공학박사학위논문

Ergonomics studies on quantitative evaluation of accommodation level considering variability in driver preference data

운전자 선호 데이터의 변동성을 고려한 정량적 제품 수용도 평가에 관한 인간공학 연구

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이 논문을 공학박사 학위논문으로 제출함

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정재문의 공학박사 학위논문을 인준함

2023 년 8 월

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Abstract

Ergonomics studies on quantitative evaluation of accommodation level considering variability in driver preference data

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Designing vehicle interior components requires consideration of human variability in perception, behavior, and anthropometry. Accommodation level, which is an index of how well a product suits a population of users, needs to be analyzed and considered during vehicle design process to ensure driver satisfaction and safety. It is essential that designers recognize the significance of designing for human variability in order to gain an accurate understanding of accommodation level of vehicle interior components.

Drivers interact with many different vehicle interior components, which are

provided either as adjustable components (i.e., the seat, the steering wheel, the mirrors, etc.) or as fixed components (i.e., the pedals, the gearshift, etc.). Among such components, the one that interacts with the driver directly and continuously at all times between ingress and egress is the driver's seat. The driver's seat has multiple degrees of freedom, allowing adjustments of its position during driving. While many studies and standards have been proposed using different approaches for evaluating the accommodation level of vehicle interior components including the driver's seat, research gaps still exist concerning the understanding of variability in drivers' preference towards the driver's seat position, and the evaluation scheme for accurate evaluation of accommodation level that incorporates different types of variability in driver preference towards vehicle interior components.

Therefore, the following research questions were generated:

1) "What are the geometric and mathematical characteristics of driver-selected seat positions (DSSPs)?",

2) "How can we evaluate accommodation level of an adjustable product considering different types of variability in human preference?", and

3) "How can we evaluate accommodation level of a non-configurable product considering different types of variability in human preference?".

In order to address the research questions above, three studies were conducted. Study 1 investigated the characteristics of human preference data regarding drivers' preferred seat positions. Many previous vehicle ergonomics studies and standards have utilized DSSPs as a basis for evaluating the accommodation level of vehicle interior designs. However, little research has examined the basic characteristics of DSSPs. Therefore, Study 1 analyzed empirically obtained DSSPs to explore geometric, mathematical and statistical properties of individuals' DSSP point clouds, each consisting of repeatedly measured DSSPs. Six quantitative indices pertinent to the size, shape, orientation and location of a DSSP point cloud were employed. Normality of the DSSP point clouds, and, also, possible correlational relationships among the indices and those between the indices and selected anthropometric dimensions were statistically tested. The results suggested that 1) DSSP prediction and simulation modelling must reflect the unimodal, non-normal nature of individuals' DSSP distributions and the correlational structures identified, and 2) intra-individual as well as inter-individual variability in DSSP data needs to be considered in designing and evaluating seat adjustability features and other vehicle interior functions.

Study 2 proposed an interval estimation-based approach for evaluating the accommodation level of adjustable products. Designing adjustable products requires an accurate accommodation level evaluation method for determining their proper adjustable ranges. Previous methods have employed point estimation for representing an adjustable product's population accommodation level. However, a point estimate is limited in that it lacks information regarding variability/reliability of an estimated value. Therefore, Study 2 developed an interval estimation-based accommodation level evaluation method. The method consisted of two parts: 1) individual accommodation level was evaluated on the basis of a given adjustable range of a product and preferred configuration data obtained from multiple individuals, and 2) based on the obtained individual accommodation levels, population accommodation level was determined, and a confidence interval of the population accommodation level was generated. The descriptions of the new method are provided, along with a case study demonstrating how the method can be applied to a real-world design problem.

Study 3 developed a novel accommodation level evaluation method for non-configurable products. Among many types of products, a non-configurable, single-configuration-for-all product offers advantages over other product types, such as simplicity of design problem and manufacturing process, lower design and manufacturing costs, and less effort necessary in choosing the right product variant or configuration for consumers. Despite the advantages, however, the problem of

designing a non-configurable product for population accommodation has not been fully investigated. As an effort to address the problem of accommodation level evaluation for non-configurable products, Study 3 presented a novel design optimization method, which utilized empirically obtained human preference data for optimizing a product's configuration; and, in doing so, both the intra-individual as well as inter-individual variability in human preference were considered. A case study using an example design problem is provided to demonstrate the new design method.

The characteristics of DSSPs and the accommodation level evaluation methods presented through the studies would be useful knowledge for not only the design of driver's seat and vehicle interior components, but also the design of non-configurable/adjustable products in general.

Keywords: accommodation, adjustable product, driver-selected seat position, human preference, inter-individual variability, interval estimation, intra-individual variability, non-configurable product, product design

Student Number: 2014-31102

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Chapter 1

Introduction

1.1 Research background and outline

Designing vehicle interior components requires consideration of human variability in perception, behavior, and anthropometry. Accommodation level, which is an index of how well a product suits a population of users (Roe, 1993; Happian-Smith, 2002), needs to be analyzed and considered during the design process to ensure driver satisfaction and safety. It is essential that designers recognize the significance of designing for human variability in order to gain an accurate understanding of accommodation level of vehicle interior components.

Drivers interact with many different vehicle interior components, which are provided either as adjustable components (i.e., the seat, the steering wheel, the mirrors, etc.) or as fixed components (i.e., the pedals, the gearshift, etc.). Among such components, the one that interacts with the driver directly and continuously at all times between ingress and egress is the driver's seat. The driver's seat has multiple degrees of freedom, allowing adjustments of its position during driving. While many studies and standards have been proposed using different approaches for assessing the accommodation level of vehicle interior components including the driver's seat, research gaps still exist concerning the understanding of variability in drivers' preference towards the position of the driver's seat, and the evaluation scheme for accurate assessment of accommodation level that incorporates different types of variability in driver preference towards vehicle interior components.

Many studies and standards have been proposed using different approaches for assessing seating accommodation levels of different products/environments, including passenger cars and trucks (Parkinson and Reed, 2006; SAE International, 2008, 2011), exercise cycles (Garneau and Parkinson, 2013), and military vehicles (Zerehsaz *et al.*, 2017). However, research gaps still exist concerning the understanding of variability in driver preference towards the position of the driver's seat, and the evaluation scheme for an accurate evaluation of accommodation level for fixed/adjustable vehicle interior components that incorporates variability in driver preference.

Therefore, as efforts to address the research gaps, three research studies were conducted based on three research questions generated as follows:

1) What are the geometric and mathematical characteristics of driver-selected seat positions (DSSPs)?

2) How can we evaluate the accommodation level of an adjustable product considering different types of variability in human preference?

3) How can we evaluate the accommodation level of a non-configurable product considering different types of variability in human preference?

The current dissertation contains the results of three research studies that addressed each of the research questions listed above.

Study 1 investigated the characteristics of human preference data regarding drivers' preferred seat positions. Many previous vehicle ergonomics studies and standards have utilized DSSPs as a basis for evaluating the accommodation level of vehicle interior designs. However, little research has examined the basic characteristics of DSSPs. Therefore, Study 1 analyzed empirically obtained DSSPs to explore geometric, mathematical and statistical properties of individuals' DSSP point clouds, each consisting of repeatedly measured DSSPs. Six quantitative indices pertinent to the size, shape, orientation and location of a DSSP point cloud were employed. Normality of the DSSP point clouds, and, also, possible correlational relationships among the indices and those between the indices and selected anthropometric dimensions were statistically tested. The results suggested that 1) DSSP prediction and simulation modelling must reflect the unimodal, non-normal nature of individuals' DSSP distributions and the correlational structures identified, and 2) intra-individual as well as inter-individual variability in DSSP data needs to be considered in designing and evaluating seat adjustability features and other vehicle interior functions.

Study 2 proposed an interval estimation-based approach for evaluating the accommodation level of adjustable products. Designing adjustable products requires an accurate accommodation level evaluation method for determining their proper adjustable ranges. Previous methods have employed point estimation for representing an adjustable product's population accommodation level. However, a point estimate is limited in that it lacks information regarding variability/reliability of an estimated value. Therefore, Study 2 developed an interval estimation-based accommodation level evaluation method. The method consisted of two parts: 1) individual accommodation level was evaluated on the basis of a given adjustable range of a product and preferred configuration data obtained from multiple individuals, and 2) based on the obtained individual accommodation levels, population accommodation level was determined, and a confidence interval of the population accommodation level was generated. The descriptions of the new method are provided, along with a case study demonstrating how the method can be applied to a real-world design problem. It should be noted here that Study 2 was conducted as a follow-up study to Study 1, and that the dataset collected from Study 1 was again used for the case study presented in Study 2.

Study 3 developed a novel accommodation level evaluation method for non-configurable products. Among many types of products, a non-configurable, single-configuration-for-all product offers advantages over other product types, such as simplicity of design problem and manufacturing process, lower design and manufacturing costs, and less effort necessary in choosing the right product variant or configuration for consumers. Despite the advantages, however, the problem of designing a non-configurable product for population accommodation has not been fully investigated. As an effort to address the problem of accommodation level evaluation for non-configurable products, Study 3 presented a novel design optimization method, which utilized empirically obtained human preference data for optimizing a product's configuration; and, in doing so, both the intra-individual as well as inter-individual variability in human preference were considered. A case study using an example design problem is provided to demonstrate the new design method.

1.2 Dissertation outline

This dissertation consists of six chapters, three of which report the results of research studies regarding human preference and accommodation. All of the research studies have been carried out based on the three research questions defined previously.

In Chapter 1, an introductory outline of this dissertation is presented, including research background, research questions, and the overall structure of the dissertation.

Chapter 2 provides a review of previous literature on the body of knowledge on two main topics to be discussed in this dissertation – variability in human preference regarding drivers' preferred seat positions, and preference accommodation level evaluation methods.

Chapter 3 presents results of a study on driver-selected seat positions. The study investigated geometric and mathematical characteristics of driver preference with regards to seat position.

Chapter 4 is the first of two method development studies presented in this dissertation, presenting a novel accommodation level evaluation method for determining a proper adjustment range of an adjustable product.

Chapter 5 presents the second method development study, which is concerned with accommodation level evaluation method for determining a single optimal configuration for a non-configurable product.

Chapter 6 provides concluding remarks, including implications of the research and directions for future research.

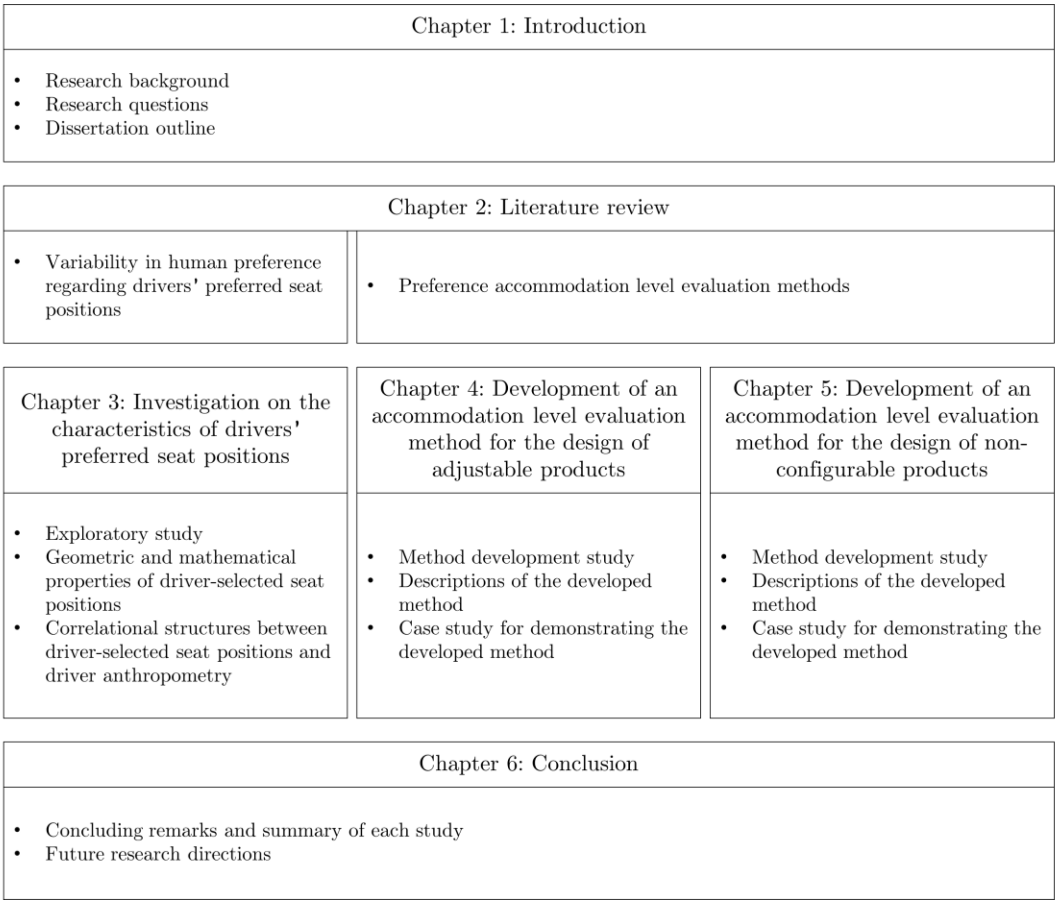


Figure 1.1: The overall structure of the dissertation.

Chapter 2

Literature review

2.1 Variability in drivers' preferred seat positions

Much research has been done to provide tools for designing and evaluating seat adjustment ranges on the basis of driver-selected seat position (DSSP) data.

Most notably, the Society of Automotive Engineers (SAE) has provided Recommended Practices, such as SAE J4004 (SAE International, 2008) and SAE J1517 (SAE International, 2011). SAE J4004 is a design guideline for seat track lengths of Class A vehicles (light trucks and passenger cars); SAE J1517, for those of Class B vehicles (heavy trucks and buses). These design guidelines, which were developed through analysing empirically obtained DSSP data, provide seating reference point (SgRP) curves corresponding to different driver accommodation percentages. The SgRP curves are utilized for determining H-point travel paths, that is, seat adjustment ranges, represented as either one-dimensional line segments or two-dimensional quadrilaterals. These travel paths account for the anthropometric variability in driver-selected seat positions.

In addition to the abovementioned standardized guidelines, multiple research studies have investigated applying empirical DSSP and driving posture data to the seat adjustment range design and other interior design problems.

Reed and Flannagan (2000) investigated on previously developed linear regression models that predicted DSSPs and driving postures utilizing driver anthropometric dimensions as predictors. This study pointed out that regression models have relatively large residual variances, which represent the variability that cannot be accounted for by driver anthropometry. The study suggested that such non-anthropometric variability, termed "postural variability", be considered when predicting driving postures to evaluate vehicle interior designs in driver population accommodation.

Some studies presented approaches for evaluating and optimizing vehicle interior designs for different vehicle station types, such as exercise cycles (Garneau and Parkinson, 2009) and military vehicles (Zerehsaz *et al.*, 2017). Garneau and Parkinson (2009) combined the regression models with stochastic simulation to evaluate vehicle interior designs. Zerehsaz et al. (2017) developed an analytical solution to a seat adjustment range determination problem. These studies utilized linear regression models that predicted a driver's DSSP and driving posture as functions of anthropometric variables. The residual terms of the regression models representing the non-anthropometric postural variability played an important role in design evaluation and solution generation.

With regards to the definition and understanding of variability that lies within each person and its effects toward the accommodation level of vehicles, Garneau and Parkinson (2013) utilized the concept of just noticeable difference (JND) to describe individual sensitivity to certain product configurations. This study applied JND to each of the person's preferred positions according to their sensitivities, and used the resulting data ranges for calculating percentile accommodation.

Peng, Wang and Denninger (2018) investigated the effects of seat height and anthropometric dimensions on preferred driving postures. This study found that preferred driving postures expressed in terms of intersegmental angles were not dependent on the anthropometric dimensions. It also revealed considerable inter-individual and intra-individual variability in the preferred driving posture and vehicle interior layout data.

2.2 Preference accommodation level evaluation methods

Many studies have been conducted as efforts to establish the definition of accommodation, and apply such definitions to accommodation level evaluation methods.

Parkinson and Reed (2006) presented an approach for optimizing driver accommodation by making it into a percentile accommodation problem, while considering the variance factors regarding sitting posture using regression.

Parkinson et al. (2007) investigated the optimization of truck cab layout for driver accommodation, which provided different design scenarios for truck cab layout by applying optimization techniques and virtual fitting to find the optimal adjustable ranges of the seat and the steering wheel, and the optimal height of the roof that can accommodate a certain percentage of the driving population.

