

Analytic Hierarchy Process Model for the Diagnosis of Typhoid Fever

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Research article

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Posted Date: December 8th, 2020

DOI: <https://doi.org/10.21203/rs.3.rs-120646/v1>

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ANALYTIC HIERARCHY PROCESS MODEL FOR THE DIAGNOSIS OF TYPHOID FEVER

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Abstract

Typhoid fever is a global health problem, which seems neglected, but is responsible for significant levels of morbidity in many regions of the world, with about 12 million cases annually, and about 600,000 fatalities. Diagnosis of typhoid poses a great deal of challenge because its clinical presentation is confused with those of many other febrile infections such as malaria, yellow fever, etc. In addition, most developing countries do not have adequate bacteriology laboratories for further investigations. Decision support systems have been known to increase the efficiency and effectiveness of the diagnosis process, in addition to improving access; however, most existing decision support models for diagnosis of diseases have largely focused on ‘non-tropical’ conditions. An effective decision support model for diagnosis of tropical diseases can only be developed through the engineering of experiential knowledge of physicians who are experts in the management of such conditions. In this study, we mined experiential knowledge of twenty-five tropical disease specialist physicians to develop a decision support system based on the Analytic Hierarchy Process (AHP). The resulting model was tested based on 2044 patient data. Our model successfully determined the occurrence (or otherwise) of typhoid fever in 78.91% of the cases, demonstrating the utility of AHP in the diagnosis of typhoid fever.

Keywords: typhoid, tropical diseases, diagnosis, analytic hierarchy process

1.0 Introduction

The World Health Organization (WHO, 2018) population estimate of the global typhoid fever burden lies between 11–21 million. Also, up to 161,000 associated deaths have been reported annually, and a greater proportion of this statistic comes from poor and vulnerable communities such as South and South-East Asia including sub-Saharan Africa. Without appropriate tests, typhoid fever could be misdiagnosed, leading to complications and possible death (Iheukwumere, Nwachukwu, & Kanu 2013) since it presents with symptoms (e.g. fever, headache, fatigue, chills and loss of appetite) that overlap with other febrile diseases. Most developing countries plagued with infectious diseases lack adequate medical facilities to conduct appropriate laboratory tests. They are also characterized by low health care expenditure—as the average per capita health expenditure in Africa, for instance, is \$105, compared to \$3,599 in the Americas (WHO, 2015). Furthermore, the number of doctors per 10,000 population is estimated at 2.7 and 5.9 in Africa and the South East Asia, respectively, compared to 32.1 in Europe. This disturbing statistic corroborates the prevalence of tropical infectious diseases in these regions and is responsible for the growing rate of self-medication and other alternative sources of health care, which often prove counterproductive.

Some diseases are often neglected even when they cause serious fatalities to the populace and pose significant burden on public health and economic stability of societies around the world. One of such diseases is typhoid fever, which is not given adequate attention accorded other tropical diseases like malaria, hepatitis, cholera. Typhoid fever is a disease that is caused by bacteria called salmonella typhi. It is also known as Enteric fever and has numerous symptoms such as fever, constipation, diarrhoea, abdominal pain and many more. Unfortunately, typhoid fever is responsible for a great number of morbidities in Africa and other tropical regions of the world, as travellers to these regions suffer a great deal of infectious symptoms. Worse, the lack of access to medical facilities and shortage of medical personnel in the few health facilities have hugely contributed to high rates of fatalities from febrile tropical diseases. Hence, accurate and timely diagnosis/therapy are essential conditions to the reduction of complications associated with most tropical diseases (Djam et. al., 2011). Medical diagnosis, like other diagnostic processes, is made more complex because of the level of imprecision involved. Patients may not be able to describe exactly what has happened to them or how they feel; doctors and other health care practitioners may not understand or interpret exactly their observations; laboratory reports are not instantaneous and may come with some degree of error (Szolovits, Patil and Schwartz 1988). This conundrum is compounded when a pathological process presents with

ambiguous symptoms like those of other conditions, as in the case of several tropical diseases, or in situations when expert medical practitioners are inexperienced or in short supply and pressured (Driver, 2009). Thus, corroborating the urgent need to increase access to healthcare in developing countries.

The shortage of qualified doctors has necessitated the training and use of frontline health workers (FHWs), such as midwives, nurses, and community health workers, to improve patient care and access to life critical interventions (WHO, 2018). Studies have shown that these workers are able to diagnose some common diseases using established manual process (Kayemba et al., 2013). Currently, WHO (2017) uses teams located in nearby towns to reach conflict zones by helicopter, setting up mobile clinics run by FHWs with basic screening tools, and characterized by long waiting lines. The use of procedure manuals by FHWs is often a slow process that could lead to diagnosis errors and delays. A very crucial aspect of medical diagnosis is the process of gathering data from a patient. During an interrogation by a medical doctor, a patient is hardly prevented from divulging details about his state of health. It is the responsibility of the doctor to decipher and separate the tangible from the intangible. This, he does by comparing one piece of information with another and based on his experience of the disease he determines the degree of importance of the pair he compares. This task becomes daunting in the face of so many patients waiting to be attended to by few medical doctors. To attend to most of them, most inexperienced doctors (or FHWs) are prone to diagnosis errors, especially if the disease suspected is the type that presents confusable symptoms. The clinical presentation of typhoid fever is one of such diseases which symptoms are often confused or in conflict with diseases like malaria, hepatitis, urinary tract infection and others. The outcome is misdiagnosis and attendant consequences of late diagnosis resulting in high morbidity and mortality rate.

