

# Fuzzy Random Utility Choice Models: The Case of Telecommuting Suitability

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## Abstract

Random utility models have been widely used in many diverse fields. Considering utility as a random variable opened many new analytical doors to researchers in explaining behavioral phenomena. Introducing and incorporating the random error term into the utility function had several reasons, including accounting for unobserved variables. This paper incorporates fuzziness into random utility models to account for the imprecision of data intrinsic in human perception and statement. Fuzzy variables are contrasted with random variables, and a model is presented of relationships among real, perceived, and stated/reported conditions. The proposed fuzzy approach is applied to modeling telecommuting suitability, using data gathered from 242 employees in Tehran, Iran to construct fuzzy membership functions of job-tasks to the fuzzy set of telecommuting suitability. The resulting utility function can be viewed as representing the global wisdom of respondents. The enhancement in the fuzzy random utility model results, although modest, is promising and sets the stage for further research in the field of fuzzy logit models.

**Keywords:** Fuzzy random utility model, global wisdom, telecommuting suitability

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## 1. Introduction

Random utility models have been widely used in many diverse fields. Considering utility as a random variable opened many new analytical doors to researchers in explaining behavioral phenomena. Introducing and incorporating the error term into the utility function had several reasons, including accounting for unobserved variables. Since in reality, not all explanatory variables are available to be explicitly incorporated in the model, stochasticity issues inevitably arise, leading to the introduction of the random error term. This form of uncertainty needs to be distinguished from the uncertainty resulting from imprecision of the data, referred to as fuzziness. This paper employs concepts from fuzzy set theory to incorporate fuzziness into random utility models to account for the imprecision of data intrinsic in human perception and statement. The proposed fuzzy approach is applied to modeling telecommuting suitability, a Transportation Demand Management (TDM) technique for reducing peak period traffic that has attracted the attention of transportation planners and researchers [Bernardino & Ben-Akiva 1996, Mokhtarian and Salomon 1996 and Yen & Mahmassani 1997]. TDM is generally an important part of any solution package for large metropolitan areas suffering from congestion and its related negative impacts (air pollution, fuel consumption, etc.). Viewed as a TDM strategy, telecommuting has the potential to reduce urban transportation problems and

their negative impacts. Naturally, the extent of that potential is directly proportional to the level of adoption of telecommuting, which in turn depends on its suitability for the population of employees. Singh et al. (2013) developed a joint model embracing three dimensions of telecommuting—option, choice, and frequency—to estimate telecommuting days per month, with an emphasis on “option” as a key in telecommuting decisions.

Conceptual frameworks in the field of telecommuting adoption generally use random utility models such as logit and probit. Thus, in this paper the job-based suitability of telecommuting is modeled with binary logit, whose probabilistic nature takes into account the objective inability to perfectly measure every factor relevant to telecommuting suitability and/or to perfectly specify the functional form taken by the relationship. However, fuzziness of the explanatory variables is also incorporated into the random utility modeling of the job-based suitability of telecommuting, to account for the subjectivity of the decision-maker in the choice process. Because fuzzy concepts are still relatively-little studied in travel behavior modeling, the main purpose of this paper is to increase the knowledge and understanding of them, and to illustrate their application. The particular content of the application is of secondary interest.

Accordingly, the paper proceeds as follows: in the next section the literature on fuzzy set theory and fuzzy logit models is reviewed. Then,

a conceptual framework regarding fuzziness and randomness is discussed. Fuzzy variables are contrasted with random variables, and a model is presented of relationships among real, perceived, and stated conditions. To show the applicability of the proposed concepts, including that of global wisdom, data gathered from a sample of 242 employees from several (private and public) organizations in Tehran, Iran is introduced in the next section. Model results are reported in the following section, in which it is shown that fuzzy explanatory variables reconstruct the observed decisions slightly better than do the traditional explanatory variables. Finally, conclusions and suggestions for further research are presented.

## 2. Fuzzy Set Theory

About four decades have passed since the publication of Zadeh's seminal paper (1965) on fuzzy sets, and since then, many papers and books have been published in this field [Zimmerman, 1991; Kosko, 1993; Wang & Klir, 1992; Zadeh, 1996]. Many papers in transportation and related literature have also been devoted to this subject in the past decades [Lien and Chen 2002; Teodorovic 1999]. Fuzzy sets, and in particular fuzzy logic, have been employed in many diverse sub-fields of transportation studies and research, such as trip generation, trip distribution, mode choice, route choice (traffic assignment), investment projects, traffic control, traffic corridors, network control, accident analysis and preven-

tion, level of service analysis, air transportation, and river transportation [Teodorovic, 1999].

