INFORMATION SCIENCES **1**, 9–29 (1994)

Individualizing User Interfaces: Application of the Grade of Membership (GoM) Model for Development of Fuzzy User Classes

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ABSTRACT

Application of fuzzy set theory [35] provides a conceptual framework for empirical development of fuzzy user classes for measurement of computer users. *Fuzzy* classes generalize discrete (fixed boundary) classes by assigning scores that relate each person to each class for representing within-class heterogeneity [13, 25]. Use of fuzzy classes permits individual heterogeneity to be represented by a relatively few analytically defined types [14]. Applying the properties of fuzzy set theory to user classification will result in the definition of a user's membership within a series of fuzzy user classes within the user space. These fuzzy classes can be considered an alternative method for defining stereotypes by empirically defining potential categories into which users can be assigned. The major difference between fuzzy user classes and stereotypes lies in the application of grades of membership to directly measure simultaneous membership in multiple categories. Thus, variability can be very accurately measured and represented using fuzzy sets and grades of membership. These fuzzy classes or user types represent archetypical users or *fuzzy users*. Application of fuzzy set theory provides an opportunity to extend the current classification methods to measure the differences between users more accurately. This increase in accuracy assists in developing effective adaptive human computer interfaces.

1. INTRODUCTION

Users are increasingly demanding more effective man–machine interfaces to assist in accomplishing computer-related tasks. These demands are supported by research that recommends that interface designs should consider a user's cognitive style [22] as well as his skill level [5].

This suggests the need for interfaces which adapt to individuals. An adaptive interface is defined as an interface that operates in specific ways that are dependent upon the current context, the current user, and the current task [16]. Thus, characteristics of individuals must be available to the interface to determine when and how to adapt. Further, methods must be developed to classify users based upon their individual characteristics.

Accurate classification of users is essential to ensure that the system reacts appropriately to the specific user. However, the inherent differences between users are multidimensional and change over time as individuals learn [2, 4]. Dimensions which differentiate users include overall experience, intelligence, problem-solving, ability, cognitive style, and problem domain knowledge [2, 22, 23]. These dimensions define the universe of possible users or the user space. Classifying a user can be accomplished by assigning a score to each dimension. These scores can be simultaneously evaluated to determine the user's location within the user space. Further, these dimensions must be independently and simultaneously measured for each user and updated periodically to track changes in each user [3].

1.1. *USER MODELS*

User models are utilized within adaptive systems to store individual characteristics that describe a specific user. User models include information considered important for recognizing differences between users as well as their cognitive abilities [22, 27] and are accessed to predict behavior [2]. Norcio and Stanley as well as Rissland state that user models are necessary components of intelligent and adaptable human–computer interactive systems [16, 18]. Kass and Finin describe user models as a knowledge source embedded within a system that contains explicit assumptions on aspects of the user that may be relevant to the behavior of the system [9].

User models offer several benefits to the system designer and to the user. Successful application of the information within user models can assist in adapting the interface and in creating an *economy of interaction* [3]. That is, the task is completed as quickly as possible with the fewest number of intermediate steps. In addition, a system that adapts appropriately to a user will gain user acceptability and will be perceived as an effective and efficient system.

User models are beneficial to systems which exhibit one or more of the following: 1) the system seeks to adapt to individual users, 2) the system assumes responsibility (or shares responsibility with the user) for ensuring the success of the user–system communications, and 3) the class of

potential users or the potential users of the system is diverse [8]. However, the inherent differences between users and the different methods used for human problem solving makes development of user models a difficult task [23].

1.2. *USER CLASSIFICATION METHODS*

Current classification schemes attempt to address the dimensions which differentiate users by defining broad, fixed boundary categories of users such as novice, intermediate, or expert. It has been noted by Kaiser that this technique of creating global categories of users is inadequate [7]. These categories or states carry an inherent linguistic definition that is based upon software designers' experience and opinions. Other methods use more specific categories called *stereotypes* that divide the user space into additional subcategories or clusters [17]. Stereotype categories are more restrictive in their membership than broad categories such as novice, intermediate, and expert, and therefore can define more variability across users. For example, a stereotype may have the description "expert programmer" to differentiate a subset of users within the expert category.

