

Decision Tree-Based Transdisciplinary Systems Modelling for Cognitive Status in Neurological Diseases

Yeliz Karaca[1(✉)] and Elgiz Yılmaz Altuntaş[2]

[1] University of Massachusetts Medical School, Worcester, MA 01655, USA
yeliz.karaca@ieee.org
[2] Galatasaray University, Istanbul, Turkey
elyilmaz@gsu.edu.tr

Abstract. This paper addresses the concept of an up-to-date transdisciplinary system modelling based on decision tree within the framework of systems theory. Systems theory constructs effective models for the analysis of complex systems since this comprehensive theory is capable of providing links between the problems and dynamics of systems. Particularly, for the complex and challenging environments, the solutions to the problems can be managed more effectively based on a systems approach. Neurological diseases concern the brain which has a complex structure and dynamics. Being equipped with the accurate medical knowledge plays a critical role in tackling these neurological problems. The interconnected relationships require a carefully-characterized transdisciplinary approach integrating systems conduct and mathematical modelling. Effective solutions lie in cognitive status, namely awareness and a satisfactory level of health knowledge. Within this framework, this study aims at revealing the lack of required general and medical health knowledge on neurological diseases (Alzheimer's, dementia, Parkinson's, stroke, epilepsy and migraine) among individuals. For this purpose, an online survey was conducted on 381 respondents, through which awareness on medical knowledge and general health knowledge were assessed for each disease. The following approaches (methods) were applied: firstly, rule-based decision tree algorithm was applied since its structure enables the interpretation of the data and works effectively with feature computations. Subsequently, statistical analyses were performed. The decision tree analyses and statistical analyses reveal parallel results with one another, which demonstrate that when compared with the knowledge of elder people, the knowledge of young population is limited in general and medical health knowledge. Compared with previous works, no related work exists in the literature where a transdisciplinary approach with these proposed methods are used. The experimental results demonstrate the significant difference between medical knowledge and general health knowledge among individuals depending on different attributes. The study attempts to reveal a new approach for dealing with diseases, developing positive attitudes besides establishing effective long-term behavioural patterns and strategies based on required knowledge and mindfulness.

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1 Introduction

Every system is characterized by its structure, shaped by time and space while being affected by the factors in its environment. Within this framework, systems theory consists of transdisciplinary study of the systems with a coherent combination of interconnected components. Models constructed accordingly provide advantages for the analysis and depiction of complex systems due to being beneficial for supporting interaction between the system components. Approaches based on the systems theory also help observe the links between problems and the system dynamics, which require a complex analysis for identification and solution of problems [1]. Systems approach has become extensively-employed concept in research and practice in changing environments along with various disciplines such as engineering, natural sciences, social sciences, medicine and so forth [1,2]. The complexity of neurological diseases requires sophisticated means of analysis. Artificial Intelligence (AI) and related techniques have gained prominence due to their capability of providing applicable solutions to complex problems. Some of the key categories of AI applications include healthcare and medicine, especially for the diagnosis and treatment aspects, patients' medical information, their engagement and observance to the treatment regimen [3]. There is an extensive body of work in the literature regarding AI and its applications concerning neurological diseases. The study of [4] employed the decision tree algorithms for classifying stroke patients' activities and postures. The study revealed that the decision tree algorithms could measure the patients activities accurately.

Neurological diseases concern the disruption of the Central Nervous System (CNS) functions. Neurological diseases are considered to be challenging to identify, diagnose and manage track because of the complexity CNS displays [5]. Consciousness and mindfulness of the individuals afflicted by the disorder and people in their circle also play a critical role for an efficient management efficiently so that life quality can be maintained satisfactorily level. Alzheimer's, dementia, Parkinson's, stroke, epilepsy and migraine addressed in this study, are among the most prevalent ones.