Park et al. (2012) developed a method for quantifying driver accommodation levels of vehicle interior designs, which considers not only inter-individual but also intra-individual variability in DSSPs and driver-selected steering wheel positions. The proposed method was free of assumptions regarding the probability distribution of DSSP/steering wheel position data and utilized such data as-is in computing accommodation levels. The study empirically demonstrated that DSSPs and driver-selected steering wheel positions, when repeatedly selected by a driver, form a point cloud with certain geometric properties, and can exhibit a substantial degree of inter-trial, that is, intra-individual, variability.

Garneau and Parkinson (2013) utilized the concept of just noticeable difference (JND) and implemented it into artefact design optimization problem, which calculated and applied JND to each of the person's preferred positions according to their sensitivities, and used the resulting data ranges for calculating percentile accommodation.

Also, many studies on the evaluation of accommodation level using vehicle interior designs, occupant anthropometry, and postures have made use of manikins or avatars (Reed *et al.*, 1999; Park and Reed, 2018), computer-based modeling (Reuding and Meil, 2004; Vogt, Mergl and Bubb, 2005; Yang *et al.*, 2007), and regression analysis (Philippart *et al.*, 1984; Flannagan *et al.*, 1998; Reed *et al.*, 2002; Parkinson and Reed, 2006; Parkinson *et al.*, 2007) to accelerate the evaluation process. Although these types of approaches can save time and effort, they cannot incorporate intra-individual variability, as they are predictions extrapolated from a set of data obtained from humans.

Chapter 3

Investigation on the characteristics of driver-selected seat positions

3.1 Introduction

Among many interior components considered in the vehicle occupant packaging practice, the one that interacts with the driver directly and continuously at all times between ingress and egress is the driver's seat. The driver's seat in modern cars is adjustable with multiple degrees of freedom, allowing drivers to adjust to one of the seat positions they feel most comfortable for driving. Such a position is often referred to as a driver-selected seat position (DSSP). Accommodating individual drivers by supporting their DSSPs is important for ensuring driver performance, safety and experience.

DSSPs can vary significantly across different individuals. Providing a sufficiently large seat adjustment range is a straightforward solution to accommodating different individuals within the driver population. However, while increasing a seat adjustment range would certainly improve the level of population accommodation, it would, at the same time, incur additional design and production costs, and, also, could conflict with other engineering design considerations. Therefore, for appropriate sizing and placement of a seat adjustment range, design decisions must be made by analysing empirical data describing DSSPs.

Much research has been done to provide tools for designing and evaluating seat adjustment ranges on the basis of DSSP data. Most notably, the Society of Automotive Engineers (SAE) has provided Recommended Practices, such as SAE J4004 (SAE International, 2008) and SAE J1517 (SAE International, 2011). SAE J4004 is a design guideline for seat track lengths of Class A vehicles (light trucks and passenger cars); SAE J1517, for those of Class B vehicles (heavy trucks and buses). These design guidelines, which were developed through analysing empirically obtained DSSP data, provide seating reference point (SgRP) curves corresponding to different driver accommodation percentages. The SgRP curves are utilized for determining H-point travel paths, that is, seat adjustment ranges, represented as either one-dimensional line segments or two-dimensional quadrilaterals.

In addition to the abovementioned standardized guidelines, multiple research studies have investigated applying empirical DSSP and driving posture data to the seat adjustment range design and other interior design problems. Reed and Flannagan (2000) investigated linear regression models that predict DSSPs and driving postures utilizing driver anthropometric dimensions as predictors. The regression models have relatively large residual variances, which represent the variability that cannot be accounted for by driver anthropometry. The study suggested that such non-anthropometric variability, termed "postural variability", be considered when predicting driving postures to evaluate vehicle interior designs in driver population accommodation.

Some studies presented approaches for evaluating and optimizing vehicle interior designs for different vehicle station types, such as truck cabs (Parkinson *et al.*, 2007), exercise cycles (Garneau and Parkinson, 2009) and military vehicles (Zerehsaz *et al.*, 2017). These studies utilized linear regression models that predicted a driver's DSSP and driving posture as functions of anthropometric variables. The residual terms of the regression models representing the non-anthropometric postural variability played an important role in design evaluation and solution generation. Parkinson et al. (2007) and Garneau and Parkinson (2009) combined the regression models with stochastic simulation to evaluate vehicle interior designs. Zerehsaz et al. (2017) developed an analytical solution to a seat adjustment range determination problem.

Park et al. (2012) developed a method for quantifying driver accommodation levels of vehicle interior designs, which considers not only inter-individual but also intra-individual variability in DSSPs and driver-selected steering wheel positions. The proposed method was free of assumptions regarding the probability distribution of DSSP/steering wheel position data and utilized such data as-is in computing accommodation levels. The study empirically demonstrated that DSSPs and driver-selected steering wheel positions, when repeatedly selected by a driver, form a point cloud with certain geometric properties, and can exhibit a substantial degree of inter-trial, that is, intra-individual, variability.

Peng, Wang and Denninger (2018) investigated the effects of seat height and anthropometric dimensions on preferred driving postures. This study found that preferred driving postures expressed in terms of intersegmental angles were not dependent on the anthropometric dimensions. It also revealed considerable inter-individual and intra-individual variability in the preferred driving posture and vehicle interior layout data.

Despite the past research efforts, however, research gaps still exist concerning the understanding and utilization of DSSPs. One such gap pertains to geometric, mathematical and statistical characteristics of DSSP data at the single individual level, that is, at the level of a point cloud of DSSPs obtained from an individual driver. Surprisingly little research has examined DSSP point clouds of individuals and their geometric, mathematical and statistical properties. The lack of information seems to hinder further improving the modelling and prediction/simulation of DSSPs and its applications, including the seat adjustment range evaluation and optimization.

Therefore, the objective of the current study was twofold: to characterize and analyze DSSP point clouds of individuals employing quantitative indices and statistical tests pertinent to the size, shape, orientation, location and probability distribution of a DSSP point cloud, and, to explore possible correlational relationships among the indices and between the indices and a set of driver anthropometric dimensions. Practical implications of the analysis results on the prediction and simulation modelling of drivers' DSSP clouds are discussed.

3.2 Data collection

DSSPs were collected from 108 drivers (54 males and 54 females) recruited from the Auburn/Opelika area in Alabama, USA. The recruitment was done using advertisements and flyers, and only midsize sedan owners with a valid driver's license were recruited. The drivers were selected to represent a large variation of stature, body mass, and body mass index (BMI) (see Table 3.1 for the descriptive statistics). All drivers were informed of the experiment protocol, and signed an informed consent form prior to data collection. The experiment protocol was approved by the Institutional Review Board of Auburn University.

A seating buck, illustrated in Figure 3.1, was used for the data collection. It was equipped with a fixed pedal, a steering wheel with tilt angle adjustment and telescoping capabilities and a driver's seat with fore-aft and vertical adjustability. The adjustable ranges of the seat and the steering wheel were at least twice the ranges provided by conventional vehicles of different types/classes. The use of the large adjustable ranges was to ensure that 1) DSSPs would not be censored by the available adjustable ranges, and 2) DSSPs collected would not be specific to a particular vehicle design or particular vehicle categories but be relevant to various possible scenarios, including previous vehicle designs/categories. This is consistent with the fact that due to technological changes (e.g., electric vehicles, automated driving, etc.), more freedom is given and fewer constraints are imposed on vehicle interior design, and, different types of vehicle interiors are being explored in the automotive industry (Sun, Cao and Tang, 2021).

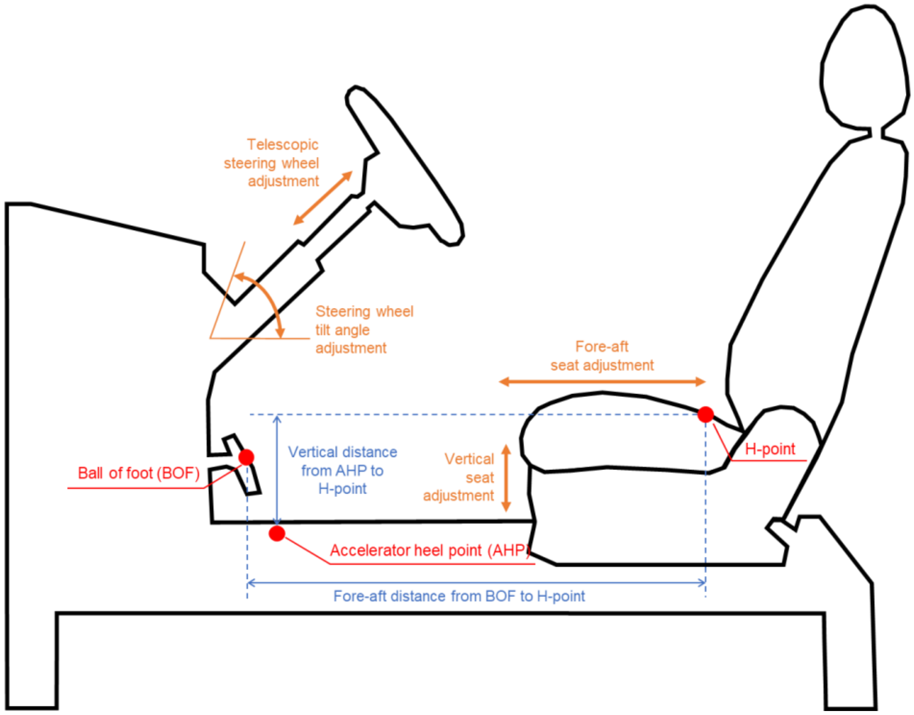


Figure 3.1: A graphical illustration of the seating buck used for data collection: reference points (in red), recorded seat positions (in blue), and available adjustments (in orange).

The drivers were first asked for their demographic information, which was then followed by a series of anthropometric measurements. The collected demographic/anthropometric data are summarized in Table 3.1.

Table 3.1: Summary of demographic and anthropometric data of the drivers.

Variable	Mean ± SD	Min.	Max.
Age (years)	38.81 ± 14.34	20	74
Stature (cm)	169.21 ± 9.92	149.0	193.0
Body mass (kg)	104.21 ± 26.07	48.76	177.35
Body mass index (kg/m^2)	36.26 ± 7.92	19.93	54.59
Shoulder-to-fingertip length (cm)	75.11 ± 7.04	60.6	99.2
Shoulder depth (cm)	13.35 ± 2.24	7.6	20.1
Bideltoid breadth (cm)	49.4 ± 5.24	38.7	65.7
ASIS height (cm)	94.36 ± 7.55	72.0	115.0
Inter-ASIS distance (cm)	33.48 ± 5.65	20.5	51.5
Sitting height (cm)	85.53 ± 4.87	71.1	99.9
Seated hip breadth (cm)	45.82 ± 7.09	29.5	70.2
Seated knee-to-buttock length (cm)	62.08 ± 5.35	39.6	72.5
Seated popliteal-to-buttock length (cm)	50.94 ± 3.77	41.3	66.0
Ankle width (cm)	7.04 ± 0.93	4.0	10.0

For each DSSP self-selection trial, each driver was asked to enter the seating buck and adjust the seat and the steering wheel to his/her most preferred configuration. Prior to each trial, the seat and the steering wheel were set to random initial configurations within their respective adjustment ranges. The randomization was done to minimize the effect of initial seat positions on self-selected positions, since our goal was to determine the spatial distribution of DSSPs for an individual, fully and without any systematic biases – relatedly, Peng, Wang and Denninger (2018) showed that initial seat positions affect self-selected seat positions. The order of adjustment for the two vehicle interior components was not specified. At the completion of the self-adjustment process, the fore-aft and vertical distances (in millimeters) between the ball of foot (BOF) and the center of the seat hinge that connects the seat pan and the seat back were recorded (see Figure 1). The fore-aft and vertical distances were then converted to fore-aft distance from BOF to H-point, and vertical distance from accelerator heel point (AHP) to H-point, respectively, measured according to definitions in SAE J826 (SAE J826, 2002). These distances were used to represent the DSSP position. Each driver repeatedly performed 21 self-selection trials, creating a point cloud of DSSPs (henceforth, a DSSP cloud) – this was done to capture as much of the underlying preference towards seat position as possible while preventing fatigue.

As a result, 2268 DSSPs were collected from the 108 drivers. After performing multivariate outlier detection and removal using the Mahalanobis distance method (Rousseeuw and van Zomeren, 1990), a total of 2259 DSSPs were used for all subsequent analyses.

3.3 Data processing and analyses

3.3.1 Indices for characterizing the DSSP cloud of each driver

A total of six indices were employed for characterizing each of the DSSP clouds gathered from the participants. The list of indices employed is provided in Table 3.2. The referent of each index, that is, what is being measured by each index, is also included in the table.

Table 3.2: List of indices employed for characterizing the DSSP cloud of each driver.

No.	Index	Referent
1	Number of modes in a DSSP cloud	Modality
2	MAEE area	Size
3	MAEE length-width ratio	Shape
4	MAEE angle	Orientation
5	Fore-aft position of MAEE centroid	Location
6	Vertical position of MAEE centroid	Location

Note: Indices 2~6 are determined for each cluster of points within a DSSP cloud.

Indices 2 to 6 are computed on the basis of the minimum area enclosing ellipse (MAEE) created using DSSPs of an individual driver. An MAEE is defined as the bounding ellipse with the minimal area of an individual DSSP cloud, as illustrated in Figure 3.2. In this study, MAEEs were determined and visualized using the mvee function included in package tlocoh in R (Moshtagh, 2005). Each of the six indices is described in detail in what follows.

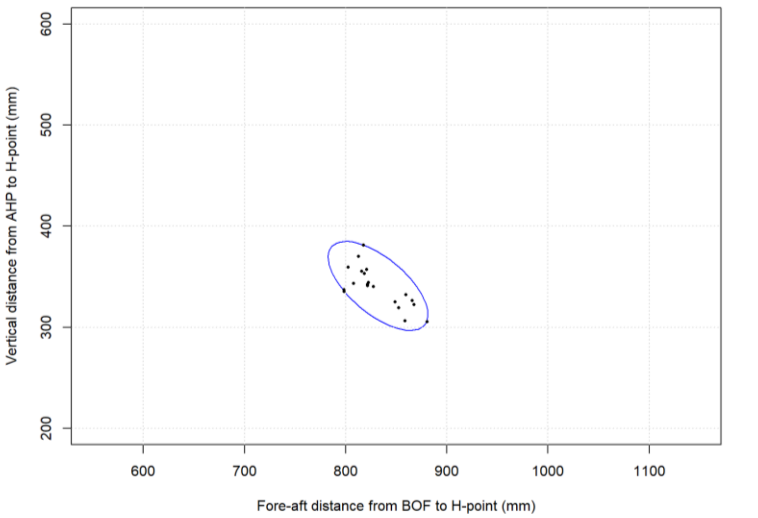
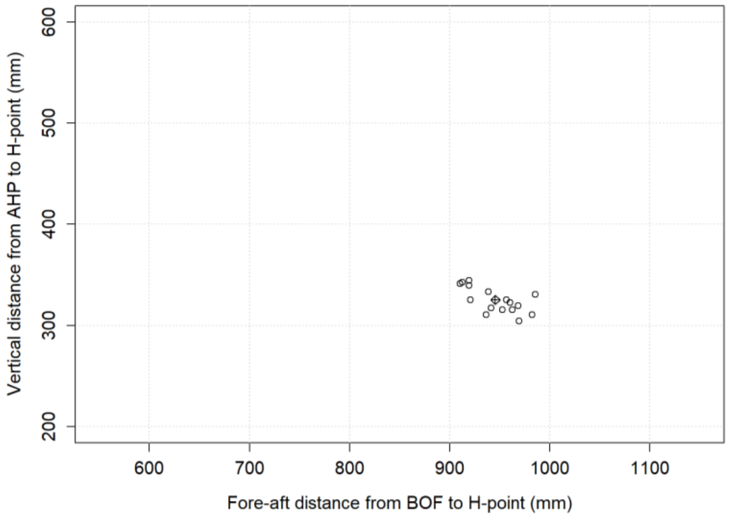


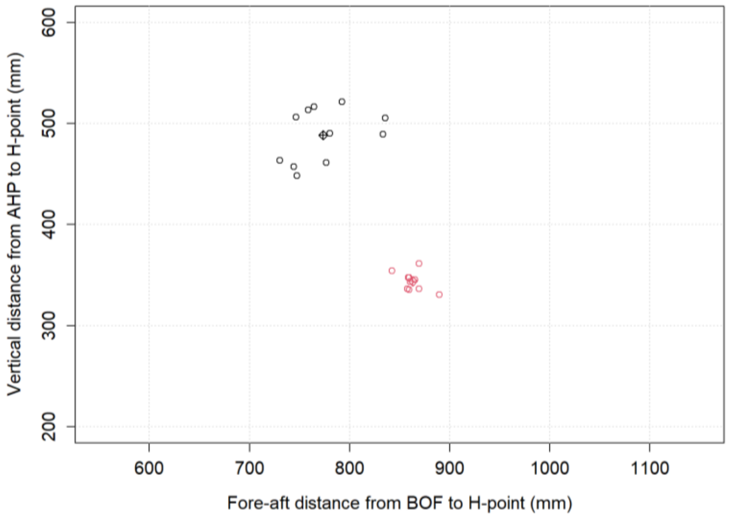
Figure 3.2: An example MAEE created from a DSSP cloud (dots).