Stereotypes are assigned a label that is intended to be descriptive of the contents of the group. Interpretation of the label assigned to a category of users involves a degree of linguistic inexactness. As an example, when describing the weather, broad classifications such as partly cloudy or cloudy are employed. The linguistic inexactness of the terms "partly cloudy" and "cloudy" causes differences in the interpretation from one person to another. A textbook definition exists for these descriptions: partly cloudy is the character of a day's weather when the average cloudiness, as determined by frequent observations, has been from 0.4 to 0.7 for the 24-hour period, and cloudy is the character of a day's weather when the average cloudiness, as determined from frequent observation, has been more than 0.7 for the 24-hour period [1]. However, if several meteorologists are asked to describe the difference between average cloudiness of 0.7 and 0.75, different descriptions would probably emerge.

This linguistic inexactness and the interpretation of linguistic variables illustrates the uncertainty that is naturally inherent in many real world situations. Similarly, the classification of users into categories is also uncertain. Consequently, assignment is problematic. Many categories developed within natural language exhibit these characteristics: tall people, expensive cars, beautiful paintings. Thus, interpretation of the labels as well as assignment to the category can vary since the boundaries for these categories are not clearly defined. Further, transition from membership to nonmembership between the categories can be viewed as a gradual process with a continuum of grades of membership [11].

User categories, whether they are broad or narrow, are explicitly defined within a system by a fixed set of classification rules that assign a user to a single category. As such, these categories represent *crisp sets*. The characteristic function of a crisp set assigns the value 0 or 1 each individual in the universal set (all users), thereby discriminating between members and nonmembers of a particular crisp set [11]. The use of crisp sets is common within computer system design as they allow straightforward translation of a characteristic function into a specific rule that determines membership within a given set. The if–then–else structure of traditional rule-based systems operationalize the characteristic functions for determining membership in predefined crisp sets.

Operationally, users move between these categories in increments as experience and knowledge increase or decrease. Therefore, a rule-based system must include a superset of rules for determining movement between the crisp sets. However, the process of learning (the movement of a user between categories) does not follow a predefined path nor do users progress between categories at the same speed. Further, users may exhibit characteristics of several categories simultaneously, which violates the membership function of crisp sets.

The use of broad, fixed boundary groups systematically removes variability among users. Differences between users within these groups are suppressed to fit within the available stereotypes [12]. Further, the location of two users within the same stereotype may be on opposite sides of the stereotype (cluster), and therefore may exhibit different characteristics. Similarly, users on opposite sides of a stereotype boundary may be very similar, but will be assigned to different stereotypes. These situations occur when a user exhibits characteristics of several stereotypes. Thus, fixed categories cannot accurately describe an individual who exhibits traits from several groups, nor can they describe any situation where people fall along a continuum [29].

Since users exhibit characteristics of several categories simultaneously, the system designer is left with the difficult tasks of determining: a) the "best" group to which a user should be assigned, b) when a user has moved from one fixed boundary group to another fixed boundary group, and c) translation of these assignments into discrete actions of the system.

1.3. *FUZZY USERS*

Application of fuzzy set theory [35] provides a conceptual framework for empirical development of fuzzy user classes which will support more accurate measurement of users. Applying the properties of fuzzy set theory to user classification results in the definition of a user's membership within a series of *fuzzy* classes within the user space. *Fuzzy* classes generalize discrete (fixed boundary) classes by assigning scores that relate each person to each class for representing within-class heterogeneity [illegible]. The use of fuzzy classes permits individual heterogeneity to be represented by a relatively few types that are analytically defined [14]. These fuzzy classes or user types represent archetypical users. Users are assigned a score within the unit interval [0, 1] which represents the users membership within each fuzzy class. Thus, variability can be very accurately measured and represented using fuzzy sets and grades of membership within the fuzzy classes identified in the user space.

Such classes with a continuum of grades of membership (such as user types) are defined as *fuzzy sets* [35]. Inclusion in a fuzzy set is defined by a membership function that assigns a value for the user within the unit interval [0,1]. A membership function is a formal method of assigning a value to an element indicating its degree of membership in a fuzzy set [24]. This value represents the individual's grade of membership within the fuzzy class. Continuing the previous example, a partly sunny day may have a grade of membership of 0.2 within the fuzzy set "sunny day," while a partly cloudy day may have a grade of membership of 0.8 within the fuzzy set "sunny day." Normally, the cumulative score of a single individual for all identified fuzzy sets is constrained to equal 1.0 This feature is useful as this allows the scores to be used as blending coefficients.

A fuzzy class in the context of classifying users can be considered an alternative method for defining stereotypes, and is very similar to the social prototypes present in psychology [6, 19, 20]. Fuzzy classes have certain characteristics that make them ideally suited for the development of generalizable methods for user classification:

1) fuzzy classes are empirically derived with known statistical properties [26];
2) using the statistical properties of the fuzzy classes, the "correct" (minimum necessary) number of pure types is determined statistically using the likelihood ratio test [26]; and
3) fuzzy classes can be dynamically redefined as changes occur in the underlying user space.