This study proposes the use of the Analytic Hierarchy Process (AHP) in the development of a decision support system for diagnosing typhoid fever. AHP (Saaty 1980) provides a suitable mechanism for evaluating complex multicriteria decision variables, such as that presented in the diagnosis of tropical diseases, which in most cases could be challenging in terms of the combinatorial analysis of symptoms and their degrees of intensity in the diagnosis process. The AHP technique has been applied in various facets of human endeavour, including health care (Liberatore and Nydick 2008; Uzoka, et al., 2011; Agapova et al. 2017) and provides a mechanism for evaluating consistency in the pairwise comparison of decision variables in the knowledge engineering process (Zyoud and Fuchs-Hanusch 2017). In Saaty (2008), AHP is seen as a theory of measurement through pairwise comparison and relies on the judgment of experts to derive priority scales. These scales measure tangibles in relative terms. In section 2, we review literature on the use of decision support systems in the diagnosis of some tropical diseases. The conventional method of diagnosis of typhoid fever is discussed in Section 3, while our study methodology is shown in section 4. The results are presented and discussed in section 5, while some conclusions are drawn in section 6.

2. Medical Decision Support Systems for Diagnosis of Typhoid

The first efforts at creating decision support tools for medical diagnosis began with the pioneering works of Kulikowski (1970) and Shortliffe (1974). These works attempted a paradigm shift from purely engineering approaches toward a deeper ‘cognitive model’ consideration that explains physicians thinking processes and reasoning in medical diagnosis. However, it was later observed that purely rule-based systems were only good for narrow domains of medicine, because most serious diagnostic problems were so broad and complex that straightforward attempts to chain together larger sets of rules encountered major difficulties, hence such systems lacked the model of the disease or clinical reasoning (Szolovits, Patil and Schwartz 1988). As research in the application of DSS in medical diagnosis deepened, emphasis shifted to the representation and utilization of unstructured, imprecise, and dynamic knowledge. It is noted in (Kaeding and Flor 1995) that uncertainty and imprecision characterize the sources of information available to medical DSSs. These sources include the patient, physician, laboratory and other technical methods of evaluation, including the mathematical models that simulate the diagnostic process; thus, medical DSS researchers have resorted to soft-computing techniques for the management of issues of uncertainty and imprecision in medical diagnosis (Song and Kasabov 2003). Medical decision support systems have gained significant attention and utilization in the past decade, bringing to actualization, series of improvements over the past four decades. Soft-computing technologies – a multicriteria decision-support methodologies have been variously harnessed in the development of medical decision support systems. Marsh et al. (2014) assessed the value of health care interventions using multicriteria decision by reviewing the literature of the approaches adopted. Focus of their search was on EMBASE and MEDLINE where 40 studies were identified with 41 examples of MCDA in healthcare. The studies were

observed to have been undertaken in 18 different countries where majority of the studies focused on the design to support investment (56%). Research on MCDA was found to be mostly done in Europe (46.3%) with South America (0.02%) and Australia (0.02%) as the least. The combination of experts' opinion and literature (44%) of measuring criteria was the most used method while AHP (26.8%) was the most used tool for eliciting weights. The approach of using value for measuring comparison (93%) was found to be the most used approach. Grosan Abraham & Tigan (2007) proposed a multicriteria programming methodology for medical diagnosis and treatment of neurectomy, while Hancerliogullari, et al. (2017) used multi-criteria decision-making models (Fuzzy Analytic Hierarchy Process) in evaluating anaesthesia method options in circumcision surgery.

The alarming mortality rate of tropical diseases such as malaria, pneumonia, tuberculosis, cholera and others due to shortage of medical staff prompted a proposal of an Android-based expert system for diagnosis of selected tropical diseases (Olaniyan and Alegbeleye, 2019). Two soft-computing methodologies (fuzzy logic and AHP) were employed in the design. Fuzzy logic was used to derive membership functions of each of the diseases and to generate fuzzy rules to drive the inference engine of the system. AHP was used for pairwise comparison of the symptoms in order to select principal symptoms based on the weights assigned by medical experts to each of the symptoms. Ajenahughrure Sujatha and Akazue (2017) proposed a system driven by fuzzy logic to classify symptoms for the differential diagnosis of tropical febrile diseases. Their system was evaluated and acceptable by system users, especially with respect to cost and potentials for improved diagnosis effectiveness. A number of tropical diseases decision support systems powered by fuzzy logic and/or AHP or their variants have proven to covary with diagnosis outputs by human experts (e.g. Uzoka et al 2011, Prihatini and Putra 2012, Obot and Inyang 2014) because of the ability of fuzzy logic to handle vagueness in symptom elicitation and the strength of AHP in the development of multi-criteria models.

Typhoid fever is one of the often-misdiagnosed diseases in low-to-middle income countries (LMICs) due to self-diagnosis resulting from poor access to quality health care and lack of access to pathogenic testing. Most poor communities in LMICs have high incidence of malaria (due to poor vector control) and typhoid fever [due to poor sanitation, drug resistance, and self-diagnosis] (Ajibola, Omisakin, Eze, & Omoleke 2018). Fever is a commonly reported symptom in several tropical diseases, and without localized features and appropriate tests, diagnosis often erroneously defaults to malaria (Crump et al 2017) without consideration to other pathogens (Acestor et al 2012). In the absence of accurate laboratory tests, presumptive diagnosis would require a careful analysis of symptoms presentation and other clinical/non-clinical parameters (Luvira et al 2019).

Decision support systems have been previously proposed/developed for the diagnosis of typhoid fever. Oguntimilehin et al (2013) proposed a machine learning approach, using 18 symptoms, 100 training datasets and 50 testing datasets, with a 95% detection rate. Though the results are impressive, the number of data sets utilized for training and testing were few. Moreover, using 18 symptoms would likely reduce the efficiency of diagnosis. Santosa et al (2018) applied fuzzy logic Sugeno methods to the diagnosis of typhoid fever and Dengue hemorrhagic fever. The similarity of the symptoms of these two diseases necessitated the use of soft-computing methods, with 80.2% diagnostic accuracy; but also, with a small set of 86 data. Several other researchers have developed hybrid systems for the diagnosis of typhoid with varying degrees of diagnostic accuracy. For examples, Asogbon, et al. (2016) deployed an enhanced neuro-fuzzy system which was applied in genetic algorithm for medical diagnosis. Their aim was to optimize performance of an Adaptive Neuro-Fuzzy Inference System (ANFIS) in terms of its connection weights which is usually computed based on trial and error when used to diagnose typhoid fever. The study used Genetic Algorithm (GA) technique to automatically evolve optimum connection weights needed to efficiently train a built ANFIS model used for typhoid fever diagnosis, 104 medical records were adopted for the study with 15 to 75 age range. This was used to test the performance of the multi-technique decision support system. 70% of the dataset was used training data, 15% was used for validation while the remaining 15% was used to observe the performance of the proposed system. Genetic Adaptive Neuro Fuzzy Inference system (GANFIS) gave an average diagnosis accuracy of 92.7% compared to 85.5% recorded by the ANFIS.

