evidently be implied that personality traits play a pivotal role in career success and should be accounted for in the process of career selection or selecting the right personnel for the right job. This issue has not gone unnoticed in previous studies.

Excellently reviewing the studies on personality traits and personnel selection, Salgado and De Fruyt [16] pointed out that conscientiousness, Neuroticism, and agreeableness were valid job performance predictors, and The Big Five traits were predictors of leadership and job satisfaction.

Another review article by Rothstein and Goffin [17] explored the use of personality assessment for personnel selection. It was concluded that personality measures, if appropriately used, add value to personnel selection operations, with the Five-Factor model as the popular choice for this purpose.

Some studies tried to investigate or compare the personality traits for certain careers specialties or how personality traits affect a student's major selection.

For instance, Lysack et al. [31] examined the relationship between personality traits and job choice by analyzing occupational and physical therapists using the Keirsey-Bates personality inventory. They found remarkable differences between the two groups' personalities.

In another study, using the Multidimensional Personality Questionnaire (MPQ), Larson et al. [38] looked into the roles that personality traits, self-efficacy, and interests play in selecting an education major. They gathered data from a sample of 368 undergraduate students in order to investigate the relation between 11 personality traits of the MPQ model on occupational areas chosen from Holland's [80] career framework, which suggests six areas known as RIASEC domains, including realistic interests (R), investigative interests (I), artistic interests (A), social interests (S), enterprising interests (E), and conventional interests (C). The results of this study indicated that personality traits play a role in distinguishing among choice actions. The results also demonstrated that self-efficacy and interests are more proximal factors of those choice actions than personality.

Chen and Simpson [39] employed Holland's personality model and Social Cognitive Career Theory (SCCT) to probe the factors that influence students' choice to join STEM majors (Science, Technology, Engineering, and Mathematics). The results demonstrated that stronger investigative personality types are most likely to choose STEM majors. In contrast, artistic and enterprising personality types are less interested in these majors.

Surveying 399 university students in Kenya, Kemboi et al. [40] studied the connection between personality types and undergraduate students' career choices. The results confirmed that there is a correlation between them. They based their study on Holland's Personality Theory of Career Choice [80] and the previously mentioned RAISEC domains.

Alkhelil [41] examined the relationship between personality traits and career choice and whether these traits can affect the students' choice of major in the university/college, using the Big five personality model and considering three types of careers, including managerial, research, science, and technical jobs. He used the data gathered from 178 personnel consisting of students randomly selected from five secondary schools in Damascus, which resulted in finding a significant relationship between personality traits and career choice.

This matter has been especially the center of attention in the medical sector.

Buddeberg-Fischer et al. [32] conducted a study on how personality traits, gender, career motivation, and life goals influence doctors' career specialty choice among Swiss medical school graduates. They found that personality, career motivation, and life goals have an impact on specialty choice. They used the "Sense of Coherence Scale," "Rosenberg-Self-Esteem-Scale," and "German Extended Personal Attributes Questionnaire" in order to measure the participants' personality traits.

Studying a sample of UK medical students and using the Big Five personality model and Holland's RIASEC framework, Woods et al. [33] examined the role personality plays in occupational specialty choice by.

McLarnon et al. [34] assessed how traditional cognitive predictors and personality traits could predict students' academic and clinical performance in medical school. The personality predictors increased the prediction of both areas above the traditional ones.

In another study on medical schools, Mullola et al. [35] explored how personality traits affect medical career and specialty choice after graduation. Studying 2837 Finnish physicians with covariance analysis found that personality traits were associated with their specialty choice, particularly openness and agreeableness.

Nawaiseh et al. [36] investigated the link between Five Factor Model (FFM) personality traits and specialty preference among over 1000 medical students in Jordan. They discovered that students with higher levels of extraversion and conscientiousness and lower Neuroticism preferred surgery-oriented specialties rather than medicine-oriented ones.

On a study on accounting students, Holt et al. [37] found that students with high levels of openness to experience are more interested in auditing.

Using an ANFIS learning approach, Martinez et al. [42] developed a neuro-fuzzy model for extracting personality patterns based on the Big Five model for Software Engineering roles. In a similar study, Martinez et al. [43] employed the same method to extract different Engineering students' personality patterns.

Some relevant works introduced a career recommendation system, such as Todd and Zhang [44]. They developed a discrete choice dynamic programming (DCDP) model of decision-making for schooling and occupational choices that included personality traits in the form of the Big Five model. This model used the HILDA dataset from Australia.

In another study, using fuzzy logic, Krishnamurthi and Goyal [45] proposed a career recommendation based on the participants' personalities. They also used Holland's Code theory for personality traits and their corresponding career domains. There were also other uses of fuzzy logic.

