A fuzzy linguistic model for the prediction of carpal tunnel syndrome risks in an occupational environment

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This research presents the development and evaluation of a fuzzy linguistic model designated to predict the risk of carpal tunnel syndrome (CTS) in an occupational setting. CTS has become one of the largest problems facing ergonomists and the medical community because it is developing in epidemic proportions within the occupational environment. In addition, practitioners are interested in identifying accurate methods for evaluating the risk of CTS in an occupational setting. It is hypothesized that many factors impact an individual's likelihood of developing CTS and the eventual development of CTS. This disparity in the occurrence of CTS for workers with similar backgrounds and work activities has confused researchers and has been a stumbling block in the development of a model for widespread use in evaluating the development of CTS. Thus this research is an attempt to develop a method that can be used to predict the likelihood of CTS risk in a variety of environments. The intent is that this model will be applied eventually in an occupational setting, thus model development was focused on a method that provided a usable interface and the desired system inputs can also be obtained without the benefit of a medical practitioner. The methodology involves knowledge acquisition to identify and categorize a holistic set of risk factors that include task-related, personal, and organizational categories. The determination of relative factor importance was accomplished using analytic hierarchy processing (AHP) analysis. Finally a mathematical representation of the CTS risk was accomplished by utilizing fuzzy set theory in order to quantify linguistic input parameters. An evaluation of the model including determination of sensitivity and specificity is conducted and the results of the model indicate that the results are fairly accurate and this method has the potential for widespread use. A significant aspect of this research is the comparison of this technique to other methods for assessing presence of CTS. The results of this evaluation technique are compared with more traditional methods for assessing the presence of CTS.

1. Introduction

Carpal Tunnel Syndrome (CTS) has become one of the largest problems facing ergonomists and the medical community because it is developing in epidemic proportions within our society. In addition, practitioners are interested in identifying accurate methods for evaluating the risk of CTS in an occupational setting. It is hypothesized that many factors impact an individual's likelihood of developing CTS. This disparity in the occurrence of CTS for workers with similar backgrounds and work activities has confused researchers and has been a stumbling block in the development of a model for widespread use in evaluating the development of CTS.

A fuzzy linguistic model was created to evaluate the risk of developing cumulative trauma disorders (CTDs) of the forearm and hand including CTS, tendinitis, tennis elbow and other occupational-related musculoskeletal injuries (McCauley-Bell 1993). CTS appears to be the most prevalent type of CTD affecting hand intensive industrial tasks (Crumpton 1993), hence the fuzzy linguistic model was further defined to quantify the risk associated with the development of this neuropathy. The fuzzy linguistic model described in this research contains two important characteristics that minimize the problem that past researchers have encountered in estimating the development of CTS. First, the model was designed to capture a holistic set of data that was considered relevant to the development of an injury. For instance, the model was developed to include task-related characteristics and personal characteristics deemed important by experts in the development of CTS. Additionally, a third category, organizational characteristics, was identified for inclusion into the model. Second, fuzzy set theory was used to approximate and represent the system parameters. This approach provides a quantitative method for analysing vague and imprecise information while still permitting a sound approach to problem evaluation. One of the most significant strengths of fuzzy set theory is the ability to model and quantify linguistic variables. The methodology and results section will further illustrate the strength of this approach in the evaluation of CTS.

2. Objective

The objective of this research was to develop a fuzzy linguistic model that can be used to predict the risk of CTS in an occupational setting. The purpose for utilizing linguistic variables at the user-interface is to allow for the analysis of levels or qualitative values associated with the variables associated with the development of CTS. Natural language was used in model development to facilitate a smooth translation of this methodology to an occupational setting.

3. Methodology

The methodology that was used to establish the initial model consisted of a literature search and detailed interview knowledge acquisition. This paper presents a brief overview of the stages in the model development (for more details on this specific model development see McCauley-Bell 1993). The literature search revealed a considerable amount of information regarding the suspected cause of CTS. At times the results varied and were even conflicting in the literature. However, the final analysis of the research did reveal a core of consistent information about the suspected risk factors associated with CTS.