Most of the studies on the use of soft-computing and multicriteria methods for the diagnosis of typhoid fever produced encouraging results in terms of the matching diagnoses; however, they mostly used small datasets, which makes the outputs difficult to generalize. In addition, they failed to provide the false positive and false negative values. The false positive (FP) is a Type-1 error because it indicates that the patient actually has the

disease, whereas a confirmatory test proves the initial test result to be false. A false negative (FN) result is a Type-II error, whereby the diagnosis fails to reject a false null hypothesis. The existence of false positive and false negative results underscores the need for further confirmatory investigations with a higher degree of sensitivity. According to Ioannidis, Tarone and McLaughlin (2011) the FP and FN results do not necessarily lead to the same consequences, and their relative importance may vary in different investigations, which indicates that the acceptable threshold may also vary. In general, an acceptable threshold value could be from 0.5 accuracy for a random classifier but a close accuracy value which is close to 1 could be better. Cooper (2013) established that threshold can be addressed by selecting symptom-based cut-off points to distinguish between disorder and normality which may be more or less wisely chosen so that results obtained should be widely accepted.

Typhoid fever is one the diseases that is responsible for high mortality rate in the tropical regions of the world. The high mortality rate is occasioned by misdiagnosis due to its confusable symptoms that overlap with symptoms of other febrile diseases. Inadequate medical facilities and personnel has also contributed to the high mortality and morbidity as patients resort to self-medication which complicate the symptoms resulting into deaths. Most patients suffering from typhoid fever find it difficult to express how they feel making it difficult for a medical doctor to decipher the cause of their illness. This uncertainty and imprecision though not peculiar to typhoid fever has necessitated the use of soft computing techniques for the management and processing of these uncertainties and imprecisions to medical diagnosis. AHP is found to be the most used tool for eliciting weights of symptoms of diseases while fuzzy logic is known to be the most popular tool in managing uncertainties and imprecision. A strong correlation has been found in most AHP/Fuzzy logic diagnostic system and human experts' diagnosis, though most of such systems use small datasets. Such systems are also not found to use the false positive and false negative values which underscores the need for further confirmatory investigations with higher degree of sensitivity. In the light of this, the results produced by such systems are not generalised.

3. Conventional Method of Diagnosis of Typhoid Fever

Typhoid fever presents with clinical features that are similar to many other febrile illnesses in developing countries. Thus, making a diagnosis require more than just a good clinical acumen as there are an array of other infectious diseases presenting with similar symptoms. In a study by Andrews et al (2018) only 4.1% of patients with an empirical diagnosis of enteric fever had positive blood cultures for *typhoidal Salmonella* organisms. The implication of their study is that >90% of the patients clinically diagnosed with Typhoid fever had a febrile illness from other causes. Febrile illness like malaria, dengue, sepsis, leptospirosis and many others are difficult to differentiate from typhoid fever in endemic countries without diagnostic tests. This highlights the need for better diagnostic approaches to limit inappropriate use of antibiotics and adequate treatment of other causes of febrile illnesses (Parry et al., 2011& Andrews and Ryan, 2015).

Microbiological cultures

The isolation of the causative organism, *Salmonella enterica serovar Typhi (Salmonella Typhi)*, is the gold standard for the diagnosis (WHO, 2018). Body fluids like blood, bone marrow, stool, urine, rose spots, gastric and intestinal secretions may be cultured. Blood culture gives a definitive diagnosis. However, the rates of positive culture are usually higher when using bone marrow aspirates for the culture (Sultana et al, 2016). In a systemic review by Mogasale et al. (2016), the proportion of *Salmonella Typhi* detection was 61% from blood cultures compared to 96% from bone marrow aspirate cultures. The use of bacteriological cultures for the diagnosis of typhoid infection is cost-intensive and technically difficult, hence the need for other diagnostic tests.

Antibody detection tests

These are rapid serologic tests designed for early and easy point-of-care use. The Widal Test is based on the measurement of antibodies (agglutinins) against somatic (O) and flagellar (H) antigens of *Salmonella typhi* in the sera of patients. Diagnosis is made by demonstrating a 4-fold increase in the antibody titre in paired samples collected 10 – 14 days apart. Although widely used in many developing countries because of its low cost, Widal test is limited by lack of standardized methods of assay and misinterpretation of results (Bharmoria Shukla and Sharma 2017 & Sultana et al, 2016). This has led to the overestimation of the number of patients presenting with acute febrile illnesses diagnosed with Typhoid fever (Ammah et al., 1999 & Nsutebu Ndumbe and Koulla 2002). A systematic review by Mengist and Tilahun (2017) revealed poor reliability, low sensitivity

and specificity of the Widal test. Alternative serologic tests detecting *S. typhi* specific antibodies have been developed. There are many types using different methods of serologic assay like the rapid dipstick assays, dot enzyme immuno-assays and agglutination inhibition tests. (Sultana et al, 2016).

