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USING DISCRETE CHOICE ANALYSIS IN DESIGNING FOR HUMAN VARIABILITY

A Thesis in

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by

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ABSTRACT

The overall goal of preference modeling methodologies in the field of designing for human variability (DfHV) is to accommodate (i.e., satisfy the safety and comfort requirements of) the desired percentage of the target user population while concurrently ensuring efficient use of the manufacturer's resources (time, money, and effort). User anthropometry (body dimensions) play a key role in these accommodation analyses, since they are known to have a significant influence on users' preferred styles of interacting with products. DfHV's regression-based approach (RBA) is used to study the influence of user variability (in terms of anthropometry, capabilities, and demographic variables such as age and gender) on the variability of preference within the target population. Results of such studies may be used to make informed design decisions. In contrast, the area of discrete choice analysis (DCA) is replete with methodologies aimed at predicting users' choices from among given sets of alternatives. Variables used in these choice-prediction models may be alternative-specific (e.g., design specifications, pricing) and/or user-specific (income levels, family size).

This research draws on the individual strengths of both the RBA and DCA preference modeling approaches in an effort to develop a more robust design decision-making methodology. The basis of this methodology is the division of the design process into independent analyses of safety and comfort accommodation of the target population. RBA models are recommended for safety accommodation problems while a hybrid of DCA and RBA methods is suggested for the analysis of comfort accommodation. The inclusion of appropriate anthropometric variables in the set of user-specific predictors in DCA models is shown to help enhance the reliability of the models. A case study involving the interaction of a sample population with doorways of a variety of sizes is used to demonstrate and evaluate the application of this decision-making methodology.

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CHAPTER I

INTRODUCTION

The accommodation afforded by a design may be defined as the design's ability to satisfy certain performance objectives for a desired percentage of the target user population. The broad category of performance objectives can be considered to consist of a number of criteria such as comfort, safety, visibility, and ease of use. Some of these criteria are of direct concern to the manufacturer while others are mandated by regulations issued by governments or other governing agencies. User comfort is an example of the former category, since comfort influences users' satisfaction with products and hence plays a role in determining the market share for the manufacturer. On the other hand, visibility requirements in truck cabin layouts are examples of criteria regulated by governmental bodies. Safety may be mandated by governing agencies, but also otherwise be of direct concern to responsible manufacturers or those looking to avoid lawsuits from adversely-affected users of their products.

Designers typically work to satisfy all the applicable accommodation criteria in order for the product to have a greater likelihood of success in the market. However, due to constraints related to time, cost, and other resources, accommodation afforded by a product to a given target user population must be *estimated* as accurately as possible. This estimation can make use of known or easily-obtainable data about the target population (e.g., anthropometric distributions, income levels), the product itself (e.g., product specifications, pricing), and the manufacturer (e.g., advertising expenditure, competitors' market share). Work in the areas of designing for human variability (DfHV) and the marketing research field of discrete choice analysis (DCA, also known as conjoint analysis) have yielded preference modeling methodologies that make use of some of these data in order to estimate accommodation of the target user population.

DfHV's regression with residual variance-based preference modeling methodologies (henceforth referred to as *regression-based approaches* and abbreviated as RBA) have been shown to be sufficiently accurate and robust when used in virtual fitting trials, which are simulations of users' interactions with designs. This process requires the use of models that are based on information about: a) the interaction of users with products and b) measures, within the target population, of user variability in anthropometry, capability, and relevant demographic variables (e.g., age, gender). This information may be obtained either from existing databases or through experiments involving the interaction of a sample population of users with prototypes of products. These preference models can then be extrapolated to the target population. Once the required anthropometry or posture data is generated for the target user population, they may be analyzed to determine the optimal specifications for the design. This helps achieve the desired accommodation level of the target population while concurrently minimizing the resource allocation required of the manufacturer.

DCA approaches differ markedly from RBA preference modeling methodologies. DCA techniques look to formulate models to predict users' choice decisions when offered a set of product alternatives. These models are based on variables that are categorized as being either alternative-specific or individual-specific (referred to in this research as *user*-specific). DCA models are usually developed through analysis of information of real or stated choices made by users over a period of time. Examining the various parameters of these models reveals the influence of each predictor on users' choice decisions, and also help determine the relative importance of each of these predictors. The results of these findings can be used to identify optimal designs for the target user population.

While proven to be very successful at achieving their respective objectives, RBA and DCA preference modeling methodologies each have certain limitations. Current RBA techniques make the simplifying (but unrealistic) assumption of binary accommodation/disaccommodation, implying that users will either be fully accommodated or disaccommodated by designs. This assumption is not required to be made in DCA-based methods, since these techniques look to calculate, for every user, the probabilities and likelihoods associated with the choice of each of the available alternatives. This allows for continuous variation of the accommodation variable, which is a more realistic condition.

DCA models are limited in their reliability when used to solve certain design problems such as those requiring the calculation of optimal allocation of physical adjustability. This is because DCA techniques are based on users' selections from among the available product alternatives, with each alternative having a discrete set of specifications. In contrast, DfHV techniques have been shown to be capable of solving such problems.

An additional drawback of existing DCA modeling methods has to do with their choice of variables used to predict user choice. Users' preferred styles of physically interacting with products are known to be correlated to the anthropometry relevant to the product's different design specifications. Target population anthropometry can, therefore, be useful predictors of users' perceptions of the comfort and ease of use associated with different product alternatives. Omitting information about target population anthropometry in the design decision-making process results in user choice models that are lacking in accuracy and reliability. As has been mentioned in the preceding paragraphs, synthesizing and interpreting the variability of anthropometry and postures across users is one of the fortes of RBA methodologies.

Some recent research efforts have looked to leverage the benefits of discrete choice analysis in the context of decision-based engineering design (Michalek et al., 2005; Wassenaar and Chen, 2003; Wassenaar et al., 2005; He et al., 2009). However, these studies are generally not concerned with the influence of users' anthropometry on their choice decisions. In fact, marketing literature identifies the insufficient ability to model user heterogeneity as being one of the main stumbling blocks on the road to the greater accuracy of many existing choice models (Allenby and Rossi, 1999; Chintagunta et al., 2005; Wedel and Kamakura, 2002).

This thesis lays the foundation for an in-depth exploration of the discrete choice analysis methodology and its amalgamation with existing RBA preference modeling techniques. This research is another step towards the ultimate goal of developing a comprehensive design decision-making methodology for manufacturing products which users will physically interact with. Future studies will extend this line of research by leveraging knowledge from relevant areas in the fields of finance and game theory. This will broaden the scope of the decision-making methodology by accounting for topics such as the economics of manufacturing and competitors' responses to design decisions made by the manufacturer.

The following chapter contains the result of an extensive literature review, and serves to place this work in a proper context in terms of designing for human variability and discrete choice analysis. Chapter III details the two different methodologies—one discrete choice analysis-based and the other designing for human variability-based—that are used in this study. The application of these methodologies is demonstrated in Chapter IV, which presents the doorway experiment and explains the analysis of the user choice data obtained from the experiment. Chapter V examines and interprets the results of the case study, discusses the implications of this work, and outlines its potential impact in the field of product design.

CHAPTER II

BACKGROUND AND LITERATURE REVIEW

Many research efforts have focused on developing methodologies to predict user choice based on available data about the user and the specifications of products (e.g., Rossi et al. (1996); Michalek et al. (2005)). A well-designed product will concomitantly satisfy the many criteria that comprise its performance objectives (user comfort, user safety, visibility requirements, ease of use, etc.), and will do so for the desired percentage of the target user population. Determining the specifications that might maximize the appropriateness of the product to the target population would enable a manufacturer to increase profits by capturing a large market share (DeSarbo et al., 1995). User choice analysis is, therefore, an area of research that finds widespread application across a diverse set of industries. The increasingly popular field of decision-based design is founded on the principles of user choice analysis. Ongoing studies are looking to increase the robustness and broaden the scope of existing decision-making methodologies in order to make them more applicable to manufacturers' design efforts.

2.1 Preference

The task of modeling user choice is complicated by the variability of user preference across individuals within target populations. User preference refers to an individual's unique (and partially unpredictable) way of interacting with a product; this term is commonly used in designing for human variability (DfHV) research (Garneau and Parkinson, 2009a). A similar set of terms is used in the discrete choice analysis (DCA) domain, which is concerned with studying the evolution of a user's behavior from their *perception* (beliefs about a product) through the stages of preference (which refers to a user liking a particular alternative more than another) and utility assessment (quantifying preference) and finally to the user's choice (Lilien and Rangaswamy, 2004). Interestingly, DCA studies do not discount the possibility of users' choices differing from their actual preferences for a variety of reasons that include irrational behavior (Ding et al., 2005; Ding, 2007). Note that for the purpose of this work, the terms "preference" and "perception" are used interchangeably.

Every user's preference is determined by a host of factors, only some of which are known and quantifiable. When designing a product, it is essential to account for the variation of preference across the target user population. One of the differences between DfHV and DCA methodologies has to do with the selection of factors used to quantify this variation of preference. DfHV approaches look to explain this variation in terms of user anthropometry, which is in turn dependent on factors such as gender, age, and race/ethnicity (Nadadur and Parkinson, 2009a). In contrast, DCA methodologies usually use factors such as income and education levels, product pricing, and advertising expenditure (Train, 2009) to describe user preference.

Note that some marketing research also considers the role of *usage contexts* or *usage situations*, which are defined as time- and location-specific factors, not individual-specific or related to the available choice alternatives, that can affect users' choices (Belk, 1974). Several studies have shown that users may choose different products when placed in different usage situations (e.g., Ratneshwar and Shocker (1991); Warlop and Ratneshwar (1993)). This phenomenon is termed *preference construction* in the field of behavioral psychology (Slovic, 1995). However, the application of methodologies based on the utility theory often involves the simplifying assumption to ignore preference construction (MacDonald et al., 2009).

User choice models rely upon some of the aforementioned quantifiable factors to estimate individuals' preference. These factors are henceforth referred to as *predictors* since they, to varying extents, help predict users' choices. Total user preference can now be thought of as consisting of two independent components (Figure 2.1): a) preference that is perfectly correlated with the chosen predictors (henceforth referred to as

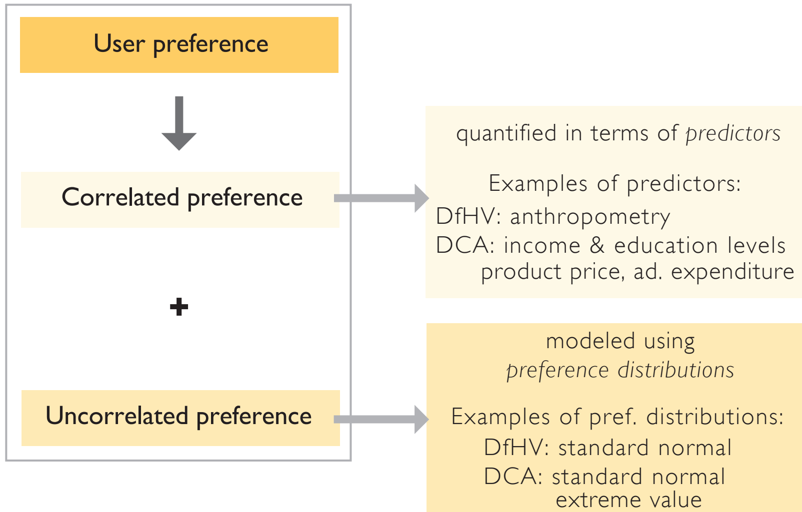

Figure 2.1: The two independent components of user preference: a) a component that is completely correlated with the selected predictors and b) a component that is completely uncorrelated with the predictors.

correlated preference) and b) preference that is completely uncorrelated with the predictors (henceforth referred to as *uncorrelated preference*).

Correlated preference is easily quantified in terms of the selected predictors, which may be anthropometric distributions across the target population in the case of DfHV research, or data about variables such as income and education levels, product pricing, and advertising expenditure in the context of DCA research. If the number of predictors used in the model is increased, the percentage of total user preference that is composed of correlated preference will also increase; the higher the number of predictors, the greater the predicting power of the model. However, the choice of predictors is constrained by: a) the availability of required data about the predictors, b) possible time and cost constraints, which may render infeasible the collection of new data, and c) the trade-off between a model's predictive power and its simplicity (Little, 1970). This results in there always being some amount of uncorrelated preference associated with user choice models.

Uncorrelated preference is by definition impossible to estimate (Nadadur and Parkinson, 2009a) using the chosen predictors. It may, however, be simulated using an appropriate distribution that ensures the statistical equivalence of the predicted and actual user choices. Such statistical equivalence allows for the development of accurate user choice models for different products and target populations.

2.2 Designing for human variability

As stated in the previous section, user anthropometry plays an important role in product design using DfHV techniques. Accommodation of the target population is studied using constraints that are formulated between anthropometry and product specifications. In the absence of existing databases that accurately represent the target user population at hand, anthropometry for the target population must be synthesized. Following synthesis of the required anthropometry, relations between product specifications and anthropometry may be developed, constraints set up, and accommodation levels estimated for different design decisions through a process known as *virtual fitting*. This section describes the evolution of anthropometry estimation techniques before presenting the RBA methodology, which has been the foundation for designing for human variability research. A number of virtual fitting methods are also compared with the one that is commonly in use in DfHV.

2.2.1 Traditional anthropometry estimation methodologies

One of the oldest anthropometry estimation techniques is based on proportionality constants (Drillis and Contini, 1966), which are average ratios of various body measures to stature (Figure 2.2). Given the stature data for a target population, the required body measure may be obtained by simply multiplying stature with the appropriate proportionality constant.