The interview analysis was conducted to provide accurate expertise about the current state of CTS evaluation. However these findings also enhanced and corroborated the findings in the literature. This three-part methodology included the following:

(1) Factor identification and classification,
(2) Analytic Hierarchy Processing (AHP) to obtain relative weights of risk factors, and
(3) Factor qualification and quantification.

Traditional interview analysis and concept mapping interview techniques (McNeese, Zaff and Gomes 1992) were used to identify and classify the risk factors. The traditional interview analysis involved asking a series of questions about how an expert evaluates a situation for CTD related risk factors. This was extended until the expert felt that he had exhausted all potential categories and risk factors. Concept mapping is a knowledge acquisition tool that is designed to capture and graphically represent the relationships that exist between concepts in the domain expert's understanding of the problem space.

3.1. *Analytic Hierarchy Process (AHP): establishment of relative weights*

Experts were asked to do pairwise comparisons involving all pairings of the risk factors determined in the knowledge acquisition session. Pairwise comparisons were conducted within the three categories of risks identified to determine the relative importance of the six risk factors within each category. This was necessary to obtain the relative significance for each of the modular risk elements in the final determination of categorical risk. This same methodology was utilizied to rank the three categories (task-related, personal and organizational) or modules. The pairwise comparisons again resulted in a determination of the relative significance of each of the three categorical modules.

3.2. *Quantification of risk factors*

After completion of stage I in the knowledge acquisition, the experts were asked to consider what the levels or break-points were for the classification for the risk factors. They were also asked to rank or rate the extent of risk associated with each level of the risk factors. For example, given the risk factor *force*, the expert may have suggested approximate break-points that indicate minimal force exertion by the hand is approximately 0·5 N or less and moderate force exertion is approximately between 0·4 N and 0·8 N. After identifying the approximate ranges the amount of risk associated with each range was identified. After completion of this stage of the research the analysis indicated that four to five levels of linguistic variables would be useful for each of the risk factors. The responses yielded categories synonymous with the following risk levels:

(1) *minimal, little or no risk*: very little risk for the particular level of the given risk factor;
(2) *less than average or mild risk*: some risk for the particular level of the given risk factor;
(3) *average, moderate risk*: average risk for the particular level of the given risk factor;
(4) *strong risk*: greater than average or considerable risk for the particular level of the given risk factor; and in some cases
(5) *very strong risk*: definite risk for the particular level of the given risk factor.

The linguistic levels for each risk factor were established using these linguistic variables.

3.3. *Development of membership functions*

Defining graphical representation of the data consisted of determining two sets of membership functions for each variable. The first set of membership functions involved utilizing the linguistic risk level obtained in stage I of the knowledge acquisition. Each of the determined linguistic variables possesses an individual and overlapping membership curve that travels throughout the entire interval [0, 1]. The overlapping membership functions were used to illustrate the degree of belonging in each of the respective categories. The reason for using overlapping functions is that all of the experts and the literature concurred that the linguistic levels have 'grey' boundaries. Thus the system should represent an array of conditions and accommodate the perception of a variety of users. The membership function representing the linguistic risks is presented in figure 1.

The second membership function was used to rate the possibility of hazard associated with a particular linguistic variable (Stage II of the knowledge acquisition). Thus each linguistic variable must be rated on another membership function that indicates the degree of hazard associated with the linguistic risk levels (figure 2). The goal of the second membership function was to rate the hazard or risk associated with the particular category identified in the first membership curve. This second membership curve attempted to 'normalize' the results obtained from the initial membership function. Normalization was in the sense that all factors obtained in the knowledge acquisition stage can be rated on this hazard curve, and the data set contains values that travel throughout the entire continuum of the membership curve [0, 1]. This is a significant aspect of the research because the linguistic variables