As can be seen, there have not been many works concentrating on automated self-learning career recommendation systems that focus on personality to predict the suitable job for the individual. However, other studies have developed prediction or recommendation models based on fuzzy logic, which is our work method. But they ignored personality as a factor.

Drigas et al. [50] introduced a neuro-fuzzy expert system for matching unemployed candidates with offered jobs by comparing the candidate's qualities to job requirements in fields like age, education, computer science, and experience.

Canós and Liern [48] proposed a fuzzy model to facilitate decision-making in personnel selection and optimal staff design that

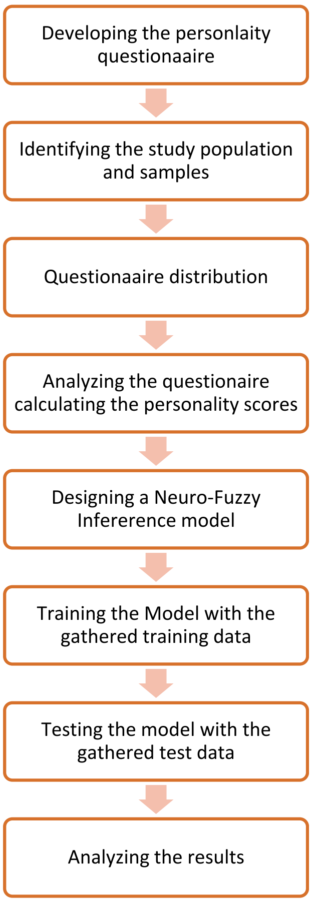

Fig. 1. Research framework.

ranks the applicants for a particular job by using Hamming distance measures. This model could also give weight to more important criteria based on an expert's opinions using ordered weighted averaging (OWA).

Göleç and Kahya [46] developed a multi-factor competency-based fuzzy AHP model for selecting and evaluating employees. Competency facets were used as selection factors, such as communication skills, personal traits, self-motivation, interpersonal skills, decision-making ability, technical knowledge-based skills, and management skills.

Daramola et al. [49] explained how they used a Fuzzy Expert System (FES) for proper personnel selection using criteria, such as age, course of study, degrees, and years of experience, each with its own linguistic values.

Kilic and Cevikcan [47] implemented a job selection model based on a fuzzy AHP. Their model was made of three levels. The first level was the job selection problem. The second layer consisted of the criteria, including the revenue of the job, loving the job, the social position, social assurance, the business environment and physical conditions of the job. The last layer was labeled as alternatives, indicating working in government, working in the private sector, and having their own job.

Patel et al. [51] carried out similar work for course selection. They used Institutional and Employability Factors, Academic Evaluation, Personal Information, and some psychological factors, such as motivation and self-confidence, as the inputs of an ANFIS. Each input was labeled with low, medium, or high values for predicting the right course for the students.

As can be seen, few studies focused on self-learning prediction approaches in the Personality-Career selection works. On the other hand, in the studies that focus on such prediction models, personality does not capture any attention. Therefore, in this paper, we use a Neuro-Fuzzy model to analyze the experts of two career fields' personality patterns and predict the proper career for each interested individual based on the Big Five personality traits model.

3. Methodology

3.1. Questionnaire and data gathering

The methodology and framework of this study are presented in Fig. 1.As shown, the first step was developing the questionnaire. Using the NEO-FFI (NEO five-factor inventory), utilizing 60 questions, and employing the Likert scale for the answers (i.e., fully disagree, disagree, neutral, agree, and fully agree), we developed our questionnaire to test the participants' personality traits, which evaluates Neuroticism (N), Extraversion (E), Openness to experience (O), Agreeableness (A), and Conscientiousness (C) traits. The questionnaire also consists of a few different questions at the beginning of the survey regarding the participants' demographic and personal information, area of expertise, and whether they were already occupied or are interested in these fields. The participants were chosen from the LinkedIn social network. Using profile job tags and related communities of practice in this network, we identified Data Science and Software Engineering experts. The questionnaire was distributed by an online survey webpage. The survey link was directly messaged to the identified experts or shared in the communities. We gathered 171 valid completed test results from the experts, including 91 Data Scientist experts and 80 Software Engineers. This data set served as our training data. A second set of data was collected by the same method after a time gap, which was used as the testing data. This data set consisted of 50 completed surveys, including 20 software engineers and 30 Data Science experts.

After collecting the results, we integrated the answers, gave each question its corresponding value, and calculated each person's personality scores. There are 12 questions for each trait, with a score from 1 to 5, resulting in 5 personality scores ranging from 12 to 60.

3.2. The ANFIS model

The architecture of a Fuzzy system can be divided into four parts, as shown in Fig. 2.