Some information on the neurological diseases included in this study for the model proposed are outlined as follows: Alzheimer's disease is a progressive disorder leading the brain cells to degenerate which is one of the most common reasons for dementia [6–8]. Dementia, with a chronic or a progressive nature, is one of the most frequent forms of Alzheimer's disease, characterized by the disturbance of higher cortical functions Mainly older people are affected [9]. Parkinson's disease is a progressive disorder, affecting movement, with noticeable tremors [10]. Stroke is a medical condition occurring when blood supply to the part of the brain is disrupted. Brain cells die in such a condition. Other symptoms

are numbness, vision problems and trouble with walking [11,12]. Epilepsy is a chronic disorder characterized by epileptic seizures, [9,13]. Migraine occurs a result of certain changes in the brain, causing severe head pains [9,14,15].

Being aware of the symptoms may not be adequate, it is also important to have mindfulness, is in medical context defined as self-regulation of attention and adopting an orientation along with transparency, acceptance as well as wanting to learn more about the medical condition [16]. The study [17] indicates the feasibility of computer-based virtual coaching strategies for patient education for helping patients have behavioural changes in the long-term. Another study [18] emphasizes the effectiveness of patient education is based on Internet. Based on the structural equation modelling approach, the study results confirmed empirically the effectiveness and accessibility of the system. These studies show the importance of accessing and having the accurate information effectively while dealing with different health conditions. Health literacy plays a significant role in maintaining good health since it represents the cognitive and social skills that determine the individuals' motivation and ability to understand, gain access to, and use related information [19]. When people's access to health information is improved, capacity of them to use it effectively also increases, and thus health literacy becomes critical for empowerment. The theoretical model related to health communication in this study is based on cognitive theories and communicating health messages. Cognitive theories provide 'continuum accounts of behaviour' (Rutter and Quine) [20], arguing that particular beliefs or perceptions predict a behaviour. In the cognitive theories, Theory of Planned Behaviour [21] and Health Belief Model (HBM) belonging to Becker 1974 [22–24] are two principal approaches applied to the contexts of health communication.

Complex nature of neurologic diseases requires an integrated approach with a transdisciplinary framework and its applications. Mathematical modelling with AI, due to its capability of crafting precision, makes up a transdisciplinary framework including various scientific disciplines. Health communication (HC) is the study and use of communication strategies for informing and influencing individual decisions so that health of the person will be enhanced [25] HC plays an important role in conveying accurate information about healthcare problems to patients, patient acquaintances, public and healthcare practitioners so that efforts are put in to capture the attention and establish awareness among related parties. In order for health communication to achieve effective outcomes, it is important to integrate transdisciplinary approaches [26–30]. Knowledge in the field of health is categorized as general health knowledge, which refers to public medical and healthcare knowledge as well as public medical knowledge, and special health knowledge, which is concerned with individual experiences, medical records as well as personal health status [31].

The approach adopted in this study attempts to be more extensive since it is based on a transdisciplinary framework and its applications while dealing with the data. The dataset of the present study is made up of undergraduate, graduate and PhD Students and employees at Galatasaray University (Istanbul, Turkey). Convenience sampling method was applied to survey the respondents