This method, while simple, is also inherently flawed in some respects (Fromuth and Parkinson, 2008). Human beings are not all equally proportioned as is implied by the calculation and use of proportionality constants; two people of the same stature may have different arm and leg lengths, for example. This variation in body proportions within and across populations results in inaccuracies in accommodation studies (Moroney and Smith, 1972; Roebuck, 1995; Fromuth and Parkinson, 2008). This is especially true in design problems involving the simultaneous consideration of multiple body measures.

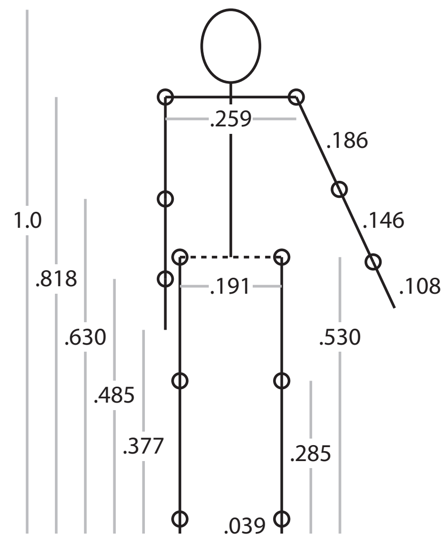

Figure 2.2: Proportionality constants, adapted from Drillis and Contini (1966).

In contrast to proportionality constant-based methods, regression approaches (not to be confused with RBA) avoid making the assumption of constant human body proportions. Regression techniques are suitable for use in cases where data about the predictor anthropometry are available for the target population. In such cases, an existing database (e.g., ANSUR and NHANES, described in Section 2.4) may be chosen as the *reference population*. Regression relations can be formulated in the chosen reference population between the data to be estimated ($\mathbf{Y}$), which may be either relevant anthropometry or postures, and the predictors ($\mathbf{X}$). Due to their being mutually uncorrelated and also readily-available or easily-measurable for numerous target populations, stature and body mass index (BMI, a normalized ratio of weight to stature) are commonly chosen as predictors. The regression relations can then be *extrapolated* to the target population by driving the equations using data about the predictors in the target population (Nadadur and Parkinson, 2009a). Data for the required anthropometry is thus generated. Equation 2.1 shows the general form of the regression equations formulated using this technique.

$$\mathbf{Y}_i = \mathbf{c}_i + \mathbf{a}_{1i} \cdot \mathbf{X}_{1i} + \mathbf{a}_{2i} \cdot \mathbf{X}_{2i} \tag{2.1}$$

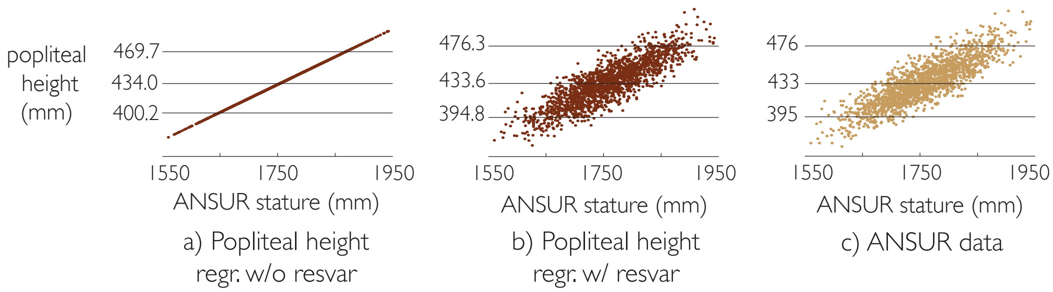

Figure 2.3: A comparison of anthropometry estimation at the 5th, 50th, and 95th percentiles using regression without and with residual variance. Also shown is the actual anthropometry from the ANSUR (Gordon et al., 1989) database. Adapted from Nadadur and Parkinson (2008).

where $\mathbf{Y}$ are estimated variables, $\mathbf{X}$ are predictors ($\mathbf{X}_1$ is stature and $\mathbf{X}_2$ is BMI), i is the number of relevant anthropometry, $\mathbf{a}$ are regression coefficients of the predictors, and $\mathbf{c}$ is the regression constant.

Regression techniques are the foundation of anthropometry estimation tools such as Open Ergonomics Ltd. (2008), which, through regression and weighting procedures, calculates percentile values of different anthropometry for a variety of target user populations.

There are three main drawbacks associated with this type of regression approach. The first drawback is due to the underlying assumption that people with the same values of predictors will also always have the same values of the estimated variable. This assumption is incorrect; two people of the same stature can have different sitting heights and can have different preferred sitting postures, for example. The second limitation is the lack of accuracy in simulating anthropometry for the upper and lower tails of the distributions. This lack of accuracy is illustrated in Figures 2.3 a) and c). Since design decisions are made based on anthropometry at the upper and lower tails of the distributions, users at these percentiles are most likely to be adversely affected by bad decisions. It is, therefore, of utmost importance to accurately estimate anthropometry at these percentiles. The third drawback of the regression approach has to do with its inability to model uncorrelated preference, which represents human variability.

These three drawbacks are overcome to a large extent by the RBA methodology, which is an important component of the designing for human variability toolkit.

2.2.2 DfHV's regression-based approach

The residual variance of regression, which is also referred to as the error of variance ($\mathbf{S}^2$), is a measure of the difference between actual data and those estimated using the regression equation. In other words, residual variance is a quantification of the variability that is uncorrelated with the chosen predictors. The robustness of RBA methodologies (Parkinson and Reed, 2006b; Parkinson, 2007; Parkinson and Garneau, 2009) stems from the recognition of the fact that residual variance can be considered to represent uncorrelated preference of target user populations. This is especially advantageous since most variables of interest to designers are either already normally distributed or can be transformed into normal distributions, thus satisfying regression techniques' implicit assumption of normality of the underlying variables.

As mentioned earlier, the sources of variation in user preference include distributions of age, gender, race/ethnicity, income and education levels, cultural influences, etc. Part of the impact of these factors may be quantifiable; user anthropometry itself is influenced by some of these same factors (Nadadur and Parkinson, 2009a). The unquantifiable impact of these sources of variability can be conveniently measured using the residual variance of regression.

Accordingly, in comparison with the procedure represented by Equation 2.1, the RBA methodology incorporates an additional step involving the reintroduction of residual variance into the regression relation as a stochastic component (Equation 2.2). This stochastic component is a random selection from a normal distribution with mean $= 0$ and standard deviation $\mathbf{S}$ equal to the square root of the residual variance for the regression fit on that measure.

$$\mathbf{Y}_i = \mathbf{c}_i + \mathbf{a}_{i1} \cdot \mathbf{X}_{i1} + \mathbf{a}_{i2} \cdot \mathbf{X}_{i2} + \mathrm{N}(0, \mathbf{S}_i^2) \tag{2.2}$$

Nadadur and Parkinson (2009a) compares the regression methods given by Equations 2.1 and 2.2 and proves that the latter technique generates more accurate anthropometry estimations, even at the upper and lower tails of the distributions (Figure 2.3 b) and c)). The RBA method is also shown to be more robust when the compositions of the reference and target populations are significantly different. This is again primarily due to the incorporation of residual variance into the technique.

The limitations of the RBA methodology are twofold:

1. The assumption of binary accommodation/disaccommodation. In reality, while certain accommodation criteria may be assumed to vary in a binary fashion (e.g., accommodation based on visibility requirements), the same is not true of all accommodation criteria. For example, user safety may be considered a binary variable, with a user deemed as being either safe or unsafe while interacting with the design. In contrast, a user's perceptions of comfort must be considered to be a continuously-varying state; a minute change in the value of a single design parameter is unlikely to change a user's perception from liking to disliking a product, which is a possibility in binary accommodation-based approaches.

2. The inability to accurately model certain discrete choice sets. A number of user choice decisions (e.g., about what vehicle model to purchase) are influenced by a wide variety of factors. Some of these factors are either continuously-varying (e.g., some modern vehicle seat adjustment capabilities) or monotonic and discrete (e.g., older vehicle seat adjustment capabilities). The influence of such factors on user choice may be accurately modeled using RBA techniques. However, there are a number of influential factors (for example: differences in terms of color, seating capacity, and fuel efficiency between the available vehicle models; the user's education level, family size, location of residence) that do not fall into either of these categories, and cannot be included in RBA-based analyses.

2.2.3 Virtual fitting

Virtual fitting is based on the fundamental principle of identifying anthropometry or postures that are related to each design specification, setting up relations between design specifications and the corresponding relevant anthropometry or postures, and examining the impact of changes in design specifications on the accommodation levels afforded by the design. This allows for the identification of optimal design specifications that will

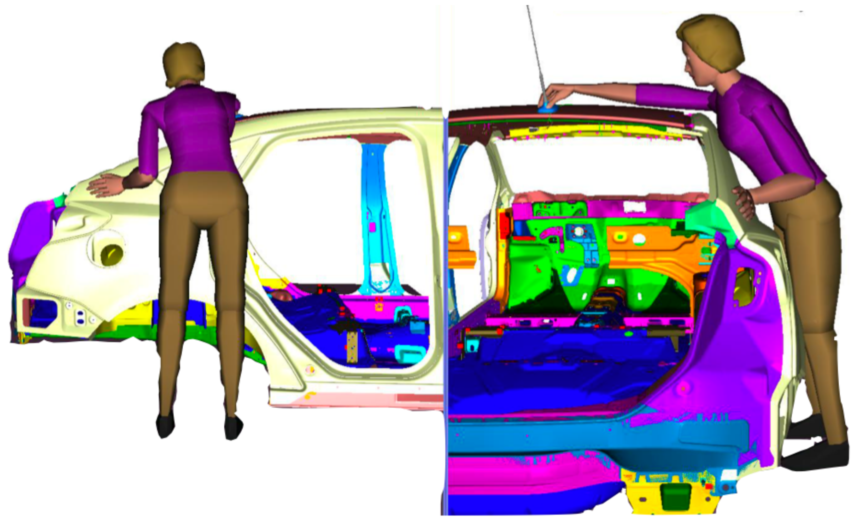

Figure 2.4: An illustration of the use of digital human models, adapted from Nadadur et al. (2009).

achieve the desired accommodation level of the target population while concurrently minimizing the amount of adjustability required. Minimizing adjustability results in low manufacturing costs for the product (Garneau and Parkinson, 2009b).

Manikin-based methods are widely used in industry to predict target population accommodation. Manikins are essentially virtual or physical representations of users, and are used to simulate the interaction of users with the product at hand. Techniques that make use of digital human modeling software or boundary manikins are popular in the industrial community.

Digital human models are two- or three-dimensional representations of users, and are frequently used in conjunction with computer aided design (CAD) models of products (Figure 2.4). The human models can be of the required percentile of stature or BMI, and can be positioned to visualize real-life interactions of humans with products. Common digital human modeling software are Jack (Siemens PLM Software, 2009), RAMSIS (Human Solutions, 2009), and SAFEWORK (Dassault-Systemes, 2000). Their application involves the generation of *boundary manikins* that are representative of the upper and lower percentiles that are most influential in the design decision-making process.

A-CADRE (Bittner, 2000) is an example of manikin-based approaches that use families of boundary manikins to conduct accommodation studies. The families of manikins (numbering 17 in the case of A-CADRE) are generated with the intention of capturing the variation of anthropometry in the target user population. A design is considered to accommodate the entire target population if every single manikin in the family can be "fitted" within the spatial constraints imposed by the design.

The main drawback associated with the use of these manikin-based techniques lies in the complete omission of user preference from the design effort; the posturing of the manikins is dependent solely on the designer. This drawback may be overcome through the improved practices of population modeling, quantitative virtual fitting, and posture prediction employed by DfHV methodologies (Parkinson et al., 2005; Parkinson and Reed, 2006a; Garneau, 2009). The RBA technique plays a critical role in each of these practices.

The process of population modeling is initiated with experimental studies that involve the selection of a sample population, preferably one that is representative of the target user population. The tails of the distributions of measures of interest within the population may be oversampled so as to allow for closer study of the variation of anthropometry or postures at these upper and lower percentiles. The interaction of the participants in this sample population with prototypes of the product is then observed, and data about user anthropometry and posture are collected (Flannagan et al., 1998; Reed et al., 2000; Jahns et al., 2001). Models can be formulated to estimate user posture based on the selected anthropometric predictors. The Cascade model for vehicle driver posture (Reed et al., 2002) is an example of this methodology.

2.3 Marketing research

As described in Section 2.1, marketing research efforts are concerned with understanding and predicting the four stages leading up to the user making a decision and choosing a particular product from among all the available alternatives. These four stages of evolution are: a) forming initial *perceptions* about the product alternatives, b) developing *preferences* by consciously and subconsciously comparing the various attributes of the alternatives, c) consciously and subconsciously appraising the *utility* of each alternative *based on their preferences* , and d) making a *choice* (Lilien and Rangaswamy, 2004). Utility is thus a quantification of preference (Chipman, 1960). Logic dictates that users always select the alternative with the highest utility, which is the rational choice (Ben-Akiva and Lerman, 1985). In reality, users could make irrational choices; there is the possibility of the user's actual choice differing from the rational choice (Morikawa, 1989; MacDonald et al., 2009). This contradicts one of the key principles of utility theory: the rationality of users' choices. However, rationality of users continues to be a simplifying assumption made in many marketing studies that are based on the validity of the utility theory.