Fuzzy set theory (FST) was introduced as a tool for analyzing problems under uncertainty and fuzziness, as a generalization of classic set theory. In classic set theory, sharp boundaries separate the elements that belong to a set from those that do not. In other words, the membership function ( $\mu_A(x)$ ) of an element ( $x$ ) to a set ( $A$ ) is dichotomous and defined as:

$$\mu_A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases}$$

Many sets encountered in practice, however, do not have such sharp boundaries. In FST, each element can be a member of the set with a membership value equal to any point in the closed interval of 0 to 1, that is [0,1]. Thus, the basic difference between the two set theories lies in the definition of the membership function. In this sense, classic set theory is a special case of FST, where only the two end points of the membership space are considered. Theoretically, a fuzzy set  $\tilde{A}$  is defined as the set of ordered pairs  $\tilde{A} = \{x, \mu_{\tilde{A}}(x)\}$ , in which  $\mu_{\tilde{A}}(x)$  represents the membership of the element  $x$  to the set  $\tilde{A}$ .

Human thoughts, measurements and statements are generally not as precise as the language of conventional crisp mathematics can convey, and often, realistic situations are described less precisely using natural human languages. In such cases, where statements are

not exactly either one or zero and some intermediary point holds, conventionally, they are assumed as either one or zero in mathematical models. However, it is also possible to use concepts from FST as an appropriate tool for modeling phenomena in such situations and treat them as degrees between one and zero. As Kosko (1993) proclaims in support of FST: “*Everything is a matter of degree*”.

### Literature on Fuzzy Logit Models

Logit models have been used in many diverse fields for modeling discrete phenomena. Their tractability, ease of computation, and capability of estimating the share of new alternatives are among the major reasons for the vast range and widespread use of this type of model. However, there are some drawbacks to these models, and it has been suggested [Lien and Chen, 2002; Bierlaire et al. 1993] that using concepts from fuzzy set theory can improve their realism. So far, though, this idea has attracted rather little attention (at least for transportation applications), partly because FST is a highly specialised and abstract field and partly because it is a fairly new one.

Teodorovic (1999) presents a rather comprehensive review of fuzzy logic systems for transportation engineering, in which many typical transportation problems are posed using a fuzzy logic or approximate reasoning approach. He states that in particular cases, fuzzy logic models gave considerably better results than those obtained from the logit

model.

Lien and Chen (2002) propose a fuzzy logit model combined with the Fuzzy Linguistic Scale (FLS) to estimate the probability of housing location choice. They assume that location choice has a multinomial structure that leads to a fuzzy multinomial logit (FMNL) model, and therefore, utilize this idea to deal with the problem of qualitative variables in subjective perception. The authors believe that fuzzy concepts are more capable of dealing with the problem of qualitative variables than conventional methods are. Thus, qualitative aspects are represented as linguistic labels using linguistic variables, namely variables whose values are not numbers but words or sentences in a natural language. Indicating that there has been very little literature on the application of fuzzy concepts to discrete choice models, like logit, these authors claim that the improved interpretative capacity of FMNL can overcome most of the shortcomings of multinomial logit (MNL). Furthermore, they claim that their model is closer to actual human cognition and decision making behavior for housing consumption.

### 3. Fuzzy Based Choice Modeling

Basically, fuzzy concepts do not exist in nature and the real world: things are exactly what they are. Rather, fuzzy concepts are devised by humans, to reflect human perception, thoughts, and statements about nature and the environment (Fig. 1). For example, the mean

level of importance of the personal computer (PC) in accomplishing one's job tasks for an employee with certain job characteristics is some definite value (for the specified circumstances), but unknown precisely (to the individual, who is asked about it). If different respondents are asked this question for a completely known situation, different responses would be presented. If **more precise** responses (e.g. on a 0 to 100 scale) are sought, responses would be **less reliable** (in the sense of reflecting the exact truth and being answered in exactly the same way if asked multiple times of the same person, although they may be generally accurate), and the respondents would admit it too. If coarser response categories like "not important", "important", and "very important" are used, then the responses would be **more reliable** (in the sense of reflecting the truth in a general way, and being answered in the same way if asked multiple times of the same person), however **less precise**.