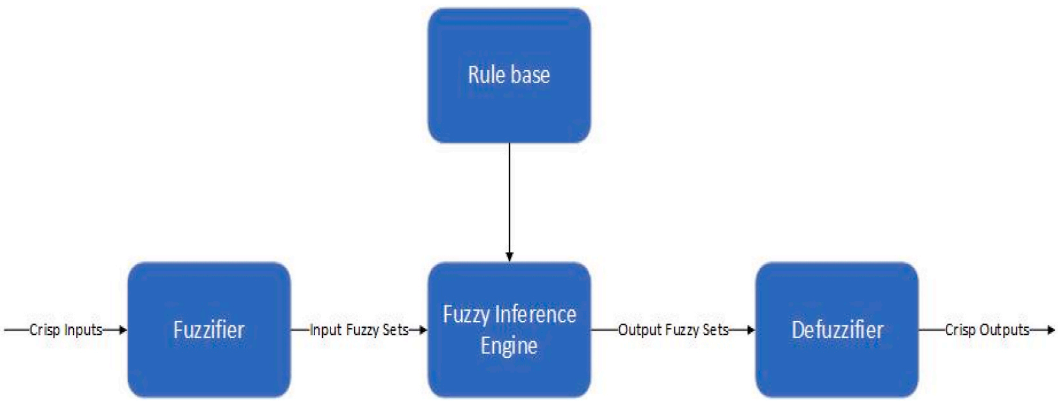

Fig. 2. Fuzzy system architecture.

- The first part is a fuzzifier agent that converts the crisp values of inputs into fuzzy sets with certain membership degrees in the form of membership functions. Membership functions help us measure linguistic terms and graphically represent a fuzzy set.
- The second part includes some fuzzy rules in the shape of *IF-THEN* statements.
- The third part is the Inference engine, where inputs are processed, such as human reasoning, and turned into outputs using the IF-THEN rules.
- And the Fourth part, which is called a defuzzifier, converts the fuzzy outputs into numeric values.

In this study, we use a Takagi-Sugeno-Kang (TSK) inference system. A TSK inference system employs singleton output membership functions, resulting in outputs in constant values or linear functions of the input values. A simple form of a first degree TSK rule are as follows:

If x = A AND y = B, THEN z = px + qy + r Equation 1:

A and B are fuzzy sets, and p, q, and r are all constant values.

A first-degree TSK ANFIS generates the rules based on the input data and consists of 5 layers, as shown in Fig. 3. In order to extract the rules, the input and output data are fed to the ANFIS. The Fuzzifier layer consists of adaptive nodes that give membership degrees to the inputs. The fixed nodes of the Rule layer set the firing strength of rules by multiplying the membership degrees (using s-norm for OR operators or t-norm for AND operators). The nodes in the third layer are also fixed and normalize the firing strength of the rules. With adaptive nodes, the 4th layer acts as a defuzzifying one, demonstrating how much each rule contributes to the final output. Finally, the single node on the last layer takes the rules' outputs and sums them into one final crisp output.

In our model, we use each traits' score as an input variable introduced as x = {N, E, O, A, C}. Two Gaussian membership functions are used for each input, resulting in 2^5 or 32 rules. The two-software engineering and data science fields are the two linguistic values for our output variable, which show the individuals' jobs or expertise.

In a first-degree TSK model, the k-th rule is defined as:

$$IF\ (x_1\ is\ B_1^k)\ AND\ (x_2\ is\ B_2^k)\ AND\ (x_3\ is\ B_3^k)\ AND\ (x_4\ is\ B_4^k)\ AND\ (x_5\ is\ B_5^k)\ THEN\ R\ is\ f^k(x) \qquad \text{Equation 2:}$$

Where:

$$f^k\ (x) = p_1^k x_1 + p_2^k x_2 + p_3^k x_3 + p_4^k x_4 + p_5^k x_5 + p_0^k \qquad \text{Equation 3:}$$

Membership functions are formulated as:

$$\mu_{B_i^k}(x_i) = exp\left[-\frac{1}{2}\left(\frac{x_i - m_i^k}{\sigma_i^k}\right)\right] \qquad \text{Equation 4}$$

In these formulas, p_I^k is a linear parameter, m_i^k expresses adjustable centers, and B_I^k shows Gaussian membership functions: i = 1, 2, 3, 4, 5 and k = 1, 2, 3, …, 32.

Using MATLAB, we developed a TSK FIS model and then trained it with the training data collected from the experts. The initial FIS was generated using grid portioning. For training the model, a hybrid optimization method was used with 10000 epochs and 0 error tolerance. This method uses a combination of backpropagation and least-squares regression to tune the FIS parameter.

Fig. 4 shows the ANFIS model architecture visualized by MATLAB.