Of the many existing marketing methodologies to estimating user choice, discrete choice analysis (DCA) is the most intensely researched and widely used. The following sub-section focuses on DCA, discusses its basic principles and statistical foundation, and presents a few popular DCA methodologies.

2.3.1 Discrete choice analysis

Discrete choice analysis (also referred to as conjoint analysis) is usually conducted on existing data obtained in the form of user feedback. The aim of DCA is to quantify the value (or part-worth), from the users' perspective, of each attribute of the set of product alternatives (termed *choice set* in marketing literature). DCA requires choice sets to satisfy certain conditions (Ben-Akiva and Lerman, 1985; Train, 2009): a) the product alternatives must be mutually exclusive (the choice of a particular alternative necessitates the rejection of the other alternatives), b) the choice set must be exhaustive (it must contain every alternative available to the user), and c) the number of alternatives must be finite.

In a manner similar to the RBA method, DCA techniques divide user utility into two components, as shown in Equation 2.3:

$$\mathbf{U}_{nj} = \mathbf{V}_{nj} + \epsilon_{nj} \tag{2.3}$$

where $\mathbf{U}_{nj}$ is the utility of alternative j to user n. $\mathbf{V}$ (*representative utility*) is given by the Equation 2.4:

$$\mathbf{V}_{nj} = \mathbf{V}(\mathbf{x}_{nj}, \mathbf{s}_n) \tag{2.4}$$

where $\mathbf{x}$ are the attributes of the product alternatives and $\mathbf{s}$ are the attributes of the user. The variable $\mathbf{V}$ in Equation 2.3 thereby represents the quantifiable portion of user utility

$\mathbf{U}$, and is thus similar to the predictors $\mathbf{X}$ in Equation 2.2. The variable ϵ in Equation 2.3 is a quantification of the component of utility that is unrelated to the factors included in $\mathbf{V}$, and thus resembles residual variance $\mathbf{S}$ in Equation 2.2. Like $\mathbf{S}_i^2$, ϵ is modeled using a suitable distribution. It is, in fact, the choice of this distribution that is used to classify DCA techniques into logit, generalized extreme value (GEV), probit, and mixed logit models (Train, 2009). Before briefly describing each of these groups of models, a short introduction to extreme value distributions is necessary, since this type of distribution is the basis for logit, GEV, and mixed logit models.

Extreme value theory is concerned with simulating the behavior of maximum and minimum of IID (independent and identically-distributed) random variables (Kotz and Nadarajah, 2000). There are, in fact, three types of extreme value distributions: Gumbel (Type 1), Fréchet (Type 2), and Weibull (Type 3). Gumbel distributions are most frequently utilized and have a variety of applications, including in models for: a) risks associated with market equity and insurance, b) material strength of composite fibers, and c) natural phenomena such as floods, wildfires, and weather. Gumbel distributions are described by the formula:

$$\mathbf{Pr}\left[X \leqslant x\right] = \exp\left[-\exp\{(x-\mu)/\sigma\}\right] \tag{2.5}$$

for all real X and x. Note that the parameters X and x are different from the variables $\mathbf{X}$ and $\mathbf{x}$. Figure 2.5 is an illustration of the standard normal and standard gumbel distributions.

Logit models

Logit modeling involves the assumption that ϵ_{nj} (Equation 2.3) conforms to an IID extreme value distribution for every alternative j. The assumption of IID implies that the unquantified factors represented by ϵ_{nj} are mutually uncorrelated and have the same variance. This assumption, while very effective in simplifying the analysis, is also a critical limitation of this modeling technique.

Generalized extreme value models

Generalized extreme value models allow for correlations to exist between the unquantifiable factors represented by ϵ_{nj}. When these correlations are zero, GEV models reduce to

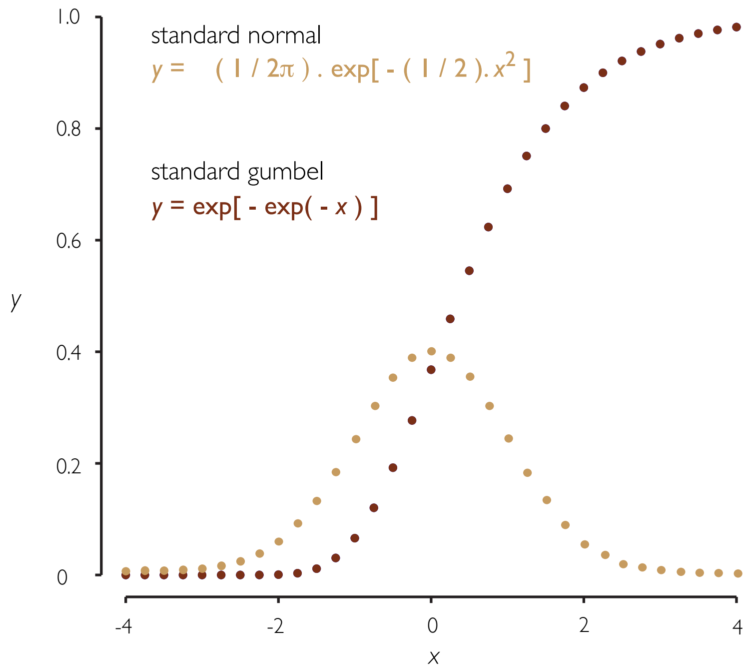

Figure 2.5: A comparison of the standard normal and standard gumbel distributions.

logit models. An additional advantage of GEV modeling techniques lies in their suitability for nested analyses, which involve the grouping of unquantifiable factors into *nests*, with correlations existing between the factors in each nest but not between factors in different nests.

Probit models

Probit models assume joint normal distributions of ϵ_{nj}, which can be a major disadvantage in some scenarios. For instance, a user's willingness to pay for a desirable product attribute is always positive. Since normal distributions lie on both sides of the zero value, assuming that the "willingness to pay" variable is normally distributed would be incorrect. This limitation notwithstanding, the covariance matrix used to describe the normal distributions can contain diverse information about correlations and heteroskedasticity in the factors and data. This enables probit models to support correlations across alternatives and also over time.

Mixed logit models

The ϵ_{nj} variable in mixed logit analysis is divided into two components. One of the components is modeled to describe the correlation and heteroskedasticity in the factors and data, and can be assigned absolutely any distribution. The other component is assumed to follow an IID extreme value distribution. Such a structure gives mixed logit techniques an incredible amount of flexibility, allowing them to be capable of simulating any DCA model.

2.3.2 Logistic regression

The general form of a multinomial logistic regression equation is as shown in Equation 2.6.

$$\ln[\mathbf{Pr}(choice = j)/\mathbf{Pr}(choice = 1)] = \mathbf{d}_j + \sum_k [\mathbf{p}_{jk} \cdot \mathbf{X}_{pk}] + \sum_l [\mathbf{q}_{jk} \cdot \mathbf{X}_{qk}] \quad (2.6)$$

where $\mathbf{d}$ is a constant, k is the number of alternative-specific predictors, l is the number of user-specific predictors, and $\mathbf{p}$ and $\mathbf{q}$ are the coefficients of the alternative- and user-specific predictors $\mathbf{X}_p$ and $\mathbf{X}_q$, respectively.

The output of such an equation (i.e., the term $\ln[\mathbf{Pr}(choice = j)/\mathbf{Pr}(choice = 1)]$) is called the *logit* of the corresponding alternative to the user. The user's probability of selecting each choice can be obtained by first computing the exponential to base $\mathbf{e}$ of the logits, then scaling the resulting values. The scaling is done with the knowledge that the probabilities of all available alternatives must sum to 1.

2.3.3 Bayesian estimation

The field of Bayesian statistics offers alternate ways of formulating DCA models of user choice, and has, therefore, been an area of interest in marketing research. The main advantage of Bayesian procedures lies in their underlying concept involving *prior* and *posterior* distributions of the variables comprising the model. The designer may develop an initial model of the user choice scenario based on data available at the time; this model is termed the prior. Over a period of time, the designer may obtain more data about the design problem at hand, and will look to update the prior with this information; the model that results is termed the posterior. Bayes' rule describes the precise relation between the prior and posterior, and thus allows the designer to easily formulate and update the user choice model based on data available to them at various periods during the design process.

Bayesian estimation methods have recently come to be of interest in research efforts in the area of engineering design. Hoyle et al. (2009) is an example of the exploration of the applicability of these techniques to design problems. However, these and other relevant techniques are not the focus of this thesis, and are hence not described in greater detail.

2.4 Designing for human variability and discrete choice analysis

At first glance, the field of designing for human variability and discrete choice analysis appear to employ starkly differing approaches to product design. The two areas of research explore problems of user choice and accommodation from very different viewpoints. Furthermore, user anthropometry is fundamental to the deployment of any DfHV technique. In contrast, DCA models are based on factors such as income and education levels of the users, pricing of the product alternatives, and advertising effort by the company, which are factors that existing DfHV models have not sought to employ. However, while there certainly are a number of points of difference between the two areas of research, there are also some similarities in the foundation and formulation of their methodologies. An example of these similarities is highlighted by Equations 2.2 and 2.6, which are observed to resemble each other in their construction. These differences and similarities are examined in greater detail in this section.

2.4.1 User accommodation

The term accommodation is used to describe a design's ability to satisfy certain performance objectives for target users. From the user's perspective, accommodation refers to the user's ability to safely interact with the product in the manner of their choosing. However, from the manufacturer's perspective, a design must satisfy certain additional criteria in order to be considered to accommodate the users. These criteria may include, for example, standards/regulations (environmental, safety, etc.) that are meant to ensure the safety of not just the user but also of the community in general.

In the case of unadjustable and immovable artifacts, tasks, and environments (e.g., doorways, stairways), the number of accommodation criteria may be reduced to just two: comfort and safety. These criteria are discussed below:

1. Safety accommodation. Safety standards for a manufacturer may be either self-imposed (in order to ensure user safety and thereby avoid lawsuits from adversely affected users) or mandated by external authorities. The latter category of standards may include the numerous regulations issued by governmental agencies specify the conditions to be satisfied in order for a product to be certified as being "safe" and permitted to be sold in the market. Examples of such regulations are the Federal Motor Vehicle Safety Standards and Regulations issued by the U.S. Department of Transportation (National Highway Traffic Safety Administration, 1998). Many research efforts (Michalek et al., 2004; Parkinson, 2007; Parkinson and Garneau, 2009) have focused on such regulations and have proposed design methodologies for manufacturers to satisfy these standards with reduced expenditure of their resources.

2. Comfort accommodation. In the set of factors that influence users' perceptions of products, comfort can be considered as being one of the most important. Increasing comfort accommodation levels is required to improve the desirability of a product to the target user population, and, therefore, to increase the market share of the company.

The objective of a company might be to accommodate an optimal percentage of the target user population in their design. Satisfying every single user's requirements will entail, among other things, high amounts of adjustability in the design (which would result in high manufacturing costs) and unprofitably low product pricing. Therefore, in many cases, the desired accommodation level of the target user population is some other level, such as 95%.

Accurately accounting for the variation of anthropometry within the target population is one of the keys to efficient analyses of safety accommodation. In contrast, since users' perceptions of comfort are functions of their preference, accurate comfort accommodation analyses are dependent on developing good models of the variation of user preference in the target population. There are, however, many products which require simultaneous consideration of safety and comfort accommodation (e.g., vehicle head restraints; Parkinson and Garneau (2009)). These products are not the focus of this research, and will be discussed in later chapters of this thesis.

In DfHV research, accommodation studies are based on simulations of the physical interaction of users with products. Accommodation afforded by a design is determined by the variation of anthropometry in the target user population. Basic anthropometry such as stature or BMI may be used to predict user posture or other, more directly relevant anthropometry. A set of constraints are then developed as relations between the product specifications and user anthropometry or postures (Nadadur and Parkinson, 2009b; Nadadur et al., 2009; Garneau and Parkinson, 2009b; Parkinson and Reed, 2006a). Users are considered accommodated only if they satisfy each one of these constraints. Note that a limitation in DfHV approaches is due to the treatment of accommodation as a binary problem, with users being either fully accommodated or disaccommodated by the design.

Marketing research employs a multitude of statistical tools to study user accommodation. Maximum likelihood estimation (McFadden, 1980) and Bayesian methods (Rossi and Allenby, 2003) are the basis for numerous marketing models aimed at analyzing user choice analysis (Train, 2009). These approaches frame the design problem in terms of "degrees" of accommodation. A user may not be completely satisfied with the product, but may not be dissatisfied either. In some cases, users may be willing to change their preferred mode of interaction with the product in order to be accommodated by the design. These scenarios can be simulated using methodologies developed in the marketing domain.

2.4.2 Sources of data

Since DfHV techniques are based on the variation in users' body dimensions, their application requires knowledge of anthropometric data for the target population. The tremendous variety (in terms of distributions of age, gender, race/ethnicity, etc.) of target user populations negates the possibility of there being comprehensive anthropometric databases for every possible population. However, there exist a few databases that frequently find application in design efforts.

The Anthropometric Survey (ANSUR) database was released in 1989, and is a comprehensive collection of body measures of 2208 women and 1774 men in the U.S. military (Gordon et al., 1989). The ongoing National Health and Nutrition Examination Survey (NHANES) is conducted periodically by the U.S. Centers for Disease Control and Prevention (Centers for Disease Control and Prevention, 1994; U.S. Centers for Disease Control and Prevention, 2008; Centers for Disease Control and Prevention, 2004). The subjects of the survey are representative of the general population of the U.S. The Civilian American and European Surface Anthropometry Resource (CAESAR) database (Robinette et al., 2002), on the other hand, is composed of random volunteers, and consists of data from 3-dimensional body scans of the subjects (Blackwell et al., 2008).