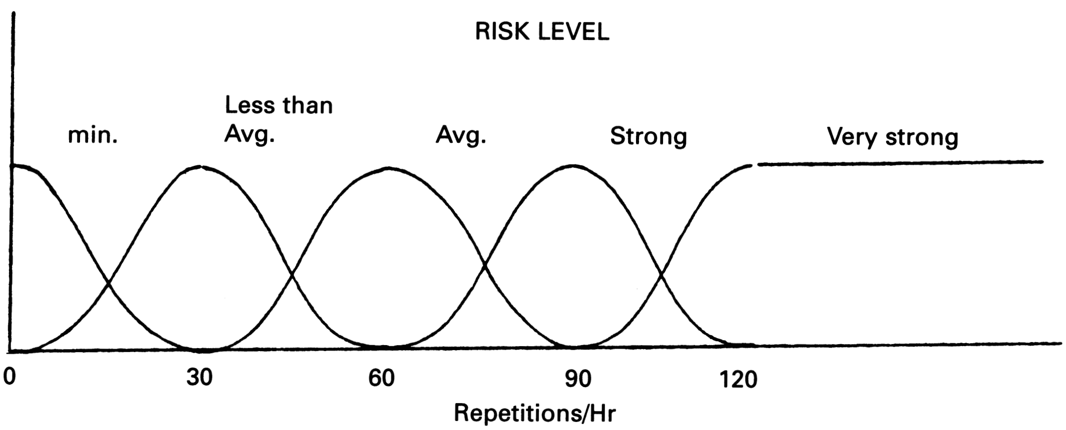

Figure 1. Repetition membership function.

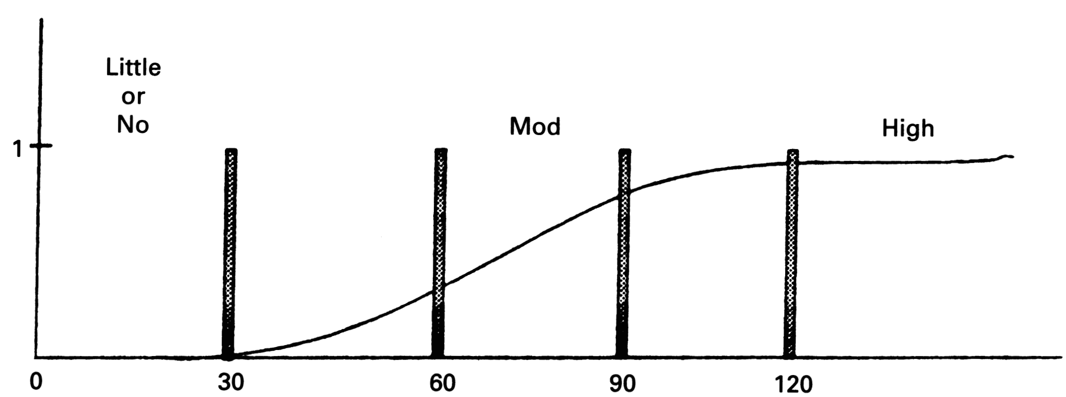

Figure 2. Hazard level membership/possibility function.

produced for each factor may have different levels of hazard associated with them in the overall development of injury. For instance, if a linguistic rating for the risk factor repetition is 'average' and the linguistic rating of task duration is 'average' these two factors, both being at the 'average' linguistic risk level may not necessarily have the same degree of hazard. The level of average repetition may result in an above average risk on hazard curve whereas the level of 'average' for the task duration factor may result in minimal risk on the hazard curve. The values were then used to provide risk quantification.

3.4. *AHP analysis results*

The relative or priority weights obtained for the analysis of the task-related risk factors are listed in table 1. It is notable that number of years of task performance did not surface as one of the primary risk factors in the concept mapping or interview analysis knowledge acquisition sessions. Analysis of the personal factors hypothesized to contribute to the development of CTDs yielded relative weights (Table 2). Previous history of a CTD was identified as the personal factor with the highest relative weight thus implying that it is the most significant risk faactor in this category. When evaluating the organization risk factors, equipment (level of automation) was the most significant factor. The order of importance and priority weights for each of the risk factors are listed in table 3. This module resulted in relative weights for seven factors. The awareness and ergonomics programme categories were combined because, according to the experts and the literature, one of the goals of an ergonomics programme is to provide awareness about the ergonomics risk factors present in a workplace.