These attributes are absent in more ad hoc classification schemes and are critical for the development of generalizable methods for user classification within adaptive systems. These attributes provide an opportunity to extend the current classification methods to identify differences between users more accurately.

Using the conceptual framework of fuzzy set theory, a method can be developed which combines the benefits of user modeling and user classification. The resultant method should support the empirical development of user classes through use of fuzzy set theory and should support direct measurement of users. Further, the method should simultaneously assign users to these classes and have provisions for assigning of new users based upon the classes. Finally, the method should be applicable across task domains and user populations with little or no modifications and have a sound empirical and statistical basis.

2. GRADE OF MEMBERSHIP (GoM) MODEL

The Grade of Membership (GoM) model[1] is proposed as an alternative for defining fuzzy user classes and directly classifying users [34]. The Grade of Membership (GoM) model is a specific implementation of fuzzy set theory combined with maximum likelihood theory [26]. GoM was initially developed to describe complex medical diagnosis and symptom patterns to overcome the inadequacy of Bayesian models for diagnosis and patient classification [32, 33]. The GoM model simultaneously identifies groups or types with "fuzzy boundaries" (fuzzy classes) and assigns a grade of membership score for each object (person, facility, etc.) for each class.

A central feature of the GoM model is the use of the grade of membership vector as the state variables vector of a stochastic system. Use of the grade of membership in this mode provides an operational component via statistical estimation and likelihood ratio tests for the number of fuzzy classes in the fuzzy partition [31]. Functionally, GoM incorporates maximum likelihood procedures to develop classes within the data which explain as much nonrandom variation in the data as possible.

Since its inception, GoM has been successfully applied as a general pattern recognition model [33]. Recent applications of the model have involved the analysis of population based surveys such as the National Long Term Care Survey [14].

2.1. *A FORMAL DESCRIPTION OF GRADE OF MEMBERSHIP*

The Grade of Membership model is formally defined in terms of four basic quantities: data, number of pure types, lambda coefficients, and grade of membership scores [29].

Data. The data for a person, i, can be coded into a set of j binary variables (variables where yes $= 1$ and no $= 0$). For example, the question,

[1]The GoM model was developed by Dr. Max Woodbury at Duke University's Center for Demographic Studies.

"Does this person have an Information Systems Major?" can be answered yes or no, and thus is a binary variable. If a given variable has multiple response levels, it must be coded in L_j binary variables where there is one binary (0 or 1) variable for each response level. That is, a variable such as number of years of education is divided into several categories such as "less than 12," "12 years," "more than 12," etc., and each of these can be answered yes or no. These binary variables are designated as x_{ijl}. All of the variables used by Grade of Membership are coded in this way.

Pure Types. The second quantity of the model is the number of pure types that are necessary to capture all of the nonrandom variation in the j observed variables (i.e., all of the nonrandom variation in the data). The number of pure types is referred to as k. Pure types represent archetypical users. The number of pure types needed to describe a given population is determined empirically such that all of the nonrandom variation in the data is captured. This is not the case for stereotypes or other classification schemes where the number of categories is determined by the researcher. The individual pure types are referred to as Type I, Type II, etc.

Lambdas and GoM Scores. The third and fourth quantities of the model are the two sets of coefficients generated by the analysis that predict the x_{ijl}, i.e., to predict the actual responses of the users. The first coefficients are the λ_{kjl}. These represent the probability that a person who is exactly one of the pure types will have the lth response to the jth variable. That is, these coefficients are the probability that John Smith, who is 100% like Type One, will answer yes to a particular question. These coefficients are similar to factor loadings (i.e., the correlation between the observed variables and the analytically derived factors), except that they are generated for discrete response data. These coefficients are used for several purposes, including the identification of the pure types themselves.

The second type of coefficient is the GoM score for a given person, called g_{ik}. The Grade of Membership scores represent the degree to which a given person is represented by a particular pure type. The g_{ik} are linear weights that vary between 0 and 1.0 and sum to 1.0 for a person. In other words, they are scores which indicate that Mary Smith is 50% like Type One, 25% like Type Two, and 25% like Type Four.

With these quantities, the Grade of Membership model can be defined as

$$x_{ijl} = \Sigma g_{ik} {}^{*} \lambda_{kjl} \tag{1}$$

where x_{ijl} is the probability predicted by the model that the ith person has the lth respond of the jth variable. Note that a discrete partitioning (crisp sets) is a special case of Grade of Membership, where the g_{ik}s must be either 0 or 1 for a given person.