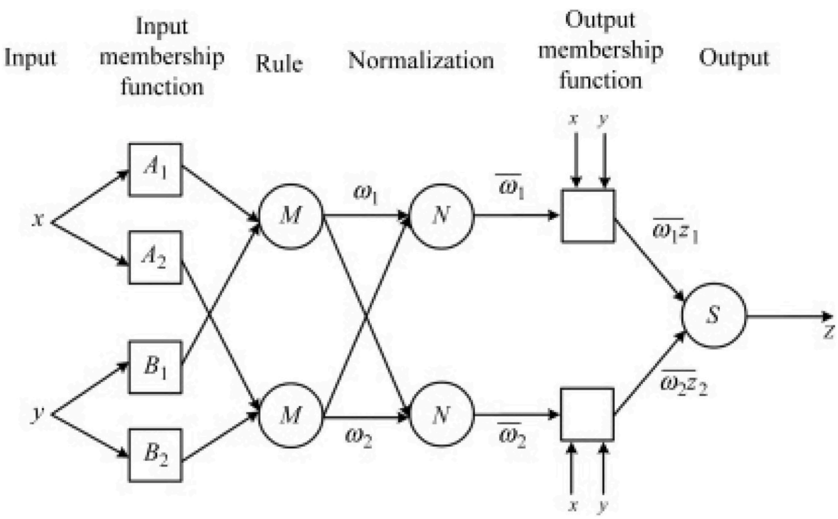

Fig. 3. Anfis architecture.

4. Results

4.1. Personality traits analysis

Among the participants, 91 were data science specialists and 80 software engineers, and among the data scientists, 31 individuals were former software engineers who pursued data science. The average of the test results and some variance analysis indicators are shown in Table 1, which demonstrate significant variance differences between the means of the two groups. The average results are also shown and compared in Fig. 5 for better understanding. Each trait value is in the range of 12–60.

As you can see in Fig. 5, both groups have a similar degree of Neuroticism. However, Neuroticism is the lowest average trait for data science experts. In all other traits, data scientists have a higher average, sometimes with a relatively large margin. For software engineers, openness holds the lowest average value among all traits, while for data scientists, openness has a high average value. The highest average value for software engineers is agreeableness. As for data scientists, consciousness holds the highest value. As a whole comparison, except for Neuroticism, data scientists have a higher average value in all other traits, especially in Consciousness and Openness.

It is also noticeable that the data related to the data scientists' shows a much lower deviation compared to the software engineers.

4.2. ANFIS model

As mentioned before, we used the first set of collected data from the participants to train our ANFIS system in the MATLAB environment. A very important factor helping the ANFIS predict the outcomes more accurately is the number of training epochs, leading to a decrease in the model error. Table 2 shows the changes of model error with increasing numbers of epochs, with an error tolerance of 0. The last value on model error is the model's final accuracy since it did not reduce subsequently.

Fig. 6 indicates the testing results of the ANFIS against training data, with stars displaying the ANFIS prediction and blue dots representing the real values for each individual.

Afterward, the ANFIS model was tested versus the test data from our second data set, which were not included in our model's training process.

Fig. 7 demonstrates the performance of our trained ANFIS model versus the test data. The distance between the predicted output and the actual output indicates how suitable the experts are to their chosen careers according to their personality traits. A shorter distance means being more fit for the job. This model can also be used to predict which career is preferable for students who are interested in the fields and are unsure which one they must put their effort into. As shown in Fig. 7, the predictions of the ANFIS are mostly close to the experts' careers with an average testing error of 0.23358.