After the factors within the modules were compared, an AHP analysis was conducted to determine the relative significance of each of the modules. The priority weights obtained for the task, personal, and organizational characteristics modules are listed in table 4. As expected, the most significant category of risk was the task-

Table 1. AHP results: task-related risk factors.*

Ranking	Factor	Relative weight
1	Awkward joint posture	0·327
2	Repetition	0·206
3	Hand tool use	0·196
4	Force	0·136
5	Task duration	0·135

*These AHP weights are modified for CTS risk prediction.

Table 2. AHP results: personal risk factors.

Ranking	Factor	Relative weight
1	Previous CTD	0·383
2	Hobbies and habits	0·223
3	Diabetes	0·170
4	Thyroid problems	0·097
5	Age	0·039
6	Arthritis	0·088

Table 3. AHP results: organizational risk factors.

Ranking	Factor	Relative weight
1	Equipment	0·346
2	Production rate/layout	0·249
3	Ergonomics programme	0·183
4	Peer influence	0·065
5	Training	0·059
6	CTD level	0·053
7	Awareness	0·045

Table 4. AHP results: module risk comparison.

Ranking	Module	Relative weight
1	Task	0·637
2	Personal	0·258
3	Organizational	0·105

related module with a relative weight of 0·637. The personal module had a relative weight of 0·258, less than half of the relative weight of the task-related characteristics module. The organizational module received the smallest relative weight 0·105.

3.5. *Quantification of risk factors*

Owing to the multiple inputs necessary to obtain a final risk level in the determination of injury risk and the use of relative measures in factor significance, it was determined that Fuzzy Quantification Theory I (Terano *et al.* 1992) quantitative regression analysis was a feasible method to utilize as a basis for model development. Fuzzy Quantification Theory I involves determining a linear function of risk factors values (levels), which was done for each of the modules within the system. The objective of Theory I is to find the relationships between the qualitative descriptive variables and the numerical object variables in the fuzzy groups.

Each of the factors in the three modules was considered as an element in a linear function. As in linear regression, each of the factors may or may not have some degree of contribution to the overall model. For this case, the overall value obtained by the linear model for the given module represents the degree of risk associated with the particular module.

When all of the input values have been selected, the next step is to examine the degree of significance (a_i) where $i = 1-5$. In this case the a_i values represent degree of significance or relative priority weight for each of the five factors. The values that represent the relative significance were obtained for each variable from the AHP analysis. In order to produce a crisp risk value, the product of the linguistic risk value for a given task and the AHP value are taken and the summation of these products represents the overall risk for the module. Equation 1 represents the model formula used to calculate the numeric risk value (R_1) for the task (T) module. The model that was developed in the initial research (McCauley-Bell and Badiru 1996a, 1996b) contained six factors in the task characteristics module. However, this model is specific to the evaluation of CTS in an office environment and expert consultation revealed that the sixth factor, vibration, was not an important issue in office setting. The assumption is that the individuals in office environments seldom, if ever, utilize items that produce the amount of vibration indicated as a risk. The numeric risk levels for the personal and organizational characteristics are represented by equations 2 and 3, respectively.

$$R_1 = F(T) = a_1w_1 + a_2w_2 + a_3w_3 + a_4w_4 + a_5w_5 \tag{1}$$

$$R_2 = F(P) = b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6 \tag{2}$$

$$R_3 = F(O) = c_1y_1 + c_2y_2 + c_3y_3 + c_4y_4 + c_5y_5 + c_6y_6 \tag{3}$$

In equation 1, the w_i values represent the numeric values obtained from the linguistic user inputs for each of the five risk factors and the a_i values represent the ratings obtained from the AHP analysis. Likewise, the values of $x_{j,}$ where $j = 1-6$ (equation 2) and y_k, where $k = 1-6$ (equation 3) represent the user inputs for a given task while the values b_{1-6} and c_{1-6} represent the AHP weights for the personal (P) and organization (O) characteristics, respectively. Since the model is based on Fuzzy Quantification Theory (Terano *et al.* 1992), rather than using CTD epidemiological data to establish the regression weights, the relative weights derived from the AHP analysis were used. As previously stated, the AHP utilized qualitative descriptive measures of importance among the avariables to generate the relative weights of importance from expert assessment.