The main drawback of CAESAR lies in it not being representative of any particular population. This makes CAESAR unfit for user choice analyses without appropriate weighting of the data. In contrast with CAESAR, ANSUR and NHANES are representative of specific populations (U.S. military and U.S. civilian, respectively). Despite this, however, even these databases need to be used with caution, since the actual target population may differ considerably from either of these populations. For example, the U.S. target user population for agricultural equipment will be very different from the U.S. target population for a sports car. Neither ANSUR nor NHANES can be assumed to represent either of these target populations; some re-weighting of the data will be called for.

Since ANSUR is a military population, the subjects are more homogeneous in terms of BMI and age distributions. NHANES and CAESAR are more diverse, and contain subjects with wider ranges of BMIs than ANSUR (Table 2.1).

There exist numerous other anthropometric databases that are the result of surveys and censuses in countries across the globe. Examples of such databases are Germany's Mikro-Zensus, Japan's Human Engineering for Quality of Life, and China's Human Dimensions of Chinese Adults (GB 10000-88). Each of these databases represents a certain population, and, when weighted and processed appropriately, can be used to simulate other target user populations (Parkinson and Reed, 2009; Nadadur and Parkinson, 2009a).

Table 2.1: A comparison of female ANSUR, CAESAR, and U.S. Civilian (weighted NHANES 2003-06) anthropometry at certain crucial percentiles. Lengths are in mm, BMI is a dimensionless number. Adapted from (Nadadur and Parkinson, 2009a).

		percentile					
measure	database	2.5th	5th	50th	95th	97.5th	range (2.5th to 97.5th)
stature	ANSUR	1507	1529	1628	1737	1758	251
	CAESAR	1508	1524	1637	1768	1791	283
	NHANES	1487	1508	1622	1733	1755	268
BMI	ANSUR	19	19.6	23.6	28.6	29.8	10.8
	CAESAR	18.4	19.2	23.9	38.4	42.2	23.8
	NHANES	18.6	19.4	26.8	41.6	46.0	27.4

Marketing models are based primarily on data collected in the form of user feedback. There exist a number of global market research firms that specialize in obtaining, organizing, and even analyzing these data. Notable examples of such firms are ACNielsen and J.D. Power & Associates. Databases compiled and distributed by these firms typically contain minimal information about user demographics and instead contain vast amounts of data about the product alternatives available to users and the choices they made. These data are ideally suited for marketing models based on the principles of discrete choice analysis.

2.5 Chapter summary

This chapter reviewed the existing designing for human variability methodologies and also presented the discrete choice analysis branch of the field of marketing research. Despite being seemingly disparate, the two fields of research were shown to be similar in terms of their treatment of user preference and its variation across target populations. These similarities are an indication of the potential for synergies between the two fields of research.

As mentioned in Section 2.2.2, the assumption of binary accommodation/disaccommodation and the inability to accurately model certain categories of choice decisions are the two major limitations of the RBA approach. However, the great importance placed on the accurate use of target population anthropometry in the design effort is the main source of RBA methodologies' strength. These DfHV methods have been proven highly capable of handling safety accommodation problems and, in many cases, comfort accommodation issues as well.

Discrete choice analysis-based approaches, by contrast, disregard the accommodation/disaccommodation problem by focusing purely on the choice decision of users when presented with a set of alternatives. DCA-based methods are ideally suited for analyzing user decisions that are equivalent to discrete data (e.g., decisions on the type of vehicle to purchase). However, existing DCA-based techniques fail to take into account user anthropometry, which have a significant influence on users' perceptions of comfort and, therefore, on their choice decisions. Furthermore, DCA techniques cannot be used to analyze problems involving allocation of adjustability in products, and are less capable of carrying out the kinds of analysis required to study accommodation based on criteria such as safety, visibility requirements, and ease of use.

Amalgamating the individual strengths of the discrete choice analysis and DfHV's regression-based approaches seems to be a way to develop a robust methodology capable of efficiently carrying out safety and comfort accommodation analyses and accurately estimating users' choices in various scenarios. The following chapters will build on this theme and look to further examine these opportunities for synergies.

CHAPTER III

METHODOLOGY

Chapter II laid the groundwork for an exploration of the fundamental merits and drawbacks of DCA and RBA methods in a product design context. This led to the formulation of the goal of this thesis: to propose a methodology that leverages the strengths of both approaches and allows for efficient and accurate analyses of the accommodation problems associated with the design of any product. This chapter proposes the makings of such a methodology, and incorporates only two of the many performance objectives accommodation criteria—comfort and safety—in the procedure. While this results in a simplified version of the targeted methodology, it provides a robust foundation and direction for future work.

3.1 Safety accommodation analysis

As mentioned in Section 2.4.1, manufacturers must adhere to certain user safety standards, some of which may be in the form of governmental regulations. Many of these regulations are specified in terms of spatial relations between user anthropometry and product specifications. For example, FMVSS 202a (National Highway Traffic Safety Administration, 1998), a standard that defines the safety requirements of head restraints in the U.S., defines design specifications in terms of the minimum and maximum distances between the rearmost point of a driver's head and the front of the headrest.

A company may be capable of manufacturing and offering a wide variety of product alternatives by selecting from ranges of possible product specifications. However, some of these alternatives may not provide users with the required levels of safety. The method of safety accommodation analysis proposed in this section can help to quickly identify and filter out these alternatives. At the end of this process, the designer is left with a smaller set of potential product alternatives. Comfort accommodation analyses (described in the following section) can then be carried out on these remaining product alternatives to determine the most preferred specifications for the given target population.

3.1.1 RBA method

Their ability to simulate and interpret anthropometric variability in any target population makes RBA methodologies well-suited to handle the kinds of problems encountered in safety accommodation analysis. Parkinson and Garneau (2009) is an example of the application of RBA techniques for this purpose.

Existing approaches for RBA-based accommodation analysis involve the following steps (Garneau, 2009):

1. Obtaining relevant anthropometry for target user populations. When anthropometric data for the target user population is not readily available, the population must first be defined in terms of demographic parameters such as distributions of age, gender, race, and ethnicity. Anthropometry for the target population may then be synthesized by drawing from existing databases (e.g., ANSUR (Gordon et al., 1989), NHANES (Centers for Disease Control and Prevention, 2004), CAESAR (Blackwell et al., 2008)) and ensuring the statistical equivalence, in terms of means and standard deviations, of the estimated and actual anthropometry. The estimated anthropometry is called a *virtual population*.

2. Accurately modeling user preference. The designer can conduct experiments involving the interaction of a sample population with prototypes of the product. The data gathered through such experiments can be the basis for preference models. However, if an appropriate model has already been developed by a previous study, then it may be selected for application in the case at hand.

3. Extrapolating the preference model to the virtual population. This generates simulations of the variation of preference in the target user population.

4. Interpreting the simulated preference data to solve the accommodation problem at hand. This may be done by studying either the binary accommodation or the probability of accommodation of each member of the virtual population.

This methodology, which may involve the simultaneous consideration of multiple accommodation criteria, is well-suited to handle even complex design problems involving optimal allocation of adjustability. However, for less complex design scenarios (involving unadjustable products, for example), the designer may make use of a simplified DfHV methodology that consists of the following steps:

1. Obtaining relevant anthropometry for target user populations to create the virtual population.

2. Analyzing the virtual population to solve the accommodation problem. The analyses can consist of basic multivariate percentile analyses to directly compare the relevant anthropometry with corresponding design specifications. For example, the design of an unadjustable seat without a backrest would require the use of data about knee height and buttock-knee length to calculate the seat height and seat pan depth required to accommodate the desired percentage of the target population. The designer must exercise care, however, to avoid oversimplifying multivariate design scenarios by reducing them to independent univariate problems. This will result in lesser-than-expected accommodation due to body measures being correlated to one another (Moroney and Smith, 1972; Roebuck, 1995).

The case study described in Chapter IV makes use of this simpler methodology to analyze the safety accommodation problem.

3.1.2 DCA approach

Discrete choice analysis looks to model the influence of different product alternative- and user-specific factors on user choice decisions. User preference is the only consideration in these analyses; user safety does not play a role in these choice predictions. A purely DCA-based approach is, therefore, unsuited to perform safety accommodation analyses.

3.2 Comfort accommodation analysis

Analysis of users' perceptions of comfort requires the use of appropriate preference models. Experiments must be conceptualized and conducted to gather the data that are the basis for such models. These models predict various measures of user comfort or choice based on a set of predictors that consist of variables that are alternative-specific (e.g., product specification, pricing) and user-specific (e.g., anthropometry, income and education levels).

Once formulated, the estimation models are extrapolated to the target population. The values of the predictors for the target population are used to drive the models, thus generating estimates of the variation of comfort across potential users of the product.

Regression-based models are not well-suited to directly model user choice decisions in their entirety since these may involve simultaneous consideration of multiple design criteria, some of which cannot be modeled as even discretely-varying variables. For example, regression approaches cannot directly predict the decision about what type of vehicle a user might purchase from among the available alternatives—sedans, SUVs, etc. This decision is influenced by a number of considerations, some of which are suitable for regression-based models (e.g., amount and location of seat-related adjustability, various aspects of the design of the vehicle interior). Accordingly, the ultimate vehicle-purchase decision may be partially broken down into *sub*-decisions involving each of these variables. However, certain user choice criteria (e.g., required seating capacity, vehicle color, fuel efficiency) are not conducive to regression-based analyses. DCA-based approaches may be better suited to take these criteria into consideration in user choice models.

3.2.1 Experimental setup

Experiments must be setup to provide data in the form suited for the chosen method of analysis. Optimal experimental setups for RBA and DCA approaches will, therefore, differ in some respects.

RBA method

Experiments to collect data for RBA-based models may be setup in either of two ways:

1. Each participant may be asked to adjust the product's specifications to the configuration that maximizes the participant's comfort. Preference models thus formulated will then be capable of directly estimating design specifications that optimize users' interaction with the product.

2. Each participant may be required to evaluate multiple product alternatives, each with a unique set of design specifications, and provide feedback (e.g., perceived comfort or ease of use), preferably on a visual analogue scale. The visual analogue scale consists of a continuous line between the maximum and minimum values of the feedback variable. The participant may select any point on this line as being representative of their feedback. Obtaining feedback on a visual analogue scale, while not always essential, makes the feedback continuously-varying, thus ensuring that it is well-suited for regression-based analyses.

The former experimental approach might be preferable in most situations, since it allows for direct estimation of the optimal design specifications. The latter approach relies on feedback that is *indicative* of preference, and thus makes for indirect estimation of the optimal design. However, an experiment involving the evaluation of multiple product alternatives may be a more realistic representation of a user's decision-making process. This is, therefore, the approach that is suggested for use in RBA-based comfort accommodation analyses.

Note that since the RBA approach is best suited to model continuously-varying variables, not using the visual analogue scale for feedback could result in a regression model with lower values of goodness-of-fit measures. The RBA approach is equipped to perform satisfactorily even under these conditions, since the reintroduction of residual variance compensates for the lack of correlation between the dependent and independent variables in the model. However, higher values of goodness-of-fit measures are desirable, since these will indicate greater robustness of the underlying equation.

DCA method

DCA approaches by definition are aimed at predicting users' choices when offered sets of product alternatives. The appropriate experimental setup for DCA-based methodologies will, therefore, involve multiple choice sets, with each set consisting of the same number of alternatives. Participants will be required to indicate a choice decision in each set of the experiment. The decision to reject all alternatives available in a set may also be permitted.

The number of alternatives per choice set must be decided carefully. The number must be high enough to allow the participant to conduct sufficient trade-off analyses of the attributes of the different alternatives. If not, the preference model will lack in predictive capability. However, unreasonably high numbers of alternatives per set might confuse the participant and result in the decision-making process being unduly illogical. This too will give rise to highly inaccurate preference models.

3.2.2 Extrapolation of the preference model to the target population

Preference models based on data from sample studies are extrapolated using target population data about the predictors. Depending on the decision-making approach adopted, this process generates either estimates of the relevant comfort measures for the target population (RBA method) or the optimal product alternative for the population (DCA approach).

RBA method

The extrapolation of RBA-based models synthesizes estimated variability of the required data for the target population. The variation of different measures of comfort can thus be predicted. This predicted data can then be analyzed to study the impact of various design decisions on user comfort. An example of this analysis is illustrated in Figure 3.1, which contains a contour plot showing the dependence of the average comfort of airline passengers on seat height and pitch.

These estimated data can also be used in more complex studies involving analyses of the trade-off between user comfort and design cost. For example, the contour plot in Figure 3.1 reveals that average airline passenger comfort is greatest when seat height is

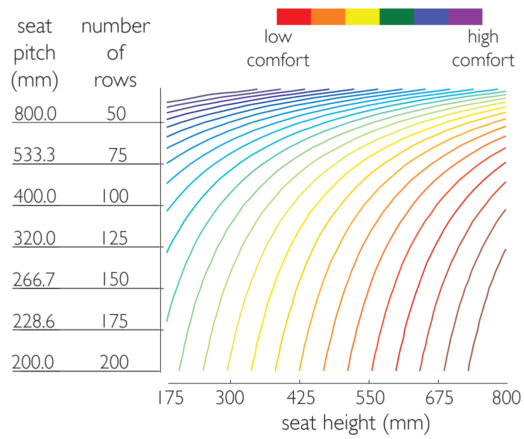

Figure 3.1: An example of comfort accommodation analysis using RBA techniques. The figure illustrates the simulated impact of variation in seat height and pitch on the average comfort score of airline passengers. Adapted from Nadadur and Parkinson (2009b).

low and seat pitch is high. However, such a seating configuration would adversely affect the revenue of the airline, since the number of rows, and hence the total number of seats, would be reduced. The airline can, therefore, use the contour plot to select a seating configuration that might help achieve the required balance between revenue and average passenger comfort. This example is an illustration of the basic procedure proposed for RBA-based comfort accommodation analyses.