This equation says that two numbers must be estimated in order to match the actual answers to the questions (the x_{ijl}) as closely as possible. The first set of numbers that must be estimated are the Grade of Membership scores for each observation in the data set (the g_{ik}s). The second set of numbers that are estimated are the coefficients that describe the pure types (the λ_{kjl}s). The estimation of the g_{ik}s and λ_{kjl}s is done by maximum likelihood procedures. That is, iterative procedures are used to select the values of g_{ik} and λ_{kjl} that maximize the likelihood function. In other words, the model picks first one number, then, based on the results using that number, it selects the second number. This process is repeated until the estimated answers are as close to the actual answers as possible. The likelihood function also offers a way of testing if an adequate number of groups has been selected in order to explain all of the nonrandom information in the data.

The estimators produced by the maximum likelihood procedures have known statistical properties [26]. The ability of the model to describe the input data is measured by the χ^2 (chi-squared) model statistic generated from the ratio of likelihood values for the models with k pure types and $k+1$ pure types. Operationally, the model is executed for k pure types, then $k+1$ pure types, etc., until a model with the minimum number of types needed to describe the input data is determined. The number of pure types usually ranges from 3 to 5, but has been known to range as high as 17 statistically significant pure types.

3. METHODOLOGY

To apply GoM to user classification, a file of characteristics which describe specific users was developed. A questionnaire was designed and administered to a sample of individuals to collect these characteristics. The objective of the questionnaire was to structure the development of a database on user characteristics which could be analyzed using the Grade of Membership model.

The design of the questionnaire was intuitive, and was based upon input from faculty and students in the Information Systems Department at University of Maryland, Baltimore County. Information was collected on: 1) demographic and job title information, 2) academic background and course work, 3) programming languages, 4) use of application packages, 5) operating systems, and 6) computer operations during a typical week. These areas address a range of factors which were conjectured to be important for the classification of users.

The questionnaire was distributed to 101 undergraduate students at Anne Arundel Community College. The classes included introductory computer courses, introductory spreadsheet courses, programming courses in C, Pascal, and Cobol. Six additional surveys were completed by members of the graduate staff at the University of Maryland, Baltimore County and computer professionals in the field. A complete review of the questionnaire answers can be found in [15].

GoM directly describes individuals in terms of the user classes observed within the population. This direct measurement of individuals maintains user heterogeneity and reduces the need for a truly representative sample of users [28]. Therefore, it is more useful to have a very heterogeneous data source when defining the user classes. If no extremes exist in the sample population, that is, all individuals are clustered together, very few user classes would be defined. The sample of individuals who completed the questionnaire was designed to include instances of extreme types of individuals of the expected population; the corners of the user space were included in the sample data. The sample data are very heterogeneous, and include individuals with little or no computer experience to individuals with many years of experience. The sample of individuals who completed the questionnaire is not intended to be representative of any specific population, nor is it presented as representative as this work is considered exploratory in nature. Thus, the space explored is the possibility space.

3.1. *DATA ANALYSIS*

The raw data were preprocessed into a format compatible with the GoM model. This preprocessing included the recoding of continuous variables into discrete variables (with negligible loss of information as continuous distributions can be represented by well-chosen discrete categories) [21]. Frequency distributions were computed to assist in recoding continuous variables into stratum and categorical variables into binary response levels. Continuous variables, such as the number of 3 credit undergraduate systems analysis courses, were divided into stratums of 0 classes, 1 class, and 2 or more classes and were assigned values of 0, 1, and 2, respectively. Cutoff points for the stratum are derived by determining the median response value of the distribution, assigning cutoff points to represent quartiles of the distribution. If the distribution is not sufficiently rich or if the response vector is in reality binary (as was observed in many of the variables in the current analysis file), the stratum simply illustrates the existence or absence of the characteristic. Categorical variables such as Age were recoded into discrete values corresponding to the categorical labels. Age less than 25 was recoded to 1, Age 25–34 was recoded to 2, etc.

A specific variable is indicated as a seed variable which GoM uses to develop initial estimates of pure types. This variable should be selected based upon its intuitive capability for defining classes of individuals. In nursing home data, age is frequently used for this purpose. For the user database, a binary variable was created which indicated if the respondent was a Student or not. This assignment was based upon the response to the question on "current job title." If the respondent indicated that his or her current job title was an undergraduate student or a graduate student, then the binary variable Student was set to 1. Otherwise, the variable was set to 0.