In summary, the previous equations produce a numeric output accomplishing the following:

(1) defining the relationships among the variables through the AHP using the experts;
(2) identifying the level of each risk factor and assigning a linguistic value and numeric value to each linguistic variable; and
(3) combining the products of these two outputs into a linear equation that produces a crisp numeric output between 0 and 1.

The numeric risk values obtained from each of the modules and the weights obtained from the inter-module AHP analysis were used to obtain the final crisp output. The final output is a value that suggests the risk of subject injury for a specific task in a given workplace. The following equation was used to quantify the overall risk of injury:

$$Z = d_1R_1 + d_2R_2 + d_3R_3 \tag{4}$$

where Z = overall risk for the given situation; R_1 = the risk associated with the task characteristics; d_1 = weighting factor for the task characteristics; R_2 = the risk associated with the personal characteristics; d_2 = weighting factor for the personal characteristics; R_3 = the risk associated with the organizational characteristics; d_3 = weighting factor for the organizational characteristics.

The weighting factors (d_1, d_2, d_3) represent the relative significance of the given risk factor category's contribution to the likelihood of injury. These factors were determined through the AHP model. After each of these values is obtained, the above equation calculates the crisp numeric value that represents the risk of CTS injury.

4. Model of evaluation

Upon completion of the fuzzy linguistic model, a research study was conducted to evaluate the accurary of the model in predicting the presence of CTS. Seventeen participants ranging in age from 24 to 72 years were used in this analysis; 88% of the participants were female and 12% were male. The participants represented a variety of occupations, such as reservationists, technicians, data entry operators and cooks.

Each of the participants' hands (34 in total) were evaluated and diagnosed by an orthopaedic hand surgeon as having CTS or not having CTS. The physician's diagnosis was based on formal electromyography (EMG) testing and clinical examinations. Table 5 contains a summary of the physician's diagnostic findings for the participant population used in this study.

Questionnaires were used to collect information on all personal, task-related, and organizational risk factors represented in the fuzzy linguistic model from each of the participants. The respective categorical information was entered into the fuzzy linguistic model. The accuracy of the model was evaluated by calculating the number of correct and incorrect predictions made by the model as compared to the physician's findings. For example, the model was considered successful if it predicted that the person should be at *high* or *very high* risk of injury and the diagnosis of the physician revealed that they were currently experiencing CTS or early symptoms of the disorder. In addition, sensitivity and specificity indices were calculated for the model's predictions. The sensitivity index represents the ability of the model to accurately identify persons with CTS from the pool of participants diagnosed by the physician as having CTS, while the specificity index represents the ability of the model to accurately identify persons not having CTS from the pool of participants diagnosed by the physician as not having CTS.

In order to evaluate the accuracy of the system, the ranges of potential system outputs were categorized. Table 6 presents a definition for five ranges of crisp output values. These ranges of outputs were used to provide a level of expectation associated with the numeric output from the model. Thus the final numeric value obtained from the equation was categorized according to the classifications listed in table 6 and very high levels imply the expectation of a CTS. For example, if the crisp numeric output is 0·62 the overall risk associated with the condition would be high. In cases where the overall crisp risk level is determined by the model was above average (determined as greater than 0·60 through expert knowledge acquisition), the individual being evaluated is expected to have experienced a CTS or be currently experiencing at least early symptoms. It is important to note that although crisp

Table 5. Population description.

Hands	CTS	Non-CTS
Left	12	5
Right	16	1
Total	28	6

Table 6. Crisp output ranges.