DCA method

Extrapolating DCA-based preference models to target user populations entails the following steps:

1. Deciding on the set of available product alternatives and thus calculating the values of the alternative-specific predictors. The product alternatives chosen are the design options being considered by the manufacturer. These alternatives must be of the same type as the ones used for the experimental study.

2. Preparing arrays (or vectors) of values of the user-specific variables for the target population. Every array contains a unique value for each individual in the target population. For example, the array of target population stature will be composed of the statures of all target users.

3. Using the values and arrays set up in the previous two steps in the preference model. A 3-alternative preference model may be in the form of Equations 3.1, 3.2, and 3.3. This step produces the *logit* (i.e., utility) of every alternative to each user.

4. Calculating the exponential to base **e** of every logit to find the unscaled probability of selection of each alternative (Equation 3.4).

5. Dividing each unscaled probability by the sum of all the unscaled probabilities, thus computing the scaled probability of selection of each alternative for every user (Equation 3.5). Each user is assumed to choose the alternative with the highest probability of selection.

6. Calculating the percentage of users who will select each alternative and thus finding the comfort accommodation level afforded by each alternative.

$$\mathbf{logit}(alternative = I) = [\mathbf{t} \cdot \mathbf{X}_{1 \cdot I} + \mathbf{u} \cdot \mathbf{X}_{2 \cdot I}] \tag{3.1}$$

$$\begin{aligned} \mathbf{logit}(alternative = II) &= \ln[\mathbf{Pr}(alternative = II)/\mathbf{Pr}(alternative = I)] \\ &= \mathbf{d}_{II} + [\mathbf{t} \cdot \mathbf{X}_{1 \cdot II} + \mathbf{u} \cdot \mathbf{X}_{2 \cdot II}] + [\mathbf{v}_{II} \cdot \mathbf{X}_3 + \mathbf{w}_{II} \cdot \mathbf{X}_4] \end{aligned} \tag{3.2}$$

$$\begin{aligned} \mathbf{logit}(alternative = III) &= \ln[\mathbf{Pr}(alternative = III)/\mathbf{Pr}(alternative = I)] \\ &= \mathbf{d}_{III} + [\mathbf{t} \cdot \mathbf{X}_{1 \cdot III} + \mathbf{u} \cdot \mathbf{X}_{2 \cdot III}] + [\mathbf{v}_{III} \cdot \mathbf{X}_3 + \mathbf{w}_{III} \cdot \mathbf{X}_4] \end{aligned} \tag{3.3}$$

where $\mathbf{d}$ is a constant, $\mathbf{t}$ and $\mathbf{u}$ are the coefficients of the alternative-specific predictors $\mathbf{X}_1$ and $\mathbf{X}_2$, and $\mathbf{v}$ and $\mathbf{w}$ are the coefficients of the individual-specific predictors $\mathbf{X}_3$ and $\mathbf{X}_4$. $\mathbf{X}_1$ and $\mathbf{X}_2$ vary across the product alternatives. In contrast, $\mathbf{X}_3$ and $\mathbf{X}_4$ are arrays containing unique values for every user in the target population; $\mathbf{X}_3$ and $\mathbf{X}_4$ vary across users but are constant across alternatives.

$$\mathbf{Pr}_{unscaled}(alternative = j) = \exp[logit(alternative = j)] \tag{3.4}$$

where j is I, II, or III.

$$\mathbf{Pr}(alternative = j) = \mathbf{Pr}_{unscaled}(alternative = j) / \sum_{j} \mathbf{Pr}_{unscaled}(alternative = j) \tag{3.5}$$

Figure 3.2 illustrates the DCA-based comfort accommodation analysis process when each choice set comprises of three design alternatives. For every choice set, a corresponding set of logits is calculated for each user based on Equations 3.1, 3.2, and 3.3. The probability of selecting each alternative is then computed using first Equation 3.4, then Equation 3.5. If, for example, the probability of selecting alternative I is greater than probabilities of selecting either alternatives II or III, then alternative I can be considered that set's most preferred design, and hence the likely choice, of the user.

When the total number of design alternatives is greater than three, multiple choice sets may be formed. Using the DCA-based comfort accommodation analysis procedure described in the preceding paragraphs, the most preferred alternatives may be selected from each of these sets. These "winning" designs can then once again be grouped into choice sets of three alternatives, and the process can be repeated. In this way, the user choice problem may be formulated as a multiple-iteration DCA analysis, the final iteration of which will produce the optimal design alternative.

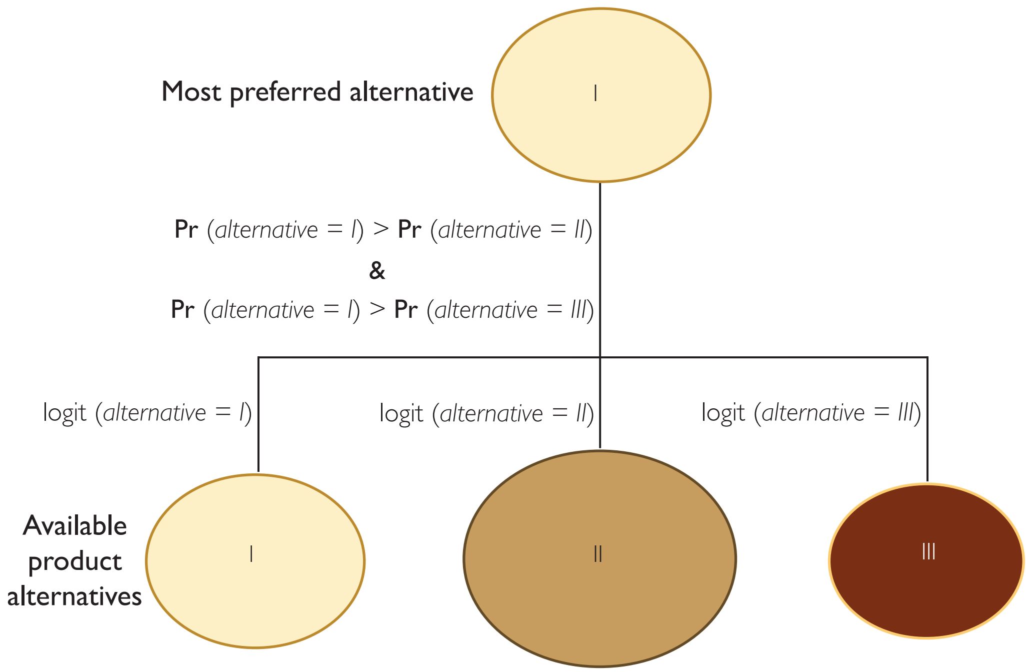

Figure 3.2: An illustration of the DCA-based comfort analysis process with three design alternatives in each set of products.

3.3 Principal contributions

This research serves as a preliminary exploration of the synergies that exist between the fields of designing for human variability and discrete choice analysis. For the sake of simplicity, accommodation analyses is assumed to involve only two criteria: comfort and safety. Methods are suggested for the analyses of comfort and safety accommodation.

The ability of existing RBA techniques to conduct accurate and efficient safety accommodation analyses is proven knowledge. These techniques can, therefore, continue to be used for this purpose. However, a DfHV-influenced DCA method is introduced and suggested as being better suited for comfort analysis in certain design scenarios. This methodology is expected to simplify the consideration of multiple accommodation criteria, some design-related and others related to user anthropometry. Chapter IV evaluates and demonstrates the application of these recommended safety and comfort analysis methods.

Validation of this methodology would lay the groundwork for further exploration of relevant DfHV and DCA techniques in an effort to develop for manufacturers a decision-making methodology that can account for most, if not all, the criteria that may influence a product's design. The comprehensiveness of such a methodology would be further increased by incorporating tools from the fields of finance and game theory. Product design efforts employing the resulting technique may be able to concomitantly consider factors such as user accommodation, manufacturing capability and costs, resource (manpower, material, and infrastructure) availability, future financial plans of the company, and competitors' responses.

CHAPTER IV

CASE STUDY

A simple case study involving the interaction of users with doorways of different sizes was used to evaluate and demonstrate conclusions proposed in Chapter III. The reasons for selecting doorways as the product for the study were the following:

1. Doorways are exceedingly simple products which everyone interacts with multiple times every day. There would be no learning curve associated with the sample population's interaction with the product at hand.

2. The duration of the conceptualized experiment would only be about 15 minutes per user. The possibility of occurrence of user fatigue and boredom during the experiment would be minimal.

3. Not considering aesthetics-related factors, users' perceptions of doorways could be thought of as being influenced solely by the relations between the sizes (heights and widths) of the doorways and their own anthropometry. The positions of the doors relative to each other might have some effect on users' perceptions, but this could be accounted for in the study.

4. The relevant anthropometry required for this study—stature, weight (to calculate BMI), and biacromion breadth—would be simple and easy to measure.

The following sections describe: a) the experimental procedure, b) the formulation of preference models using RBA and DCA methods, c) extrapolating these models to the target user population and performing safety and comfort accommodation analysis using the methods outlined in Section III.

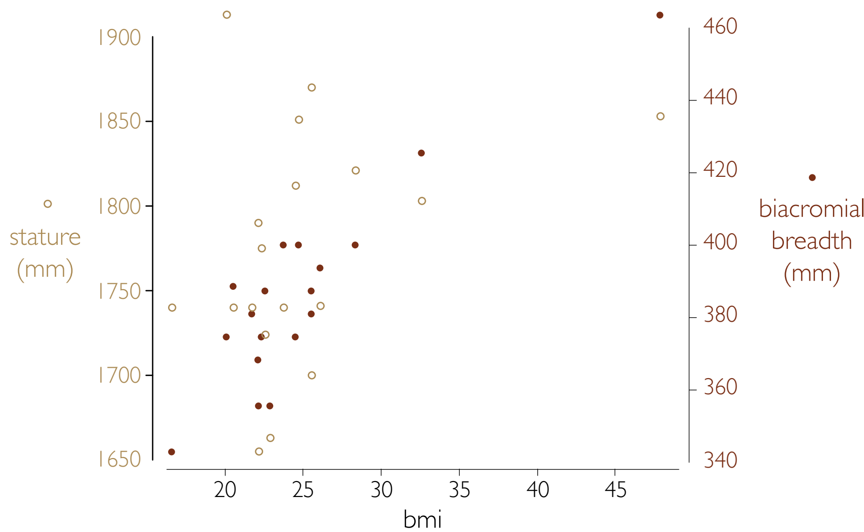

Figure 4.1: Anthropometry of the sample population for the doorway experiment.

4.1 Experimental setup

Details of the experimental procedure were reviewed and approved by the internal review board at Penn State University.

Sample population

The sample population for the study consisted of 17 participants, all student volunteers, at Penn State University. The stature, weight, and biacromion breadth of each participant were noted before the start of the experiment. Figure 4.1 shows the variation of the measured anthropometry for the sample population. Note that while the sample size for the study is within acceptable limits for an product design problem, it is unacceptably low for a marketing problem.

Doorway sizes

A range of doorway sizes was selected for the study, with doorway heights varying between 68" (1727.2mm) and 84" (2133.6mm) and widths varying between 24" (609.6mm) and 44" (1117.6mm), both in discrete increments of 2" (50.8mm). Each participant was required to interact with 8 sets of doorways, with each set containing 3 uniquely-sized doorways. The sizes of the first set of doorways were constant—height: 84" (2133.6mm);

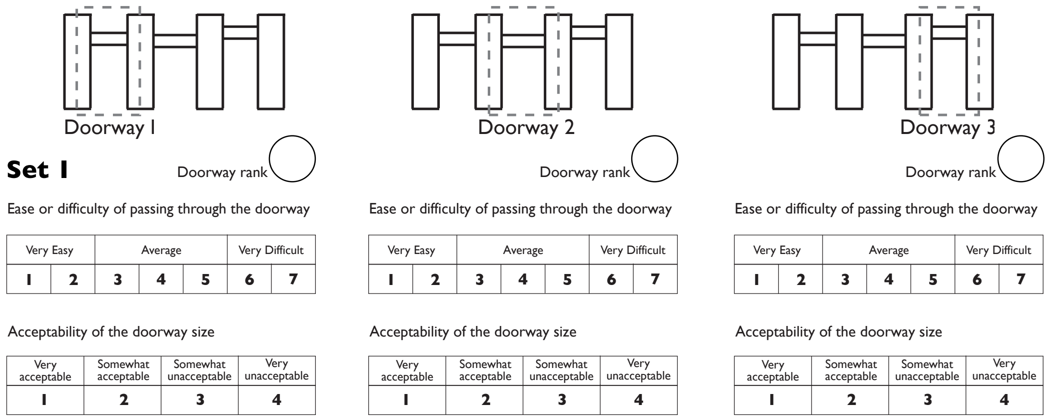

Figure 4.2: Feedback collected from the participants in the doorway experiment.

width: 28" (711.2mm), 32" (812.8mm), and 36" (914.4mm)—for all participants, and thus served two purposes. First, they allowed each participant to establish a subconscious standard against which future doorway sizes could be compared. Second, they acted as a baseline across all 17 participants for the formulation of the discrete choice model.