4. RESULTS

Data are processed iteratively through the GoM model to define different numbers of pure types. The initial cycle utilizes the seed variable for creation of two (2) pure types only. Subsequent iterations use data from the previous iteration to optimize the development of additional pure types. The model chi-squared statistic, Wilson–Hilferty t, and the Akaike criterion are computed for each iteration and are evaluated to determine the appropriate number of pure types for the data.

The model chi-squared statistic is used for nested models and for testing the hypothesis that the difference in the parameters of the model with $k+1$ pure types is significantly (or not) better than the model with k pure types. Since the same data are processed for the k and $k+1$ pure type models, the k pure type model is nested within the $k+1$ model.

The Akaike information criterion (AIC) is designed to evaluate models which are not necessarily nested. The AIC is directly evaluated for choosing the "best" model. Usually, the model with the highest AIC is selected.

The Wilson–Hilferty formula translates the chi-squared distributed deviation from the expected value into a normal equivalent deviate [30]. This simplifies calculation of the p value of the chi-squared test through use of the normal equivalent tables. The Wilson–Hilferty formula provides a better estimate than the computationally simpler Fischer formula [10]. This value should have a positive change from iteration to iteration.

The model chi-squared statistic, Wilson–Hilferty t value, and the Akaike criterion from GoM cycles of two, three, four, and five pure types are presented in Table 1. An analysis of the changes in the likelihood ratio

TABLE 1

Comparison Statistics from GoM Analysis Selecting 5, 4, 3, and 2 Pure Types

Number of Pure Types	5		4		3		2
No. of zero GoMs	319.000	106.000	213.000	93.000	120.000	77.000	43.000
No. of zero PROBs	824.000	188.000	636.000	219.000	417.000	220.000	197.000
No. nonzero PARMs	1452.000	225.000	1227.000	207.000	1020.000	222.000	789.000
No. of total DFs	2076.000	519.000	1557.000	519.000	1038.000	519.000	519.000
Chi-squared	3114.000	317.800	2796.205	511.300	2284.905	700.289	1584.616
Wilson–Hilferty t	13.994	−7.269	18.052	−0.219	20.575	5.096	21.803
Akaike criterion	519.000	−201.200	720.200	−7.710	727.910	181.290	546.620

for three–four pure types indicates that four pure type model explains about the same amount of variance within the data, but the increase from four to five pure types was not significant. This conclusion is drawn from several indicators. First, the model chi-squared statistic increases from three pure types to four pure types, 511.3, which is slightly smaller than the number of total degrees of freedom. While this is smaller than the change from two pure types to three pure types, 700.289, and is smaller than the total degrees of freedom for the model, the four pure type model is very similar to the three pure type model. However, since the direction of the change shows a reduction in the overall chi-squared value, it is not likely that five pure types would provide a better fit of the data, which in fact was the case.

The Wilson–Hilferty t statistic had a slight negative change, −0.219, from the three pure type model to the four pure type model. As the test is conservative, the very slight negative change indicates that the four pure type model is indistinguishable from the three pure type model. Further, the objective is to select an appropriate model of the data and not to perform rigorous hypothesis testing. Had the t value been more negative, then one may reject the four pure type model in favor of the three pure type model. In these instances where the statistics provided by the GoM model do not identify a clearly better model, the structure of the data must be evaluated to provide additional input into the model selection decision.

The output of the GoM model also indicates the number of "individuals" assigned to each pure type. These values are referred to as the GoM sums. The GoM sums refer to the sum of the GoM scores assigned to individuals. The GoM sum for pure type I was 8.7675. This can be loosely nterpreted as the number of individuals in the population assigned to pure ype I. The GoM sums for remaining pure types are as follows: pure type I GoM sum = 13.8226, pure type III GoM sum = 36.0241, and pure ype IV GoM sum = 48.3858.

.1. DISCUSSION OF PURE TYPES

The four pure type model was selected as the model which best lescribes the data. It is often convenient to attach a one or two word label of the pure types to simplify referencing. A label is developed through nalysis of the variables which influenced the definition of the pure type. The information presented in the GoM report is supplemented by an dditional statistic: Z-values. A Z-value is associated with every variable, nd represents the ranked importance of the variable in defining the pure ype. The statistic is referred to as the Z-value due to its resemblance to he standard normal curve. Table 2 illustrates the Z-values for the top 10 ariables associated with pure type I.

Based upon a review of the GoM output and the Z-values, the following inguistic labels were developed for the pure types. Type I consists of *Expert* computer Users, type II consists of *Intermediate Technical* computer sers, type III consists of *Intermediate Nontechnical* computer users, and ype IV are *Novice* computer users. Each user type is discussed in terms of he response levels which led to the linguistic interpretation of the pure ypes.