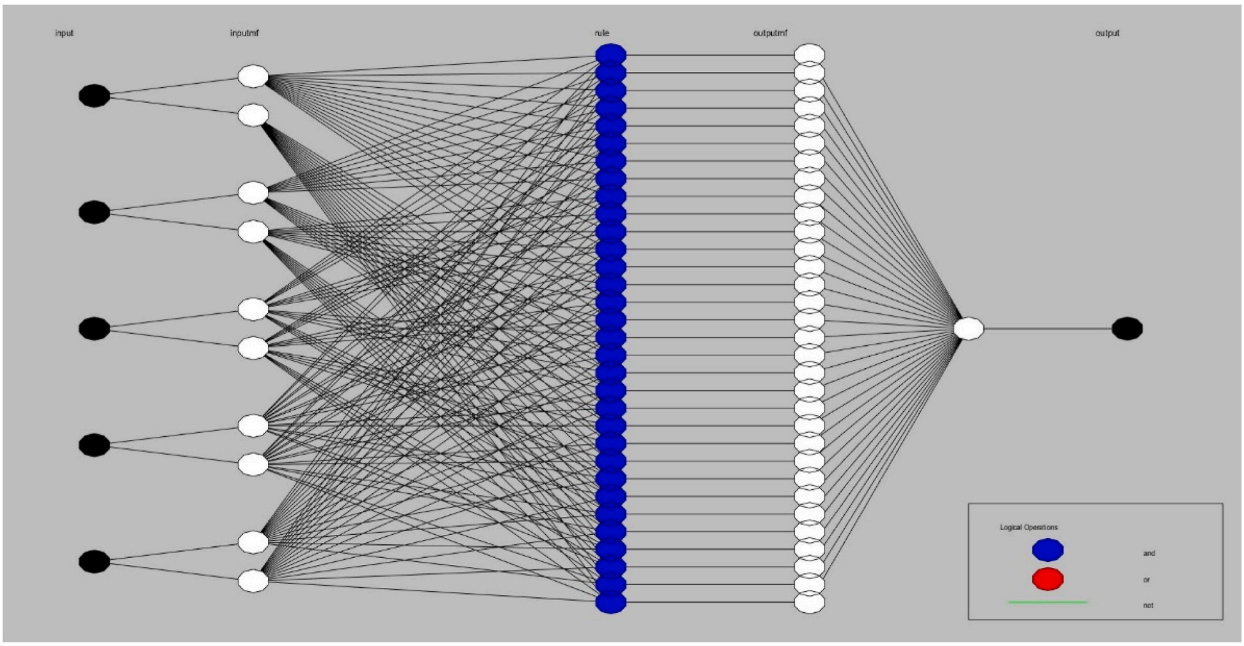

Fig. 4. ANFIS model structure.

Table 1
Test results.

	N	E	O	A	C
Average					
Data Scientists	30.46	42.55	42.69	41.65	47.79
Software Engineers	29.84	30.59	27.93	35.01	29.40
Variance					
Data Scientists	80.05	50.51	27.91	21.94	33.18
Software Engineers	167.34	166.29	118.39	212.69	158.17
F-Test					
F	2.12	3.3	4.25	9.7	4.77
F-Critical	1.43	1.43	1.43	1.43	1.43

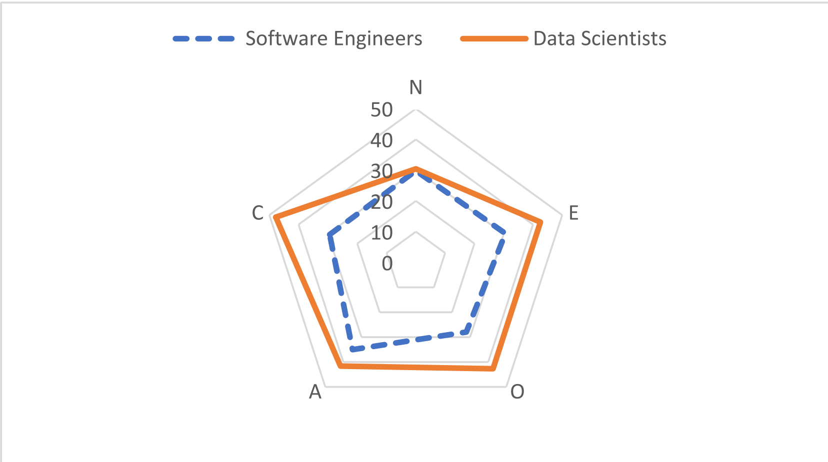

Fig. 5. Comparison of data scientists and software engineers personality traits.

Table 2
Changes of model error.

Model Error	Number of Epochs
0.1870	5
0.1848	100
0.1544	1000
0.1244	2000
0.0908	5000
0.0888	10000

5. Conclusion

In this research, the main focus was on creating a model based on fuzzy logic and neural networks capable of learning and predicting an individual's suitable career using personality analysis. This model is a fuzzy inference system that takes a person's five personality traits and predicts the ideal career as its output based on those inputs. This model was trained with survey results of 171 Data Science and Software Engineering experts. Then, it was first tested with our training data, and as the final test, tested with another data set of 50 experts, both resulting in predictions with reliable and decent accuracy. We also analyzed the questionnaire data and demonstrated personality traits for each group, realizing that Data Scientists have a very high average of consciousness and higher overall standards in all traits, except for Neuroticism, which is their lowest trait average. However, our selected Software Engineers have a high average in agreeableness and a low average on openness.

Although we chose data science and software engineering as our discussed jobs, this model is not limited to these areas and can be used to compare or select any pair of occupations or even multiple careers for a person, based on the job's personality requirements. The proposed ANFIS can be used by students who are unsure which careers is more fitting for them, or assist job counselors to help them make the better choice. It can also serve as a tool for organizations and HR departments to validate the applicants' compatibility with their demanded job positions, facilitate recruitment decision-making, or investigate their current staff's compatibility with their jobs in terms of personality.