Typhidot (Malaysian Biodiagnostic Research SDN BHD, Kuala Lumpur, Malaysia), is an Enzyme-Linked Immunosorbent Assay (ELISA)-based method, modified into an immunodot test format; TUBEX (IDL Biotech, Sollentuna, Sweden) detects antibodies using agglutination inhibition tests and Enterocheck-WB (Zephyr Biomedicals, Goa, India), a dipstick test, which IgM antibodies. Many other rapid tests kits are available, but its use is limited by low sensitivity, low specificity and the cost. (Parry et al., 2011)

Antigen detection tests

Many methods have been employed to detect *S. typhi* antigens in body fluids like serum and urine. Monoclonal and polyclonal antibodies targeting somatic, flagellar and Vi antigens found on *S. typhi* (Parry et al., 2011) are evaluated using Enzyme immuno-assay, counter immune electrophoresis and co-agglutination tests. These tests also have low specificity and sensitivity when compared to Blood cultures (Ajibola et al, 2018).

Molecular assay

The need to overcome the challenges posed by the inadequacies of using serologic tests and cultures have led to exploration of molecular methods for the diagnosis of typhoid fever. DNA-based detection methods, such as Polymerase Chain Reaction (PCR) has shown better sensitivity and specificity than blood cultures. The results are even better with the use of nested multiplex PCR (Sultana et al, 2016 & Srivastava et al., 2020).

4. Methodology

4.1 Data Collection

Data collection for the development and testing of the typhoid fever model was obtained in Nigeria, which is a tropical country with a high population and a fairly significant prevalence of tropical diseases. Two data collection instruments were designed for the purpose of the study. The first instrument obtained experiential knowledge from 25 physicians, experienced in the diagnosis of tropical diseases, for the development of models to diagnose the following tropical diseases: malaria, typhoid, chicken pox, measles hepatitis B, yellow fever and UTI. In this paper, we report on the model for the diagnosis of typhoid fever. The knowledge extraction instrument also elicited the following physician demographic information: age range, gender, professional experience, type of clinic they work in (public or private) and experience in diagnosing and treating the tropical diseases under consideration. The instrument required the physicians to carry out pairwise comparison of various symptoms (obtained through literature search) that are associated with the diseases on a 9-point linguistic scale. Prior to the administration of the AHP questionnaire, we employed the assistance of a physician and an epidemiologist in reviewing our model to ensure that the correct symptoms are captured for each of the diseases. Overall, eighteen symptoms were considered relating to the diagnosis of typhoid: fever, headache, abdominal pain, fatigue, vomiting, coughing, loss of appetite, chills, rash, and diarrhoea. The second instrument was administered to 40 physicians who provided patient consultation and diagnosis data for 2199 patients, for purposes of model testing – 2044 were found usable after data cleaning. In addition to the tests with real life patient data, we requested 13 physicians to do a validation of the results generated by our model.

4.2 Processing

This study adopted the classical AHP methodology (Saaty, 1981) in the development of a model for the diagnosis of typhoid fever. The AHP modeling was based on the group decision analysis using an online Excel template (<https://bpmmsg.com/ahp-excel-template/>). Based on the results of the AHP computation, we developed the diagnosis model. The key elements of the AHP are: pairwise comparison of variables; measurement of consistency, and priorities derivation, all of which are detailed below:

Pairwise comparison of variables

One distinguishing trait of AHP is its ability to permit the evaluation of quantitative as well as qualitative criteria and alternative on the same preference scale of nine levels.

Let A_1, A_2, \dots, A_n be evaluation variables, the priority of A_i , over A_j be represented by an $n \times n$ matrix

$$A' = (a_{ij}), i, j = 1, \dots, n \quad (1)$$

Then the entries are defined by the following rules:

Rule 1: If $a_{ij} = p$, then $a_{ji} = p^{-1}, p > 0$. (2)

Rule 2: If A_i is judged to be of equal relative importance/intensity, as A_j
Then $a_{ij} = a_{ji} = 1$ which symmetric in nature, in particular, $a_{ij} = 1 \forall i$

Measurement of consistency

The levels of consistency and consensus of judgments by experts in AHP decision modelling are crucial pointers to the model's reliability and reflection of the dependability of the expert judgments in relation to the pairwise comparison of the decision variables. A consistency check must be conducted since priorities make sense only if they are derived from consistent or near consistent matrices. Saaty (1977) proposed a consistency ratio, which is related to the eigenvalue method. Deviations from the consistency are represented by the consistency index (CI). Related to the CI is the consistency ratio (CR), which is the ratio of the CI to a random consistency index (RI). CI is calculated as:

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (3)$$

and the consistency ratio is given as:

$$CR = CI/RI \quad (4)$$

λ_{max} = maximal eigenvalue, and n is the number of variables in the pairwise comparison matrix.

RI is the random index determined by Saaty (1977) as follows:

n	3	4	5	6	7	8	9	10
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

A consistency ratio of 0.1 is the maximum acceptable value (Saaty, 1981).

Priorities Derivation Procedure

The online AHP template performs the synthesis of the pairwise comparison judgments. It involves the computation of the eigenvector, which presents linear relationships among the evaluation variables; thus, establishing the priority model. For each PWC matrix, priorities are calculated based on the eigenvalue method to produce a priority vector P, given as:

$$P = \begin{pmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{pmatrix} \text{ and } \sum_{i=1}^n p_i = 1 \quad (5)$$

$$p_i \text{ is generated as } p_i = \left(\sum_{j=1}^n v_{ij} \right) / n \quad (6)$$

v_{ij} is the eigenvalue corresponding to element a_{ij} of the PWC matrix. This is obtained from the matrix of eigenvectors. The matrix of eigenvectors V is computed as:

$$V = \begin{bmatrix} \frac{a_{11}}{\sum_{i=1}^n a_{i1}} & \cdots & \frac{a_{1n}}{\sum_{i=1}^n a_{in}} \\ \vdots & \ddots & \vdots \\ \frac{a_{n1}}{\sum_{i=1}^n a_{i1}} & \cdots & \frac{a_{nn}}{\sum_{i=1}^n a_{in}} \end{bmatrix} \quad (7)$$

If there are lower levels in the hierarchy, then the global priority is obtained by factoring in the eigenvector value of the priority at the level above the current hierarchy. If μ_i is the eigenvector value associated with the upper level criteria directly above the set of variables (s_i) under consideration, then the global priorities would be given as:

$$GP_i = \mu_i (\overline{p_L, x_L}) \quad (8)$$

where GP_i is the global priority associated with the vector of variables and weight pairs $(\overline{p_i, x_i})$. The variables are $x_{i1}, x_{i2}, \dots, x_{in}$; while p_i represents the lower level priority weights $(p_{i1}, p_{i2}, \dots, p_{in})$ associated with $x_{i1}, x_{i2}, \dots, x_{in}$.