The heights and widths of each of the remaining 7 sets of doorways were randomly selected from a set of "allowable sizes". This set of allowable sizes was made dependent on the anthropometry of each participant, and was decided based on the condition that the height and width of any doorway was to always be greater than or equal to the individual's stature and biacromion breadth, respectively.

Procedure and feedback

The participants were kept unaware of the exact sizes of the doorways. Each individual was asked to observe and walk through all 3 doors in each set and then provide the following feedback (Figure 4.2):

1. A ranking for each door in the set

2. A rating, on a scale of 1 to 7, of the ease or difficulty of passing through the doorway, with ratings of 1 and 7 signifying "very easy" and "very difficult", respectively

3. A rating, on a scale of 1 to 4, of the acceptability of that doorway size, with ratings of 1 and 4 signifying "very acceptable" and "very unacceptable", respectively

4.2 Formulating preference models

Preference models were required in order to conduct comfort accommodation analyses of the target user population. Two separate models were developed for this purpose, one using the basic RBA technique and the other based on DCA methods.

RBA method

As mentioned in Section 2.2.2, RBA-based methods are widely used in DfHV studies. This is due to their ability to generate very accurate statistical estimates of the actual data. However, the application of regression requires continuously-varying dependent and independent variables. This gives rise to a limitation of the RBA method: the inability to accurately predict users' choice decisions when the choices are in the form of discrete data.

The design scenario involving direct prediction of users' choices from among different sets of doorways is, therefore, not a case for the use of the RBA method. Instead, this method can be used to estimate the ease and acceptability ratings assigned by users to different doorway sizes. This is because these ratings, despite being collected as discrete numbers during the experiment, can be allowed to vary continuously when estimated. Since ease and acceptability ratings may be considered indirect indicators of users' choices, models formulated to estimate these ratings can used as indirect predictors of choice decisions.

Accordingly, regression models of the form of Equation 4.1 were developed with ratings of ease and acceptability chosen as the dependent variables. Doorway height and width were selected to be the alternative-specific variables, and stature and BMI formed the set of user-specific variables. The parameters of this regression analysis are contained in Table 4.1.

$$\mathbf{Y}_i = \mathbf{c}_i + [\mathbf{a}_{1i} \cdot \mathbf{X}_{1i} + \mathbf{a}_{2i} \cdot \mathbf{X}_{2i}] + [\mathbf{a}_{3i} \cdot \mathbf{X}_3 + \mathbf{a}_{4i} \cdot \mathbf{X}_4] + \mathrm{N}(0, \mathbf{S}_i^2) \tag{4.1}$$

where i = 1 (ease) or 2 (acceptability), $\mathbf{X}_1$ is door height, $\mathbf{X}_2$ is door width, $\mathbf{X}_3$ is stature, $\mathbf{X}_4$ is BMI. $\mathbf{X}_3$ and $\mathbf{X}_4$ are arrays of length equal to the number of users in the target population.

Table 4.1: Parameters of regression models formulated to estimate the ease and acceptability criteria (Equation 4.1).

	c	a_1	a_2	a_3	a_4	R^2	S
ease	2.4835	0.0036	-0.0301	-0.0027	-0.0001	0.0387	1.6940
acceptability	3.896	0.0012	-0.0254	-0.0017	0.0000	0.0602	0.9193

DCA method

All three kinds of feedback (doorway ranking, ease rating, and acceptability rating) obtained in the experiment (Figure 4.2) were in the form of discrete data. DCA was, therefore, expected to be well-suited to model these feedback variables. However, attempts to develop DCA-based models to predict ease and acceptability were unsuccessful; logistic curves were unable to fit the experimental data. The reasons for this failure are discussed in Section 5.1.2.

Next, DCA techniques were used to try to formulate models to directly estimate user choice based on the selected predictors. The doorway ranking feedback was used as a direct indicator of the choice of the user: the doorway that was ranked highest in each set was assumed to be the user's choice. Once again, the predictors comprised of both alternative-specific (doorway height and width) and user-specific (stature and BMI) variables. The choice model thus generated was of the form of Equations 3.1, 3.2, and 3.3. Table 4.2 contains the values of the parameters of the equations.

Table 4.2: A comparison of three multinomial logit models for estimating door choice (Equation 3.1, 3.2, and 3.3).

	$\mathbf{X}_1$ & $\mathbf{X}_2$	$\mathbf{X}_3$ & $\mathbf{X}_4$	[$\mathbf{X}_1$ & $\mathbf{X}_2$] & [$\mathbf{X}_3$ & $\mathbf{X}_4$]
$\mathbf{d}_1$	-0.2196	2.4142	6.9905
$\mathbf{d}_2$	-0.6935	-9.3741	-3.7597
$\mathbf{h}$	0.0011	-	0.0010
$\mathbf{w}$	0.0004	-	0.0007
$\mathbf{stat}_1$	-	0.0001	0.0020
$\mathbf{stat}_2$	-	0.0064	0.0087
$\mathbf{BMI}_1$	-	-0.1167	-0.0279
$\mathbf{BMI}_2$	-	-0.1109	-0.0323
McFadden R^2	0.6788	0.6960	0.6995
log-likelihood	-143.99	-136.28	-134.68
likelihood ratio test	χ^2 =1.1173	χ^2 =16.5420	χ^2 =19.7490
	p-value = 0.5720	p-value = 0.0024	p-value = 0.0031

4.3 Doorway sizing analysis for the target user population

The purpose of this analysis was *not* to identify and recommend an optimal doorway size for the target population. The process described in the following sections was aimed at better understanding and demonstrating the use of the proposed design methodologies.

4.3.1 Selecting the target user population

Section 2.4.2 briefly described three commonly-used anthropometric databases: ANSUR, NHANES, and CAESAR. ANSUR is representative of the U.S. military population in the late 1980s. NHANES is comprised of a series of surveys, currently conducted every two years, and describes the U.S. civilian population. In contrast with ANSUR and NHANES, both of which are representative of clearly-defined populations, CAESAR is a randomly-composed database that contains information about European and North American participants who volunteered to undergo 3-dimensional body scans. Therefore, while CAESAR contains comprehensive anthropometric data about its subjects, it is not directly representative of any user population.

ANSUR is the more comprehensive and well-organized of the two mentioned representative databases. Furthermore, since it is composed of participants in the military, thus ensuring that the individuals are between certain fixed age limits and maintain high fitness levels, ANSUR is also relatively more homogenous in terms of distributions of age and anthropometry. The homogeneity is somewhat similar to the composition of the participants in the doorway experiment. For all these reasons, all the subjects in ANSUR were selected to constitute the target user population for this analysis.

4.3.2 Safety accommodation analysis

The first step of the safety accommodation analysis involved selecting the ranges of doorway heights and widths. The ranges used in the experiment were retained for the purpose of this analysis. Doorway heights were allowed to vary between 68" (1727.2mm) and 84" (2133.6mm) and widths could vary between 24" (609.6mm) and 44" (1117.6mm), both in discrete increments of 2" (50.8mm).

Next, the desired safety accommodation level was set at 95% of the target population. An examination of the biacromion breadths of the ANSUR subjects revealed that the 100th percentile of this body measure was 17.75" (451mm), less than the minimum allowed doorway width; none of the widths were required to be eliminated from consideration. This observation resulted in the safety accommodation analysis being reduced to a 1-dimensional problem: accommodation would be decided based solely on target population stature.

The 95th percentile of ANSUR stature was found to be 72.36" (1838mm). Therefore, in order to achieve the desired safety accommodation level of 95% of the target population, two doorway heights (68", 70", and 72") were eliminated from the analysis.

4.3.3 Comfort accommodation analysis

Comfort accommodation analysis was commenced by creating a set of all possible doorway configurations. This was done by finding every possible combination of the doorway heights and widths that remained after the safety accommodation analysis.

RBA method

Ease and acceptability ratings for every available doorway configuration were calculated using the RBA equations represented by Equation 4.1. Stature ($\mathbf{X}_3$) and BMI ($\mathbf{X}_4$) were in the form of arrays, with each array containing unique values for every individual in the target population. This resulted in the ratings calculated for each doorway configuration also being in the form of arrays of the same length as stature and BMI variables, with the arrays consisting of unique ratings estimated for each individual.

The output of this process was thus a set of ease and acceptability ratings arrays for each doorway configuration. These arrays could be studied in a variety of ways. One of the more information-intensive and easily-understandable ways to interpret this information was in the form of contour plots. The contour plots were generated through the following process:

1. A certain threshold value was decided on for the ease or acceptability ratings.
2. Ease and acceptability arrays were calculated for each doorway configuration using Equation 4.1.
3. Users with ratings below the threshold value were deemed accommodated in terms of comfort. The percentage of such users was calculated at each doorway configuration.
4. Contour plots were generated showing the percentage of comfort accommodation at each doorway configuration.

Figures 4.3 and 4.4 are examples of contour plots generated using the above procedure. The plots allow designers to easily interpret the impact of design decisions (i.e., different doorway configurations) on the comfort accommodation level achieved.

DCA method

When extrapolating a DCA model to a target population, it is necessary to structure the analysis to resemble the experiment whose data is the basis for the model. The output of the extrapolation is a prediction of the most popular product alternative. In this case, the experiment consisted of multiple sets of doorways, with each set comprising of 3 doorways. The extrapolation process must preserve this framework. This explanation is illustrated in Figure 4.5. For a given set of doorways, the DCA model predicts the probability of the choice of each alternative for every user in the target population. This allows for the selection of the most popular alternative in every set. Following completion of the first iteration of this process, the remaining doorway configurations can again be formed into sets of 3 alternatives, and the choice prediction process can be repeated. These iterations can continue until one final alternative is chosen as the most popular configuration for the target user population.

Accordingly, the first step in the DCA-based extrapolation process was to randomly draw from the set of available doorway configurations to constitute multiple doorway sets, each containing 3 alternative configurations. For reasons that are obvious from Figure 4.5, it was desirable to form $3^{\mathbf{n}}$ sets of doorways, where $\mathbf{n}$ is the number of iterations expected in the DCA extrapolation process. The initial number of permissible doorway configurations following completion of the safety accommodation analysis was 66. The number of sets of alternatives that could be directly formed by selecting from these alternatives was 66/3 = 22. Forming 27 sets would satisfy the $3^{\mathbf{n}}$ rule. Therefore, an additional 5 sets were generated by allowing some doorway configurations to be repeated in the analysis. This was permissible since it would not impact the final outcome of the choice prediction process.

The DCA model represented by Equations 3.1, 3.2, and 3.3 was now applied on each of the 27 sets of doorways. Now, there was a possibility of a bias in the model due to the relative positioning of the different doorway sizes. For example, an individual might simply be biased in favor of doorways in the leftmost position. Such a bias would skew the feedback data collected, and might result in inaccurate choice predictions if the model were to be extrapolated to a target population. Therefore, an additional precaution was taken in order to eliminate the influence of this bias on choice predictions. The DCA model was applied 6 times for every set of doorways, each time with different relative positions of the doorways. The final choice from that set would then be the doorway with the highest probability among all 9 calculated probability values.

This basic process was implemented with 4 iterations until only a single doorway configuration remained. Despite the entire DCA-based choice prediction process being repeated multiple times, each time with randomly-generated doorway configurations, only one particular configuration always remained as the most popular alternative. This configuration was, unsurprisingly, the largest allowable door size, with a height of 84" (2133.6mm) and width of 44" (1117.6mm).

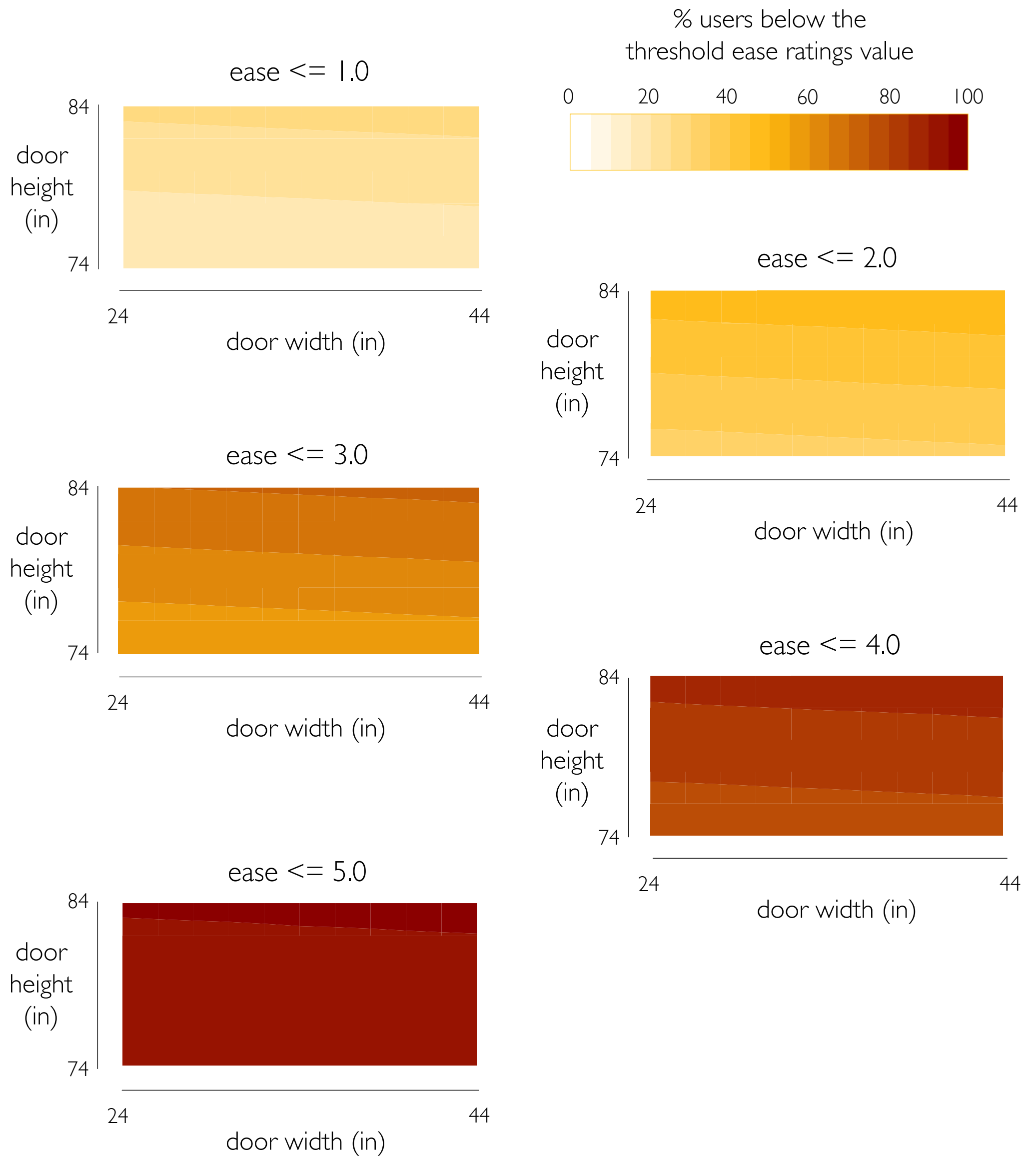

Figure 4.3: Contour plots, at different threshold values of the ease rating, of the percentage of target users accommodated in terms of comfort. The plots show the percentages of accommodated users at different doorway configurations.