This study's findings have to be seen in the light of some limitations; only one prediction model was used in this study. Besides, the

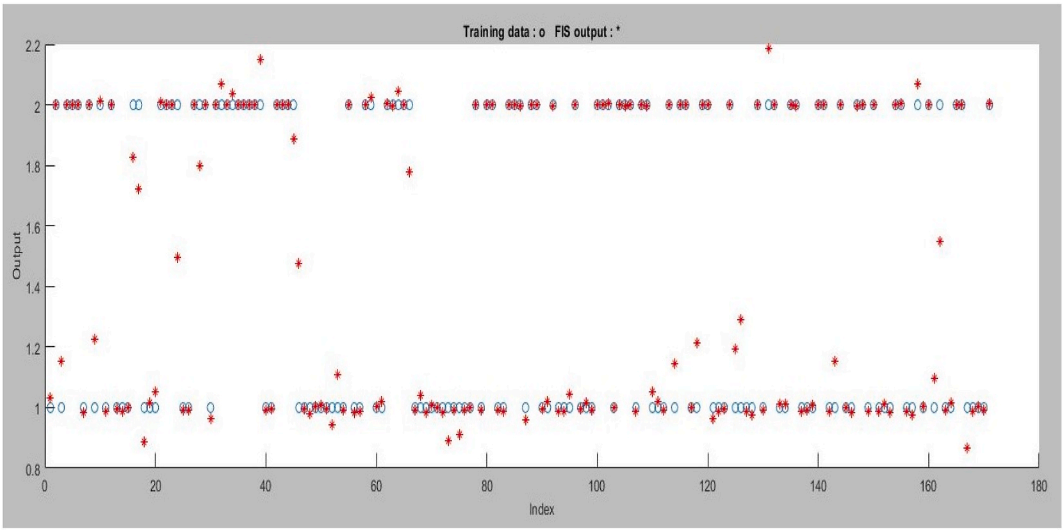

Fig. 6. FIS testing results against training data.

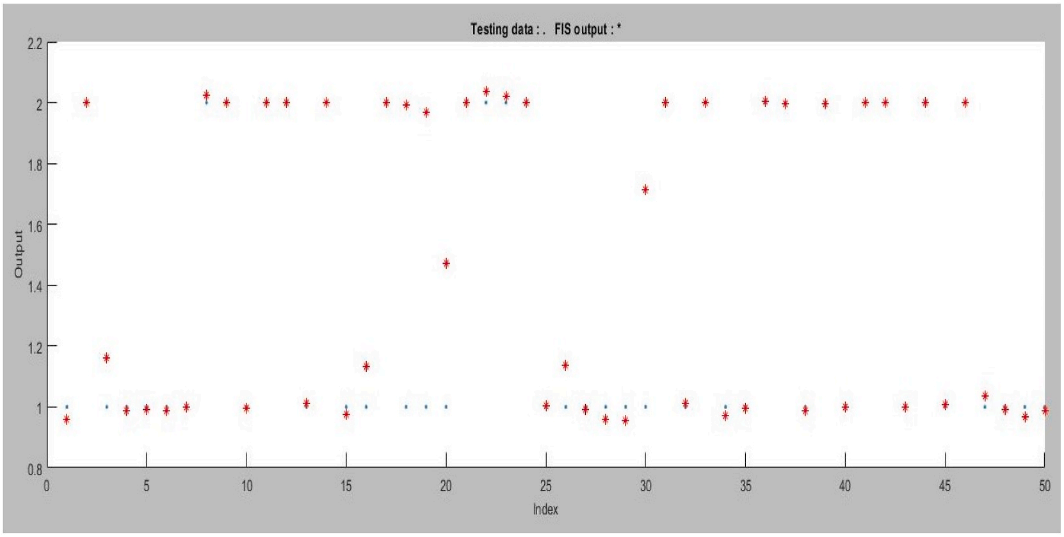

Fig. 7. FIS testing results against testing data.

participants were chosen from LinkedIn but only from Iranian users, which leads to a lack of demographic diversity in our sample. For future researches, we recommend performing this investigation on different samples from different locations. This model can also be tested with other groups of occupations to investigate this model's validity further. It can also solve problems other than career selection, which could employ fuzzy problem-solving approaches. This model only uses personality traits as the deciding factors, thus it can be further expanded and improved upon by adding other impactful factors and criteria to the model, to make it a more comprehensive prediction system. It is also recommended to use other problem-solving models on this problem and compare them to this model and illustrate a better solution for this kind of problem.

Ethics statement

All participants provided informed consent to participate in the study and were fully informed of the reason, objectives and the process of the study, how and why their data was going to be used, the anonymity of the gathered data and their right to opt out from the study at any time.

Data availability statement

All the anonymized data gathered and used in this study are included in the appendices.

CRediT authorship contribution statement

Ali Rezaiee Fard: Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Babak Amiri:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e34130.

Appendix A

The Data

This appendix presents the anonymized data used in the model. N, E,O,A and C columns stand for Neuroticism, Extraversion, Openness to experience, Agreeableness, and Conscientiousness traits score, respectively. The Output column shows the careers which the value of 1 is for Data Scientists and 2 shows Software Engineers.