(381) enrolled online between 27 November 2019 and 27 January 2020. The study was ethically approved by the department administrators at Galatasaray University and the respondents were assured about the confidentiality. The main goal of the paper is to assess the respondents' knowledge and attitudes towards neurological diseases (Alzheimer's, dementia, Parkinson's, stroke, epilepsy and migraine). When it is compared with earlier works [16–19,26–31], the proposed method in the present study is a novel one conducted for the first time in the literature with the application of the following steps: firstly, decision tree algorithm was applied due to its rule-based structure which enabled the interpretation of the data and feature computations. Next, statistical analyses were performed using ANOVA, Tukey test and t-test. Based on the procedures of the first and subsequent steps, the respondents' medical knowledge scores for each type of disease revealed an average score of (53.98%). Migraine was found out to be the most known disease (83%), while epilepsy indicated the lowest score in terms of general health knowledge (36%). On the other hand, stroke and Alzheimer's diseases are known by people at equal levels (55%) and the knowledge related to dementia follows them (45%). It has also been found that if an individual has or has had a neurological disease, this result is related to only general health knowledge of migraine. People with any kind of neurological disease have greater migraine knowledge score than the people who do not have the disease ($p < 0.05$). From the perspective of the medical knowledge regarding the diseases, epilepsy ($x = 42$, $SD = 26.4$) and migraine scores ($x = 88$, $SD = 16$) of the patients are significantly higher than the scores of healthy individuals ($p < 0.05$). Considering the age characteristic, the highest score for Alzheimer's and dementia was observed among 46–55 age group, for epilepsy and migraine, 36–45 age group had the highest score and finally, for the remaining two diseases, Parkinson's and stroke, individuals aged 55 and above had the highest scores. The last data is significant since Parkinson's and stroke affect elderly population. Overall, these results suggest that young population has a limited level of general and medical health knowledge compared to the knowledge of elder people. The decision tree analyses and statistical analyses performed for the study reveal parallel results with one another. Accordingly, the experimental results demonstrate the significant difference between medical knowledge and general health knowledge among individuals depending on different attributes. These indicate the importance of showing a new approach to tackle diseases, besides developing favourable attitudes and maintaining effective long-term behavioural strategies based on accurate and up-to-date medical knowledge and general health knowledge.

1.1 The Motivation of the Transdisciplinary Proposed Method

The novelty of this paper relies on the concept of transdisciplinary system modelling based on decision tree within the framework of systems theory. When the complex systems are in question, a carefully characterized transdisciplinary approach is required to analyse the interconnected relationships in the system. The principal motivation of this work is derived from providing an integrated

approach with the systems approach and mathematical modelling to reveal the knowledge awareness and attitudes towards neurological diseases.

Another contribution concerns revealing the lack of required medical and general health knowledge on neurological diseases among individuals through the decision tree and statistical analyses. Since neurological disorders concern brain which has a complex structure and dynamics, it is important to have access to accurate medical knowledge.

This study is the first of its kind conducted in Turkey. The survey used in this study with its questions is from a novel perspective so that the lack of information concerning the diseases could be revealed. This is important globally because health education programmes and national awareness campaigns should be based on the proof of what individuals know, instead of on what policy educators and experts assume individuals know. Therefore, the relevance of research on public knowledge and understanding of neurological diseases should not be underestimated.

The information flow regarding neurological diseases is also a complex phenomenon since it involves uncertainty or non-linear communication pattern. To deal with the processes effectively, an integrated approach with the support of a transdisciplinary framework and its applications. Health communication plays an important role in transmitting the accurate information about healthcare problems to the patients, patient acquaintances, public and healthcare practitioners so that health communication can achieve effective outcomes.

Based on the transdisciplinary approach and its contribution, the results indicate the significant difference between medical knowledge and general health knowledge in individuals with different attributes. Thus, endeavours come to the foreground to reveal a novel approach for dealing with the diseases, while forming positive attitudes and establishing effective behavioural patterns and strategies in the long term based on mindfulness.

The paper is organized as follows: Sect. 2 includes Materials, with the subheading of Subjects and Design of the Study, and Methods, with the subsections on Decision Tree Structure and Statistical Analyses (ANOVA, Tukey test and t-test). Section 3 handles the Experimental Results and Discussion. Finally, Conclusion is provided in Sect. 4.

2 Materials and Methods

2.1 Materials

Subjects and Design of the Study. The approach followed in this study attempts to be more comprehensive since the study is based on a transdisciplinary framework and its applications while dealing with the data. The dataset of the present study includes undergraduate, graduate and PhD Students and employees at Galatasaray University (Istanbul, Turkey). Convenience sampling method was used to survey the respondents (total of 381) enrolled online. The study was ethically approved by the department administrators at Galatasaray University; and the respondents were made sure about the confidentiality of the

data since their identity was not collected. The principal goal of the paper is to assess the respondents' knowledge and attitudes towards neurological diseases (Alzheimer's, dementia, Parkinson's, stroke, epilepsy and migraine). The demographic form included variables to elicit information related to the respondents' gender, age, education level, whether they or their family have any neurological disease, if yes, type of this disease (see Table 1 for demographic characteristics of the respondents).