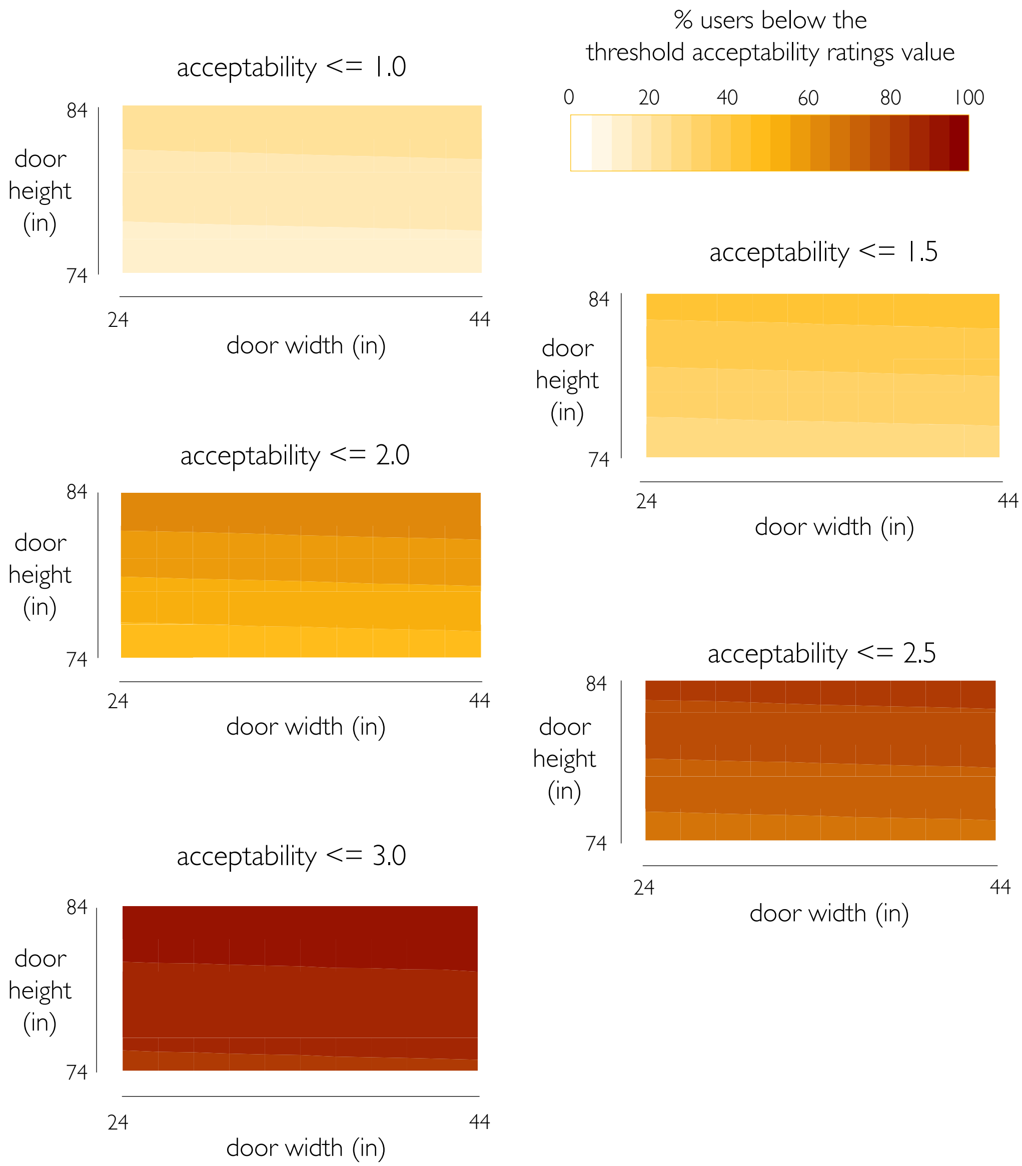

Figure 4.4: Contour plots, at different threshold values of the acceptability rating, of the percentage of target users accommodated in terms of comfort. The plots show the percentages of accommodated users at different doorway configurations.

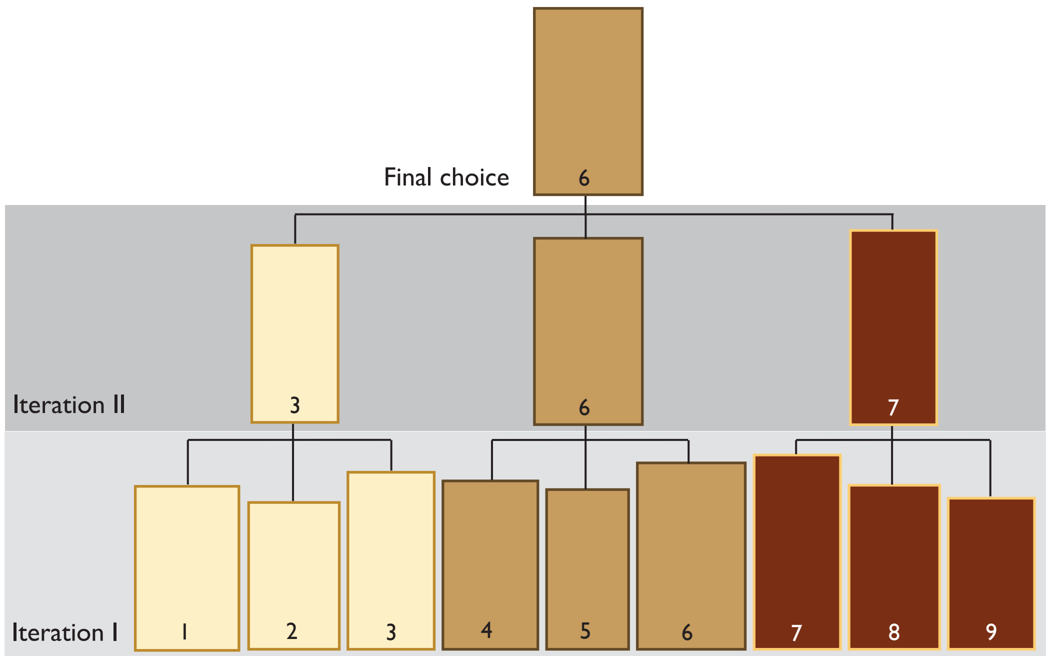

Figure 4.5: The structure of the DCA-based choice prediction process.

4.4 Chapter summary

This chapter presented a case study used to demonstrate the basic methodology proposed in Chapter III. The case study is intentionally simple, consisting of an experiment involving the selection and rating of varying doorway sizes. The intention is not to optimize doorway sizing, but just to provide a venue for the application of the RBA-based safety accommodation analysis and RBA- and DCA-based comfort accommodation analyses techniques.

The safety accommodation analysis in the case study was found to reduce to a 1-dimensional problem, and was easily solved through the application of percentile analysis. The RBA-based comfort accommodation method was shown to be an indirect choice-prediction technique. The contour plots of Figures 4.3 and 4.4 were shown to be quick and efficient ways of interpreting the results of this method. The DCA-based accommodation technique, by contrast, produced a direct prediction of the most popular door choice for the target user population at hand.

Chapter V examines these methods and results in detail. Applications of this research and plans future work are also outlined.

CHAPTER V

DISCUSSION AND CONCLUSIONS

This research aimed to develop a design decision-making methodology by harnessing the strengths of existing RBA and DCA approaches. To this end, the general product design process was divided into safety and comfort accommodation analyses of the target user population. Emphasis was placed on the proper use of appropriate user anthropometry in these analyses.

To illustrate the proposed decision-making methodology, a simple choice experiment involving multiple sets of 3 doorway sizes was developed. Feedback obtained from participants in this study was used along with information about pre-determined alternative- and user-specific variables to develop two choice prediction models: one RBA-based and the other DCA-based. These models were then extrapolated to the target user population (ANSUR) and were used to study the comfort accommodation resulting from different design decisions (i.e., the different doorway sizes). The model based on regression with residual variance was found to be suitable for utilization as an indirect predictor of doorway choice while the DCA-based model was capable of directly predicting users' choice decisions.

The results of these analyses and other observations are interpreted and discussed in the following sections. The limitations and principal contributions of this work are then summarized, and some of the broader applications of this research are suggested. These limitations and applications will be the focus of future work.

5.1 Discussion of results

The doorway choice experiment described in Chapter IV provided a venue for the application the proposed design-making methodology. The aim of the experiment was not to develop an efficient model to predict users' doorway choices. Instead, the study was intended to illustrate a way to concomitantly harness the strengths of RBA and DCA techniques. Therefore, the discussion contained in this section looks only to present the benefits and limitations of this design decision-making methodology.

5.1.1 Safety accommodation analysis

The safety accommodation analysis methodology described in Section 3.1 and implemented in Section 4.3.2 consisted of basic percentile analyses of the anthropometry most directly affecting the design variables considered. In the case of the doorway sizing case study, the percentile analysis was easily reduced to a 1-dimensional problem, resulting in an exceedingly simple analysis of safety accommodation. Had the problem remained multivariate, the complexity of the percentile analysis problem would have been significantly greater. This is because the analysis would then have had to account for the correlations existing between the different anthropometry. Failure to do so would result in lesser-than-expected accommodation (Moroney and Smith, 1972; Roebuck, 1995).

This method of safety accommodation analysis has a major limitation. It may not always be possible to perfectly divide the overall accommodation problem into independent analyses of safety and comfort accommodation. In order to ensure users' safety, designs may have to consider the variation of the users' preferred styles of interaction with the product. An example of such design problems are vehicle head restraints, which are the focus of Parkinson and Garneau (2009). The need to comply with governmental safety regulations might force designers to compromise on user comfort. However, users who are uncomfortable with a product might themselves modify the product to permit their preferred styles of interaction with it. Parkinson and Garneau (2009) described how some vehicle drivers had pulled their vehicle head restraints out of their seats, rotated them through 180 degrees, and fitted them again to the seats. Products thus modified do not ensure the safety of users.

In contrast, safety accommodation analysis of doorways does not require consideration of user preference. The proposed safety accommodation analysis method is, therefore, applicable to the problem in the case study. Products that, like doorways, are unadjustable and permanently fixed in certain locations could be other applications of this method.

5.1.2 Comfort accommodation analysis

Two separate methods, one RBA-based and the other DCA-based, were used to predict choice decisions in the target user population. The RBA-based model was an indirect predictor of choice since it was only able to estimate target users' appraisals of the product's ease and acceptability ratings, which were considered indicators of choice. The DCA-based model, by contrast, produced direct choice predictions.

RBA method

Section 4.2 mentioned the main reason for the RBA-based approach not being well-suited to analyses of data obtained from the doorway experiment: participant feedback was collecting in the form of discrete data (door rankings, ease ratings, and acceptability ratings). Regression-based methods work best when the predictors and estimated variables are allowed to be continuously-varying. Nevertheless, the RBA technique was utilized to formulate a model to predict each user's appraisal of the ease and acceptability of the available doorway sizes.

As can be seen in Table 4.1, the values of the $\mathbf{R}^2$ parameter, an indicator of the goodness of fit of the regression model to the underlying data points, are very low for both the ease (0.0387) and acceptability (0.0602) ratings estimation equations. $\mathbf{R}^2$ values may vary between 0 and 1, with 0 implying no fit and 1 implying perfect fit of the regression equation and the underlying data. The reliability of the ease and acceptability prediction relations thus formulated is, therefore, minimal.