Index 1. Number of modes in a DSSP cloud

Number of modes in a DSSP cloud describes the number of distinct regions that can be observed from DSSPs collected from a single driver. It is determined using the combination of the k-means clustering algorithm and the elbow method (Hastie, Tibshirani and Friedman, 2009; Gareth *et al.*, 2017). The elbow method heuristically determines the number of clusters (number of modes) by performing k-means clustering analyses for different values of k (1 to 10 in this study) and calculating the within-cluster sum of squared distances for each k. Then, based on the line chart of the within-cluster sum of squared distances, the value of k where the line shows a noticeable dip or an "elbow" (i.e., where the sum of squared distances falls drastically) is chosen as the optimal number of clusters. Example DSSP clouds with different numbers of modes are provided in Figure 3.3.



(a)



(b)

Figure 3.3: Example DSSP clouds with (a) a single mode and (b) two modes.

Index 2. MAEE area

MAEE area quantifies the size of a DSSP cloud of an individual. This index is related to the level of dispersion of DSSPs – the larger the MAEE area, the more dispersed the DSSPs. This index is calculated using the formula for the area of an ellipse (Equation (3.1)), where a is the length of the semi-major axis (half of the major axis length) and b is the length of the semi-minor axis (half of the minor axis length).

$$\text{MAEE area} = \pi ab \tag{3.1}$$

Index 3. MAEE length-width ratio

MAEE length-width ratio is defined as the ratio between the length of the major axis of an MAEE and that of the minor axis, which can be expressed as below (Equation (3.2)).

$$\text{MAEE length}-\text{width ratio} = \frac{\text{major axis length}}{\text{minor axis length}} \tag{3.2}$$

The ratio is greater than or equal to one since the major axis of an ellipse is always greater than or equal to its minor axis in length. This index describes the shape of an MAEE, specifically the degree of elongation of a DSSP cloud (or a cluster within it if it is multimodal) in a single direction.

Index 4. MAEE angle

MAEE angle is defined in this study as the angle between the major axis of an MAEE and the horizontal x-axis, as illustrated in Figure 3.4. This index describes the orientation of an MAEE, and, thus, that of a DSSP cloud. The possible values of MAEE angle range from -90° to 90°. A negative MAEE angle value denotes that the MAEE is trending downwards from front to rear, while a positive value denotes that the trend is upwards from front to rear. The value of 0° means that the MAEE is perfectly horizontal, while the values of -90° and 90° both indicate that the MAEE is perfectly vertical.

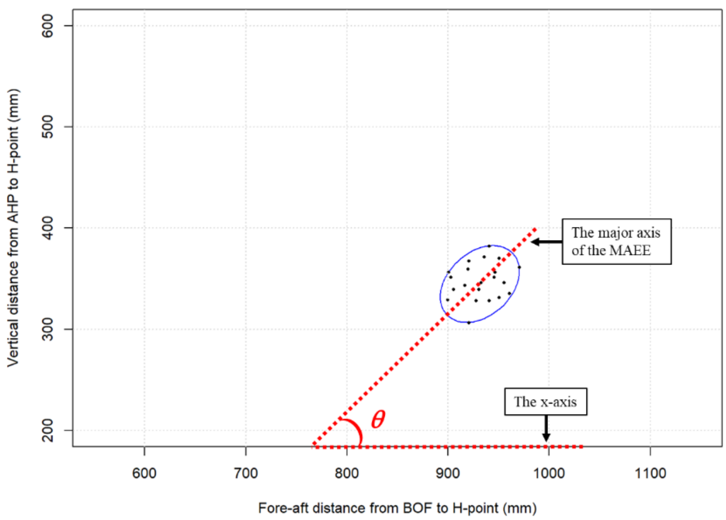


Figure 3.4: An example DSSP cloud with a positive MAEE angle (shown as theta) of 42°.

Index 5. Fore-aft position of MAEE centroid

Fore-aft position of MAEE centroid is defined as the x-coordinate of the centroid of an MAEE, that is, the horizontal (fore-aft) distance between the BoF reference point to the centroid of an MAEE. This index provides a representative value (measure of center) of the fore-aft locations of the DSSPs within a point cloud.

Index 6. Vertical position of MAEE centroid

Vertical position of MAEE centroid is defined as the z-coordinate of the centroid of an MAEE, that is, the vertical distance between the BoF reference point to the centroid of an MAEE. This index provides a representative value (measure of center) of the vertical locations of the DSSPs within a point cloud.

3.3.2 Statistical analyses

For number of modes in a DSSP cloud (Index 1), a basic frequency analysis was performed to count the numbers of drivers for each value of the index. Descriptive statistical analyses and visualizations were conducted for Indices 2 to 6. The goal of the descriptive statistical analyses was to characterize the basic features of the dataset for each index, especially focusing on the inter-individual differences. The descriptive statistics employed were: the mean, standard deviation, median and range. Histograms, bar graphs and scatterplots were utilized to visualize and describe the data distribution for each index. The visualizations were performed using Microsoft Excel and R.

In addition to the descriptive statistical analyses and visualizations for the indices, a series of multivariate normality tests were performed to determine if the DSSPs of each driver, and as well as those of all drivers combined, can be well-modelled by a normal distribution. Among many available multivariate normality tests, the Henze-Zirkler test was chosen – it had previously been recommended on the basis of its acceptable levels of Type I error control and power against different types of distributions (Mecklin and Mundfrom, 2000).

Also, in order to test the correlational relationships among the indices

(Indices 2~6) and those between each index (Indices 2~6) and each of the anthropometric variables listed in Table 3.1, Pearson correlation tests were conducted. The alpha level was set at 0.05. The magnitude of the correlation is often categorized into a number of descriptors, such as 'weak', 'moderate' and 'strong', based on rule-of-thumb cutoff points using the absolute value of the correlation coefficient. This study utilized the cutoff points for Pearson's r suggested by Davis (1971), which classified the correlation magnitude into five categories, 'very strong' ($r \geq 0.7$), 'substantial' ($0.5 \leq r < 0.7$), 'moderate' ($0.3 \leq r < 0.5$), 'low' ($0.1 \leq r < 0.3$) and 'negligible' ($0.01 \leq r < 0.1$). The correlation analyses were performed using the function rcorr in Hmisc package in R.

3.4 Results

3.4.1 Descriptive statistical analyses

<u>Number of modes in a DSSP cloud</u>

The k-means clustering analysis with the elbow method showed that 107 out of the 108 drivers produced unimodal DSSP clouds. The only exception was one driver (Driver 1), who produced a bimodal DSSP cloud (Figure 3.5). Driver 1 was excluded from the analyses using Indices 2 to 6 – this was to consistently assign one value to each participant for each of the indices.

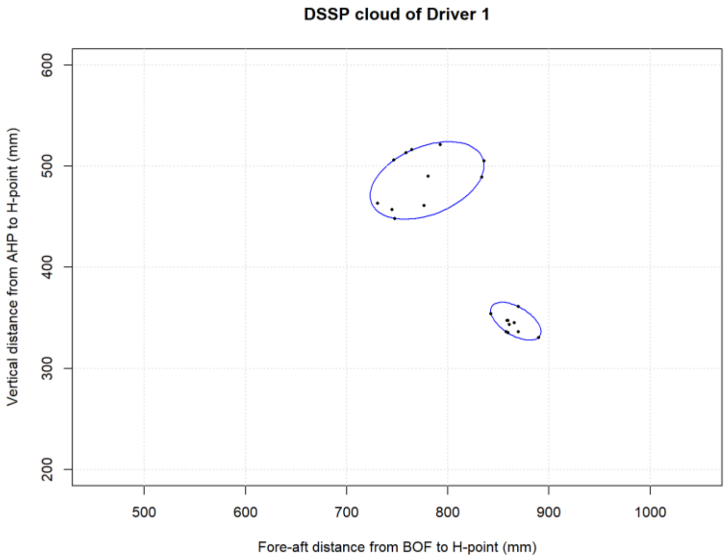
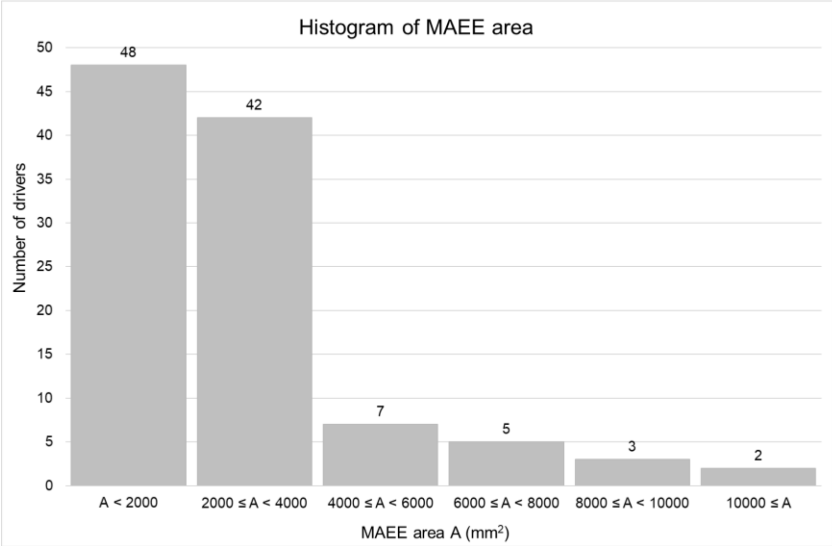


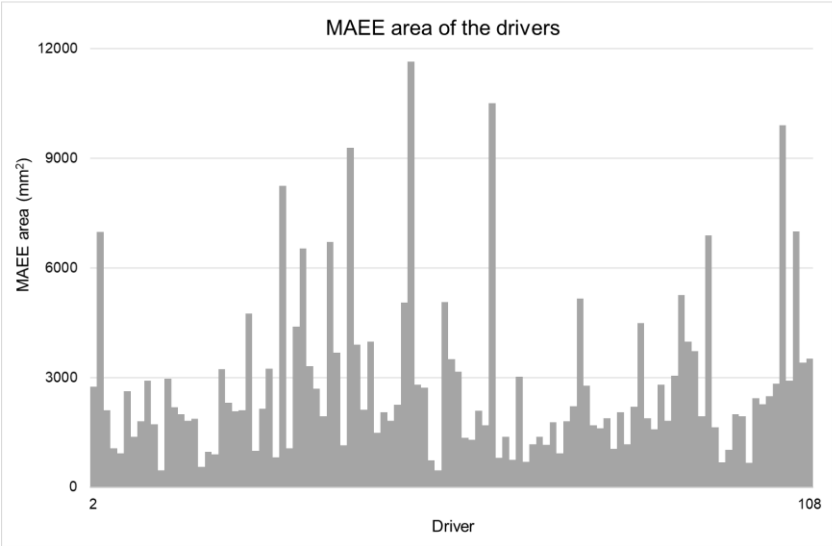
Figure 3.5: The single case of bimodal DSSP cloud produced by Driver 1.

MAEE area

MAEE area (Index 3) ranged from 454.13 mm^2 to 11643.33 mm^2. Its mean was 2777.18 mm^2 with the standard deviation of 2181.32 mm^2, and the median was 2097.95 mm^2. Most of the drivers (90/107) had MAEE area less than 4000 mm^2 (Figure 3.6(a)). Figure 3.6(b) presents a multiple-bar graph showing MAEE area of each of the 107 drivers.



(a)



(b)

Figure 3.6: Two visualizations of MAEE area: (a) histogram of MAEE area, and (b) multiple-bar graph of MAEE area of the 107 drivers.

MAEE length-width ratio

The mean and the standard deviation of MAEE length-width ratio (Index 2) were 1.90 and 0.73, respectively. This index ranged from 1.03 to 5.53, with the median of 1.71. A majority of the drivers (75/107) produced DSSP clouds with MAEE length-width ratio less than 2.0 (Figure 3.7).

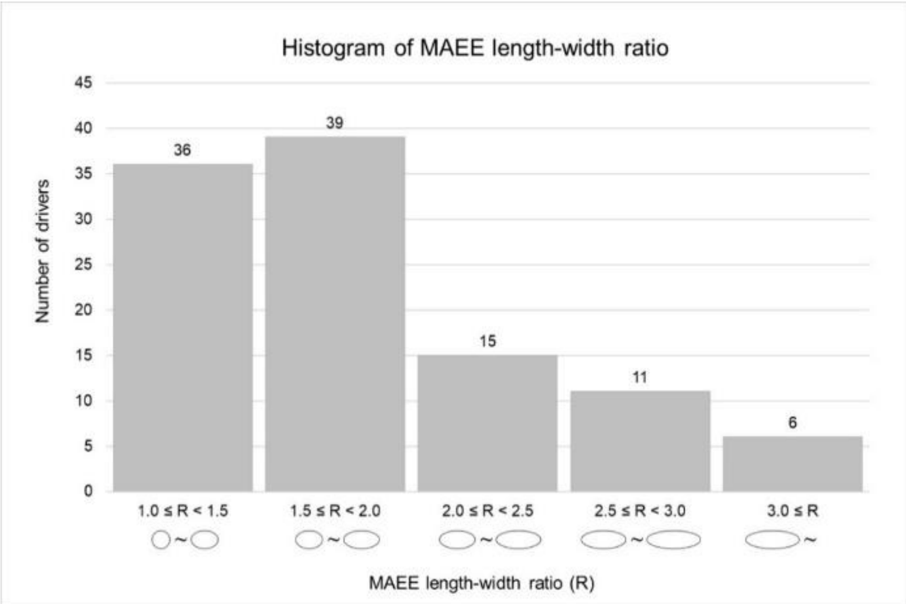


Figure 3.7: A histogram of MAEE length-width ratio. Below each bin is an ellipse or a pair of ellipses with the corresponding length-width ratios of the bin.

MAEE angle

As for MAEE angle (Index 4), the mean and the standard deviation were -11.13° and 40.04°, respectively. The minimum and the maximum were -85.60° and 88.26°; the median was -8.85°. Figure 3.8 presents a histogram showing the distribution of MAEE angle.

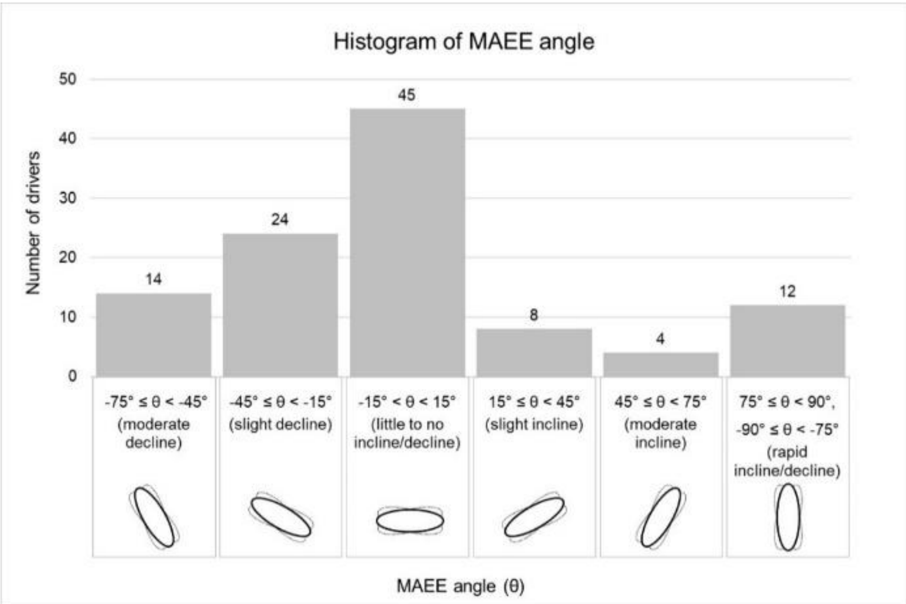


Figure 3.8: A histogram of MAEE angle. Bold ellipses represent the median angle of the respective bin, and dotted ellipses behind the bold ellipses represent the minimum and maximum angles of the bin.

Fore-aft and vertical positions of MAEE centroid

A scatterplot of MAEE centroids of the 107 participants is provided in Figure 3.9. The mean and the standard deviation of fore-aft position of MAEE centroid (Index 5) were 880.90 mm and 55.14 mm, respectively. The minimum and maximum values of fore-aft position of MAEE centroid were 755.96 mm and 1002.74 mm, respectively, and the median was 880.78 mm.

