Fuzzy Tsukamoto Implementation to Detect Physiological Condition on IoT-Based e-Learning Users

F. Pradana, F. A. Bachtiar, and E. R. Widasari

***Abstract*—Science and technology advancement drives humans to adapt to the digital world. IT development is proven to positively affect the education area through the concept of electronic learning (e-learning). This is especially true during the COVID-19 pandemic where traditional classrooms teaching was transferred to e-learning. This technological development demands individuals to adapt to the advancement. Despite its benefits, technological advancement may affect the physical condition of e-learning users. When the e-learning users fail to adjust, they might have physical condition problems that cause depression. Therefore, we propose an Internet of Things (IoT)-based system to detect the physiological conditions of e-learning users. By implementing Fuzzy Tsukamoto as artificial intelligence on IoT technology, we can identify the physiological condition of e-learning users such as relaxed, calm, anxious, and stressed conditions. Structurally, the proposed system consists of three stages: 1) Sensor data acquisition, 2) Physiological condition detection using Fuzzy Tsukamoto, 3) Display the output directly to the website. We evaluate the effectiveness of the proposed system in the task of detecting the physiological condition of the ten e-learning users. Based on experimental results, the proposed system presents 84.01% of accuracy. This result indicates that the proposed system is able to reliably detect physiological conditions on IoT-based e-learning users. By detecting psychological conditions, e-learning is expected to become an adaptive learning system so that it can adapt to the characteristics of each user.**

***Index Terms*—Fuzzy Tsukamoto, physiological condition, Internet of Things, e-learning.**

I. Introduction

In the education environment, the implementation of technology to facilitate the learning process has become more popular. One of the benefits enjoyed by education from IT development is the concept of electronic learning (e-learning) [1]. This is especially true, during the COVID-19 pandemic where the traditional classrooms needed to transfer to e-learning. E-learning could potentially be developed into a smart classroom in today's education [2]. The concept of a smart classroom integrates several sensory equipment, actuator, and microcontrollers, and learning management system programs. The smart classroom utilizes automatic technology to control the class using an Internet of Things (IoT) device. IoT technology today is commonly used in several services, including event-based middleware [3], cloud-based data center [4], and actor-based middleware [5]. Furthermore, the learning process can be carried out IoT-based using mobile, wearable, or multimedia devices to provide easier access between students and teachers [6].

In reality, this shift of lifestyle requires individuals to adapt and compete with others to survive. This competition can cause individuals to suffer from being tired and physiological condition problems due to difficulty adjusting to the development. Furthermore, the physical condition problem might cause depression [7]. Depression is inseparable from every life and could be worsened by the challenges due to using e-learning during the COVID-19 pandemic [8]. Accumulated depression may adversely affect individuals when they fail to manage the depression [9]. [10] has investigated that several factors are reported to lead to depression including attending school, financial difficulties, job demands, personality traits, and individual mindset. Failure to manage depression conditions may adversely affect individuals. Thus, physiological condition management skills are important. One's physiological condition response to depression may include increased heartbeat, higher blood pressure, and shivering. Furthermore, the physiological condition can be divided into four categories, such as relaxed, calm, anxious, and stressed [11]. Early physiological condition detection can prevent chronic disease caused by depression [12]. With this regard, studies on physiological conditions and monitoring are important to prevent depression.

In the last decade, there have been several studies that investigated physiological condition detection and monitoring. A study [13] employed a classification method based on Finite State Machine (FSM). This study has a satisfactory result in a real-time depression detection system. However, the method has not been implemented in an IoT device. Another study was conducted by [14], reporting that machine learning offers a more affordable solution for depression detection. This study focused on detecting depression levels only in social media using activity and features. Furthermore, the immediate psychological responses of students in the e-learning environment have been considered by [15]. Nevertheless, they only use strict statistical analyzes and have not been implemented in an IoT device. Even though several works have investigated physiological conditions, limited works have applied IoT devices to detect physiological conditions for e-learning users using classification methods.

To this end, we propose a reliable system to detect physiological conditions based on IoT for e-learning users. By implementing Fuzzy Tsukamoto as artificial intelligence on IoT technology, we can carry out the physiological condition of e-learning users. Fuzzy Tsukamoto is one of the method of the Fuzzy Inference System. Where on the Tsukamoto method, every consequent in the if-then rule must

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be represented by a set fuzzy with a monotone membership function. [16]. Fuzzy Tsukamoto has a flexible method and tolerance for existing data [16]. Moreover, this classification method is faster in the computational process, more intuitive, and accepted by many parties [17]. Therefore, we expected that Fuzzy Tsukamoto is able to detect physiological conditions properly and precisely.