Table 1. Demographic characteristics of the respondents

Variable	Frequency	Percentage(%)
Gender (n = 381)		
Male	51	13.39%
Female	330	86.61%
Age group (n = 381)		
17–25	43	11.29%
26–35	103	27.03%
36–45	160	41.99%
46–55	61	16.01%
56- +	14	3.67%
Education level (n = 381)		
Bachelor Degree	227	59.58%
M.sc Degree	130	34.12%
Ph.D Degree	24	6.30%
Neurological Disease History in the Family (n = 381)		
Yes	198	52%
No	183	48%
Neurological Disease History in the Individual (n = 381)		
Yes	61	16%
No	320	84%
Types of Diseases seen in the Individual (n = 61)		
Epilepsy	3	5%
Epilepsy, Migraine	2	3%
Stroke, Migraine	2	3%
Migraine	54	89%

The sampling frame consists of the respondents' health knowledge levels as investigated through validated scales. For Alzheimer's, the Alzheimer's Disease Knowledge Scale (ADKS) [32] was used. For Parkinson's, questions were adapted based on the informative presentation of Neurology Association; and for dementia, Dementia Knowledge Assessment Scale (DKAS) [33] was employed.

Finally, National Hospital Seizure Severity Scale [34] was used for epilepsy and The Migraine Disability Assessment (MIDAS) questionnaire [35] and Headache Impact Test (HIT) [36] were used for migraine. The knowledge for stroke symptoms was assessed using a portion of the CDC's 2011 Behavioural Risk Factor Surveillance System Questionnaire [37], including the five signs of stroke, was used in line with the National Institute of Neurological Disorders and Stroke [38]. These validated tools comprised of 54 items in total; 24 items with true/false responses and 27 items with a nominal scale including agree, disagree, undecided options.

2.2 Methods

This paper presents an up-to-date transdisciplinary system modelling based on rule-based decision tree within the framework of systems theory. The interconnected relationships in a system require a carefully-characterized transdisciplinary approach that integrates systems conduct and mathematical modelling, which is blended, in this study, in two approaches: the application of decision tree and statistical analyses along with their comparisons.

Decision Tree Structure. As one of the most common approaches for rule modelling, a decision tree method represents decisions made in visual form. The decision tree has a top-down approach to choose the best split. It is used for labelling the elements correctly on a rule based structure. The labelling presents a random work performed line with the distributions of the label. The formula is applied as in (1) below [39–42].

$$I_G(p) = \sum_{i=1}^{J} p_i \sum_{k \neq 1} p_k = \sum_{i=1}^{J} p_i (1 - p_i)^2 = \sum_{i=1}^{J} p_i - \sum_{i=1}^{J} p_i^2 = 1 - \sum_{i=1}^{J} p_i^2 \quad (1)$$

I_G refers to the measure quantity Gini Impurity for a set of items with J classes in which i ranges from 1 to J, and p_i denotes the fraction of items which is labelled with the class i.

Rule based decision tree has mainly two steps, which are generation of rules and the selection of Interesting Rules [39,43]. For the application, (2), (3 (4) are used: The support $S(A)$ of an item set A is defined as follows:

$$S\ (A) = (number\ of\ transactions\ including\ the\ item\ set\ A)\ (total\ number\ of\ transactions) \quad (2)$$

The confidence C of a rule $(A \rightarrow B)$ is defined as [42,43]

$$C(A \rightarrow B) = S(A \cup B)/S(A) \quad (3)$$

$$The\ lift\ L\ of\ a\ rule\ (A \rightarrow B)\ is\ defined\ as\ L(A \rightarrow B) = \frac{S(A \cup B)}{S(B) * S(A)} \quad (4)$$

Statistical Analysis. Original and innovative statistical methodology and complex approaches oriented towards statistical data analysis have recent applications in many fields. Used for the collection, collecting, analysis, organization and interpretation of data, statistical analysis plays a vital role in diverse areas.