Type I: Expert Computer Users. Expert computer users are individuals vith college degrees in technical and nontechnical disciplines and are not

TABLE 2
Top 10 Z-Values for Pure Type I: Expert Computer User

Rank	Variable Name	Z-Value
1	Master of Science Degree	4.3540
2	20 + dBase Prgs Written	3.9816
3	20 + Fortran Prgs Written	3.6985
4	20 + ASM Prgs Written	3.4180
5	Graduate Descriptive Stats	3.1850
6	20 + Pascal Prgs Written	3.1425
7	3 credit Fortran Course	3.0412
8	5 + Years WordPerfect Use	3.0310
9	BS in Mathematics	2.9640
10	5 + Years DOS Use	2.9592

likely to be students. They have written more than 20 programs in a variety of technical and nontechnical programming languages such as dBase, Fortran, Assembler, Cobol, and Pascal. They have completed course work in technical topics such as calculus, database design, descriptive statistics, differential equations, systems analysis, and operations research. They have five or more years of experience with DOS, LOTUS 1-2-3, WordPerfect, and UNIX. They are more likely to use DOS and Windows during the week than a Macintosh or UNIX. They actively use computer-based applications during the week, including programming languages, WordPerfect, and Excel.

Similarly, expert computer users are likely to have indicated some experience in computer languages and applications, will have at least a Bachelor's degree, and will have completed at least one course in most computer-related technical courses. They will have exposure to most operating systems, and will indicate that they actively use one or more application programs during the week. These description repeat those presented above; however, they were derived through a review of the negative Z-values. Application of a double negative provides similar descriptions as determined by a review of the positive Z-values. This may not always be the case; therefore, it is recommended that the negative Z-values should always be reviewed when deriving pure type descriptions.

Collectively, these analyses indicate that Type I has a high level of education, as well as a high level of education in the technical aspects of computers. Further, they have experience in multiple computer languages and application packages, indicating that the use of computers has been assimilated into their work habits. In general, they are active, experienced, and trained users of computers. These individuals represent the high end of the spectrum for expertise and use of computers.

Type II: Intermediate Technical Computer Users. Intermediate technical computer users are individuals who have a wide exposure to computer applications and nontechnical programming languages. They may be students, and are likely to use DOS or UNIX. While this profile may appear to indicate an expert computer user as described in Type I, their actual level of usage and experience is low. The use of application programs is from one to nine hours a week, they have written from one to nine programs in nontechnical languages such as Cobol, Basic, or Pascal, and have from one to three years of experience with operating systems and application programs. This is a much lower level of exposure than evidenced by the expert users of Type I.

Intermediate technical users are likely to have some experience or exposure to computer applications, courses, and languages. A review of the bottom Z-values reveals response levels that indicate no experience or exposure to a wide range of characteristics. This is consistent with the positive Z-values which indicate a wide but low exposure or experience to most characteristics.

These analyses led to an initial description of Type II as intermediate computer users. The individuals use computers actively, but have received little formal education in computers or computer-related courses. It is hypothesized that these individuals might be at the beginning of their computer learning curve. The students may progress to Type I as more formal education is received. The nonstudents will probably remain in Type II even if more experience is gained. However, if computer usage patterns become less technical, then Type II individuals may move toward Type III.

The initial description for Type II was intermediate computer users. However, an analysis of Type III indicated that a similar description would be appropriate (see below). Therefore, additional characteristics of Type II were analyzed to develop a more specific description. The GoM results indicate that individuals in Type II use technical languages more than nontechnical languages and have received training in technical computer-related courses. Therefore, the description for Type II was modified to Intermediate Technical computer users.

Type III: Intermediate Nontechnical Computer Users. Intermediate nontechnical computer users have experience in computer applications, and in contrast to Type II, they are likely to have a nontechnical college degree such as business, architecture, or political science. They are likely to indicate little exposure to technical courses and technical computer languages, and may or may not be students. The types of computer applications which these individuals are likely to use during the week include Lotus, WordPerfect, and database retrieval. They are likely to have fairly extensive experience in DOS and WordPerfect and use DOS predominantly. Computer languages include Cobol, Pascal, and Basic, all traditionally nontechnical computer languages.

These individuals will indicate everyday usage of basic computer applications, including word processing, spreadsheets, and WordPerfect. Similarly, they will indicate some experience with DOS, Lotus, and WordPerfect. They are not likely to be programming or performing project management, and are somewhat likely to be using statistics. Thus, these individuals actively use computers at a basic level to support their work. However, their level of experience and exposure is less than Type II and Type I.