For the purpose of the study, an IoT-based system was used to collect the data. Furthermore, we perform three stages of the proposed method: 1) Sensor data acquisition, the sensor parameters used in this work included temperature, GSR, and heartbeat, 2) Physiological condition detection using Fuzzy Tsukamoto, where these three-sensor data were processed using a microprocessor and detected using Fuzzy Tsukamoto to make decisions on user's physiological conditions when engaging in e-learning. 3) Display the output directly to the website, the output data were displayed on the website, demonstrating the process of detecting the physiological condition, and used in user's data management. This is done to figure out the user's autonomy, comprehension, communication skills and to figure out the user's physiological condition when independently engaging in e-learning. The results of this psychological detection can be one of the parameters in developing adaptive e-learning based on user conditions and behavior.

II. Material and Proposed System

A. Data Description

In this work, we evaluate ten subjects that consist of 19 – 49 years old e-learning users for two males and eight females. All participants fully understood the experimental procedure, and they provided written informed consent before participating in the study. For this work, participants with a history of any of the following were excluded: 1) had chronic inflammatory or cardiovascular disease, 2) had fever, and 3) were drug or alcohol abuse. Each user needs to access e-learning about practice programming skills according to the following links: https://html-css.learningmedia.my.id/. The duration to access the e-learning material is 30 minutes.

B. IoT-Based e-Learning

The first stage of the proposed system is sensor data acquisition. The sensor data was collected using an IoT system and the website is used to display the data tracking of the sensor parameter as shown in Fig. 1. Using the IoT concept will make education smarter and available [18]. The data collection process was performed by putting on the temperature sensor, skin sensor (GSR), and heartbeat sensor on e-learning users. Furthermore, data from these sensors were processed by a microprocessor. Then, the data were collected during the e-learning system test. The collected data were stored in the database to allow easier access.

C. Fuzzy Tsukamoto

The second stage of the proposed system is physiological condition using Fuzzy Tsukamoto. In Tsukamoto Fuzzy, each rule is represented as fuzzy sets with monotonous member functions. To determine the crisp output value (Z), the input value should be changed from the input (i.e., fuzzy set) obtained from the fuzzy rules into the number in the fuzzy set domain, a process known as defuzzification. The defuzzification method used in the Tsukamoto method is the centralized defuzzification method. The general process of Fuzzy Tsukamoto as shown in Fig. 2.

Fig. 1. IoT device and website data communication interface.

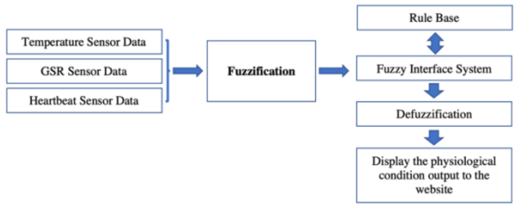

Fig. 2. General process of Fuzzy Tsukamoto.

1) Fuzzification

Fuzzification is the stage to map the input and output values in the fuzzy set. The input data were the crisp set to be transformed to the fuzzy set based on the range of each input variable. There are two aspects that should be taken into consideration during the fuzzification process, namely the input and output values and the member functions, which are used to determine the fuzzy value of the input and output crisp values. Three inputs and one output were used, including the user's heartbeat, GSR, and temperature. The function number of heartbeats, GSR, and temperature as shown in Fig. 3, Fig. 4, Fig. 5, Fig. 6, and Fig. 7 [19], [20].

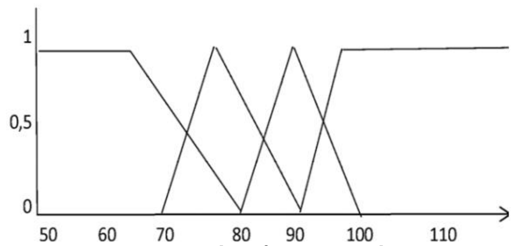

Fig. 3. Heartbeat function member.

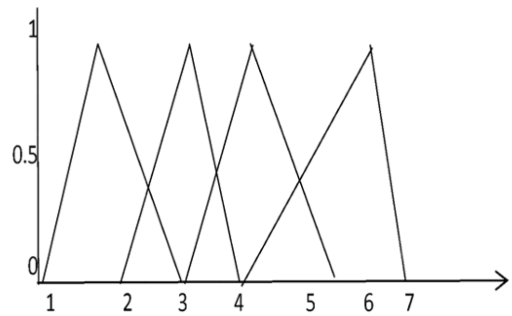

Fig. 4. GSR function member.