Table A1
The data used in the model

N	E	O	A	C	Output
26	39	35	38	46	1
43	28	23	53	34	2
31	28	34	32	44	1
34	20	23	36	13	2
13	13	16	23	20	2
44	28	16	39	19	2
20	49	45	40	54	1
28	34	24	20	38	2
25	34	45	36	48	1
54	21	60	38	22	2
14	53	42	42	51	1
39	17	28	36	53	2
28	44	36	37	49	1
26	50	45	44	56	1
35	44	42	45	41	1
19	53	34	40	34	2
27	38	36	51	23	2
40	29	45	32	46	1
21	40	44	45	50	1
18	39	47	48	47	1
19	51	29	40	13	2
28	46	22	36	15	2
19	15	22	51	29	2
25	35	36	34	36	2
33	48	50	42	52	1
30	42	45	41	54	1
14	24	21	33	15	2
34	30	31	39	19	2
40	40	36	18	27	2
38	35	41	38	47	1
40	25	21	33	44	2
21	28	31	39	28	2
42	55	49	12	19	2

(*continued on next page*)

Table A1 (*continued*)

N	E	O	A	C	Output
55	12	34	54	20	2
55	15	27	29	19	2
12	21	29	23	40	2
51	49	20	35	36	2
34	29	19	16	23	2
23	34	40	39	17	2
40	42	39	54	51	1
33	41	42	42	45	1
26	23	19	17	40	2
19	20	20	46	40	2
25	23	25	42	55	2
16	40	36	54	34	2
26	50	47	46	34	1
31	40	42	41	48	1
17	55	50	43	59	1
25	45	40	44	47	1
41	45	50	32	50	1
31	42	47	40	49	1
45	33	38	42	43	1
22	47	50	47	42	1
35	53	45	40	55	1
23	36	13	30	27	2
22	46	49	49	55	1
27	47	40	44	53	1
29	20	17	17	36	2
39	22	39	55	20	2
32	45	45	35	44	1
21	50	39	36	46	1
16	60	44	20	49	2
13	36	33	28	40	2
25	14	36	55	19	2
38	54	34	19	25	2
21	31	49	47	40	2
23	51	41	41	50	1
30	36	42	37	44	1
20	53	47	42	59	1
38	39	39	38	32	1
35	31	42	41	42	1
23	48	38	42	55	1
54	32	34	37	49	1
31	45	46	40	49	1
36	29	49	36	46	1
36	51	35	48	52	1
21	54	43	45	48	1
20	25	19	47	43	2
22	46	43	50	50	1
24	34	23	53	34	2
29	17	12	54	55	2
33	46	37	45	54	1
42	43	58	38	41	1
57	25	19	25	21	2
27	35	29	25	45	2
18	12	38	26	17	2
37	35	44	41	52	1
19	29	29	40	38	2
60	38	44	20	20	2
31	39	43	49	56	1
28	40	39	38	45	1
15	42	20	57	17	2
40	40	41	39	47	1
27	52	41	42	53	1
39	44	31	49	49	1
15	33	15	21	20	2
31	40	38	39	48	1
25	44	45	38	46	1
21	44	41	44	51	1
34	17	14	21	55	2
20	22	13	30	31	2
23	28	40	24	15	2
39	36	41	44	39	1

(*continued on next page*)

Table A1 (*continued*)

N	E	O	A	C	Output
35	16	16	12	23	2
17	34	17	60	13	2
49	19	41	26	17	2
23	48	39	44	52	1
17	19	35	29	60	2
18	44	21	46	23	2
50	36	37	45	32	1
28	44	50	35	44	1
25	46	43	45	50	1
40	47	40	24	16	2
32	28	50	41	41	1
45	34	20	57	40	2
36	24	15	45	19	2
25	51	36	41	48	1
29	30	44	38	53	1
33	13	55	25	49	2
15	39	24	20	19	2
49	35	35	33	44	1
19	44	40	51	55	1
26	44	39	40	49	1
46	19	43	13	16	2
58	32	37	35	35	1
49	26	45	37	36	1
24	52	52	46	54	1
41	37	35	44	53	1
34	18	27	29	36	2
34	41	40	40	48	1
16	40	38	55	31	2
20	39	17	60	21	2
26	40	44	44	48	1
30	39	47	45	45	1
31	18	25	34	29	2
38	55	24	49	46	2
15	50	39	48	51	1
35	41	40	46	45	1
36	40	39	32	45	1
15	55	22	59	57	2
22	60	13	60	15	2
28	50	37	48	57	1
28	35	37	42	41	1
60	36	28	19	39	2
32	45	49	37	45	1
16	56	53	54	54	1
24	19	34	19	24	2
60	29	20	60	44	2
22	51	53	43	51	1
49	12	19	16	16	2
38	37	37	38	42	1
30	43	38	40	44	1
18	46	48	40	54	1
28	60	26	22	34	2
36	35	13	60	26	2
18	56	54	43	51	1
44	48	45	44	37	1
20	27	39	39	43	2
21	50	54	39	48	1
17	39	24	13	12	2
30	36	44	38	40	1
30	16	45	35	36	2
32	42	43	47	53	1
29	37	44	43	52	1
24	23	12	42	20	2
13	21	28	18	22	2
44	31	36	39	50	1
21	47	42	43	52	1
35	40	40	43	40	1
37	45	43	41	47	1
35	40	46	15	14	2