5. Results and Discussion

The AHP questionnaire provided a basis for developing the typhoid diagnosis model based on the experiential knowledge of the 25 physicians involved in the knowledge definition process. The expert judgments were entered into the online AHP template to produce the pairwise comparison matrix shown in Table 1, with 77.4% consensus and 0.135 level of consistency. Karpetrovic and Rosenbloom (1999) found that it is possible to answer rationally and consistently and obtain a consistency ratio above 0.1. A number of studies (e.g. Cook et al 2007) have adopted a consistency cut off of 0.2 because of the large number of comparisons and variations existing in expert's institutional and disciplinary variations in terms of emphasis placed on each evaluation component. In this study, we have adopted a consistency cut-off of 0.2 due to the number of variables under consideration, the confusable and overlapping nature of tropical diseases symptoms and the number of experts involved in the study.

Table 1: PWC matrix (relative importance) with respect to the typhoid symptoms

	Fever	Headache	Fatigue	Abdominal pain	Vomiting	Chills	Diarrhoea	Coughing	Rash	Loss of appetite
Fever	1.00	0.79	0.75	0.49	0.70	0.81	0.50	0.00	0.23	0.78
Headache		1.00	0.00	0.00	0.47	0.00	0.00	0.00	0.00	0.00
Fatigue			1.00	0.46	0.68	0.00	0.00	0.00	0.00	0.00
Abdominal pain				1.00	0.69	0.38	0.71	0.00	0.30	0.59
Vomiting					1.00	0.00	0.00	0.00	0.00	0.00
Chills						1.00	0.00	0.00	0.00	0.00
Diarrhoea							1.00	0.00	0.00	0.00
Coughing								1.00	0.37	0.35
Rash									1.00	0.00
Loss of appetite										1.00

Synthesis involves the computation of eigenvalues and the eigenvector. Synthesis yields the percentage of relative priorities, which is expressed in a linear form to give the eigenvector. The implication of the eigenvector is that it expresses the relative importance of a symptom over another relating to the diagnosis of typhoid fever in the minds of the physician. Figure 1 shows the relative priorities (relevance) of symptoms in the diagnosis of typhoid fever, while the linear model (typhoid fever diagnosis factor index – TFDFI) is shown in equation (9).

$$\begin{aligned}
 TFDFI = & (\text{FeverScore} * 0.269) + (\text{HeadacheScore} * 0.184) + (\text{AbdominalPainScore} * \\
 & 0.118) + (\text{FatigueScore} * 0.137) + (\text{VomitingScore} * 0.052) + (\text{CoughingScore} * 0.016) + \\
 & (\text{LossOfAppetiteScore} * 0.083) + (\text{ChillsScore} * 0.081) + (\text{RashScore} * 0.017) + \\
 & (\text{DiarrhoeaScore} * 0.044)
 \end{aligned}
 \tag{9}$$

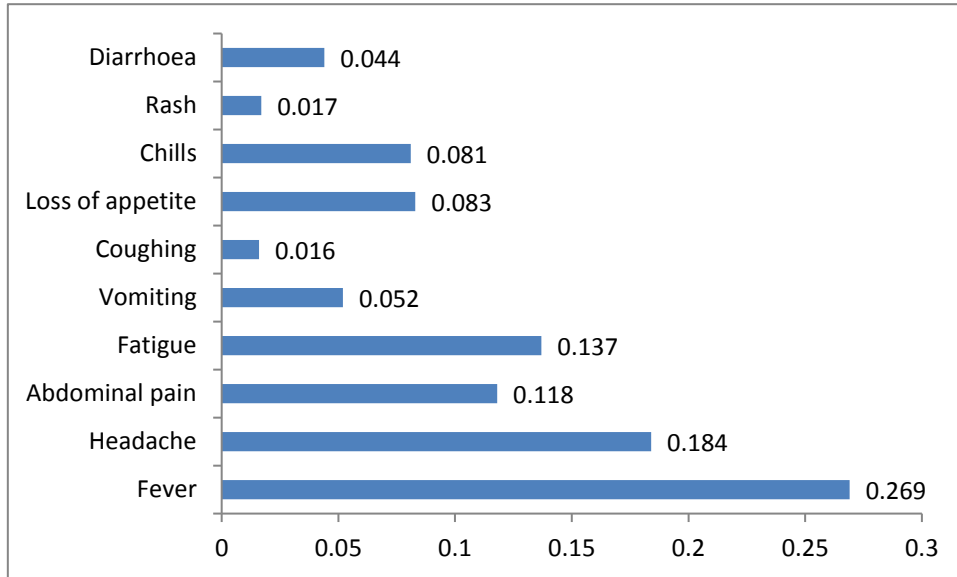


Figure 1: Priorities graph for typhoid symptoms

The TFDFI model shows that typhoid fever manifests mostly with fever (26.9%), headache (18.4%), fatigue (13.7%), abdominal pain (11.8%), loss of appetite (8.3%) and chills (8.1%). These are in agreement with the results obtained in (Bhan Bahl and Bhatnagar, 2005; Mouton et al., 2017 & Crump et al., 2004). Fever and headache are two symptoms that manifest across most tropical diseases. The confusable nature of symptom manifestations in these diseases call for methodical approaches to isolate each disease based on other peculiar symptoms. Our research shows that a combination of abdominal pain, chills, fatigue and loss of appetite in addition to headache and/ or fever are strong pointers to the possibility of typhoid presence, though a number of these symptoms could present more at the later stages of typhoid infection (Sanhueza et al., 2016 & Buzgan et al. 2007). Several researchers have revealed that there are primary symptoms of typhoid which starts with fever lasting for more than 48 hours, thereafter accompanied by intense headache of about 43-90% presentation, followed by gastrointestinal symptoms which includes; abdominal pain/cramps, nausea and vomiting, constipation or diarrhoea. All of these symptoms present the same way for both children and adults (Zein, 2017; Bhutta, 2006; Stephens and Levine, 2002 & Woodward and Smadel, 1964).