The contour plots in Figures 4.3 and 4.4 help visualize the effect of different design decisions (i.e., decisions pertaining to doorway sizing) on the comfort accommodation level of the target population. The accommodation level is dependent on, among other things, the stringency of the company and the target population's unwillingness to compromise on comfort. A very stringent company will look to provide users with products that they are most comfortable with. Uncompromising users will demand more satisfying products. These conditions would correspond to ease ratings <= 1.0 and acceptability ratings <= 1.0. Conversely, a lax company might not be as motivated to manufacture products that satisfy users' desires. Less uncompromising users will also not be as demanding, and will satisfy themselves even with designs that do not permit their preferred styles of interaction with products. Ease and acceptability ratings of <= 5.0 and <= 3.0, respectively, would characterize this scenario. Contour plots can thus be generated to reflect policies of the company and the nature of the target user population.

Based on the plots, doorway width plays only a minor role in influencing users' perceptions of ease and acceptability of the doorway size. Accordingly, Figures 4.3 and 4.4 can be modified into the form of Figures 5.1 and 5.2, thus allowing for more direct and intuitive comparisons of the influence of doorway width and height on comfort accommodation levels. As can be seen in Figures 5.1 and 5.2, doorway height is critical to changing users' interaction with the product, with comfort accommodation levels increasing noticeably with increase in doorway height. This phenomenon could be due to a possible tendency of users to be more easily influenced by doorway heights than widths. This may be because users can more quickly visually assess the relative positions of the tops of doorways. Assessing the positions of the *sides* of doorways might entail closer appraisal (i.e., greater effort) on the part of the user. In comparison to doorway height, doorway width may, therefore, have an insignificant impact on user comfort.

Also, as can be deduced from Figures 5.1 and 5.2, and as is obvious, more stringent ease and acceptability requirements are more difficult for the company to satisfy, and vice-versa; fewer users are accommodated based on these stringent requirements.

DCA approach

Ease and acceptability prediction models could not be developed based on the data from the doorway experiment. It is possible that this data did not indicate any clear trends in

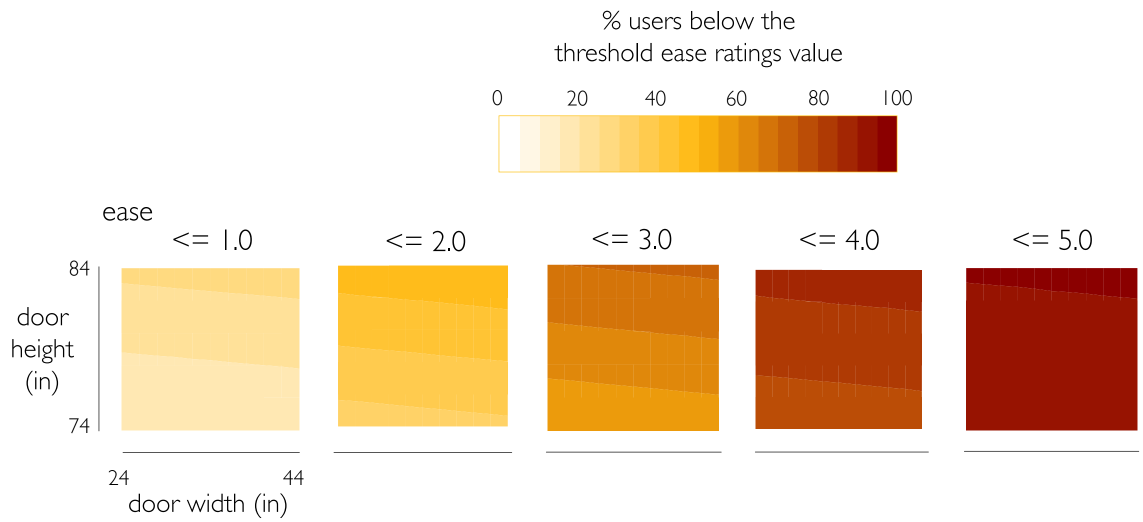

Figure 5.1: A modified, more easily-interpretable version of Figure 4.3. The contour plots show the percentages of accommodated users at different doorway configurations and illustrate, at different threshold values of the ease rating, the percentage of target users accommodated in terms of comfort.

user choice, something that is suggested by the very low $\mathbf{R}^2$ values shown in Table 4.1. In such a case, the data would be unfit for use in discrete choice analysis.

Reasons for this data inconsistency might be numerous. The high number of rating choices (1 through 4 for acceptability and 1 through 7 for ease) may have resulted in confused and inconsistent selections by the participants in the experiment. The participants might have also be uncomfortable and unduly constrained by the discrete scale, and might have preferred to make use of a visual analogue scale for this feedback.

Table 4.2 presents the parameters of three DCA models for predicting doorway choice. The predictors used in the three models are purely alternative-specific (doorway height and width), purely user-specific (stature and BMI), and both alternative- and user-specific, respectively. The accuracy and robustness of each model can be understood using three parameters:

1. McFadden $\mathbf{R}^2$. This parameter is similar to the $\mathbf{R}^2$ parameter in regression analyses, and is an indication of the accuracy of the corresponding model. The McFadden $\mathbf{R}^2$ value is observed to be lowest (0.6788) when the predictors are purely

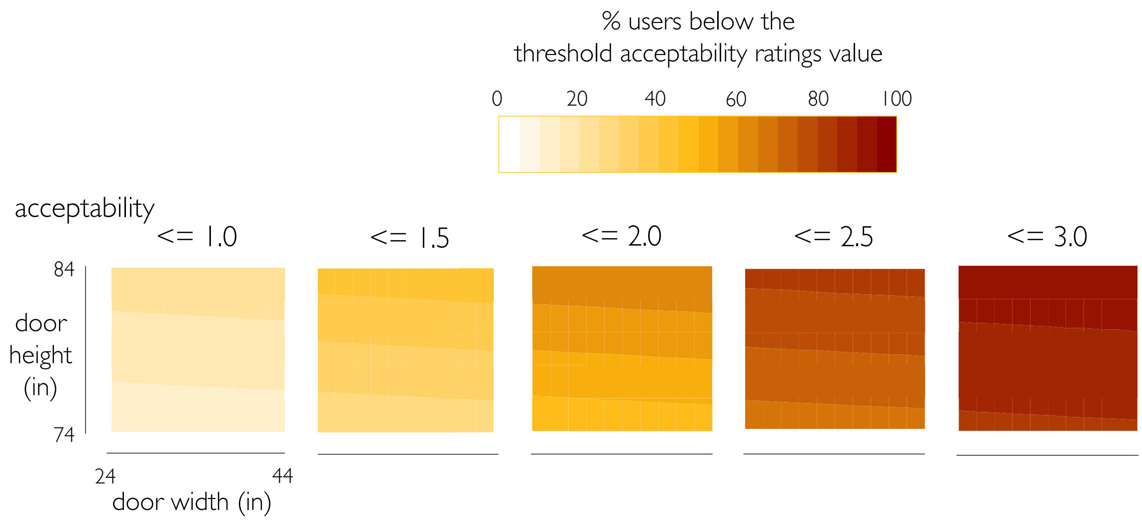

Figure 5.2: A modified, more easily-interpretable version of Figure 4.4. The contour plots show the percentages of accommodated users at different doorway configurations and illustrate, at different threshold values of the acceptability rating, the percentage of target users accommodated in terms of comfort.

alternative-specific and highest (0.6995) when the predictors are both alternative- and user-specific.

2. Log-likelihood. This parameter is a measure of the magnitude of error in the estimations generated by logistic models. Log-likelihood values are always non-positive, with a value of zero implying zero estimation error, i.e., perfect accuracy. The closer the log-likelihood is to zero, the greater is the accuracy of the model. Log-likelihood in this case is closest to zero when the model makes use of both alternative- and user-specific predictors. This doorway choice estimation model is, therefore, the most accurate of the three.

3. Likelihood ratio test. The likelihood ratio test rejects the null hypothesis if the value of the test statistic is too low, with the threshold value being decided by the chosen significance level. If p-value=0.05 is chosen as the significance level, the model with purely alternative-specific predictors fails to reject null hypothesis, implying, in this case, that the model does not produce the required goodness of fit of the underlying data. Selecting just user-specific predictors (anthropometry) as predictors produces a markedly more accurate model, as is evidenced by the higher value of the χ^2

parameter and the lower p-value. The model that harnesses both alternative- and user-specific variables as predictors is found to be the most accurate.

Based on this examination of the three DCA models, inclusion of anthropometry as user-specific predictors of choice decisions can help increase the models' reliability. This increase in reliability could be especially significant in the case of choice models utilized in user-product contexts wherein anthropometry is known to play a role in influencing the users' interaction with the product. This may be due to the fact that, in such contexts, anthropometric variability can help explain much of the user heterogeneity in the target population. The DCA model with both alternative- and user-specific variables as predictors was selected as the choice prediction model to be extrapolated to the target population.

The method for extrapolating the DCA model to the target population was described in Section 4.3.3. At the end of the fourth iteration, the model yielded a prediction of the most popular doorway size in the target population. This doorway was, unsurprisingly, the largest size permissible, with a height of 84" (2133.6mm) and width 44" (1117.6mm). This outcome is reassuring, since it is a confirmation of the accuracy of the model; users will always be most comfortable with the largest possible door size. Repeated runs of this extrapolation always yielded the same result.

A minor study was conducted on the side to check if the position of a doorway might influence users' perceptions of it. For example, some users might naturally prefer the leftmost doorway and might, therefore, give it better ratings than they would otherwise. Similarly, some users might simply dislike the doorway in the middle and might assign rate it unreasonably harshly. In order to check for this phenomenon, a number of sets of doorways were randomly chosen and the probability of choice of each doorway in each set was predicted. Every set of doorways was then shuffled to rearrange the relative positions of the doorways, and users' choice probabilities were calculated once again. Consistent user feedback would be revealed if, for a given set of doorways, the choice probabilities associated with each doorway would be independent of the relative position of the doorway. This was found *not* to be the case, thus proving the existence of a certain amount of position-related user bias during the data-collection process.

5.2 Principal contributions

This work makes two main contributions to the field of user choice analysis. First, anthropometry is shown to be an important user-specific predictor to include in DCA-based choice prediction models for products that users physically interact with. In such design scenarios, DCA models will be more accurate and reliable if they utilize information about user anthropometry.

The second contribution of this research is the introduction of a DCA tool into the field of DfHV. This is achieved in three steps: first, investigating the use of RBA- and DCA-based approaches to solving a user accommodation problem; second, leveraging the individual strengths of both approaches in a methodology for use as a tool in design decision-making; and third, demonstrating the application of this methodology in a specific design problem.

The design decision-making methodology resulting from this work consists of separate analyses of accommodation based on user safety and comfort. A purely RBA-based approach is recommended for analysis of safety accommodation; DCA techniques are not suitable for use in such analyses.

RBA models are demonstrated as being suitable for indirect comfort accommodation analysis; the regression-based method involves the use of tools (e.g., contour plots) to interpret the results from the underlying models. In contrast, the DCA-based method is shown to be capable of estimating the target population's preferred design alternative, thus allowing for direct analysis of comfort accommodation. However, underlying DCA models are augmented with some key DfHV concepts. For example, the setting up of the sample experiment involves consideration of relevant user anthropometry, and the list of user-specific predictors of choice decisions is expanded to include stature and BMI, which are commonly-used predictors in RBA methods. These changes are shown to increase the accuracy and reliability of the DCA-based approach.

This DCA-based DfHV technique is expected to be the foundation for a more comprehensive and robust methodology that incorporates relevant concepts and tools from a variety of areas of research—DfHV, marketing, decision-based design, financial options analysis, accounting, and game theory. The following section presents some limitations of the proposed technique, and outlines a roadmap for its refinement and expansion.

5.3 Limitations and future work

The limitations of this study arise mainly due to the simplifying assumptions made at different points in the analyses.

First, it may not always be possible to so easily and cleanly divide the design problem into analyses of safety and comfort accommodations. As discussed in Section 5.1.1, many design problems will require the consideration of user comfort even in the safety accommodation analyses. Not doing so would cause user discomfort, which may force some users to modify the product and thereby do away with the design features intended to guarantee safety.

Second, the process of completely separating safety and comfort accommodation analyses might constrain the application of this methodology to only certain kinds of design problems. The methodology is readily-applicable to design scenarios involving unadjustable products whose use may not pose very many safety concerns. Examples of such products are beds, couches, and desks.

Third, in order to develop the required choice prediction models, it is necessary to conduct an experiment involving the choice of different product alternatives (design configurations) by a sample group of users. Care must be taken to setup the experiment so as to prevent the undetected inclusion of intra-individual user biases in the final model. The experiment will, therefore, entail the expenditure of resources in the form of time, money, and effort by the manufacturer.

These limitations will be addressed in future work, first exploring them more thoroughly, then suggesting ways to minimize their impact on the design decision-making process. Future research efforts will also be aimed at studying areas of application of the proposed methodology. Three of the many potential areas of application are:

1. Better quantifying the just-noticeable difference parameter of users. Just-noticeable difference is a measure of the extent of change in design specifications from their optimal values that each user is indifferent to. Changing the design beyond these limits causes progressively greater discomfort to the user, and, at a certain threshold value, results in their disaccommodation in terms of comfort. The methodology proposed in this research appears to be a good starting-point for the exploration of just-noticeable difference.

2. Game theory-related applications. Some research efforts have already examined the use of game theory principles in the design decision-making process (Shiau and Michalek, 2008). The idea is to enable manufacturers to be able to account for their competitors' current market positions and predicted future decisions and responses. In some design scenarios, the proposed methodology could prove beneficial when used in concert with game theory concepts.

3. Financial options analysis. The analysis of financial options bears many parallels to the analysis of future costs and benefits associated with any design decision. This branch of knowledge could assist in the development of a comprehensive design decision-making tool for manufacturers.

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