The theoretical elements of the statistical analyses applied in this study are explained in the following sections.

ANOVA. The observations that are not reliant on one single factor need variant analysis and their definition is made through the estimation of the parameters given in (5) [43–45]:

$$Y_{ij} = \mu + \alpha_j + \in_{ij} \tag{5}$$

Y_{ij} the score of i participants that are included in j subclass, μ the average of all the scores, α_j the impact of j subclass and $\in_{ij}$ is the error term.

$\mu_j = \mu + \alpha_j$,

μ_j is the arithmetic mean of the participants included in the j subclass (for further details on this equation and hypothesis, see [46,47].

TUKEY TEST. Tukey test is a multiple procedure with a single-step, used for finding means which are different from each other significantly. The formula is for the test is given in (6) [48,49]:

$$q_s = \frac{Y_A - Y_B}{SE}, \tag{6}$$

Y_A the larger of the two means that are to be compared, Y_B: the smaller of the two means that are to be compared and SE refers to standard error of the means' sum. (for further details and hypothesis information, see [46,50].

T-TEST. As a parametric test, t-test is used to test the situation when there exists a statistically significant difference between the two independent groups. t-test formula is very similar to Tukey test formula.

Independent-test formula is given in (7)–(9) follows [51–53]:

$$t = \frac{m_A - m_B}{\sqrt{\frac{s^2}{n_A} + \frac{s^2}{n_B}}} \tag{7}$$

$$S^2 = \frac{\sum (x - m_A)^2 + \sum (x - m_B)^2}{n_A + n_B - 2} \tag{8}$$

$$df = n_A + n_B - 2 \tag{9}$$

A and B represent two different groups, where ma refers to the means of Group A and m_B refers to the means of Group B. S^2 is the estimator of the two samples' common variance refers to the Group A size while n_B represents the Group B size. df: n_A degrees of freedom (for further details and assumptions related to the test, see 46).

3 Experimental Results and Discussion

This study, based on the survey results obtained from the respondents, demonstrates a transdisciplinary system modelling which is based on rule-based decision tree within the framework of systems theory, integrating systems approach and mathematical modelling proposed with medical and general health knowledge aspects. Within this complex structure, procedures related to the steps that lead to the experimental results for the proposed method are outlined in Table 2 below:

Table 2. The steps related to the Transdisciplinary Proposed Method

Step 1: Application of rule-based decision tree analysis
Step 2: Application of statistical analysis
Step 3: Comparison of the integrated approach: rule-based Decision Tree analysis and statistical analysis

All the analyses' results in this study and the depiction of the figure outcomes were performed using the Matlab [54] and SPSS [55]. Explanations for these steps (indicated in Table 2) are elaborated below in their respective order:

Step 1: Application of Rule-based Decision Tree Analysis

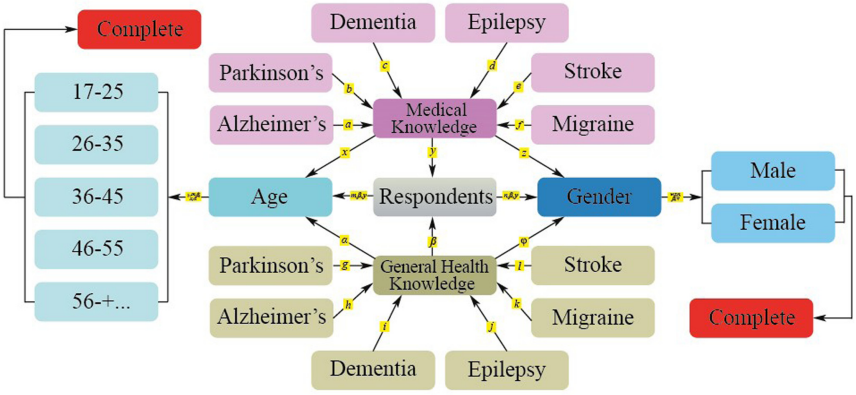

Fig. 1. An example of a decision tree that organizes the flow of questions partly selected from the questionnaire.