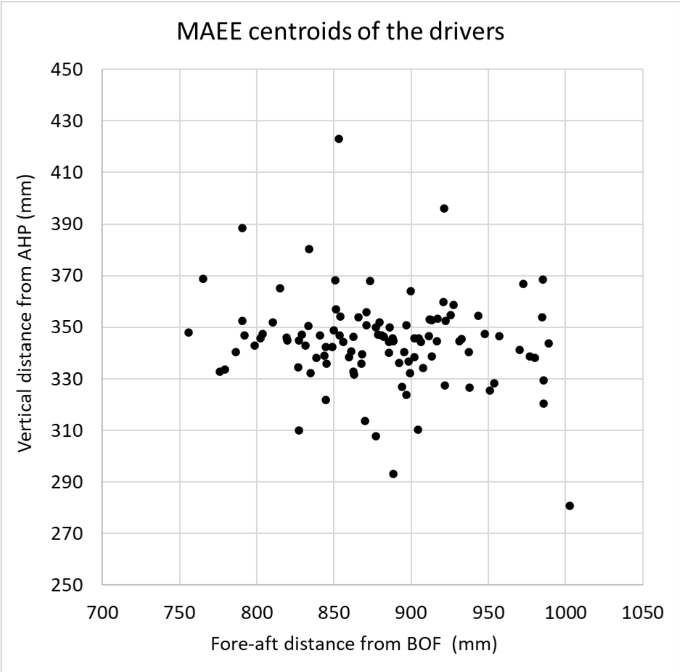


Figure 3.9: A scatterplot of MAEE centroids.

Vertical position of MAEE centroid (Index 6) showed the mean and the standard deviation of 344.25 mm and 17.90 mm, respectively. The minimum and maximum values of the index were 280.62 mm and 423.03 mm, respectively, with the median of 344.84 mm.

3.4.2 Multivariate normality tests

The Henze-Zirkler multivariate normality test was performed for each of the DSSP clouds produced by the drivers. The null hypothesis (the underlying distribution is multivariate normal) was rejected for 24 out of the 108 participants (22.2%) with p-values less than 0.05.

As for the multivariate normality of the entire dataset (the dataset consisting of the DSSPs of all participants), a chi-square Q-Q plot was drawn (Figure 3.10) in addition to performing the Henze-Zirkler test.

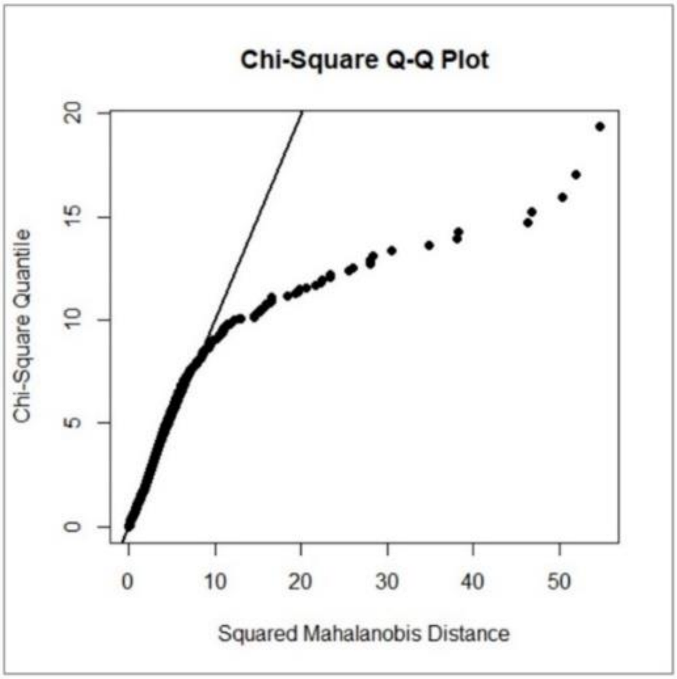


Figure 3.10: A chi-square Q-Q plot for the entire DSSP dataset.

If the dataset were indeed normally distributed, the points on the Q-Q plot would be aligned on the diagonal line, showing a linear pattern; instead, it showed a curved pattern, which suggests that the dataset is not well approximated by a normal distribution. The Henze-Zirkler statistic (HZ) was 14.815 with a p-value of less than 0.0001, indicating strong evidence that the dataset is not normally distributed.

3.4.3 Correlation analyses

The Pearson correlation coefficients between the indices are provided in Table 3.3. Four out of the 10 assessed pairs of indices showed statistical significance with p-values less than or equal to 0.05. Of the four significantly correlated pairs, fore-aft position of MAEE centroid (Index 5) showed a 'moderate' positive correlation ($r = 0.30$) with MAEE length-width ratio (Index 2), and vertical position of MAEE centroid (Index 6) showed a 'moderate' positive correlation ($r = 0.41$) with MAEE area (Index 3). The other pairs, that is, MAEE area and MAEE length-width ratio, and, vertical position of MAEE centroid and fore-aft position of MAEE centroid, showed 'low' correlations with Pearson correlation coefficients of 0.22 and –0.19, respectively.

Table 3.3: Pearson correlation coefficients between the indices (Indices 2~6).

	MAEE area (Index 2)	MAEE length-width ratio (Index 3)	MAEE angle (Index 4)	Fore-aft position of MAEE centroid (Index 5)	Vertical position of MAEE centroid (Index 6)
MAEE area (Index 2)	1				
MAEE length-width ratio (Index 3)	0.22*	1			
MAEE angle (Index 4)	-0.03	-0.01	1		
Fore-aft position of MAEE centroid (Index 5)	0.08	0.30**	0.03	1	
Vertical position of MAEE centroid (Index 6)	0.41**	0.09	0.06	-0.19*	1

* Correlation is significant at $\alpha = 0.05$.

** Correlation is significant at $\alpha = 0.01$.

The Pearson correlation coefficients between each index and each of the anthropometric variables are provided in Table 3.4. The Pearson correlation analysis results indicate that a total of nineteen pairs were correlated with statistical significance (p-values less than 0.05). Thirteen of those nineteen pairs were related to fore-aft position of MAEE centroid (Index 5), which showed 'low' positive correlations ($0.1 \leq r < 0.3$) with two anthropometric variables, 'moderate' positive correlations ($0.3 \leq r < 0.5$) with five anthropometric variables, and 'substantial' positive correlations ($0.5 \leq r < 0.7$) with six of the anthropometric variables. The rest of the statistically significantly correlated pairs (six of the nineteen pairs) showed 'low' positive correlations ($0.1 \leq r < 0.3$).

Table 3.4: Pearson correlation coefficients between each index (Indices 2~6) and each of the anthropometric variables.

	Stature	Body mass	BMI	Shoulder-to-fingertip length	Shoulder depth	Bideltoid breadth	ASIS height
MAEE area (Index 2)	0.19*	0.07	-0.02	0.16	-0.06	0.08	0.09
MAEE length-width ratio (Index 3)	0.20*	0.06	-0.02	0.18	0.01	0.09	0.18
MAEE angle (Index 4)	0.09	0.15	0.12	-0.02	0.04	0.06	0.06
Fore-aft position of MAEE centroid (Index 5)	0.62**	0.54**	0.30**	0.55**	0.28**	0.50**	0.33**
Vertical position of MAEE centroid (Index 6)	0.01	-0.03	-0.06	-0.15	0.02	-0.11	0.21*
	Inter-ASIS distance	Sitting height	Seated hip breadth	Seated knee-to-buttock length	Seated popliteal-to-buttock length	Ankle width	
MAEE area (Index 2)	0.03	0.09	0.12	0.04	0.00	0.19*	
MAEE length-width ratio (Index 3)	-0.01	-0.04	0.11	0.11	0.18	0.20*	
MAEE angle (Index 4)	0.09	0.19*	0.04	0.08	0.09	-0.07	
Fore-aft position of MAEE centroid (Index 5)	0.22*	0.32**	0.39**	0.50**	0.54**	0.39**	
Vertical position of MAEE centroid (Index 6)	-0.09	0.02	-0.08	0.09	-0.10	-0.02	

* Correlation is significant at $\alpha = 0.05$.

** Correlation is significant at $\alpha = 0.01$.

3.5 Discussion

Study 1 has explored the geometric, mathematical and statistical properties of DSSPs at the single individual's point cloud level using six MAEE-based quantitative indices (Table 3.1). Major research findings were as follows:

- Almost all of the drivers (107 out of 108) produced DSSP clouds with a single mode, showing little inter-individual variability.
- The DSSP clouds exhibited large inter-individual variability in MAEE area (Figure 3.6), MAEE length-width ratio (Figure 3.7) and MAEE angle (Figure 3.8).
- The MAEE centroid positions (Figure 3.9) showed large inter-individual variability, especially more in the fore-aft than in the vertical direction.
- The multivariate normality test results indicated that 24 out of the 108 DSSP clouds and also the entire DSSP dataset consisting of the individual DSSP clouds were non-normal.
- The correlation analyses for the MAEE index pairs (Table 3.3) found four significant correlations. Among them, the positive correlation between fore-aft position of MAEE centroid and MAEE length-width ratio, and, that between vertical position of MAEE centroid and MAEE area were 'moderate' in magnitude.
- Regarding the correlation analyses for the MAEE index-anthropometric

variable pairs (Table 3.4), fore-aft position of MAEE centroid was found to be significantly correlated with all of the 13 anthropometric variables considered in this study; on the other hand, the other indices were significantly correlated with only one or two anthropometric variables.

The observed unimodality in the DSSP clouds may be related to the findings from previous studies that investigated the ranges of comfortable joint angles for drivers (Porter and Gyi, 1998; Park *et al.*, 2000; Hanson, Sperling and Akselsson, 2006; Kyung and Nussbaum, 2009; Schmidt *et al.*, 2014; Peng, Wang and Denninger, 2017). The comfortable joint angle ranges were presented mostly in the form of a single continuous interval for each joint angle (degree of freedom). A combination of such single, continuous intervals of joint angles forms a single continuous comfortable region in the joint (posture) space spanned by the joint angles. The single continuous comfortable region in the joint space then leads to a single continuous comfortable region in the Cartesian (task) space for a body part position or the position of a vehicle interior element closely related to a body part, such as seat position. The observed unimodality is consistent with this notion.

It is worth noting that the finding on the dominance of unimodal DSSP clouds is consistent with the assumption of previous regression-based posture prediction models for evaluating interior designs in terms of driver population accommodation (Reed and Flannagan, 2000; Parkinson *et al.*, 2007; Garneau and Parkinson, 2009; Zerehsaz *et al.*, 2017) – the regression models implicitly assumed the unimodality of the DSSP distribution of an individual.

The three indices, MAEE area (Figure 3.6), MAEE length-width ratio (Figure 3.7) and MAEE angle (Figure 3.8), characterize the intra-individual variability or the inter-trial variability within the set of DSSPs repeatedly obtained from an individual. The results in Figures 3.6~3.8 indicate that the inter-individual variability in the intra-individual variability indices was substantial.

While it is not entirely clear what gave rise to the intra-individual variability observed in each driver, some possible origins are discussed in what follows. Determining a DSSP is essentially a search process with the goal of finding a desirable seat position in terms of preference. This involves repeating incrementally changing the seat position and evaluating the preference level associated with each particular seat position visited. The intra-individual variability (manifested as a "non-point" DSSP cloud) may arise during this process for the following reasons: first, the human information processing system has inherent limitations in proprioceptive acuity (Sigmundsson, Whiting and Loftesnes, 2000), which is the ability to sense joint positions, movements and forces. This limitation may inhibit drivers from distinguishing certain postures (and, therefore, corresponding seat positions) in a close proximity. Second, the internal function of postural preference perception (a function that maps a posture to its preference level) may yield multiple or a range of optimal postures that are equal in terms of preference level. In such a case, the search would stop when any one of the optimal, equally preferred postures is found. Finally, the search process may not be a strict optimization process but rather a satisficing one in which the search terminates when a satisfactory solution (seat position) is found. Related to this, the satisficing model of Simon (1956) states that it is human's rational behavior that in any item-by-item search process, the search stops not when an ideal or optimal condition is met, but when an acceptable threshold is met.

The inter-individual variability in the descriptors of the intra-individual variability (MAEE area, MAEE length-width ratio and MAEE angle) may be explained by individual differences in the abovementioned concepts – that is, individual differences in proprioceptive acuity (Adamo, Martin and Brown, 2007; Adamo, Alexander and Brown, 2009; Tsay *et al.*, 2020), those in the mathematical characteristics of the internal preference function and those in the level of satisficing behavior (the degree to which a satisfactory but non-optimal solution is accepted during a search process). In addition, different individuals may have different notions of postural preference in the context of driving. An individual's internal decision criterion or principle for selecting a preferred seat position has been hypothesized using different constructs, such as bodily discomfort/comfort (Zhang, Helander and Drury, 1996; Helander and Zhang, 1997; Kyung and Nussbaum, 2008; Kyung, Nussbaum and Babski-Reeves, 2008), muscular effort (Branton, 1969; Gyi and Porter, 1998; Gkikas, 2012) and body movement efficiency (Kolich, 2000). Also, an individual's postural preference could be related to human perceptions occurring at different parts of the physical human-machine interface, such as the seat, the steering wheel and the pedals. In selecting a DSSP, different individuals would likely use different decision criteria (for example, differently weighted combinations of the above-mentioned constructs and perceived qualities), which would naturally contribute to the inter-individual variability in the shape and size of a DSSP cloud.

The observation that fore-aft position of MAEE centroid varied far more than vertical position of MAEE centroid (Figure 3.9) may be explained by the general characteristics of a driving posture. A driving posture typically involves sitting with the upper leg segments approximately parallel to the floor and a knee included angle much greater than 90 degrees. Simple geometry and basic statistics tell us that the anthropometric variability in the dimensions of the leg segments affects the average hip joint position (and, therefore, MAEE centroid) more in the horizontal than the vertical direction.

The multivariate normality test results indicated that for a significant portion of the participants (24 out of the 108), the DSSP data at the individual level did not follow a normal distribution; nor did the pooled dataset. With regards to such results, it is worth pointing out that some previous research studies that evaluated vehicle interior designs in terms of driver accommodation assumed the normality of the DSSP distribution (Reed and Flannagan, 2000; Parkinson *et al.*, 2007; Garneau and Parkinson, 2009; Zerehsaz *et al.*, 2017). These studies utilized regression-based models for posture prediction, which were predicated upon the assumption that the underlying DSSP data and the residual variances in the models are normally distributed. While it is not certain how much the normality assumption would affect the accuracy of driver accommodation evaluation, creating new evaluation methods that do not require such an assumption may be desirable.

The correlation analysis results (Tables 3.3 and 3.4) describe the correlational structure within the MAEE indices and also the relationships between the anthropometric variables and the MAEE indices. Table 3.3 shows that some pairs of the MAEE indices covaried while others did not – some of the significant correlations, for example, the correlation between vertical position of MAEE centroid and MAEE area and that between fore-aft and vertical position of MAEE centroid, are thought to have resulted, at least partly, from inherent geometric relationships between the indices.

One notable observation from Table 3.4 was that fore-aft position of MAEE centroid showed significant correlations with anthropometric dimensions of different kinds – the index was found to be correlated with all of the 13 anthropometric dimensions that include length, width, depth and breadth dimensions in addition to body mass and BMI; 11 out of the 13 significant correlations were 'substantial' or 'moderate' in magnitude according to the cutoff points suggested by Davis (1971). On the other hand, the other MAEE indices showed 'low' correlations with only one or two anthropometric dimensions.

The significant correlations between fore-aft position of MAEE centroid and the anthropometric dimensions of different kinds seem mainly due to the general characteristics of a driving posture mentioned earlier. A driving posture typically involves sitting with the upper leg segments approximately parallel to the floor and a knee extension angle far greater than 90 degrees. This postural configuration gives rise to a positive linear relationship between the fore-aft position of a DSSP and the upper and lower leg segment lengths; and, the positive linear relationship in turn seems to result in correlations between fore-aft position of MAEE centroid and the length dimensions that are naturally correlated with the leg segment lengths, that is, stature, shoulder-to-fingertip length, ASIS height, sitting height, seated knee-to-buttock length and seated popliteal-to-buttock length.

Also, in a typical driving posture, the volumes of the body segments of a driver, such as the abdomen and buttocks, affect the DSSP in the fore-aft direction – accommodating high-BMI drivers with larger volumes of the abdomen and buttocks requires more room between the steering wheel and the seatback and therefore results in an increase in the fore-aft position of DSSPs (Jeong and Park, 2017). Body mass, BMI and the width/depth/breadth dimensions in Table 4 are naturally correlated with the volumes of the abdomen and buttocks and this may account for their positive correlations with fore-aft position of MAEE centroid.

The dearth of significant correlations between the other MAEE indices and the anthropometric dimensions seems to be because the indices do not have geometrically apparent positive/negative linear relationships with the anthropometric dimensions. Especially, as discussed earlier, the descriptors of the intra-individual variability (MAEE area, MAEE length-width ratio and MAEE angle) are thought to be related to perceptual/cognitive processes rather than anthropometry.