In other words, there is a trade-off between **precision** and **reliability** of responses: as the precision of responses (number of response items in multi-response questions) increases,

their reliability decreases, and vice-versa. Reduction of the number of response categories means a reduction in precision, an increase in the "width" of the category, and hence greater aggregation of the data. The actual reality is definite and certain (from the perspective of omniscience), however the precision of a human's statement about reality depends on his perception model and his statement apparatus (language). Since the precision in human perception and statement is generally not very high, in order to take better advantage of such kinds of data, the concept of fuzzy membership function is employed here to represent the global wisdom of respondents.

### Random Variables and Fuzzy Variables

Randomness and fuzziness are two independent concepts. In the computational sense, they may look similar, however they are intrinsically very different. Travel time, whether a random or non-random variable, can be considered fuzzy, depending on the precision of the statements used for representing it. For instance, travel time by auto can be considered a random variable due to the random factors

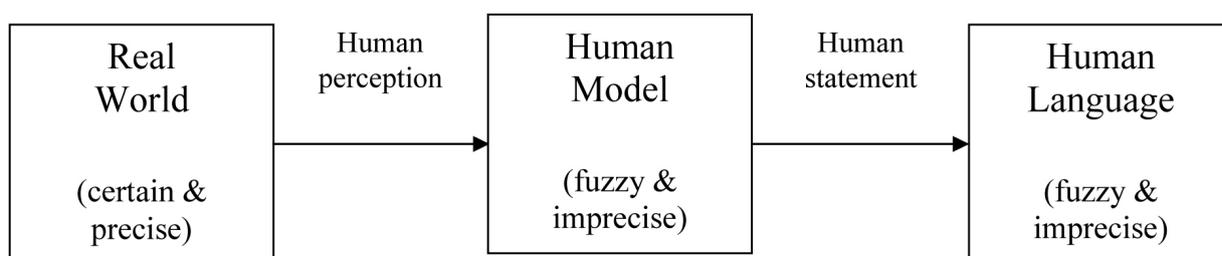


Figure 1. A model of the real world and human perception and statement.

affecting its value, such as congestion, driving style, and mechanical malfunctions. However, travel time by metro (in an ideal case) can be considered (for illustrative purposes) a non-random variable, since the metro has a reliable and fixed schedule, and can be expected to arrive at the scheduled time. For either case, travel time could be stated as, for example, “23 minutes and 48 seconds” when more data is available, or as “short” when less data is available. Travel time expressed in the former way is non-fuzzy, while the latter measurement is fuzzy. In a way, randomness of a phenomenon or procedure depends on the type and nature of that phenomenon or procedure, while fuzziness depends on data “precision” used in the statements regarding that phenomenon or procedure. In other words, randomness relates to the predictability of the different values for a random variable, while fuzziness depends on the precision of the human perception and statement regarding the values of the quantities for that variable, whether random or not. Considering the independence of randomness and fuzziness and their intrinsic natural characteristics leading to different advantages and applications, the idea in this paper is to consider the more general case of random utility models by incorporating fuzzy inputs. It is believed that a transformation of the explanatory variables to fuzzy membership functions has the potential of improving model results due to its broader perspective. Randomness in the utility function of an alternative  $i$  ( $e_i$ ) takes

into account errors and/or ignored variables and/or misspecification of the utility function ( $U_i$ ), basically considered as the objective inability to include each and every relevant factor in the real world in the model. Fuzziness, a separate trait arising when calibrating the utility function due to the imprecision of data intrinsic in human perception and statements, (e.g. as acquired in questionnaires), however, is proposed to be considered in the deterministic or systematic part of the utility function ( $V_i$ ). The utility function is (conventionally) assumed to be:

$$U_i = V_i + e_i \quad (1)$$

which, assuming a Gumbel distribution for the error term, results in the ordinary logit model for the probability ( $P(i)$ ) of alternative  $i$  to be chosen:

$$P(i) = \frac{e^{V_i}}{\sum_{j \in J} e^{V_j}} \quad (2)$$

Thus, the fuzzy membership functions of the independent variables are incorporated into the deterministic part of the utility function instead of the independent variables themselves, thereby utilizing the knowledge content of the data, here referred to as the global wisdom of the respondents. This is a more general treatment of the problem, just as complex numbers are a generalization of real numbers.