Some of the selected results that are significant as obtained from the analyses are provided below:
The decision rule as obtained from dataset in Fig. 1 is presented as Rules 1 and 2:
Rule 1: If General Health Knowledge $\geq$ 76. 416, the class is female.
Rule 2: If General Health Knowledge $\geq$ 85.678, the class is male.

Step 2: Application of Statistical Analysis
First, a pilot study was done among a group of respondents (N = 30). based on the survey results obtained from the respondents. It was revealed that the questionnaires were viable to perform the study in Turkish setting. The questionnaires were distributed to the respondents through an online survey program. Discrete variables are presented as count (%) and continuous variables as mean ± standard deviation (SD). General health knowledge scores and awareness on Medical Knowledge scores were calculated for each type of disease. These scores were subsequently compared for different demographics using ANOVA, Tukey test and t-test.

Table 3 demonstrates the medical knowledge scores of the respondents for each disease type. The Average score was found to be 53.98%. Based on the table, it is obvious that migraine is known well (M = 81.04, SD = 26.51); on the other hand, epilepsy is not known at a satisfactory level by the respondents included in the sample (M = 34.69, SD = 25.98).

Table 3. The steps related to the Transdisciplinary Proposed Method

Variable	M	SD
Dementia	43.70	26.00
Stroke	54.27	27.60
Alzheimer's	54.19	23.34
Parkinson's	55.97	29.44
Epilepsy	34.69	25.98
Migraine	81.04	26.69
Average	53.98	26.51

The results of the survey demonstrate the distribution of respondents' general health knowledge related to the neurological diseases addressed in the study. Migraine is the most known disease among other neurological diseases with a score of 83%; however, epilepsy shows the lowest score in terms of awareness and health knowledge, with a score of 36%. Stroke and Alzheimer's are known by people equally (55%) and the knowledge related to dementia follows them (45%). The overall correct answer percentage concerning the general health was found to be 56%.

The survey results indicate the percentage of the correct answers for the items related to each 6 neurological diseases. (F) refers that statement is false

and (T) refers that statement is true. For *dementia*, the following statements have been assessed: "Dementia does not often shorten a person's life.": (F) (18%, $M \pm SD = 0.18 \pm 0.25$); "Blood vessel disease (vascular dementia) is the most common form of dementia.": (F) (8%; $M \pm SD = 0.08 \pm 0.27$); "Dementia is a normal part of the ageing process.": (F) (55%, $M \pm SD = 0.55 \pm 0.23$); "Alzheimer's disease is the most common form of dementia.": (T) (54%, $M \pm SD = 0.54 \pm 0.23$); "Difficulty eating and drinking generally occurs in the later stages of dementia.": (T) (63%, $M \pm SD = 0.63 \pm 0.24$). Regarding *stroke*, "Sudden confusion or trouble speaking is one of the symptoms of stroke." (T)(62%, $M \pm SD = 0.62 \pm 0.21$); "Severe headaches with no known cause are seen as symptoms in stroke cases.": (T) (41%; $M \pm SD = 0.41 \pm 0.22$); "Sudden trouble seeing in one or both eyes is one of the symptoms of stroke.": (T) (55%, $M \pm SD = 0.55 \pm 0.21$) and "Sudden chest pain or discomfort is one of the symptoms of stroke". (F) (28%, $M \pm SD = 0.28 \pm 0.24$). The following are statements related to *Alzheimer's*: "Tremor of the hands or arms is a common symptom in people with Alzheimer's disease.": (F) (61%; $M \pm SD = 0.62 \pm 0.27$); "Alzheimer's disease is one type of dementia.": (T) (63%; $M \pm SD = 0.63 \pm 0.28$). For *Parkinson's*, "Parkinson's disease is a brain disease that progresses slowly and is characterized by loss in the brain cells.": (T) (62%, $M \pm SD = 0.62 \pm 0.22$); "Decline or loss of olfactory (smelling) senses is one of the symptoms of Parkinson's disease.": (T) (24%, $M \pm SD = 0.24 \pm 0.26$). For *epilepsy*, the statements are as follows: "Cognition (thinking, reasoning, decision-making, etc.) is affected by epilepsy.": (F) (22%, $M \pm SD = 0.22 \pm 0.28$). Finally, for *migraine*, "Migraine is a series of headache attacks that last a few hours up to a few weeks.": (T) (89%, $M \pm SD = 0.89 \pm 0.06$); "Hereditary and environmental factors play a role in migraine.": (T) (82%, $M \pm SD = 0.82 \pm 0.05$); "Dizziness, numbness, nausea and blurred vision accompany migraine pains.": (T) (88%, $M \pm SD = 0.88 \pm 0.05$).