Some practical ergonomics implications from the current study findings are provided in what follows, focusing on the DSSP prediction modelling and its applications. First, based on the overall findings on the modality and normality of the DSSP clouds, it is recommended that future studies on the DSSP prediction modelling adopt the unimodality assumption, and reject the normality assumption.

Second, the correlation analysis results in Tables 3.3 and 3.4 may inform future efforts for the DSSP prediction modelling and the development of vehicle interior design evaluation tools. For example, the authors are currently developing a novel algorithm for stochastically simulating DSSP clouds of a driver sample (individuals with known anthropometry). In this simulation algorithm, an MAEE serves as a simplified representation of a DSSP cloud – the algorithm simulates a single driver's DSSP cloud by stochastically generating the values for the five MAEE indices (MAEE area, MAEE length-width ratio, MAEE angle, fore-aft position of MAEE centroid and vertical position of MAEE centroid) that specify an MAEE. The correlation analysis results in Tables 3.3 and 3.4, as well as the empirically derived probability distributions of the MAEE indices in Figures 3.6, 3.7, and 3.8, led to the following decisions concerning the algorithm for MAEE simulation. First, a random forest regression model is used to predict fore-aft position of MAEE centroid in a deterministic fashion for a given driver with known anthropometry. The model is parameterized with the thirteen anthropometric dimensions collected in this study, as all of the anthropometric dimensions were statistically significantly correlated with fore-aft position of MAEE centroid (Table 3.4). Second, residual analyses are performed to add a stochastic component (a normal residual term) to the random forest model, which would provide some 'data-guided' randomness to each prediction of fore-aft position of MAEE centroid. Third, the rest of the MAEE indices (MAEE area, MAEE length-width ratio, MAEE angle, and vertical position of MAEE centroid) are determined by a Monte Carlo simulation based on an empirical joint probability density function of the four MAEE indices. Here, kernel density estimation is used to generate a joint probability density function, and the indices are sampled using Gibbs sampling algorithm (Geman and Geman, 1984). Finally, using the five values of MAEE indices generated, an MAEE is simulated – running multiple iterations of this process using multiple individuals creates a set of MAEEs representing a virtual population of drivers, which in turn enables evaluation of a proposed seat adjustment range in terms of a driver population accommodation level.

Third, the correlation analysis results shown in Table 3.4 indicate the inherent difficulty in accurately predicting DSSPs of a particular individual solely based on the individual's static anthropometric characteristics, without collecting some DSSP samples from the individual. This also suggests that it is difficult to develop a personalized seat position or interior setting recommendation system that does not require collecting example DSSP data from the individual driver. Further research is needed to identify factors that allow accounting for the non-anthropometric variability; or, as an alternative, research may be directed towards developing methods for efficiently collecting individuals' DSSPs with minimal efforts and costs and utilizing the information in predicting user preferences.

Fourth, the large inter-individual variability in the intra-individual variability descriptors (the size, shape and orientation of the DSSP clouds) has some implications in relation to the design of seat adjustability feature and other seat-related functions. For a driver with a small DSSP region, helping the driver to efficiently find one of the seat positions in the region is important. For a driver with a large DSSP region, less so; and, for such a driver, it may be possible for an automated system to recommend different seat positions within the region at different times, according to driving context or for reducing postural fixity (Grieco, 1986) – drivers tend to alter driving posture intermittently to reduce postural fixity and related discomfort (Andreoni *et al.*, 2002; Dhingra, Tewari and Singh, 2003).

Chapter 4

Development of an accommodation level evaluation method for the design of adjustable products

4.1 Introduction

Quantifying how well a designed artifact accommodates a target user population is an important research topic in ergonomics and product design. Accommodation level is a metric often used for representing the proportion of users that can achieve a targeted level of fit or comfort while using a certain product (Roe, 1993; Happian-Smith, 2002; Dainoff *et al.*, 2004).

Accommodation can be achieved through various product design methods, and one of the more desirable methods is to add adjustability to one or more dimensions of a product, or "designing for adjustable range" (Sanders and McCormick, 1982; Wickens *et al.*, 2014). Adjustable products, such as office chairs and vehicle seats with multiple degrees of freedom, allow users to change physical dimensions or configurations (e.g., length, width, position, and orientation) within certain adjustable ranges, increasing the chance of providing fitting/comfortable configurations for a wide range of users. Providing a large adjustable range would naturally increase a product's accommodation level towards the target population; however, an adjustable range must be determined carefully as an increased adjustable range may translate into an increase in manufacturing cost and/or physical space/clearance required to support adjustability. Generally, it is necessary to search for an adjustable range of minimal size and/or cost without compromising population accommodation (Jung, 2005; Nadadur, Raschke and Parkinson, 2016).

The search for a proper adjustable range of a product needs to be accompanied by the development of an appropriate accommodation level evaluation method that can accurately quantify accommodation level and help design decision making. Some previous studies have developed schemes for evaluating accommodation levels of different adjustable products. Park *et al.* (2012) developed an index, which quantified accommodation levels of adjustable vehicle seat and steering wheel at both the individual and the population levels, considering not only inter-individual but also intra-individual variability in drivers' preferred positions for the seat and steering wheel. Garneau and Parkinson (2013) employed the psychophysical concept of just noticeable difference for describing each individual's intra-individual variability in preferred bicycle saddle height. The study modelled each individual's most preferred bicycle saddle height as a normal random variable and evaluated the population accommodation level of a given adjustable range using virtual fitting trials. Zerehsaz *et al.* (2017) proposed a regression-based, analytical solution to a seating accommodation problem for soldiers in military vehicles. The study developed the solution based on preferred seat configuration data obtained while wearing different levels of body armor and body-borne gear.

One common aspect of the previous studies is that they described a product's population accommodation level as a point estimate. A point estimate of an accommodation level has its advantages in that it provides a single convenient numerical summary for designers to refer to in assessing a product's population accommodation level. However, a point estimate has some inherent limitations as follows. First, a point estimate does not provide information regarding the precision of an estimated accommodation level (Navidi, 2006). The precision information is crucial for understanding the variability of a product's accommodation level, which is related to the reliability of the obtained accommodation level. Second, a point estimate does not have the capability of testing for statistical significance in the difference between accommodation levels of multiple designs. Having this capability is important for determining whether or not the evaluated accommodation levels of multiple adjustable range designs indeed significantly differ from one another, which would help facilitate the search for a proper (cost-effective/cost-efficient) adjustable range of a product. All in all, a point estimate provides limited information about a product's accommodation level, which hinders accurate assessment of a product's accommodation level and proper design decision making necessary for ensuring product safety, improving user experience, and increasing product profitability (Dainoff *et al.*, 2004). Utilizing interval estimation for accommodation level evaluation would be a remedy for overcoming such limitations associated with point estimation.

Therefore, the objective of the current study is to propose a novel evaluation method that employs not only point estimation, but also interval estimation in the assessment of a product's accommodation level. The rest of the paper describes the method, illustrates the use of the method using a case study, and provides discussions.

4.2 Methods

This section consists of three elements that describe the developed accommodation level evaluation method: individual accommodation level evaluation, point estimation of population accommodation level, and interval estimation of population accommodation level.

4.2.1 Individual accommodation level evaluation

This section focuses on evaluating the individual accommodation level provided by a given adjustable range. Individual accommodation level can be defined as the probability that a set of fitting product configurations (henceforth, FPCs) selected using a certain criterion (e.g., comfort, safety, and preference) for a single individual fall within a given adjustable range. Such individual accommodation level (denoted as A_i in Equation (4.1)) can be mathematically written as follows:

$$A_i = P(X \in AR) = \int_{AR} \dots \int f([x_1, \dots, x_N]) dx_1 \dots dx_N \tag{4.1}$$

where X is a set of FPCs of an individual for N number of dimensions (denoted as $[x_1, \dots, x_N]$) of a product, AR is a given adjustable range, and $f(X)$ is the probability density function of FPCs. For example, A_i of zero means that none of the FPCs of an individual falls within the given adjustable range, and, thereby, the provided adjustability completely disaccommodates the individual. A graphical illustration of

A_i for a univariate case is shown in Figure 4.1.

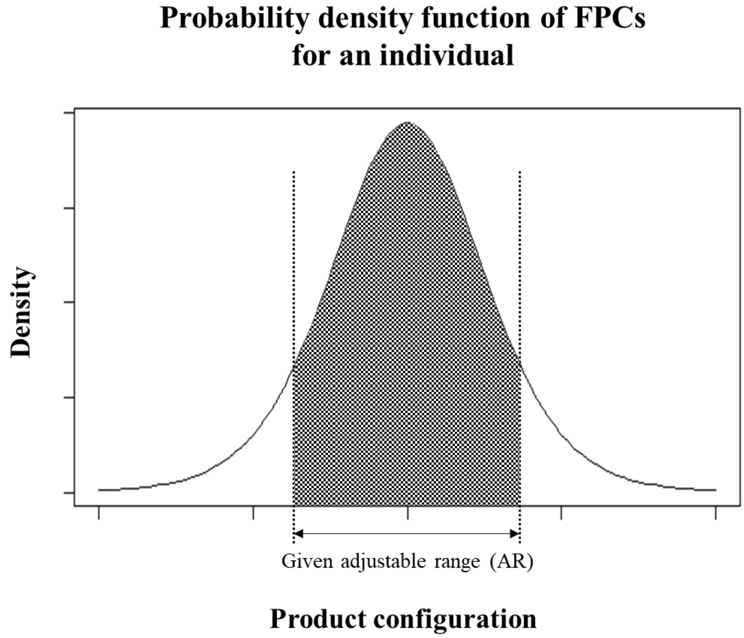


Figure 4.1: A graphical representation of A_i (shaded area).

Since an individual's probability density function of FPCs (f(X) in Equation (4.1)) is unknown in general, individual accommodation level cannot be computed mathematically using Equation (4.1); however, it can be estimated from a sample of FPCs empirically collected/generated by the individual. Consider a situation where FPCs of an individual are empirically collected/generated through multiple selection trials of mutual independence. Each FPC is either included within a given adjustable range or not, and the probability of an FPC being included within the adjustable range is the same for each independent selection trial. Therefore, each FPC selection trial can be interpreted as a Bernoulli trial with the probability of success (that is, the probability of an FPC being included within a given adjustable range), A_i; and, the entire FPC selection process, as a binomial experiment. The sample proportion of the FPCs that are included in an adjustable range (denoted as $\widehat{A_i}$ in Equation (4.2)) can be computed as follows:

$$\widehat{A_i} = \frac{n_{acc}}{n_{total}} \tag{4.2}$$

where n_{acc} represents the number of FPCs included in the adjustable range, and n_{total} represents the total number of FPCs obtained from each individual; and, therefore, each $\widehat{A_i}$ is greater than or equal to zero, and less than or equal to one. The accommodation level at the individual level, A_i, could be estimated using $\widehat{A_i}$ for it is an unbiased estimator of individual accommodation level when there is an enough number of samples, ntotal. Figure 4.2 shows an example of $\widehat{A_i}$ calculation – in this example, 17 out of 20 FPCs were included in the given adjustable range resulting in $\widehat{A_i}$ of 0.85 (85%).

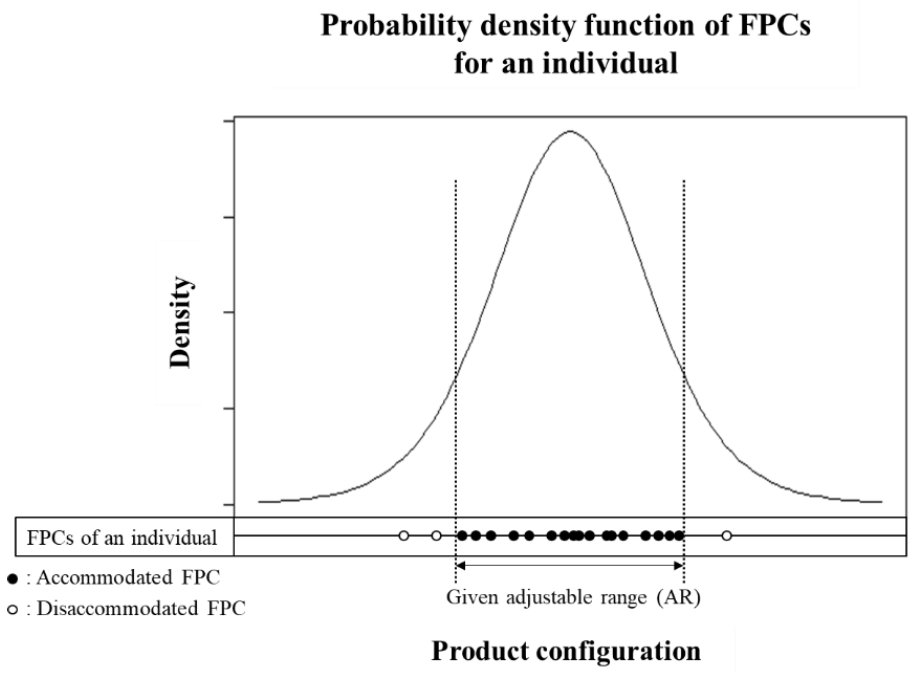


Figure 4.2: A graphical representation of an individual's FPCs and their accommodation based on a given adjustable range.

4.2.2 Point estimation of population accommodation level

$\widehat{A}_\iota$ defined in the previous section serves as a basis for estimating the accommodation level provided to a population of users by a designed adjustable range. Theoretically, each individual has a value of $\widehat{A}_\iota$ for a given adjustable range – if each individual performs multiple FPC selection trials, then $\widehat{A}_\iota$ can be determined. Consequently, population accommodation level can be thought of as the proportion of the user population that receives $\widehat{A}_\iota$ greater than or equal to a certain predetermined accommodation threshold. Such proportion (denoted as A_p

in Equation (4.3)) can be mathematically represented as follows:

$$A_p = \int_t^1 g(Y)dY = 1 - \int_0^t g(Y)dY \quad (4.3)$$

where Y denotes $\widehat{A_i}$, $g(Y)$ denotes the probability density function of $\widehat{A_i}$, and t denotes an accommodation threshold value. Figure 4.3 visually describes Equation (4.3).

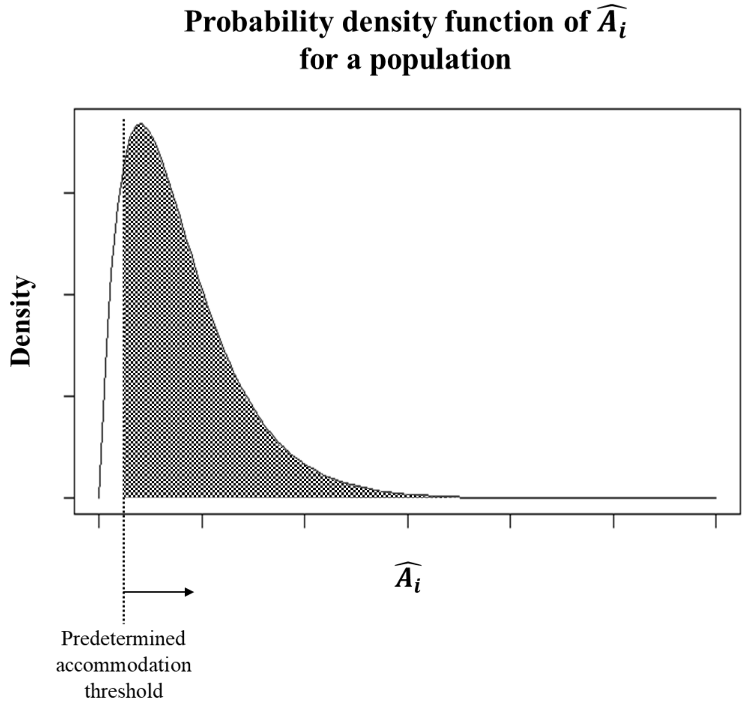


Figure 4.3: A graphical representation of A_p (shaded area).