### Applicability to Job-based Telecommuting Suitability

Most of the conceptual frameworks proposed in the analysis of the telecommuting adoption process (Mahmassani et al. 1993, Yen et al. 1994 and Mokhtarian and Salomon 1994) incorporate employer and employee perspectives: the employer decision to offer a telecommuting program (as a function of costs and benefits for the organization) and the employee decision to adopt telecommuting (as a function of costs and benefits for the individual). It is generally believed that a telecommuting program must be offered by the employer as a prerequisite, making the program available and giving the employees the right to choose whether to telecommute or not. Walls et al. (2007) concluded that workers' job characteristics substantially affected both propensity to telecommuting (as much as demographic factors did), and its frequency. Mamdoohi et al. (2006) proposed the concept of abstract job, which views jobs as composed of tasks, whose time shares can be significant to telecommuting suitability as a necessary prerequisite to its adoption. They believe that the title of a job may not be very revealing, but rather the elements that a job comprises are considered to be effective in determining the level of telecommuting for which it is suitable. An attempt was made to identify and group the basic tasks a job is composed of, pertaining to telecommuting suitability. In this regard, important and effective aspects of jobs were identified and irrelevant aspects ignored. The abstract job approach can cover all pos-

sible jobs, and in this sense can be thought of as the universal set, from which only a limited number may be encountered in society. This approach is evidently different from the usual and conventional approach of grouping and categorizing jobs based on a very general label such as "administrative support". Hence, the important constituents of jobs, called job-tasks, were identified, and the level of telecommuting for which the job is suitable was modeled as a function of the time spent on each such task. Thus, for every job  $j$ , a vector denoted by  $X_j$ , representing the durations of these tasks (or their corresponding duration codes), is assigned, which is called the job-task vector (JTV). Elements of the JTV are assumed to be represented by continuous variables. Supposing that  $x_{ij}$  is the  $i$ -th element of the JTV representing job  $j$ , where  $i = 1, 2, \dots, N$ , and  $N$  represents the total number of tasks identified as important and meaningful for the particular objective in mind, for each job  $j$ , the vector  $X_j = [x_{1j}, x_{2j}, \dots, x_{Nj}]$  denotes the mean daily time spent on, or assigned to, each job-task  $i$ .

In this paper, we incorporate fuzziness by considering job-tasks as having a fuzzy membership function to the fuzzy set of telecommuting suitability. With this approach, the answers are assumed to be vague from the very beginning and therefore, respondents are allowed to reply with a certain degree of error/uncertainty/imprecision, which we intend to treat using the concept of global wisdom as

explained below.

Consider a case where there is a set of job-task variables which determines the decision of an employee regarding telecommuting suitability, a subset of which (positive variables) make telecommuting suitable, and another subset (negative variables) which make telecommuting unsuitable. Suppose that the employee spends  $T_p$  and  $T_n$  units of time during a time period of concern (in this study, a day) on job-tasks with positive and negative effects, respectively ( $T_p + T_n$  need not sum up to the total time period, here 8 hours per day). Suppose, now, that we ask employees the following two questions:

PQ: what is the minimum value of  $T_p$  which makes telecommuting suitable?

NQ: what is the maximum value of  $T_n$  which makes telecommuting unsuitable?

Both questions produce data that may be used to form relative frequency distributions ( $f_{T_p}$  and  $g_{T_n}$ ) of respondents considering telecommuting suitable at each specified minimum time spent on positive job-tasks and respondents considering telecommuting unsuitable at each specified maximum time spent on negative job-tasks, respectively. The respective cumulative frequency distributions, namely  $F_{T_p}$  and  $G_{T_n}$ , are essentially S-shaped functions. Naturally, the cumulative frequency distribution of respondents ( $H_{T_n} = 1 - G_{T_n}$ ) considering telecommuting suitable at each specified maximum daily time spent on negative job-tasks is an inverse S-shaped function. Thus,

$H_{T_n}$  is comparable and compatible with  $F_{T_p}$  in the sense that, in both functions, the vertical axis represents the same concept: proportion considering a job to be suitable for telecommuting. From such functions, one may get an idea as to a global opinion regarding the minimum  $T_p$  and maximum  $T_n$  which make telecommuting suitable.