Based on the statements above, the proposed hypotheses have been tested as follows.

H1: General health knowledge between males and females related to neurological diseases is not equal.
H2: Medical knowledge between males and females related to neurological diseases is not equal.

To test H1 and H2, independent t-test was applied. General health knowledge of Parkinson's and dementia is significantly different between male and female ($p < 0.05$). Females' knowledge score for Parkinson's ($x = 76.52$, $SD = 20.48$) and dementia ($x = 77.05$, $SD = 21.91$) are higher than the score of the males concerning Parkinson's ($x = 68.14$, $SD = 23.49$) and dementia ($x = 66.67.05$, $SD = 31.89$). On the other hand, there is no difference between the genders in terms of general health knowledge score of Alzheimer's, dementia, stroke, epilepsy and migraine ($p > 0.05$). Stroke is the disease which is most commonly known well by both genders ($M_{female} = 85{,}76$; $M_{male} = 82.84$). Medical knowledge related to neurological diseases varies depending on gender, except for epilepsy ($p < 0.05$). It has been concluded females have more information than males on medical features

of Alzheimer's, dementia, Parkinson's, stroke and migraine ($p < 0.05$). The analysis results demonstrate that apart from migraine, medical knowledge scores of all the neurologic diseases are less than the general health knowledge for both genders.

The following hypotheses were presented related to the history in the family and its relationship with the general health knowledge and medical knowledge.

H3: Having a neurological disease history in the family is related to having general health knowledge regarding neurological diseases.
H4: Having a neurological disease history in the family is related to having medical knowledge regarding neurological diseases.

To test H3 and H4, independent t-test was applied in this study. It has been revealed that stroke is well known generally by both groups. Additionally, Alzheimer's ($x = 81.5$, SD = 14.28), Parkinson's ($x = 78.40$, SD = 19.77) and dementia ($x = 78.40$, SD = 22.90) are significantly known better by the group with a neurological disease history in their family ($p < 0.05$). For the medical knowledge scores, there exist no differences between the two groups ($p > 0.05$).

The following hypotheses were presented related to the individual history and its relationship with the general health knowledge and medical knowledge.

H5: Having an individual neurological disease history is related to having general health knowledge of neurological diseases.
H6: Having an individual neurological disease history is related to having medical knowledge of neurological diseases.

Consequently for, Hypotheses 5 and 6: Medical knowledge for dementia [$F(4, 376) = 3.35$, $p = 0.01$], Parkinson's [$F(4, 376) = 3.47$, $p = 0.008$], epilepsy [$F(4, 376) = 3.5$, $p = 0.008$] and migraine [$F(4, 376) = 4.48$, $p = 0.002$] were found greater than the age group of 17–25 for all other age groups. On the other hand, the medical knowledge scores of the respondents concerning stroke and Alzheimer's are significantly equal in each age group ($p > 0{,}05$).