Our model was tested using data from the 2044 patients, based on an aggregation procedure shown in figure 2. The patients are assessed on each of the symptoms based on a six-point linguistic scale as follows: none=0, mild =1, moderate =2, strong =3, very strong =4, extreme =5.

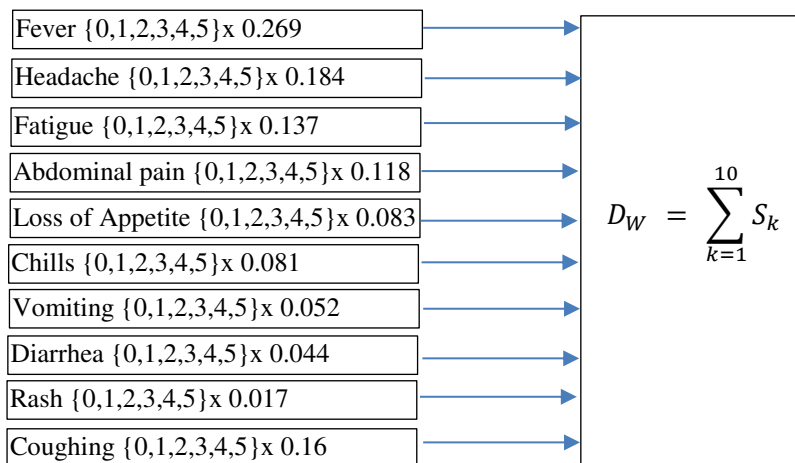


Figure 2: Diagnosis weight aggregation

We determined that on a linguistic scale any $D_w \geq 2$ (moderate or above) is considered non-trivial and as such points to the presence of typhoid fever in some degree. This was compared with the patient confirmatory tests conducted by the physicians to determine the matching diagnoses between our system and those conducted by

the physician. We also conducted the false positive and false negative analysis. The summary results are shown in Table 2.

Table 2: Summary of Diagnosis Results

Parameter	Number	Percent (%)
Acceptable classifications	1613	78.91
False Positives	208	10.18
False negatives	223	10.91
Total number of cases	2044	100

The results show 78.91% matching classifications of typhoid fever, with 10.18% false positives and 10.91% false negatives. The results align with a number of results, which have recorded false positives and false negatives of between 3% and 15% (e.g. Lee et al., 2014 & Edson, Glick and Massey 2010).

We approached 13 medical doctors to evaluate our model in terms of the results obtained and feasibility of utilizing a computer application that would be developed based on the AHP model for the diagnosis of typhoid fever. Most of the physicians were of the opinion that computational methods, such as the use of AHP, could be viable in the diagnosis of typhoid fever. There was a general opinion that the AHP model is complex to understand by non-computing (medical) experts; however, the results were considered highly encouraging and the symptom weights obtained through the AHP model align strongly with what exists in practice. Some physician's comments are shown in Table 3:

Table 3: Physicians' Evaluation of the AHP Model

Years of Experience	Hospital	Comments
Less than 5 years	Save Alive Hospital Port Harcourt Rivers State	The new model will help to save waiting time of patient suffering from these symptoms.
Less than 5 years	Dalhatu Araf Specialist Hospital Lafia. Nasarwa State	Typhoid is very common in the North area; as such this model will be of added advantage when adapted into the health system. Such a mobile application will easily drive diagnosis.
11-15 years	University of Port Harcourt Teaching Hospital (UPTH) Rivers State	Strongly agree that there are improved methods of attending to patients with typhoid, but this new method should be clear
16-20 years	University of Port Harcourt Teaching Hospital (UPTH) Rivers State	Good and interesting work, the model should be applied to more common diseases like pneumonia and tuberculosis should be considered too. Typhoid is not quite common among the paediatrics population. An interesting work!
16-20 years	Leads General Infirmary, Leeds University Teaching Hospital Trust Leeds UK	Typhoid fever is not common within UK region, expect in Africa countries. The study is a good one, it will be better if it is incorporated into a mobile application for easy detection, also other symptoms should be incorporated.
Above 20years	Zion Medical Centre Ahuoda Port Harcourt	The study is relevant, but there are improved methods of typhoid diagnosis, this new method with AHP is highly computational
Above 20years	Green Medical Centre Port Harcourt	Strongly agreed that there are conventional and improved methods for the diagnosis of typhoid fever; the new method will be an added advantage.

Though our sensitivity results (FP and FN) are within fairly acceptable thresholds (Hjalmarsson 2018; Dhouib, Kharrat & Chabchoub, 2010), there is need to reduce the FP and FN levels. This could be accomplished through: i) increase in the number of physicians providing experiential knowledge for the model development; and ii) use of Delphi method for refining the physicians expert judgments in pairwise comparison of symptoms of diseases. The physicians further pointed out the need to use our syndromic test as a first stage diagnostic tool to isolate cases for further tests. Since a number of the further tests could be expensive (Lehmann et al.,

2010; Bartlett & Stirling, 2003), especially in low-to-middle-income countries, a computational syndromic diagnosis tool could be a veritable means of methodically isolating cases for further laboratory tests. Previous studies (e.g. Uzoka, et al. 2017) have emphasized the utility of soft-computing tools in aiding inexperienced physicians and front-line health workers in syndromic diagnosis of tropical confusable diseases.