Thus, by having  $F_{T_p}$  and  $H_{T_n}$ , one may accentuate accordingly the values of  $T_p$  and  $T_n$  expressed by a respondent. In other words, in calibrating the logit suitability function,  $F_{T_p}(T_p)$  and  $H_{T_n}(T_n)$  are used, instead of  $T_p$  and  $T_n$  respectively, as membership functions of  $T_p$  and  $T_n$  to the fuzzy set of telecommuting suitability. This will transform the independent variables into a scale representing the global wisdom of respondents, which is viewed as constituting the degree of membership of an employee to the group of employees whose jobs are suitable for telecommuting, given the respective values of  $T_p$  and  $T_n$ .

#### 4. Sample Data and the Variables

In order to apply the concepts proposed in this paper, the data collected for a sample of 242 employees from 7 companies based in Tehran, Iran, were employed. The data gathered in this survey, conducted in 2003, are of the stated preference type since telecommuting is in its infancy in Tehran. In the questionnaire, which was not exactly designed to collect the data for a fuzzy approach, respondents were asked about the suitability of their job for telecom-

muting, in view of the overall characteristics of their job. The answer to this question, in a binary form (suitable vs. not suitable for telecommuting), is treated as the response variable in the models. The explanatory variables are based on the questions asking employees how much time they generally spend on the job-tasks affecting telecommuting suitability in order to accomplish their work duties. Response choices were ordered categorical values, namely *0 to 15 min.*, *15 to 30 min.*, *30 min. to 1 hr*, *1 to 2 hrs*, *2 to 3 hrs*, *3 to 4 hrs*, and *more than 4 hrs*, coded respectively from 1 to 7.

Without loss of generality in implementing the proposed approach and for ease of presentation, the job-tasks with similar effects on telecommuting suitability identified by Mamdoohi et al. (2006) are aggregated to form two general tasks, one with positive effects on telecommuting suitability, and the other with negative effects (however, a similar analysis may be done with each job-task treated separately). The times spent on each of these two general tasks are  $T_p$  and  $T_n$  in this paper.  $T_p$  and  $T_n$  are computed as the sum of the mean daily times spent on the first and second groups of tasks, respectively.

For the explanatory variables of different respondents to be comparable, their responses needed to be transformed, and were thus normalized to a 1 to 10 integer scale. For simplicity, the response variable was the binary indicator suitable for telecommuting vs. not

suitable for telecommuting.

## 5. Telecommuting Suitability Modeling Results

As discussed above, two aggregated general tasks are used as the independent or explanatory variables in this approach, one with positive effects on telecommuting suitability, and the other with negative effects. In the fuzzy implementation of the binary logit model, the S-shaped fuzzy membership functions for the two aggregated general tasks are used as the explanatory variables for telecommuting suitability.

An analysis of the  $FT_p(T_p)$  and  $HT_n(T_n)$  functions extracted numerically from the sample data suggested (inverse/) S-shaped membership functions of the form  $\exp(\alpha T^\beta)$  for the global wisdom of the sample regarding telecommuting suitability of positive and negative job-tasks, respectively. Thus, the assumed membership functions, based on some numerical and trial-and-error analysis to achieve a good fit to the sample data (it will be shown, shortly, that model results are not very sensitive to these function parameters), are as follows:

$$\mu_{\bar{T}}(T_p) = \exp(-175 T_p^{-6.2})$$

$$\mu_{\bar{T}}(T_n) = \exp(-0.0011 T_n^{4.9})$$

where  $\mu_{\bar{T}}(T_p)$  is the membership function of the aggregate general task with positive effects (represented by  $FT_p$ , the cumulative

proportion of people considering a job to be suitable for telecommuting if it involves at least  $T_p$  time spent on job-tasks having positive effects on telecommuting suitability) to the fuzzy set of telecommuting suitability ( $\tilde{\tau}$ ). In the same manner,  $\mu_{\tilde{\tau}}(T_n)$  is the membership function of the aggregate general task with negative effects (represented by  $H_{T_n} = 1 - G_{T_n}$ , as the complement of the cumulative proportion of people considering a job to be suitable for telecommuting if it involves at most  $T_n$  time spent on job-tasks having negative effects on telecommuting suitability) to the fuzzy set of telecommuting suitability. These functions are depicted in Figures 2 and 3, respectively. As can be seen from these figures,  $\mu_{\tilde{\tau}}(T_p)$  is an S-shaped membership function and  $\mu_{\tilde{\tau}}(T_n)$  is an inverse S-shaped membership function, due to the theoretically opposite impacts of  $T_{pmin}$  and  $T_{nmax}$  on telecommuting suitability.