Appendix B

The generated rules in the ANFIS

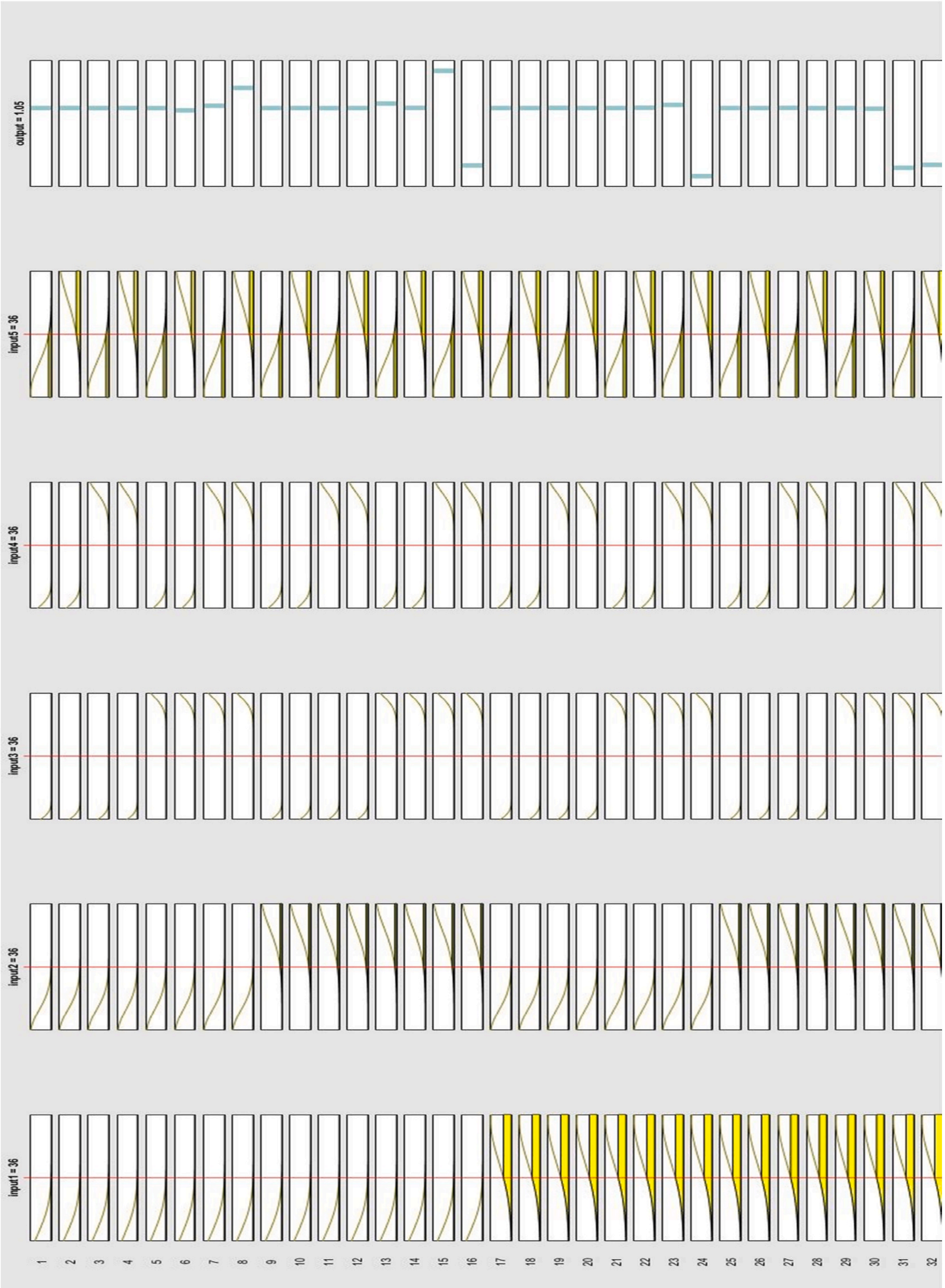

Fig. B1. A schematic view of the generated rules in the model.

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