The heartbeat input is divided into four categories:

1) Relaxed heartbeat (DR) (60 bpm – 80 bpm)
2) Calm heartbeat (DT) (70 bpm – 90 bpm)
3) Anxious heartbeat (DC) (80 bpm – 100 bpm)
4) Stressed heartbeat (DS) (> 100 bpm)

Meanwhile, the GSR input was also divided into four categories:

1) Relaxed GSR (GR) (< 2 siemens)
2) Calm GSR (GT) (2 – 4 siemens)
3) Anxious GSR (GC) (3 – 5 siemens)
4) Stressed GSR (GS) (> 6 siemens)

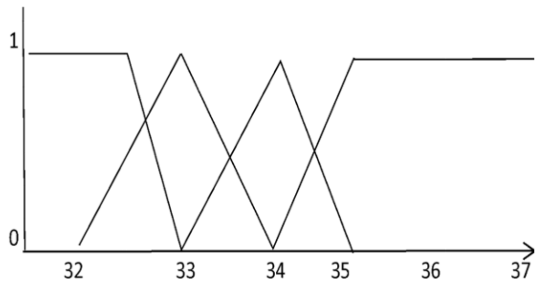

Fig. 5. Temperature function member.

The temperature input was divided into the following four categories:

1) Relaxed temperature (SR) (35 ℃ – 37 ℃)
2) Calm temperature (ST) (34 ℃ – 36 ℃)
3) Anxious temperature (SC) (33 ℃ – 35 ℃)
4) Stressed temperature (SS) (< 33 ℃)

2) *Rule base*

After establishing the function member, the next step was to develop the rule base. The rule base consists of a fuzzy logic-based rule base to state the condition. The rule base is designed based on the existing expert system, as presented in Table I [19], [20].

TABLE I: RULES BASE

No	Heart Beat	GSR	Temperature	Condition
1	Relax	Relax	Relax	Relax
2	Relax	Relax	Calm	Relax
3	Relax	Relax	Anxious	Calm
4	Relax	Relax	Stress	Anxious
5	Calm	Relax	Relax	Relax
6	Calm	Relax	Calm	Calm
7	Calm	Relax	Anxious	Calm
8	Calm	Relax	Stress	Anxious
9	Anxious	Relax	Relax	Calm
10	Anxious	Relax	Calm	Calm
11	Anxious	Relax	Anxious	Anxious
12	Anxious	Relax	Stress	Anxious
13	Stress	Relax	Relax	Calm
14	Stress	Relax	Calm	Calm
15	Stress	Relax	Anxious	Anxious
16	Stress	Relax	Stress	Anxious
17	Relax	Calm	Relax	Relax
18	Relax	Calm	Calm	Calm
19	Relax	Calm	Anxious	Calm
20	Relax	Calm	Stress	Calm

3) *Defuzzification*

Crisp value is obtained by changing the input α (i.e., fuzzy set obtained from composition of fuzzy rules) into a number in the fuzzy set domain, a process known as defuzzification. The defuzzification method used in Tsukamoto method is the Center Average Defuzzifier, formulated in the following equation [21] where Z is the defuzzification value, αi is Values created in fuzzy form and Zi is rule base value:

$$Z = \frac{\sum_{i=1}^{n} \propto iZi}{\sum_{i=1}^{n} \propto i} \tag{1}$$

Furthermore, the physical condition output data were displayed on the website according to the last stage of the proposed system.

III. RESULTS AND DISCUSSION

Firstly, the data monitoring system developed for the purpose of this study as shown in Fig. 6. This system also functions to manage the e-learning users physiological condition data. It is caused by the value of temperature, GSR and heartbeat each user will show and store on this data monitoring system. This data monitoring was performed in ten e-learning users. The detailed information of sensor monitoring result for each subject at an average time of 30 minutes is presented in Table II.

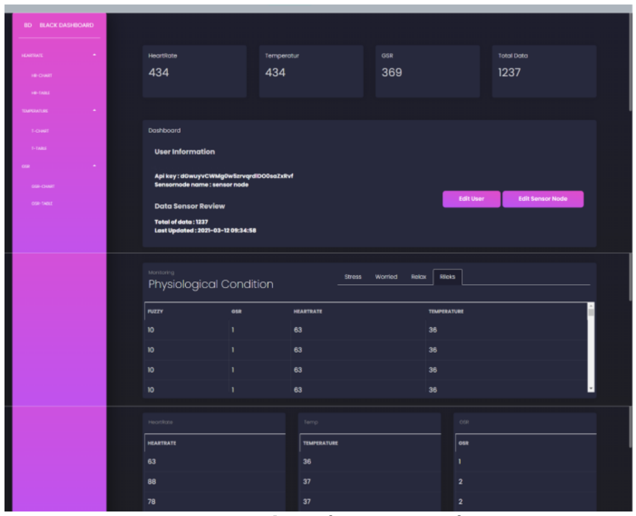

Fig. 6. Sensor data information interface.