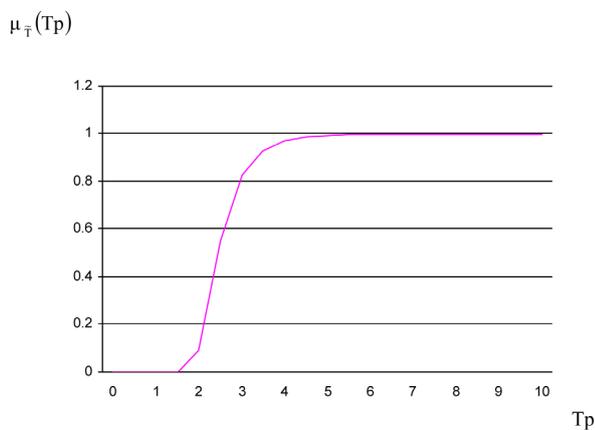


Figure 2. Membership function for positive job-tasks

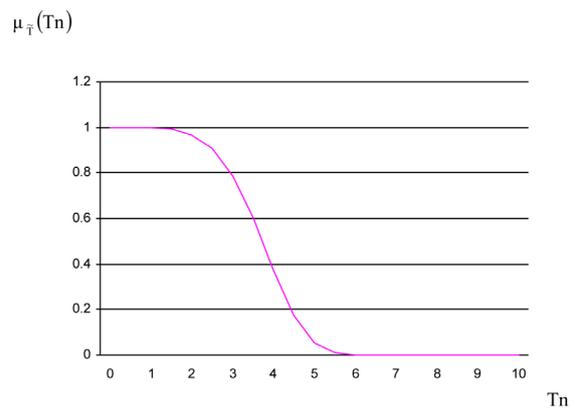


Figure 3. Membership function for negative job-tasks

The results of this model are presented in Table 1. It can be observed that both variables are clearly significant at the 0.05 level, and almost significant at the 0.01 level, unlike the constant term, showing that the two variables account for most of the information explained by the model. Coefficients of both variables are positive as expected, and about the same magnitude. The coefficient of  $\mu_{\tilde{\tau}}(T_p)$  is a little (about 5 percent) larger than the coefficient of  $\mu_{\tilde{\tau}}(T_n)$ , implying that the effect of tasks with positive impact is a little stronger than that of those with negative impact.

Introducing and incorporating the random error term into the utility function has several reasons, including accounting for unobserved variables, as widely discussed in the literature. Incorporating fuzziness into random utility models to account for the imprecision of data intrinsic in human perception and statement, however has received very little attention. Conceptually, the proposed fuzzy approach to

Table 1. Results of the fuzzy implementation of the binary logit model for employees

Variable	Coefficient	t-statistic
Constant	-0.169	-0.45
$\mu_{\bar{t}}(Tp)$	0.983	2.56
$\mu_{\bar{t}}(Tn)$	0.927	2.37

- The alternative of 0 days telecommuting suitability per week is used as a reference, with zero utility.

- Log-likelihood at zero = -167.7, at market share = -134.4, and at convergence = -127.6.

$$- \rho_{ELbase}^2(\beta) = 1 - \frac{127.6}{167.7} = 0.239, \quad \rho_{ELbase}^2(MS) = 1 - \frac{134.4}{167.7} = 0.199, \quad \rho_{MSbase}^2(\beta) = 1 - \frac{127.6}{134.4} = 0.051$$

(EL: equally likely model & MS: market share model)

- Number of observations = 242.

Table 2. Results of the non-fuzzy implementation of the binary logit model for employees

Variable	Coefficient	t-statistic
Constant	1.121	2.51
Tp	0.154	1.91
Tn	-0.186	-2.40

- The alternative of 0 days telecommuting suitability per week is used as a reference, with zero utility.