Similar to the individual user's FPC distribution discussed in the previous section, the probability density function of $\widehat{A_\iota}$ is, in general, unknown, which makes Equation (4.3) not suitable for computing the population accommodation level; however, it can be estimated from samples of $\widehat{A_\iota}$ empirically obtained from a sample of individuals. Consider an empirical data collection process in which each individual in a sample performs multiple FPC selection trials. Each individual in the sample receives a value of $\widehat{A_\iota}$ for a certain adjustable range according to Equation (4.2). The probability of accommodation (that is, having $\widehat{A_\iota}$ greater than or equal to a certain threshold value) is A_p in Equation (4.3), and is the same for each individual from the user population. Therefore, deciding if each individual in the sample is accommodated or disaccommodated is independent across individuals, and thus can be thought of as a Bernoulli trial with the probability of accommodation, A_p; and, the data collection process, as a binomial experiment. The proportion of a sample of individuals accommodated by an adjustable range (denoted as $\widehat{A_p}$ in Equation (4.4)) can be computed as follows:

$$\widehat{A_p} = \frac{m_{acc}}{m_{total}} \tag{4.4}$$

where m_{acc} represents the number of individuals considered as accommodated based on an accommodation threshold value, and m_{total} is the total number of individuals. Similar to $\widehat{A_i}$ described in the previous section, $\widehat{A_p}$, with a sufficient number of individuals, is an unbiased estimator of population accommodation level, and, thus, could be used for estimating A_p. Figure 4.4 provides a graphical representation of $\widehat{A_p}$, showing 18 out of 20 individuals accommodated for $\widehat{A_p}$ of 90%.

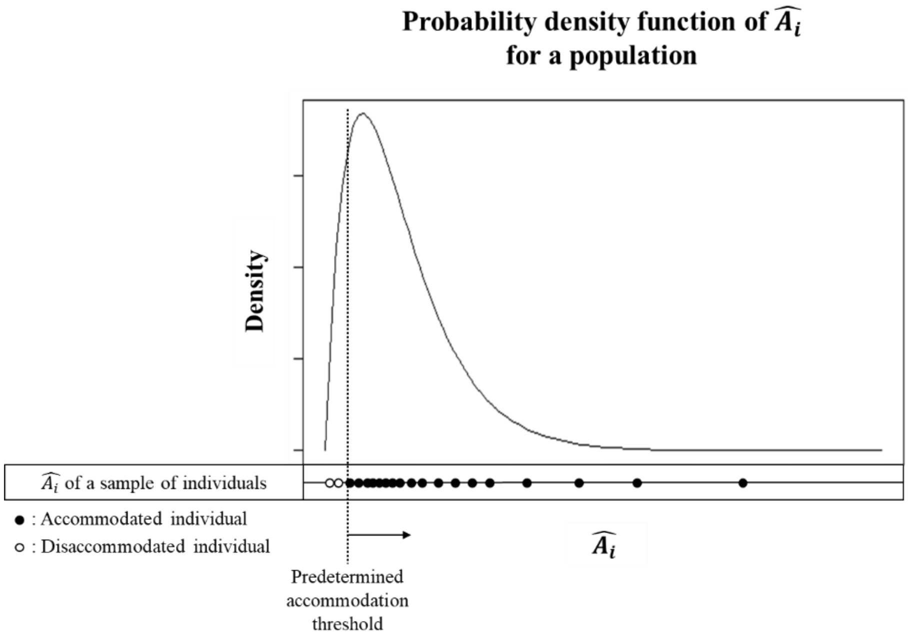


Figure 4.4: A graphical representation of $\widehat{A_i}$ obtained from a sample of individuals and their accommodation based on a certain predetermined accommodation threshold.

A couple of points regarding the use of accommodation threshold are noted here. First, in estimating the population accommodation level, the ability to control accommodation threshold quantitatively is beneficial because it may help designers see differences between alternative designs. In other words, by controlling the accommodation threshold, some designs may stand out as better-accommodating designs (that is, designs that yield many high-$\widehat{A_\iota}$ individuals). For example, two designs that show similar $\widehat{A_p}$ when a low accommodation threshold is imposed may in fact have substantially different $\widehat{A_p}$ when imposed with a high accommodation threshold. Second, determining an appropriate accommodation threshold value is crucial for accurate evaluation of $\widehat{A_p}$. An inherent relationship between accommodation threshold and $\widehat{A_p}$ is that as accommodation threshold increases, $\widehat{A_p}$ decreases, and vice versa. It is possible to simply lower the accommodation threshold value and achieve high $\widehat{A_p}$; however, in some cases, it may be inadequate to decrease the accommodation threshold value for the sheer purpose of increasing $\widehat{A_p}$. For example, imposing a stringent accommodation threshold value (that is, a value closer to 100%) may be necessary for safety-critical products that require the adjustable ranges to support as many FPCs as possible to maintain a high level of safety. In such cases, it would be inevitable to increase the adjustable range (which would translate to increased manufacturing cost) in order to achieve a decent $\widehat{A_p}$ (e.g., 90%, 95%, and 99%) while maintaining a high accommodation threshold value. Therefore, there exists a trade-off relationship where one can either lower the accommodation threshold value or increase the adjustable range (cost) in order to improve $\widehat{A_p}$. This trade-off relationship needs to be taken into account when determining an appropriate accommodation threshold value.

4.2.3 Interval estimation of population accommodation level

The last part of the evaluation is determining an interval estimate of $\widehat{A_p}$. Interval estimation of $\widehat{A_p}$ is performed using confidence intervals for binomial proportions on the basis of an assumption that accommodation is a binary random variable (either accommodated or disaccommodated). Among many alternative confidence intervals for binomial proportions, this study employed the Wilson score interval for the following reasons:

- Many previous studies (Brown, Cai and DasGupta, 2001; Rao *et al.*, 2002; Miao and Gastwirth, 2004; Dunnigan, 2008; Tan, Machin and Tan, 2012) have recommended the Wilson score interval for general use due to its good coverage probability compared to other confidence intervals for binomial proportions, such as the Wald interval, the exact Clopper-Pearson interval, and the Jeffrey's interval.
- The Wilson score interval has been recommended by a number of previous studies for use with data of small sample sizes (Agresti and Coull, 1998; Brown, Cai and DasGupta, 2001). It is important that the confidence interval provide consistent performance even with small sample sizes,

especially for ergonomics research studies since a lot of ergonomics studies collect and utilize small-sample datasets, due to high costs and efforts required to collect data from human participants. The Wilson score interval showed a relatively good coverage probability even with sample sizes of 40 or below in the previous studies.

The formula for the Wilson score interval is as follows:

$$Wilson\ score\ interval\ [L, U] = \frac{\left[\hat{p} + \frac{z^2}{2m} \pm z\sqrt{\frac{\hat{p}(1-\hat{p})}{m} + \frac{z^2}{4m^2}}\right]}{1 + \frac{z^2}{m}} \tag{4.5}$$

$\hat{p}$ = proportion of accommodated individuals

z = z-score for a given confidence level α

m = sample size

Using $\widehat{A_p}$ as input for $\hat{p}$ and the total number of participants as input for m, the Wilson score interval of $\widehat{A_p}$ can be determined for a particular error level α.

Some advantages of using interval estimation over point estimation for evaluating a product's population accommodation level are provided here. First, an interval estimate delivers information with regards to the precision of an estimated accommodation level. The confidence interval width (that is, the difference between the upper limit and the lower limit of a confidence interval) contains such information – the wider the interval width, the higher the variability of an estimated value. Therefore, minimizing the confidence interval width is important, and would be preferable for product designers, as $\widehat{A_p}$ with a narrower width would provide more certainty/reliability to the designers in their decision-making process. Regarding the precision/reliability of an accommodation level, some conceptually similar approaches have previously been proposed. For example, SAE J4004 (SAE International, 2008) employed tolerance in describing the reliability of an accommodation level with regards to a seat track travel length, and Garneau and Parkinson (2013) employed the concept of just noticeable difference to include variance deriving from user sensitivity in their accommodation model.

Second, interval estimation of population accommodation level allows statistical comparisons of the accommodation levels between multiple designs – a hypothesis test for proportions serves this purpose. Hypothesis tests would provide information regarding the statistical significance of the differences between accommodation levels of multiple adjustable range designs of a product, helping the designer to be more certain of the differences between the estimated population accommodation levels, and, thereby, facilitating the search for a proper adjustable range. Especially, hypothesis tests would be necessary for those designs that have overlapping interval estimates of $\widehat{A_p}$ – relatedly, it has been previously shown that confidence interval overlaps do not necessarily lead to the lack of statistical significance in the difference between their means/proportions (Schenker and Gentleman, 2001; Austin and Hux, 2002).

Third, utilizing interval estimation can help with the design of experiments. It has been shown by previous studies (Rao *et al.*, 2002; Ballarini *et al.*, 2009; Gungor *et al.*, 2019) that the Wilson score interval equation (see Equation (4.5)) can help determine the proper sample size to obtain a confidence interval of a given width at a specific confidence level α. By reversing the Wilson score interval equation and using a certain target accommodation level as an input for the $\hat{p}$, it is possible to calculate the required number of samples to estimate and make conclusions upon a product's population accommodation level. This information would be useful for establishing the required sample size to meet a desired reliability for the measure being estimated.

4.3 Case study

The proposed method could be applied to the design of adjustable ranges for various types of products and environments. This section provides a case study that demonstrates the use of the developed method using a practical design problem. It should be taken into account that the case study was carried out solely for the purpose of demonstrating the developed method, and, therefore, additional product-specific standards and/or design guidelines may need to be reviewed and applied when using the method for accommodation level evaluation. Some examples of such standards would be SAE J4004 (for designing vehicle seat track travel) and BS EN 1729-1 (for designing chairs and tables used in educational institutions).

4.3.1 Problem definition

Let us consider a design problem where an adjustable range of a vehicle seat currently in production needs to be comparatively examined/evaluated with two new adjustable range designs of varying positions, sizes, and manufacturing costs (see Figure 4.6). In an effort to solve the design problem, this case study evaluated and compared the population accommodation levels in terms of driver preference of the three adjustable range designs.

4.3.2 FPC dataset

The preferred seat position dataset collected in Study 1 was utilized again as the FPC dataset for this case study. In Study 1, preferred seat positions were collected from 108 healthy participants (54 males and 54 females with ages ranging from 20 to 74 years) with valid driver's licenses. The drivers were recruited so that they represented the population proportions of stature, body mass, and body mass index (BMI). A summary of demographic and anthropometric data of the drivers is provided in Table 3.1 of Study 3.

A seating buck equipped with a driver's seat, a steering wheel, a brake pedal, and an accelerator pedal (Figure 4.5) was used for the experiment. The seat and the steering wheel were adjustable in fore-aft and vertical directions, and their adjustable ranges were at least twice those provided in conventional vehicles, allowing the participants to adjust to their preferred seat positions in an unconstrained environment. The use of the large adjustable ranges ensured that the collected data would not be specific to a particular vehicle class or design but be relevant to various possible vehicle design scenarios.

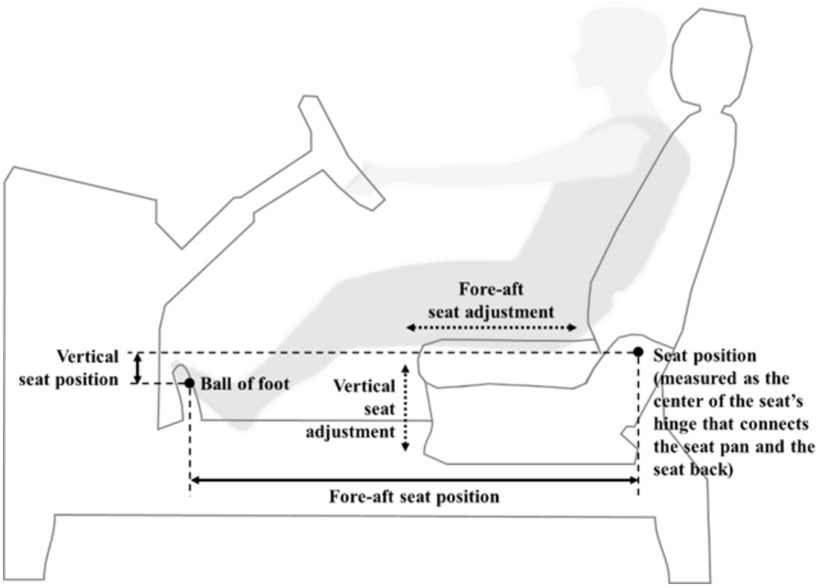


Figure 4.5: An illustration of the seating buck used for the data collection along with landmarks and distances used for recording the preferred seat positions.

The preferred seat positions were collected through multiple independent self-selection trials performed by each participant. The following steps describe the data collection process for a single participant:

1) The participant was given a randomly selected seat position as initial configuration before starting each self-selection trial.
2) The participant was then instructed to search through the available adjustable range of the seat to find and self-select his/her preferred seat position.

3) The seat position self-selected by the participant was recorded. The fore-aft and vertical distances of the seat's hinge joint center relative to the ball of foot on the pedal (in millimeters) were recorded (see Figure 4.5).
4) Steps 1) to 3) were repeated twenty-one times with sufficient amount of rest between trials to capture as much of the underlying driver preference as possible while preventing fatigue in participants.

All participants gave consent to the experiment protocol, which was approved by the Institutional Review Board of Auburn University.

The resulting scatterplot of the collected preferred seat positions is provided in Figure 4.6, along with the three adjustable range designs evaluated for the case study. The characteristics of each adjustable range design is summarized in Table 4.1.

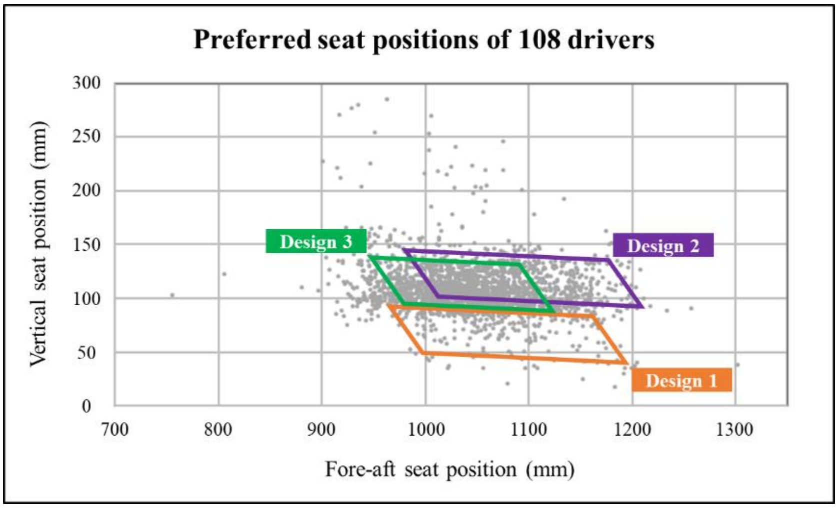


Figure 4.6: A plot with the three adjustable range designs considered (quadrilaterals with corresponding design numbers) and the preferred seat positions collected from the 108 participants (dots). The seat positions were measured as the fore-aft and vertical distances from the ball of foot to the center of the seat's hinge connecting the seat pan and the seat back.

Table 4.1: The characteristics of each adjustable range design considered.

Design number	Design characteristics
1	Current design – An adjustable range provided in a commercially available midsize sedan.
2	New design – An adjustable range with similar size and manufacturing cost as the current design (Design 1).
3	New design – A smaller adjustable range with lower manufacturing cost compared to Designs 1 and 2.

4.3.3 Accommodation level evaluation and comparison

Using the collected dataset of preferred seat positions, the accommodation levels of the three given adjustable ranges were analyzed. First, each individual's $\widehat{A_\iota}$ was determined using Equation (4.2). Figure 4.7 shows an example of $\widehat{A_\iota}$ calculation. Looking at the plots in Figure 4.7, it can be seen that the drivers are accommodated at different levels; for example, Driver 88 showed a non-zero $\widehat{A_\iota}$ of 5/21, which indicates that this driver was not completely disaccommodated by the given adjustable range (Design 3), but rather accommodated at a low level.