TABLE II: MONITORING DATA RESULT

Subject	GSR	Heart Beat	Temperature
01	0.40	82	35
02	0.32	82	35
03	0.90	77	36.3
04	0.8	66	34.9
05	0.89	89.2	35
06	0.61	93	36
07	0.32	82	35
08	0.9	74	34.9
09	0.34	90	31
10	0.9	77	36.3

As mentioned above, fuzzy rules are core of the fuzzy inference system. Fuzzy inference rules for performance measurement are based on the knowledge and experience of the expert. We used If-Then type fuzzy rules to convert the fuzzy input to the physiological condition. For User-1:

IF GSR = relax and Heart Beat = clam and Temperature = relax THEN RESULT = relax.

GSR	(3 - x)/(3-1) (3 – 0.4)/(3 - 1)	=	1.3
Heart Beat	(x-70)/(80-70) (82-70)/(80-70)	=	1.2
Temperature	(34 - x)(35 - 34) (34 - 35)/(35-34)	=	-1
Apred		=	-1
Result	25+(0,7*(50-25))	=	0

It shows that the first user condition exhibited the values of GSR =1.3, Heart beat = 1.2, and temperature = -1. The condition results in Apred = -1, leading to defuzzification = 0, which was considered an relax condition. By following the same procedure, we can obtain the physiological condition output of all subjects as shown in Table III.

TABLE III: PHYSIOLOGICAL CONDITION OUTPUT

Subject	**Condition**
01	Relax
02	Relax
03	Relax
04	Relax
05	Relax
06	Clam
07	Relax
08	Relax
09	Anxious
10	Relax

Furthermore, physiological output will display directly to the website as shown in Fig. 7 to figure out the user's physiological condition when independently engaging in IoT-based e-learning. The output is according with the calculation of defuzzification.

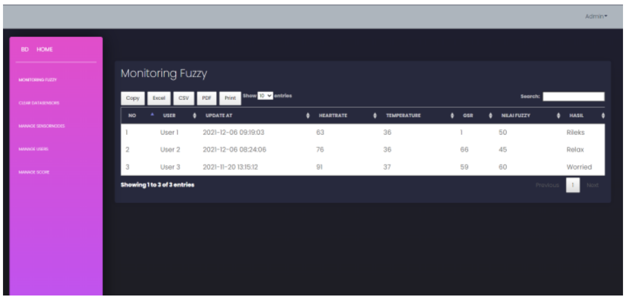

Fig. 7. Fuzzy data information interface.

In addition, Depression Anxiety Stress Scales (DASS) were used to validate physiological conditions on e-learning users. The DASS is a questionnaire to measure the related physiological condition. The self-reporting scales assess the presence and intensity of affective states of relaxed, calm, anxious, and stressed conditions when independently engaging in IoT-based e-learning on a 4-point Likert response scale. Each subscale has seven items and its total score ranges from 0 to 21 points. A higher score indicates higher symptomatology of relaxed, calm, anxious, and stressed [22]. We used the Indonesian version of DASS. As a result of the matching process with the calculation of defuzzification, the accuracy of detecting the physiological condition by using Fuzzy Tsukamoto is up to 84.01 %. This level of accuracy can be said to be high and in line with research applying fuzzy to work performance assessment [23]. In addition, Fuzzy is fast in computation and has good data tolerance when used in the case of disease detection[24]. The results of this study are in line with and can prove that fuzzy Tsukamoto can also be applied well for the detection of psychological conditions.

The results of psychological condition detection can be used as a parameter to develop adaptive e-learning. Adaptive e-learning is e-learning that can adapt to the characteristics and behavior of the user. Various forms of adaptation can be changes in visualization, learning content, challenges given, and learning routes. Some of our previous studies regarding the implementation of adaptive interfaces have been successfully implemented, taking into account user log data [25].

IV. CONCLUSION

The proposed system based on Fuzzy Tsukamoto has been used to detect the physiological condition of IoT-based e-learning users. Initially, the rules of the Fuzzy Tsukamoto system have been determined according to the expert. Accuracy of the results of this model 84.01 %. It indicates that the proposed system is able to reliably detect physiological conditions on IoT-based e-learning users. Furthermore, we can further extend the used of the proposed system for implementing the user behavior-based adaptive interface in e-learning.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, F. Pradana, F. A. Bachtiar, and E. R. Widasari; methodology, F. Pradana and F. A. Bachtiar; software, F. Pradana and F. A. Bachtiar; formal analysis, E. R. Widasari; data curation, F. Pradana and F. A. Bachtiar; writing—original draft preparation, F. Pradana and E. R. Widasari ; writing—review and editing, F. Pradana and E. R. Widasari. All authors have read and agreed to the published version of the manuscript.

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