- Log-likelihood at zero = -167.7, at market share = -134.4, and at convergence = -129.7.

$$- \rho_{ELbase}^2(\beta) = 1 - \frac{129.7}{167.7} = 0.227, \quad \rho_{ELbase}^2(MS) = 1 - \frac{134.4}{167.7} = 0.199, \quad \rho_{MSbase}^2(\beta) = 1 - \frac{129.7}{134.4} = 0.035$$

(EL: equally likely model & MS: market share model)

- Number of observations = 242.

construct fuzzy membership functions of job-tasks to the fuzzy set of telecommuting suitability can be viewed as representing the global wisdom of respondents. In order to compare numerically the results of the proposed approach with those of a conventional non-fuzzy implementation, a model was calibrated using  $T_p$  and  $T_n$  as the explanatory variables. The corresponding results are presented in Table 2.  $T_p$  (with a t-stat of 1.91) is not significant at the 0.05 level, although it is (correctly) positive. The coefficient of  $T_n$ , however, is (correctly) negative and significant. Moreover, the constant term turns out to be significant this time, indicating that unobserved variables favor telecommuting suitability, on average. Comparison of the goodness-of-fit measures of the two models indicates that the fuzzy model is slightly better than the non-fuzzy model. In addition to a better fit, the fuzzy model can reconstruct the observed decisions more accurately, with a percent correct equal to 77.7 as compared to a 75.6 percent correct for the non-fuzzy model.

At first glance, the above improvements in the fuzzy model might look marginal, however considering the fact that the questionnaires were not actually designed from a fuzzy perspective, the fuzzy model is promising despite the modest nature of its enhancements here. It needs to be pointed out here that the difference between coefficients in the two models is due to the difference in the scale of their independent variables, the fuzzy variables ranging

from 0 to 1 and the non-fuzzy ones ranging from 1 to 7, which leads to the reduction of non-fuzzy model coefficients, as expected.

To further compare the two model implementations, a sensitivity analysis was employed. To analyze the sensitivity of the results to the assumed parameters ( $\alpha$  and  $\beta_{\tilde{\tau}}$  in  $\mu_{\tilde{\tau}}(T_p)$  and  $\mu_{\tilde{\tau}}(T_n)$ ) and to show the robustness of the results, these parameters were changed one at a time, holding the other parameter constant. Model results indicated that for rather large intervals, as shown in Figures 4 to 7, the results of the fuzzy models are better than the non-fuzzy ones:

for  $T_p$ , assuming  $\beta = -6.2$  as the base,  $\alpha$  has an effective range of  $[-4250, -0.0005]$ , and assuming  $\alpha = -175$  as the base,  $\beta$  has an effective range of  $[-1000, -3.75]$ , for  $T_n$ , assuming  $\beta = 4.9$  as the base,  $\alpha$  has an effective range of  $[-0.036, -0.000001]$ , and assuming  $\alpha = -0.0011$  as the base,  $\beta$  has an effective range of  $[0.00001, 9.89]$ .

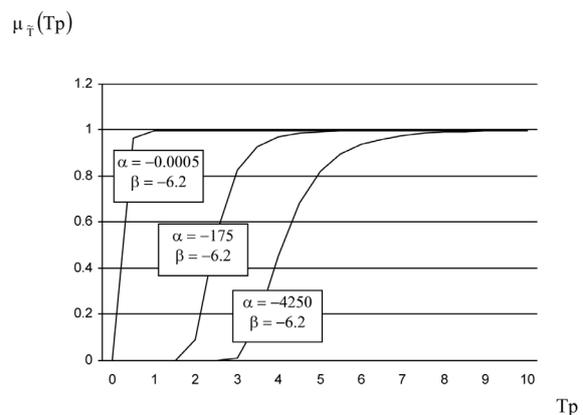


Figure 4. Membership function for positive job-tasks: range of  $s$  for which fuzzy results are superior to conventional ones