As with Type II, an initial description of the Intermediate computer user would be appropriate for the individuals in Type III. Additional analysis indicated that their use of computers is of a less technical nature for both programming languages used and everyday computer usage. Thus, the description for this type was modified to Intermediate Nontechnical computer users.

Type IV: Novice Computer Users. Novice Computer Users do not indicate any experience with computers, computer-related courses, or programming languages. They are almost all students, and do not have college degrees of any type. Usage of computers is very limited, and is probably indicative of current course work rather than general usage. Everyday usage of computers for spreadsheet, word processing, or programming is not likely.

Conversely, it is very unlikely that a Type IV individual will have extensive experience with DOS, or to use a word processor or a spreadsheet during the week. Obviously, these individuals are at the beginning of their learning curve with respect to computers. The description Novice is appropriate.

4.2. *DISCUSSION OF GoM ASSIGNMENTS TO INDIVIDUALS*

One of the strengths of the GoM model is that the above user types represent archetypes. Actual individuals will exhibit some or all of the characteristics of one or more of these user types. Thus, it is possible for an individual to be 50% Novice and 50% Intermediate Technical. This may indicate that the individual has completed enough courses and gained enough experience and exposure to begin to exhibit characteristics of an intermediate computer user. Traditional stereotype systems would require that the individual be classified as Type IV or Type II, but not both.

It is this dual (or triple or quadruple) assignment of individuals to multiple user types that is a strength of fuzzy set based applications and supports more accurate representation of users within systems. Table 3 displays the scores assigned to a selection of the individuals within the sample. Each row consists of the individual's identification number, the number of nonmissing internal answers provided by the individual, the pure type assignment for this person, and the individual GoM scores for each pure type. As can be seen from the report, the GoM scores sum to 1.0 for an individual. Some of the individuals are assigned to a single user type, and indicate that they are exactly like the archetypical individual for this user type. For instance, individual 105 is 100% like Type I, individual 4

TABLE 3
GoM Assignments for Selected Individuals

Ident	I	II	III	IV
1	0.0000	0.6339	0.0000	0.3661
4	0.0000	1.0000	0.0000	0.0000
12	0.0336	0.1270	0.2436	0.5958
26	0.2069	0.2345	0.5492	0.0092
37	0.0000	0.0000	1.0000	0.0000
42	0.0000	0.0000	0.0000	1.0000
76	0.0000	0.4641	0.0000	0.5359
105	1.0000	0.0000	0.0000	0.0000

is 100% like Type II, individual 37 is 100% like Type III, and individual 42 is 100% like Type IV.

However, for most individuals, they are assigned to multiple user types at different levels of membership. Individual 1 is assigned to Type II (0.6339) and Type IV (0.3661). This individual is mostly an Intermediate Technical computer user. However, the absence or presence of certain characteristics causes a partial assignment to Type IV, Novices. Since the variables most highly associated with Type IV indicate no experience in Lotus, WordPerfect, DOS, or Calculus, it is reasonable to assume that this individual does not exhibit any of these characteristics.

Individual 12 has partial membership in all four user types with a membership in Type I of 0.0336, Type II of 0.1270, Type III of 0.2436, and Type IV of 0.5958. This individual is most like Type IV, a Novice, somewhat like Type III, Nontechnical computer user, and only a small amount like Type I and Type II.

It is this simultaneous assignment to multiple pure types which differentiates fuzzy set methods, and specifically Grade of Membership, from traditional classification methods and most statistical methods. Cluster analysis assigns an individual to a specific "cluster" by locating groups of data points which have similar distances from a common point. The data points are assigned to one cluster only. AUTOGRP is a classification procedure which has been used to define Diagnosis Related Groups (DRGs) which are extensively used for classification and reimbursement of inpatient care, and Resource Utilization Groups (RUGs) which are used to classify nursing home residents. AUTOGRP generates fixed-boundary groups which have no within-group heterogeneity [14].

Through use of the Grade of Membership, it is possible to accurately assign individuals to groups without losing the inherent differences (within-class heterogeneity) between individuals. The GoM scores will

differ between individuals based upon the specific responses (characteristics) of the individual. While it is possible to assign an individual to a dominant user type, the degree to which a person is assigned to the user type can still be determined through direct evaluation of the GoM scores.