Post hoc comparisons utilising the Tukey's honestly significant difference (HSD) test showed that in the age group of 18–25, the mean scores for General Health knowledge of Alzheimer's (M = 71.51, SD = 22.87), Parkinson's (M = 75.39, SD = 21.06), Alzheimer's (M = 65.11, SD = 26.80), dementia (M = 62.20, SD = 20.01), epilepsy (M = 73.83, SD = 27.25), stroke (M = 42.13, SD = 28.68) are significantly less than the other age groups. Based on Tukey HSD test results, concerning the medical knowledge, in the age group of 18–25 medical knowledge of dementia (M = 34.535, SD = 27.68), Parkinson's (M = 45.93, SD = 34.47), epilepsy (M = 26.33, SD = 23.61) and migraine (M = 66.97, SD = 38.01) are significantly less than the other age groups. Overall, these results suggest young population has a more limited general and medical health knowledge compared to the knowledge of elder people.

Step 3: Comparison of the Integrated Approach: Rule-based Decision Tree Analysis and Statistical Analysis

The decision tree analyses and statistical analyses performed reveal parallel

results with one another, which demonstrate that when compared with that of elder people, the knowledge of young population is limited in terms of general and medical health knowledge. In this study where awareness status concerning general health and medical knowledge is the main subject matter. Decision tree analysis and statistical analyses yield significant difference based on gender. While the medical knowledge among males is found at 67.06% and general health knowledge is 82.84%. For females, the medical knowledge is found at 83.21% and general health knowledge is 78.86.

These results indicate that if medical knowledge is conveyed accurately through the viable means, then generable knowledge levels will also consistently rise.

4 Conclusion

In this study, the concept of transdisciplinary system modelling based on decision tree within the framework of systems theory has been addressed. Within the framework of neurological diseases, possessing the accurate medical knowledge through the applicable means and having mindfulness are important in tackling these neurological problems and developing effective strategies in the long term. The main contribution of this paper is to present an integrated approach based on decision tree and statistical analyses (with Independent ANOVA, Tukey test and t-test) through systems approach and mathematical modelling to reveal the knowledge awareness and attitudes towards the six neurological diseases. When compared to earlier works [16–19,26–31], no study exists in the literature with this approach employed. Secondly, the study has demonstrated a lack of required medical and general health knowledge regarding the neurological diseases among individuals. In the proposed method, first, decision tree algorithm was applied, which enabled the interpretation of the data and feature computations. Further, statistical analyses, ANOVA, Tukey test and t-test, were conducted. The results reveal that young population has a more limited level of general and medical health knowledge compared to elder people's knowledge. Considering that neurological disorders concern the brain which has a complex structure, it is important to have mindfulness and access to accurate medical knowledge for anxiety reduction among patients and being more careful about future strategies regarding the neurological problems and other diseases. In view of these considerations, the following may be supplied for future works as direction:

(1) The proposed model with the combination of the models can open up a new perspective with the application of decision tree concerning transdisciplinary system models,
(2) The transdisciplinary systems model of the study can guide researchers to pay attention to lack of information about diseases and thus take actions accordingly to deal with real world problems effectively,
(3) The approach presented in the study can give a new direction for future works and projects which will integrate mathematical models in transdisciplinary systems.

Consequently, this study attempts to provide a transdisciplinary guidance based on mathematical modelling for future works to be conducted in the relevant and other fields for the effective solution of real world problems.

Data Availability. The link to the survey conducted and some details of the statistical results obtained in this study can be reached if requested at: https://docs.google.com/forms/d/1mBFtl-TLHDWs1ySaHeZdWjFy7pEVB_HkOUQM-pLhYlo/edit?usp=sharing_eip&ts=5e248427&urp=gmail_link.

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