6. Conclusion and Future Research Perspective

Typhoid fever is known to cause significant morbidity and mortality in LMICs, with inaccurate estimates recorded in affected countries, especially in the South and Southeast Asia including the Sub-Saharan Africa. Furthermore, assessment of disease burden appears limited and of often trailed by high degree of sensitivity and specificity of most rapid diagnostic tests. In this study, we developed an AHP model for mining experiential knowledge, to power decision support systems for efficient diagnosis of typhoid disease. Our results are in alignment with existing knowledge (e.g. Khanmohammadi and Rezaeiahari 2014 & Liberatore and Nydick 2008) of the ability of AHP to support medical diagnosis modelling. In addition, our study adds the following contributions to knowledge:

- (i) *Pure domain knowledge mining*: Mining knowledge from experience provides opportunities for developing robust cognitive systems. This study mined experiential knowledge from domain experts, as building blocks to efficient decision support system. Our model showed 78.59% effectiveness in the classification of typhoid fever.
- (ii) *Confusable symptoms discrimination*: Confusable symptoms present a dangerous trajectory to failed treatments and misdiagnosis. Our AHP model therefore provides an approach with consistent threshold for ranking symptoms according to their relative importance. With this, a trade-off between prominent symptoms can be established, and the exact symptoms effectively isolated.
- (iii) *Cost effective solution to disease diagnosis*: Making health care solutions affordable would impact positively on the health care system and maintain access to quality treatments. This study serves as a pre-diagnostic toolkit that enables the detection of typhoid fever. It is cost effective because the trial and error detection of confusable diseases would not only be minimized but the path to quality disease diagnosis is certain.

The results of our study and their generalizability can be improved upon by increasing the number of domain experts (physicians) involved in the knowledge definition, and implementing mechanisms that could improve the consistency and consensus in pairwise comparisons by the domain experts. The consistency of the pairwise comparison could be improved by methods such as adaptive AHP approach [A³] (Lin, Wang and Yu, 2008), the linguistic preference relations [Fuzzy LinPreRa] (Wang and Chen 2008 & Wu, Huang and Xu 2019), which also improves consensus. Additional utilization of a Delphi process would also refine the experts' pairwise comparison results (Abdel-Basset, Mohamed, & Sangaiah 2018), while AHP hybridization with fuzzy logic could potentially increase the predictive ability of the model by dealing with the fuzzy nature of data that could arise during expert pairwise comparison judgment, and patient consultation. We note that typhoid co-infects with some other febrile diseases such as malaria (Baba et al., 2013 & Odikamnor et al., 2018). It will be desirable to develop a multi-criteria diagnosis system that assists in the differential diagnosis of febrile diseases, recognizing co-infection.

Declarations

Ethics approval and consent to participate: Ethics approval for this study was obtained from the Mount Royal University, Calgary Human Research Ethics Board (HREB); Number: 100038

Consent for publication: The authors hereby give Springer the consent to publish this article.

Competing interests: The authors hereby declare that there are no competing interests.

Funding: The funding for this research was received from the Faculty of Science and Technology Innovation Fund and the Research Grant Fund of Mount Royal University, Calgary.

Authors' contributions: The following are the authors' contributions to the research and manuscript:

Faith-Michael Uzoka led the research team, developed the initial research documentation, supervised data collection, participated in data analysis, and participated in writing all sections, except section 3

Chukwudi Nwokoro conducted model evaluation, participated in data analysis, and in writing sections 2, 4, & 5

Okure Obot participated in writing section 2 and did an overall review of the manuscript

Moses Ekpenyong did the initial paper review and wrote section 6

Aniema I.A. Udo wrote section 3.

Acknowledgements: We thank Mount Royal University, Calgary for funding this research. We also appreciate the efforts of all our research assistants who worked tirelessly during data collection and analysis.

Data Availability: Data for this study is available on request.