5. DISCUSSION

This paper proposes the use of the Grade of Membership (GoM) model to derive user classes dynamically based upon user characteristics. Functionally, GoM incorporates maximum likelihood procedures to develop classes within the data which explain as much nonrandom variation in the data as possible. As such, the likelihood estimators produced by the model have known statistical properties [26]. The likelihood function provides a method for testing if an adequate number of classes has been selected in order to explain all of the nonrandom information in the data. The ability of the model to describe the input data is measured by the model χ^2 (chi-squared) statistic generated from the ratio of likelihood values for the models with k classes and $k+1$ classes.

The GoM model was applied to the user characteristic data to derive user classes simultaneously and to assign individuals to these classes. Users are assigned to one or more classes with different levels of membership, depending upon their specific characteristics. An individual's grade of membership within the fuzzy class is assigned by the GoM model. Thus, the classes derived by the GoM model can be referred to as *fuzzy user classes*.

Fuzzy sets were investigated due to the limitations of fixed boundary (crisp) sets for accurately reflecting the inherent variability among individuals. Fixed categories cannot fully describe an individual who exhibits traits from several groups, nor can they describe any situation where people are classified along a continuum [29].

Variability is largely suppressed by fixed boundary categories such as stereotypes or prototypes. Indeed, GoM directly measures this variability through the grade of membership scores. Thus, through application of GoM, it is possible to accurately assign individuals to groups without losing the inherent differences (within-class heterogeneity) between individuals.

Based upon an analysis of the statistics generated by the model, linguistic descriptions were assigned to the user types: *Type I*: *Expert Computer Users*, *Type II*: *Intermediate Technical Computer Users*, *Type III*: *Intermediate Nontechnical Computer Users*, *Type IV*: *Novice Computer Users*. These types fully describe the individuals described in the characteristics database. The linguistic descriptions assigned to the user types provide a convenient method for describing individuals, and can be used in combination with the specific grades of membership within these classes to accurately describe a user who exhibits characteristics from several types simultaneously.

The user types also suggest transitions over time as an individual learns and advances. Type IV: Novice are likely to transition into Type II: Intermediate Technical or Type III: Intermediate Nontechnical, depending upon their acquired experiences and education. This conclusion is based upon an analysis of those data elements which were instrumental in deriving the user types. Similarly, individuals in Type II: Intermediate Technical will transition into Type I: Expert, while individuals in Type III: Intermediate Nontechnical are likely to remain in that class.

Individuals in Type I: Expert will also continue to learn and to become more expert. However, the model did not indicate that this user type should be divided. For instance, the statistics indicate that a fair amount of variability still exists in Type I: Expert Computer User. Further, there are relatively few individuals assigned to this user type. Additional or better data may result in Type I splitting into two separate user types as more dimensions of the type are recorded. However, it seems reasonable to expect the Expert category to be populated with "regular" experts and "super" experts. Indeed, those individuals who are 100% assigned to Type I may represent the "super" expert.

Similarly, pure Type III, Nontechnical Computer User, includes a wide variety of individuals. Additional data may also result in this pure type dividing.

Indeed, an analysis of the five pure type model indicated that pure Type III split into two pure types. While this model was not selected, analysis of its attributes may indicate the direction in which the pure types may evolve if additional individuals were added to the database.

Practical application of the user types derived by GoM will require the dynamic assignment of grades of membership to users. The scores could be applied in computer-aided instruction, development and maintenance of user models, and adaptive interfaces. Based upon an individual's grade of membership in the fuzzy user classes, the interactive system could be modified to more appropriately address the specific user. In this way, the original database of characteristics can be considered a training database. However, before the grades of membership can be applied in these systems, causal relationships will need to be developed.

Operationally, as new users access the system, the GoM scores derived for the sample can be converted into a series of multivariate formulas to facilitate assignment of membership scores. The coefficients for the formulas are derived by performing a linear regression to express the grades of

membership scores as a function of the answers provided to the survey. This results in $k-1$ linear formulas (where k equals the total number of user types).

The formulas are solved for new individuals by collecting the same information as included in the original model. Missing data would result in the elimination of that factor from deriving an individual's grade of membership scores. The results of the formulas are the grade of membership scores for the associated user types. These values can then be directly used by the system for describing the new individual.

The GoM model provides a statistically based method for identifying user classes based upon user characteristics. This work illustrates the potential of the GoM model for user classification. A test one might require of any technique is: "Do the resultant user classes and user assignments accurately parallel what one would expect given the raw data?" In other words, "Are the results of the model intuitively accurate?" This test of face validity is a prerequisite for further efforts. This exploratory work suggests that the Grade of Membership model accurately derives *fuzzy user classes* and simultaneously assigns individuals to these classes. Additional analysis is therefore warranted.

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Received 15 June 1992; revised 10 January 1993