Crisp outputs	Linguistic risk level
0·00 – 0·20	Minimal risk
0·21 – 0·40	Less than average risk
0·41 – 0·60	Average risk
0·61 – 0·80	High risk
0·81 – 1·00	Very high risk

values are used to represent the risk ranges in the model evaluation, this does not inhibit the integrity of the fuzzy model. The purpose of the ranges defined by the crisp values is to provide a base for ranking the goodness of the system outputs. This approach provides a means of differentiating between system outputs and expected relationships to case studies.

The responses to a questionnaire and an interview allowed each of the subjects to be classified as injured (currently injured or showing symptoms of CTD) or non-injured. Cases were evaluated in a 2×2 contingency table to determine if the results of the models were significant in predicting the actual cases of injury. The results of the evaluation were encouraging. The system produced one false negative, a result which predicted that the hand did not have CTS when in fact the physicians diagnosis stated that the hand had experienced CTS, and no false positives (a result which predicted that the hand had experienced CTS when the physicians diagnosis revealed that the hand had not experienced CTS). The model predicted that 16 of the individuals would be average or higher risk for the development of CTS. All of these 16 individuals had experienced a positive diagnosis of CTS in one of their wrists and these cases were considered to be successes (sensitivity = 100%). Conversely, the model predicted that one subject had a minimal risk of CTS development; however, the physician's evaluation indicated that this individual was experiencing CTS. Thus, this was considered a system error (specificity = 94·1%).

5. Accuracy of fuzzy model predictions versus traditional methods

Results obtained using the fuzzy linguistic model for predicting the presence of CTS were compared to results obtained using other techniques for assessing the presence of CTS. The other techniques included the carpal compression test, Phalen's test, vibrometry testing, and electroneurometry testing. These methods were used to analyse for a presence of CTS in all 17 participants discussed earlier in §4. A complete discussion of each testing procedure can be found in Crumpton (1993). The predictions obtained by using the fuzzy linguistic model were more accurate than those of the carpal compression test, Phalen's test, vibrometry testing, or electroneurometry testing. Evaluation of the results, or predictions of CTS condition, for each of these techniques is as follows. In comparing these techniques with the physicians findings, 82·4% of results obtained using the carpal compression technique were correct. Also, 14·7% of these results were false negatives. Also Phalen's test yielded 82·4% correct results, 8·8% false negative, and 8·8% false positive results. Vibrometry results were 70% correct in diagnosing CTS with 16·7% false negatives and 13·3% false positives. The electroneurometer testing results appear least accurate with 48·3% correct diagnosis, 41·4% false negatives, and 10·3% false positives.

Also, the sensitivity index (based on unhealthy hands) and the specificity index (based on healthy hands) were calculated for these traditional techniques. The carpal compression test was 82% sensitive and 83% specific when used to diagnose CTS. Phalen's test was found to be 82% sensitive and 50% specific for diagnosing CTS. Vibrometry was 79% sensitive and 33% specific, while electroneurometry was 50% sensitive and 50% specific.

6. Conclusions

The results of the evaluation indicate that this fuzzy model has potential for accurately predicting risks of injury for the identified risk factors. The model provides a holistic analysis of the risk factors that are expected to contribute to the development of CTS. Thus, the model also has the potential to provide a comprehensive analysis tool for predicting and reducing the risk of CTS in the occupational setting.

The results obtained in comparing the fuzzy linguistic model to the other techniques for predicting CTS are very encouraging owing the accuracy of the model results over the other techniques. An additional and very important aspect of this model, is its ability to provide a prediction of CTS risk without the need to have direct contact with the individual thus suggesting more objectivity. The other techniques require personal contact with the individual while the model has the ability to provide an output through an analysis of written and/or historical data.

While the results of this analysis are extremely encouraging it must be noted that all of the subjects were individuals who had contacted a physician for medical purposes and were thus chosen as a part of the study group. A very important step that is currently in progress for the research is the evaluation of a larger and more varied study group for a similar validation analysis.

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