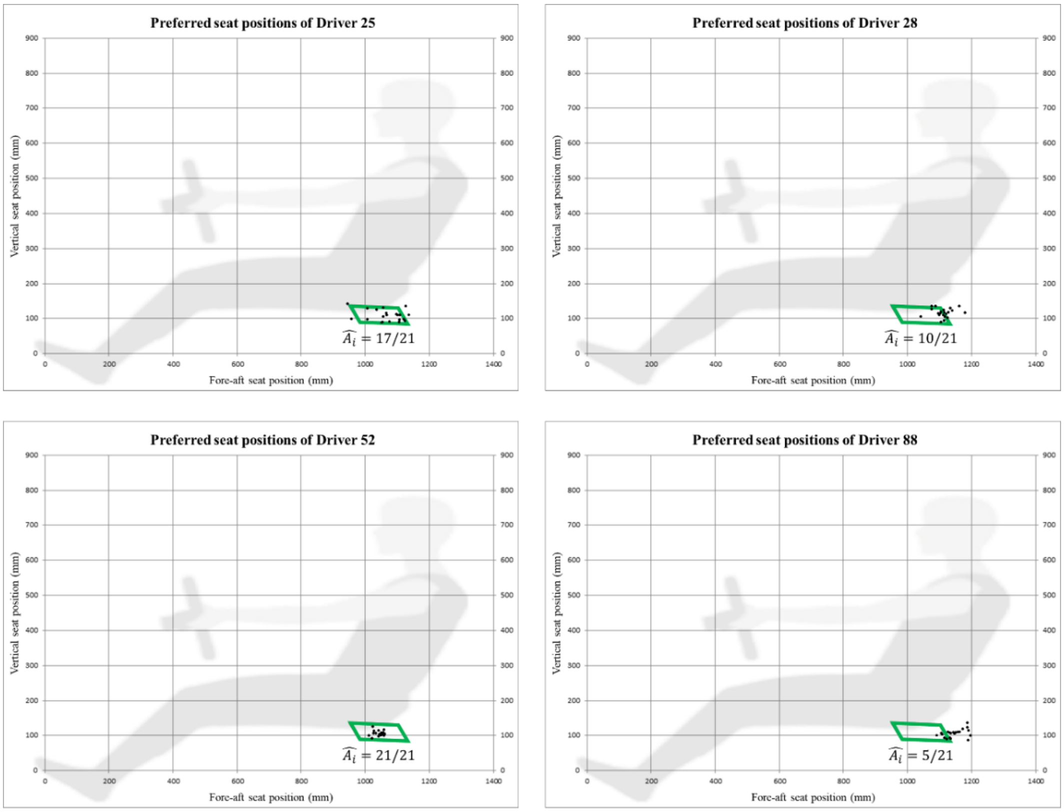


Figure 4.7: Four examples of $\widehat{A_i}$ computed (for Drivers 25, 28, 52, and 88) using Design 3 (green quadrilateral) based on each participant's preferred seat positions (dots).

Second, after evaluating $\widehat{A_i}$ for the 108 participants, $\widehat{A_p}$ was determined for each adjustable range design. This case study used a predetermined accommodation threshold value of 1/21, which means that any individual with at least one of his/her FPC included within the given adjustable range was considered as accommodated.

Third, the Wilson score intervals of the observed $\widehat{A_p}$ were determined. This study used binconf function included in an R package Hmisc (Harrell Jr., 2007) for computing the Wilson score intervals of $\widehat{A_p}$. For illustrative purposes, a commonly used confidence level of 0.95 (z=1.96) was used. The point and interval estimates of $\widehat{A_p}$ for the three given adjustable ranges are provided in Table 4.2 – the confidence interval widths are also given to show the precision of each of the population accommodation levels obtained.

Table 4.2: Point and interval estimates of $\widehat{A_p}$ for the three given adjustable range designs.

Design number	Point estimate of $\widehat{\boldsymbol{A_p}}$	Interval estimate of $\widehat{\boldsymbol{A_p}}$ (Interval width)
1	79/108 (73.15%)	64.10% ~ 80.61% (16.51%)
2	103/108 (95.37%)	89.62% ~ 98.01% (8.39%)
3	94/108 (87.04%)	79.41% ~ 92.12% (12.71%)

Finally, after evaluation, hypothesis tests were performed to confirm the statistical significance of the differences between the population accommodation levels obtained for the three designs. A series of two-proportion z-tests were conducted using prop.test function in R. Figure 4.8 shows confidence interval plots of $\widehat{A_p}$ with asterisks indicating the statistical significance of the differences.

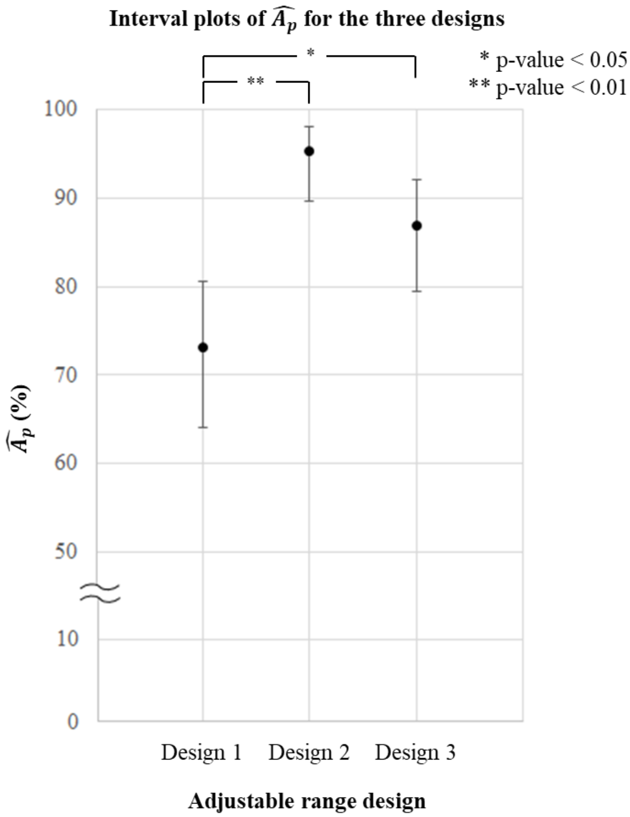


Figure 4.8: 95% confidence interval plots of $\widehat{A_p}$ for the three given adjustable range designs, with asterisks indicating the statistically significant results of pairwise comparisons.

The results in Table 4.2 and Figure 4.8 showed that Design 1 had the lowest point estimate of $\widehat{A_p}$ and the largest interval width (that is, the highest variability) among the three designs. The hypothesis test results suggested that the interval estimate of $\widehat{A_p}$ of Design 1 was statistically significantly different from those of Designs 2 and 3. Designs 2 and 3 did not significantly differ from each other in terms of their interval estimates of $\widehat{A_p}$. Based on these results, the designer would become aware that the current design (Design 1) needs to be improved, and, the improvements can be made by adopting either Design 2 (the larger adjustable range with the highest point estimate of $\widehat{A_p}$ among the three design alternatives) or Design 3 (the smaller, more cost-efficient adjustable range that was not statistically significantly different from Design 2 in terms of accommodation level).

4.4 Discussion

Study 2 has introduced a novel method for evaluating population accommodation level of adjustable products. The method consisted of three phases: 1) evaluation of individual accommodation level on the basis of a given adjustable range of a product and FPC data obtained for multiple individuals, 2) determination of population accommodation level based on the obtained individual accommodation levels, and 3) generation of an interval estimate of population accommodation level using the Wilson score interval.

Some practical implications of the developed method are discussed here. First, by utilizing the developed method, statistical comparisons between $\widehat{A_p}$ of multiple designs can be conducted, which can provide useful information for facilitating design decision making. For example, in the case study, if only the point estimates of $\widehat{A_p}$ were considered, it would have been a challenge for the designer to choose between the two competing designs, Design 2 (a higher-accommodating, but higher-cost design) and Design 3 (a lower-cost, but lower-accommodating design). The use of interval estimation and hypothesis testing helped to resolve this challenge – it was revealed that Designs 2 and 3, which showed a $\widehat{A_p}$ difference of 8%, did not have a statistically significant difference in their accommodation levels. Based on this information, it would be preferable for the designer to select Design 3, as it is a lower-cost design that does not compromise the accommodation level. As such, more reasonable and well-informed design decisions can be made using the developed method.

Second, the method developed in this study may act as a basis for search algorithms for optimal adjustable range design. For example, if a large number of adjustable range design alternatives could be generated through a certain search strategy (e.g., random or grid search), then their population accommodation levels could be evaluated/compared using the developed method to find the optimal (that is, highly-accommodating and low-cost) design solution.

Third, the case study demonstrated that the proposed method could be utilized for determining a proper sample size to obtain a confidence interval of a given width at a specific confidence level α. This information would be useful for establishing the required sample size to meet a desired reliability for the measure being estimated.

Chapter 5

Development of an accommodation level evaluation method for the design of non-configurable products

5.1 Introduction

Creating a consumer product that is capable of anthropometrically accommodating a large proportion of a target population is known to be a non-trivial problem as individuals vary significantly in their physical characteristics (Parkinson *et al.*, 2007). The problem of how to realize population accommodation for consumer product design seems to have much to do with the level of product variety or the type of product an enterprise decides to offer. The enterprise may decide to custom-design for each individual customer (e.g., a custom-tailored suit), create a reconfigurable product (e.g., a height-adjustable chair) or produce a product available in multiple varieties (Ulrich, 2011). Alternatively, it may opt for providing a non-configurable, single-configuration product for everyone in the population with rigorous optimization for product configuration design. These alternatives would require different methods for realizing population accommodation. Among the alternatives mentioned above, creating a single-configuration-for-all product (hereafter, a single configuration product) seems to offer multiple advantages over the others. From the enterprise's point of view, the main advantages would be the relative simplicity of design problem and manufacturing process, which can lead to lower design and manufacturing costs. For the consumers, they could benefit from lower product price; also, the consumers would find it advantageous to be able to use the product as is without having to make an effort to choose the right product variant or reconfigure the product.

Despite the importance, however, the problem of designing a single configuration product for population accommodation has not been fully investigated. Currently, there are two methods that are being widely utilized for single configuration product design: designing for the extremes and designing for the average. The first method focuses on accommodating the individuals at the extremes of the population distribution with an assumption that doing so would ensure accommodating fewer extreme individuals. The second method, on the other hand, aims to accommodate the people around the medium, with an implicit assumption that it will result in a good solution in terms of population accommodation. Taking the design of a door as an example, the first method is typically used for the design of the doorpost height, yet not for the design of the doorknob height, and, vice versa, for the second method. Despite their wide use, however, these methods do not always guarantee high-level population accommodation and could result in low-quality solutions for many design problems. As an effort to address the problem of single configuration product design, this paper presents a novel design optimization method. This method utilizes empirically obtained human preference data for optimizing a product's configuration; and, in doing so, both the intra-individual as well as inter-individual variability in human preference are considered. In what follows, the design method will be described using an example design problem.

5.2 Methods

5.2.1 Data collection

In solving a single configuration product design problem, the proposed design method requires collecting human preference data from a sample of users. The data collection method is proposed in a way such that it can capture variability in preferred product configurations both between individuals and within each individual. The data collection method may be conducted as follows:

1) A random product configuration is given to each participant as initial configuration before starting each self-selection trial.
2) The participant searches through the given adjustable range of the product and self-selects a preferred configuration.
3) The self-selected product configuration is recorded.
4) Repeat Steps 1) to 3) multiple times to capture as much of the underlying preference towards the given product's configuration as possible while avoiding fatigue for each participant.

5.2.2 Accommodation level evaluation and validation

With the collected data, the search for the optimal configuration can be performed by finding the position that maximizes the accommodation level of the driver population. The objective function of this maximization problem can be formulated as follows:

$$\text{Maximize } f(d) = \frac{\sum_{i=1}^{N} L_i(d)}{N} \tag{5.1}$$

In Equation (5.1), the accommodation level of a particular configuration is represented by $f(d)$, where d is the product configuration being evaluated. $L_i(d)$ is an indicator function where $L_i = 1$ when d is included in R_i and 0 otherwise. R_i represents the range of preferred product configurations selected by the i^{th} participant where $R_i = [\min(X_{ij}), \max(X_{ij})]$. X_{ij} represents a product configuration self-selected by the i^{th} participant ($i = 1, ..., N$) in the j^{th} trial ($j = 1, ..., M$). Thus, the objective of this optimization is to maximize the accommodation level, $f(d)$, by finding the value of d that maximizes the summation of $L_i(d)$.

For validating the optimal product configuration obtained using the proposed method, the current study utilized the Jackknife method, which has been proven to be a powerful validation method even with small sample sizes (Riveros, 2020).

5.3 Case study

5.3.1 Problem definition

For the case study, determining the optimal brake pedal position for a given vehicle has been selected as the example design problem. Most of the vehicles today are manufactured with fixed brake pedals, and, for a given vehicle, drivers are forced to fit themselves to the brake pedal by adjusting other vehicle components, such as the seat and steering wheel. Therefore, determining the optimal location of a fixed brake pedal is a typical example of non-configurable product design problems.

5.3.2 Data collection for the case study

For the current example design problem, self-selected, most preferred brake pedal positions of 20 drivers (10 males and 10 females) were obtained experimentally. The participants were sampled so that they represented the distributions of stature and BMI of the Korean population. The descriptive statistics of the participants' personal variables are provided in Table 5.1.

Table 5.1: Descriptive statistics of the participants' personal variables.

Variable	Mean ± SD	Min.	Max.
Age (years)	38.42 ± 10.59	22	62
Stature (cm)	166.83 ± 10.20	151.0	186.8
Body mass (kg)	65.77 ± 9.67	44.1	81.9
Body mass index (kg/m^2)	23.53 ± 1.83	19.34	27.07

Each participant repeated self-selecting his or her preferred brake pedal positions ten times. An experimental vehicle with an electrically powered adjustable brake pedal was employed.

Prior to each self-selection trial, the pedal was set to a random position. In each trial, the participants self-selected their most preferred pedal positions using the pedal position adjustment function while driving the vehicle in a safe test track environment. The brake pedal position, which is defined as the vertical distance from brake pedal center to floor mat, was recorded after each trial.

5.3.3 Results of the case study

Using the optimization model presented above, the brake pedal position that accommodates the largest number of participants was selected as the optimal brake pedal position. The optimal brake pedal position for this example problem was found to be 190.5mm. The brake pedal with this configuration accommodated 15 out of 20 participants (see Figure 5.1).

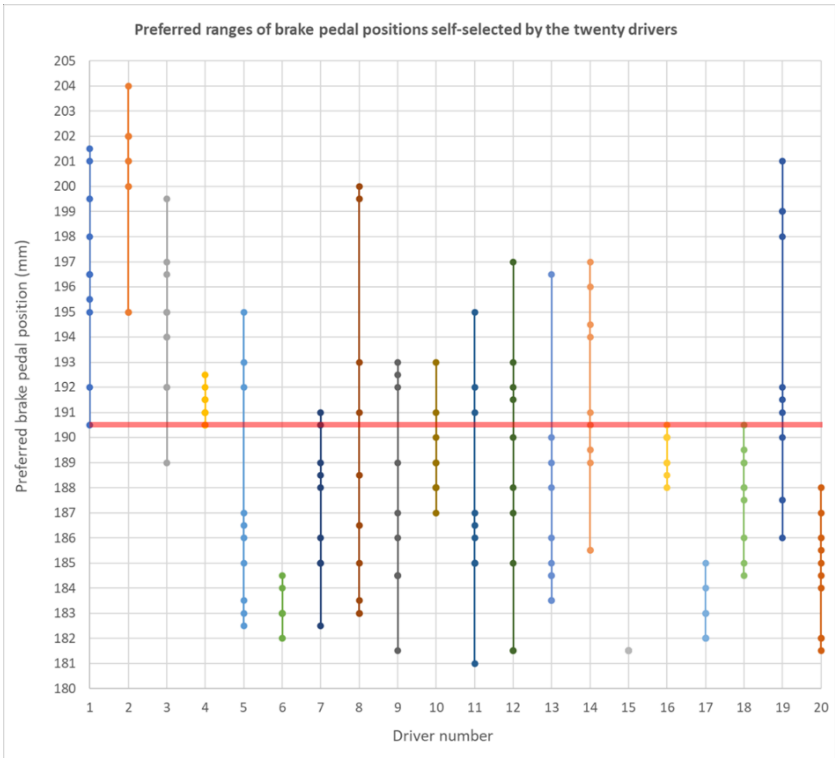


Figure 5.1: Each participant's preferred range of brake pedal positions and the optimal brake pedal position (red horizontal line).

5.3.4 Validation of the case study results

The Jackknife method was employed to test the validity of the proposed accommodation level evaluation method, that is, to test if the optimal brake pedal position obtained gives consistent estimations of accommodation level even with different datasets collected from new sets of sampled individuals. A schematic diagram for a single iteration of Jackknife method is provided in Figure 5.2. Each of the twenty individuals in the dataset was used to create Dataset 2, and, thus, the process described in Figure 5.2 was repeated twenty times.

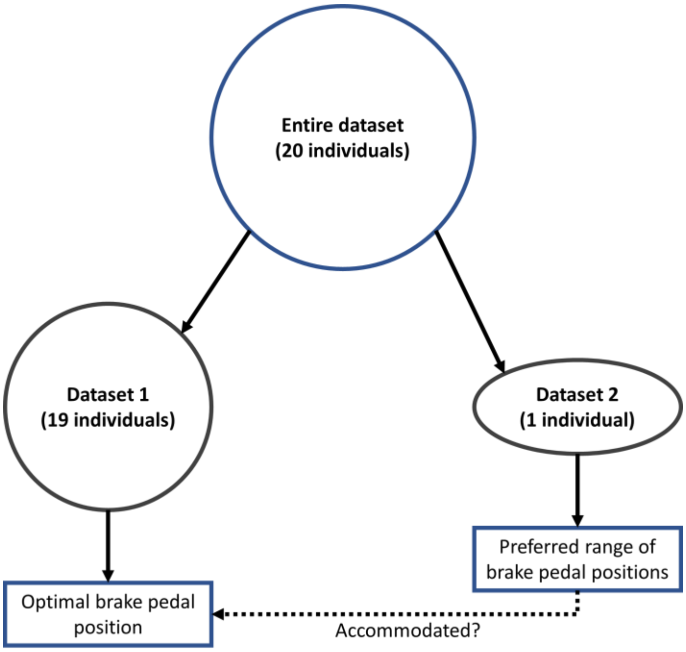


Figure 5.2: A schematic diagram of the Jackknife method employed.