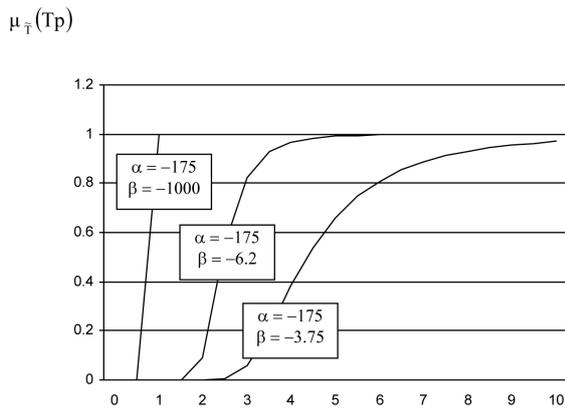


Figure 5. Membership function for positive job-tasks: range of  $s$  for which fuzzy results are superior to conventional ones

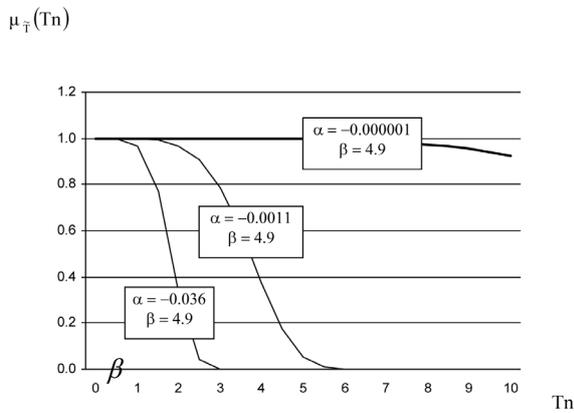


Figure 6. Membership function for negative job-tasks: range of  $s$  for which fuzzy results are superior to conventional ones

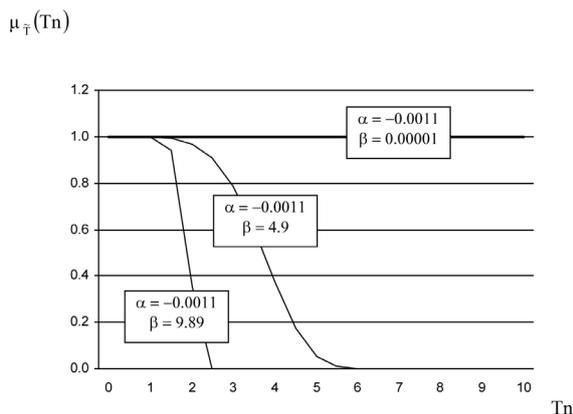


Figure 7. Membership function for negative job-tasks: range of  $\beta$  s for which fuzzy results are superior to conventional ones

## 6. Conclusions and Further Research

Randomness and fuzziness were compared and contrasted briefly and a method was suggested to consider both forms of uncertainty in a single model, a rather less attended approach. As an illustrative empirical application, the paper modeled telecommuting suitability, taking advantage of the information (global wisdom) extracted from the data gathered from 242 employees from several private and public organizations, in the form of fuzzy membership functions of job-tasks to the fuzzy set of telecommuting suitability. The suitability of telecommuting is modeled with binary logit, whose probabilistic nature takes into account the objective inability to perfectly specify the utility function through its error term. Fuzziness, however, is considered in the deterministic or systematic part of the utility function, accounting for the imprecision of data. A sample of 242 employees from several private and public organizations has been employed as the case study to show the applicability of this concept in representing the fuzziness in human responses. It was seen, given the assumptions and limitations of the study that the fuzzy explanatory variables introduced can reconstruct the observed (reported) suitability outcomes better than do the traditional explanatory variables. Sensitivity analysis of the model results indicated that for rather large intervals of the membership function parameters, fuzzy models perform better than the non-fuzzy ones.

Areas for further research include designing questionnaires to acquire data specifically for the purpose of fuzzy membership function estimation by including PQ and NQ questions. Also, efforts can be made with respect to other fuzzy approaches to telecommuting suitability modeling. The authors have examined fuzziness in other forms as well, such as defining and using trapezoidal, triangular and rectangular fuzzy membership functions for the mean daily time spent on the job-tasks as the input data to the logit models. However, the results showed that the method presented in this paper is the most effective one in replicating the respondents' decisions in the case under study.

The approach proposed in this paper, to exploit concepts from fuzzy set theory to improve the specification of deterministic utility functions in a logit model, is not restricted to the case under study and has a wider scope of application. The application to telecommuting suitability shows how such an approach can be implemented in the calibration of choice models in order to enhance the resulting models.

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