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Figures

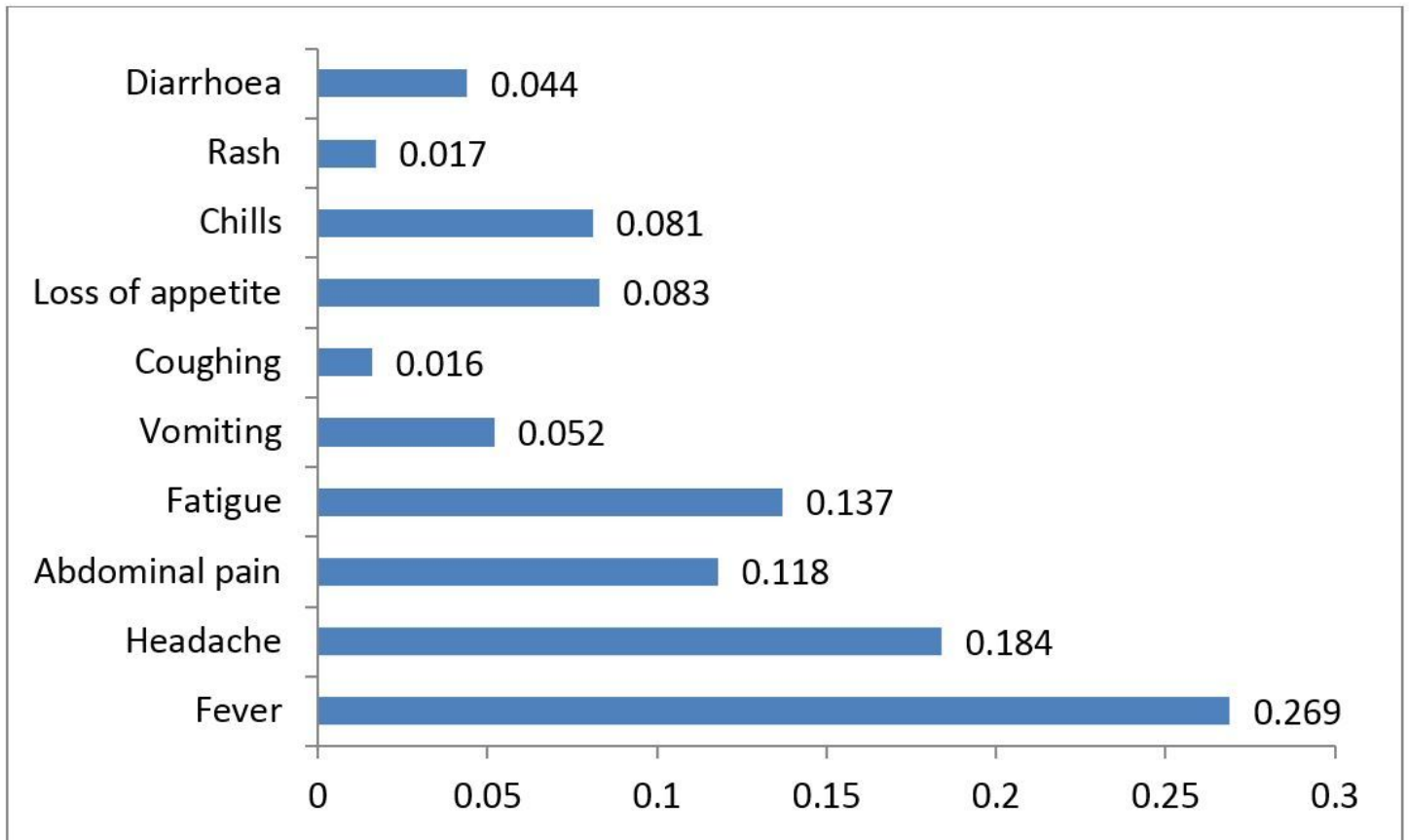


Figure 1

Priorities graph for typhoid symptoms

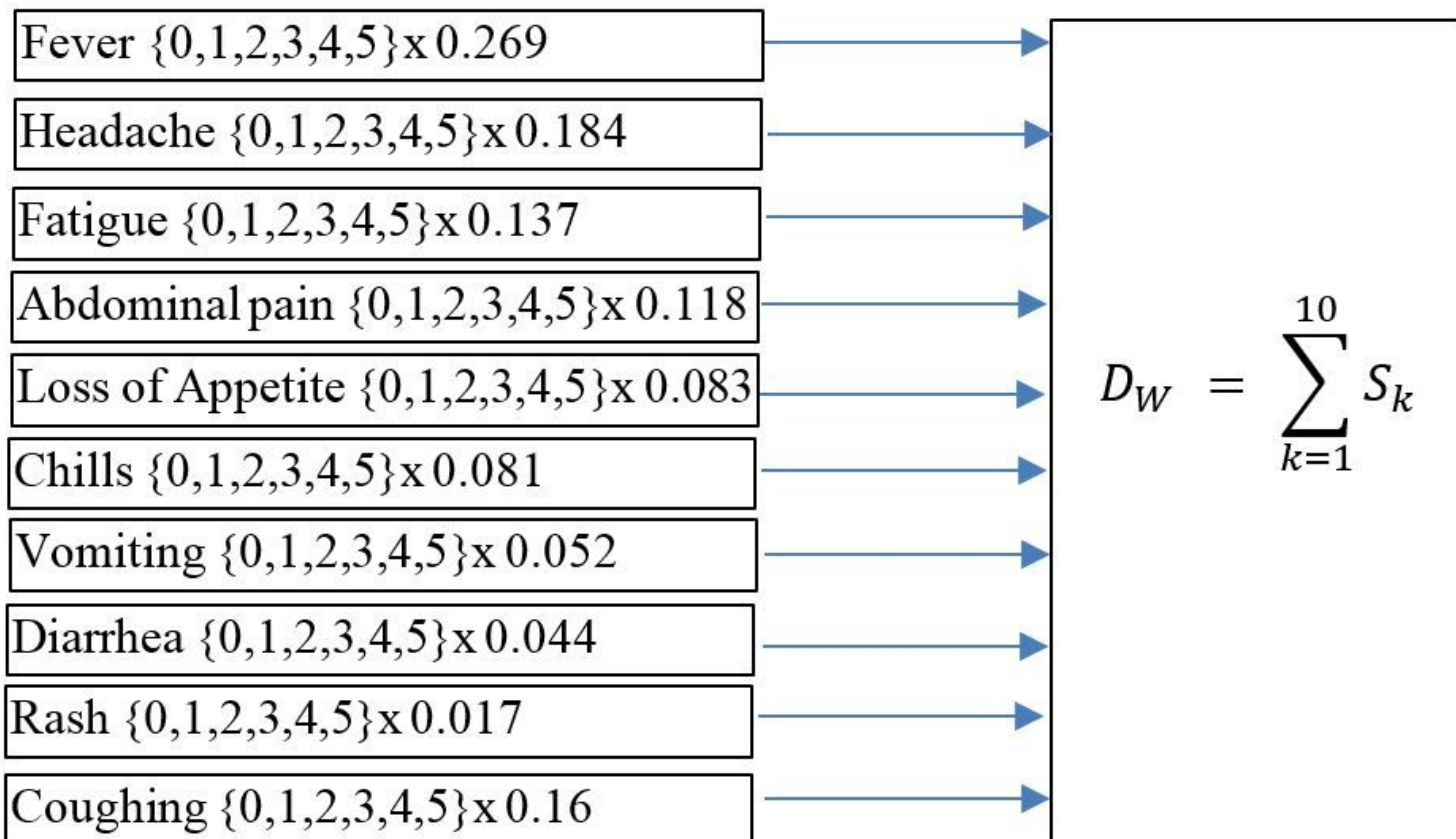


Figure 2

Diagnosis weight aggregation