Table 5.2 shows the results of the validation using the Jackknife method. The optimal brake pedal position was determined to be 190.5mm for all 20 iterations. The last column in Table 5.2 shows results of the twenty iterations of Jackknife method, whether the optimal brake pedal position determined using a set of preferred brake pedal positions of 19 drivers (excluding one driver used to create Dataset 2) is included by the preferred range of brake pedal positions of the single driver in Dataset 2. Of the 20 iterations of Jackknife validation, the optimal brake pedal position was included by the preferred range of brake pedal positions 15 times, meaning that this specific optimal brake pedal position will accommodate a newly sampled participant with a 75% probability.

Table 5.2: Validation results using the Jackknife method.

Participant used for Dataset 2	Optimal brake pedal position determined using Dataset 1 (mm)	Preferred range of brake pedal positions for the participant in Dataset 2		
		Minimum height (mm)	Maximum height (mm)	Accommodation evaluation result
#1	190.5	190.5	201.5	Accommodated
#2	190.5	195	204	Disaccommodate d
#3	190.5	189	199.5	Accommodated
#4	190.5	190.5	192.5	Accommodated
#5	190.5	182.5	195	Accommodated

#6	190.5	182	184.5	Disaccommodate d
#7	190.5	182.5	191	Accommodated
#8	190.5	183	200	Accommodated
#9	190.5	181.5	193	Accommodated
#10	190.5	187	193	Accommodated
#11	190.5	181	195	Accommodated
#12	190.5	181.5	197	Accommodated
#13	190.5	183.5	196.5	Accommodated
#14	190.5	185.5	197	Accommodated
#15	190.5	181.5	181.5	Disaccommodate d
#16	190.5	188	190.5	Accommodated
#17	190.5	182	185	Disaccommodate d
#18	190.5	184.5	190.5	Accommodated
#19	190.5	186	201	Accommodated
#20	190.5	181.5	188	Disaccommodate d

5.4 Discussion

Study 3 has presented a new accommodation level evaluation method for determining a single optimal product configuration for the design of non-configurable products. The new method is generic and can extend to a variety of product design problems, which would greatly facilitate the design of non-configurable products.

It should be noted that the discussed method was formulated under two important assumptions. First, each participant's preferred range of product configurations was assumed to be the entire interval from the lowest to the highest preferred product configuration; it was assumed that every point in the interval is equally optimal. Second, this study assumed that a participant is accommodated by a certain product configuration if the participant's preferred range of product configurations includes that particular product configuration. The first assumption may be related to the findings from previous studies that investigated the ranges of comfortable joint angles (Porter and Gyi, 1998; Park *et al.*, 2000; Hanson, Sperling and Akselsson, 2006; Kyung and Nussbaum, 2009; Schmidt *et al.*, 2014; Peng, Wang and Denninger, 2017). In these previous studies, the comfortable joint angle ranges were determined to be in the form of a single continuous interval for each joint angle. Using the case study results as an example, the brake pedal position is closely related to the comfortable joint angle of the ankle (Freeman and Haslegrave, 2004), and the interval between two extreme points of preferred brake pedal positions may be interpreted as the interval between two extreme joint angles for ankle comfort for drivers. Using this interpretation on the relationship between comfortable joint angles and single continuous range of preferred product configurations, the second assumption may also be explained – since comfortable joint angles are in the form of a single continuous interval, any product configuration that is included by the preferred range of product configurations (derived from a comfortable joint angle range) may be assumed to be accommodated. Further investigation into the correlations between preferred range of certain product configurations and relevant joint angles (for example, the relationship between comfortable joint angle of the ankle joint and preferred brake pedal positions) may help confirm such interpretation.

Chapter 6

Conclusion

6.1 Research summary

This research provided results of three studies conducted to answer each of the following three research questions:

1) What are the characteristics of driver-selected seat positions (DSSPs)?

2) How can we evaluate the accommodation level of an adjustable product considering different types of variability in human preference?

3) How can we evaluate the accommodation level of a non-configurable product considering different types of variability in human preference?

Study 1 analyzed empirically obtained DSSPs to explore geometric, mathematical, and statistical properties of individuals' DSSP point clouds. Six quantitative indices pertinent to the size, shape, orientation and location of a DSSP point cloud were employed. Normality of the DSSP point clouds, and, also, possible correlational relationships among the indices and those between the indices and selected anthropometric dimensions were statistically tested. The study findings suggested that 1) DSSP prediction and simulation modelling must reflect the unimodal, non-normal nature of individuals' DSSP distributions and the correlational structures identified, and 2) intra-individual as well as inter-individual variability in DSSP data needs to be considered in designing and evaluating seat adjustability features and other vehicle interior functions.

Study 2 proposed an accommodation level evaluation method for the design of adjustable products, which incorporated interval estimation of population accommodation level. The method consisted of two parts: 1) individual accommodation level was evaluated on the basis of a given adjustable range of a product and preferred configuration data obtained from multiple individuals, and 2) based on the obtained individual accommodation levels, population accommodation level was determined, and a confidence interval of the population accommodation level was generated. A case study was provided to demonstrate how the method can be applied to a real-world design problem.

Study 3 developed a novel accommodation level evaluation method for non-configurable products. As an effort to address the problem of accommodation level evaluation for non-configurable products, Study 3 presented a novel design optimization method, which utilized empirically obtained human preference data for optimizing a product's configuration; and, in doing so, both the intra-individual as well as inter-individual variability in human preference were considered. A case study using an example design problem was provided to demonstrate the new design method.

The characteristics of DSSPs and the accommodation level evaluation methods presented through the three separate studies would be useful knowledge for not only the design of driver's seat and vehicle interior components, but also the design of non-configurable/adjustable products in general.

6.2 Future research directions

Some future research directions regarding driver-selected vehicle component positions and human preference in general are provided first.

First, the current research findings have implications on the vehicle interior design and evaluation and the development of in-vehicle functions, such as memory seats and personalized interior setting recommendation systems. Further studies are needed to incorporate the study findings into the development of new accommodation evaluation metrics, design optimization formulations and algorithms for identifying human preferences and making personalized recommendations.

Second, arbitrary numbers of preferred product configurations were collected from each individual for each of the studies for evaluating the accommodation levels. While empirically obtained preferred/fitting product configurations are of fundamental importance for vehicle interior design and evaluation and also for creating novel in-vehicle functions, collecting such data currently requires special equipment and can be time-consuming and effortful. Future research may be conducted to develop efficient and convenient methods for collecting preferred/fitting product configurations and determine the minimum number of configurations necessary for accurately estimating the driver preference towards certain vehicle components for each driver.

Third, the data collection procedure used in this research set the relevant vehicle components (the seat and the steering wheel for Studies 1 and 2, and the brake pedal for Study 3) at random positions for each self-selection trial. Further investigation on the relationship between initial configuration of the vehicle components and preferred/fitting product configurations may help design an efficient data collection process for identifying preference distributions for each product, which does not suffer from some systematic biases but support accurately estimating such distributions. Relatedly, Peng, Wang and Denninger (2018) found initial seat height to have strong influence on preferred seat height – a low initial seat position led to a low preferred seat height.

Fourth, Studies 1 and 2 examined product configuration data collected in a seating buck that represented the driver space of conventional vehicles. Thus, the current study findings may not be generalized to different situations, such as the occupant spaces of emerging highly automated vehicles. Additional research studies are needed to study the human preferences in posture and vehicle interior setting in such new vehicles.

Fifth, further studies will be necessary to enhance our understanding of human preference accommodation in general. One future research idea would be to investigate on whether an individual's preferred/fitting product configurations can be represented as a continuous interval rather than discrete points. In Study 3, it was assumed that each participant's preferred range of brake pedal positions was the entire interval from the lowest to the highest preferred brake pedal position, and that every point in the interval is equal in terms of preference. It would be interesting to check if preferred configurations could indeed be considered as a continuous interval of configurations through experiments using different types of products.

Future study directions regarding preference accommodation level evaluation are provided here. Some extensions of the discussed accommodation level evaluation methods may be possible as follows.

First, development of new accommodation level evaluation methods may be possible for other types of products as well. One such example would be products produced in multiple discrete varieties (e.g., t-shirts, shoes, etc.). For such products, similar accommodation level evaluation schemes as proposed by Studies 2 and 3 (evaluating both individual- and population-level accommodation levels, thus considering both inter-individual and intra-individual variability in human preference) may be applicable as well; yet, different optimization model formulations would be needed to determine optimal varieties of such products that maximize accommodation level.

Second, the current study demonstrated two accommodation level evaluation methods through case studies concerning design problems of evaluating the accommodation levels of seat adjustment range and brake pedal position. These case studies are only two of many possible practical design applications, and the methods may well be applicable to adjustable/non-configurable products used in different industries, such as agriculture, construction, and commercial vehicles. Further studies should touch upon the different applications of the developed methods in such industries.

Third, development of new accommodation level evaluation methods using the mean of $\widehat{A}_\iota$ values (where $\widehat{A}_\iota$ = individual accommodation level as defined in Study 2) could be an interesting approach that may provide new insights into human preference. The current research made an assumption that accommodation is binary, and, therefore, each individual was classified as either accommodated or disaccommodated depending on whether an individual's $\widehat{A}_\iota$ exceeded a certain predetermined accommodation threshold value or not. If a contrasting assumption of accommodation being a continuous random variable rather than binary is made, $\widehat{A_i}$ values may be used to describe each individual's partial accommodation/disaccommodation, and the mean of those $\widehat{A_i}$ values to determine the accommodation level at the population level.

Lastly, in Study 2, the Wilson score interval was utilized for interval estimation of accommodation level under the premise that ergonomics studies mostly conduct small-sample experiments, and, thus, having a good coverage probability even with small sample sizes was a priority in the selection of the confidence interval. Further investigation is needed to determine which confidence interval can best represent the precision of accommodation level estimates under different conditions/contexts.

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국문초록

제품 디자인이란 다양한 사용자들이 제품에 대해 느끼는 선호, 사용 행태, 그리고 사람들의 신체 조건과 같은 변수들이 모두 적절하게 고려되어야 하는 난해한 작업이다. 이러한 제품 디자인 프로세스에 도움을 주는 정량적 평가 기준으로 accommodation level, 즉 수용도가 있다. 수용도란 제품을 사용하는 전체 인구 중 얼마만큼의 사용자들을 만족시킬 수 있는가를 표현하는 정량적 수치이며, 제품에 대한 사용자 만족도, 사용성, 안전성과 같은 제품의 품질을 파악하고 향상시키는 데 필수적으로 분석되고 고려되어야 한다. 따라서, 정확한 수용도 예측은 고객 만족도 제고를 위한 제품 디자인에 유용한 정보로 활용될 수 있으며, 이를 위해서는 다양한 사용자들의 특성과 또 그로부터 나타나는 변동성을 정확하게 파악하고, 또 이러한 변동성을 수용도 분석에 포함시키는 것이 중요하다.

제품 디자인이 필요한 다양한 분야 중 자동차 디자인 분야에서는 운전자가 선호하는 시트 위치, 핸들 위치, 대시보드 쪽에 있는 디스플레이 등의 부품에 대한 수용도 분석이 진행되고, 이를 바탕으로 디자인이 결정되게 된다. 다양한 사용자 집단 중 운전자들은 차량의 여러 실내 부품을 조작하며 운전이라는 과업을 수행하게 된다. 이러한 실내 부품들은 주로 조절 가능 범위가 제공되거나(예: 운전석, 핸들, 미러 등), 고정된 상태로(예: 페달, 변속기 등) 운전자들에게 제공된다. 자동차의 운전석은 실내/실외 디자인에 모두 영향을 끼치는 중요한 부품이며, 운전자와 가장 많은 시간 직접적으로 접촉이 이루어지는

부품이다. 이러한 운전석 디자인 관련 문제 중 하나는 운전석의 조절 가능 범위 문제인데, 주로 실험적으로 얻은 driver-selected seat positions (DSSP)라고 하는 운전자 선호 시트 위치 데이터를 수집/활용하여 시트의 조절 가능 범위가 결정된다. DSSP는 운전자마다 모두 다른 특성을 갖고 있고, 자동차 운전석의 조절 가능 범위 결정 문제를 해결하는 데 꼭 고려되어야 할 중요한 정보이다. 시트의 조절 가능 범위를 최대한 넓게 만들면 DSSP를 모두 포함시킬 수 있지만, 그 경우 불필요한 비용들이 발생할 수 있기 때문에 DSSP에 대한 정확한 이해와 또 그러한 이해를 바탕으로 한 정확한 수용도 예측 방법이 뒷받침되어야 효율적이고 효과적인 시트 조절 범위 제공이 이루어질 수 있을 것이다.

다만 아직 DSSP에 대한 심층적인 분석이 부족한 상태이며, 운전석을 포함하여 다양한 차량 실내 부품들에 대한 운전자 수용도 평가 방법을 개선할 수 있는 여지가 많이 남아있다. 정확한 수용도 예측과 최적 디자인 도출을 위해서는 DSSP의 기하학적 특성에 대한 이해가 필요하다고 생각되며, 운전자들의 제품 선호 데이터의 특성을 바탕으로 한 제품 수용도 평가 방법에 대한 연구가 진행되어야 할 것으로 사료된다. 이와 같은 현황을 바탕으로 파악한 research gaps를 바탕으로 아래와 같이 세 개의 Research Questions (RQ)를 구성하였다.

RQ 1) What are the characteristics of driver-selected seat positions?

RQ 2) How can we evaluate the accommodation level of an adjustable product considering different types of variability in human preference?

RQ 3) How can we evaluate the accommodation level of a non-configurable product considering different types of variability in human preference?

연구 1) Investigation on the characteristics of driver-selected seat positions

RQ 1을 해결하기 위해, 다양한 index와 분석 방법들을 활용해 DSSP의 특성에 대해 알아보았다. DSSP의 특성을 알아보기 위해 총 108명의 사람들로부터 DSSP data와 추가로 키, 몸무게, 앉은키를 포함해서 13개 신체 치수 데이터를 얻고, 한 사람 당 여러 개의 DSSP를 수집해서 집단의 DSSP 특성뿐만 아니라 개인별 DSSP 특성도 알아보고자 한다. DSSP의 기하학적, 통계적 특성을 알아보고, 특성 간 상관관계, 그리고 특성과 신체 치수와의 상관관계까지 알아보는 것이 본 챕터의 내용이 될 것이다.

연구 2) Development of an accommodation level evaluation method for designing adjustable products

RQ 2를 해결하기 위해, 조절 가능한(adjustable) 제품의 수용도 평가 방법을 개발하였다. 조절 가능 범위의 최적 위치 결정 문제에 대한 내용으로, 조절 범위의 최적 위치 결정에 있어서 사용자 선호 데이터의 개인 간, 개인 내 변동성을 고려할 수 있는 수용도 평가 방법을 개발하였다. 결정 방법에 대한 진행 절차 설명 및 예상 결과물 제공을 위해 시트 조절 가능 범위 결정 문제를 사용한 case study를 실시하였다.

연구 3) Development of an accommodation level evaluation method for designing non-configurable products

RQ 3을 해결하기 위해, 조절 기능이 없는(non-configurable) 제품의 수용도 평가 방법을 개발하였다. 사용자들의 개인 간 변동성 및 개인 내 변동성을 고려하여 한

개의 최적 디자인을 도출하는 데 사용할 수 있는 수용도 평가 방법을 개발하였다. 이 연구에서는 개발된 수용도 결정 방법을 설명하고, case study를 통해 해당 수용도 결정 방법을 실제 디자인 문제에 적용 시 예측되는 결과물을 제공하였다.

본 연구를 통해 얻은 DSSP에 대한 지식과 개발된 수용도 평가 방법들은 운전석 및 차량 내 부품뿐만 아니라 전반적인 제품 디자인 결정 문제에 유용한 정보로 사용될 수 있을 것이다. 특히 본 연구에서 제안하고자 하는 수용도 평가 방법은 개인 간 변동성뿐만 아니라 개인 내 변동성이 모두 고려된 수용도 평가 방법이며, 제품 선호 데이터의 확률 분포에 대한 가정이 필요 없는 방법이라는 점이 가장 중요한 기여가 될 것으로 예상된다.

주요어: 개인 간 변동성, 개인 내 변동성, 구간 추정, 사용자 선호, 수용도, 운전자 선호 시트 위치, 조절 가능 제품, 조절 불가 제품, 제품 디자인

학번: 2014-31102