The Pennsylvania State University
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CLASS B VEHICLE PACKAGING:

DESIGNING BUS CAB LAYOUT FOR U.S. BUS DRIVERS

A Thesis in
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by
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Abstract

The objective of this thesis is to examine human anthropometric and preferential variability and investigates a number of methods that have been developed to accommodate this variability within vehicle packaging. Multiple simulation approaches are described and analyzed to show the strengths and weaknesses each demonstrates in its ability to predict population accommodation. Building on previous research, a study on the driving environment of bus operators was carried out, allowing the effect of an operator's physical dimension, postural preference, and workstation geometry to be evaluated simultaneously. A population of virtual U.S. bus drivers, constructed from anthropometric surveys and workforce surveys, is applied in a cascade prediction model that locates the reference points in a bus cab and primary and secondary body landmarks of a driver within an existing or theoretical future vehicle package. This research led to the development of a web application tool and an Excel spreadsheet to assist industry users to assess spatial accommodation and driving safety of current buses and to help package future buses.

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Chapter 1
Introduction

The success of design intended for human use is determined by a wide range of factors, such as safety, aesthetics, effectiveness, portability, cost, and many more. Although one factor may be the driving force for a specific design, the impact of each factor requires a significant amount of research and is its own field of study [25]. Through theoretical analysis and practical experiment, researchers explore how each factor contributes to the overall outcome. As many industries become more agile and transparent, companies are constantly evolving as well to meet shifting needs. Among these are user-centric elements, such as human variability.

1.1 Design for Human Variability

Design for Human Variability (DfHV) considers the inherent variability within the target user population and during the creation of designed artifacts. Humans are different in various ways. Some learn through observing others; some learn through hands-on experience. Some prefer to read in order to receive information; some prefer to listen instead. This variability is to some extent determined when one is born, but they can be shaped by external influences, including but not limited to cultural background, family atmosphere, and religion [26]. Because of these differences, humans react differently. Besides cognitive capability, humans also vary in physical capability. Some are stronger; some are more flexible. Some have perfect vision; some are good at balancing. Such characteristics, as well as sex, race, or age, can dramatically impact how humans act, react, and interact [27].

While developing a solution, it is critical to clearly define the user population and understand its characteristics of said population because this knowledge will serve as a foundation throughout the design development cycle and provide bases for any pivotal design decisions [28]. In the past, many techniques have been developed to gain a fuller understanding of the users, such as constructing personas [29]. Personas are imaginary user profiles that outline the demographics, behavioral observations, pain points, and motivations of a target population [30]. They represent the majority of the population, and their use is comparable to the manikin approach in anthropometry studies, which will be explicitly discussed in Chapter 2. Establishment of detailed user profiles gives designers and engineers critical guidelines to develop user-centered solutions that can better accommodate the variability of this population.

1.2 Anthropometry

Anthropometry, one of the major fields of research in human variability, is a systematic and statistical study of measurements and proportions of the human body. A combination of these measurements and proportions describes the size and shape of a human body, which makes individuals unique [31]. There are many ways to categorize anthropometric variables. One common way is to distinguish them as length-related variables, such as stature, trochanter height (leg length), and hand length, and width-related variables, such as hip breadth, calf circumference, and chest breadth. Intuitively, taller people are also expected to be wider than their shorter counter parts. Such inference is usually true; however, there are exceptions due to human variability. For instance, width of a human body is not only an indicator of its size, but can also be a measure of obesity. In this case, body width is independent of body length. Therefore, it requires careful considerations to choose the most appropriate anthropometric indicators while making design decisions.

Anthropometry is commonly considered in industrial practice. For instance, anthropometry-focused concepts can be found in vehicle packaging, furniture designs, sport equipment innovation, clothing design, and many more. The expectation of such studies is to achieve a greater outcome while minimizing cost so that the final product is effective, yet efficient. A poorly designed product can cause discomfort and dissatisfaction in users and result in a decrease in productivity [32]. In certain circumstances, it can even put users in life-threatening danger. Thus, designers must diligently study the anthropometry of a target populations and use the associated artifacts to guide their designs.

1.3 Accommodation

A good design should accommodate its users so they are able to perform all the required tasks without encountering any limitations [3]. When a user is accommodated, they will feel safe and comfortable while doing physical tasks, which can increases their productivity. In contrast, when a user is disaccommodated, their job satisfaction level is generally low, and the likelihood of safety hazards increases largely [33]. In many cases, companies and designers invest additional resources to achieve a better accommodation level. In reality, however, perfect accommodation usually does not exist. When designing for a large audience, it usually costs a tremendous amount of resources to accommodate the users with extreme body dimensions, and as a result, companies tend to target the majority of the users, rather than all the users. This topic will be further discussed in a later section.

Although most existing designs are not expected to accommodate every user within the target population, there are times when it is necessary. In competitive indoor and outdoor activities, sports equipment is frequently custom made for best performance [34]. For instance, NBA players are known for their elite performance on a basketball court. Competing with other extraordinary athletes, it is a significant advantage to jump a little higher or change direction a little faster. This pursuit for excellence inspires top shoe companies, such as Nike and Under Armour, to take 3D scan of professional athletes' feet and analyze the loading condition on their shoes in order to design shoes specific to the athlete that enhance their in-game performance [35–37].

Customized designs can sometimes maximize the performance of a product, but they usually raise the cost significantly as well. They not only require more design considerations, but also bring challenges to the manufacturing process [34]. For instance, many plastic products are formed through injection molding, which is a process of melting and injecting molten material in a mold to form parts. Due to the dimensional precision of the molds, they are expensive to produce. With machine testing and labor cost, it is difficult to justify the cost when only a small quantity of parts are needed [38]. Alternatively, additive manufacturing saves cost on tooling, but it requires additional research and time. Because of its layered nature, it may sometimes lead to structural failures [39].

1.4 Body Dimensions

Human bodies vary significantly in size and shape, which creates a difficulty in providing universally functional solutions for a population. One of the common approaches to resolve this issue is to create various sizes of a product, and to let users or retailers determine which size is most suitable for each consumer. Shoes are a great example of this strategy [40]. In the U.S., shoe sizes are typically designed by an increment of 0.5 or 1. With help from the elasticity of the materials, this increment is small enough to accommodate most of the users [41]. One of the greatest advantages of this approach is its simplicity; however, it is not suitable when users desire different sizes. Another approach is to accommodate such variability is to implement adjustability in product dimensions. For instance, a belt allows the user to adjust the tightness of it around the waist. Instead of having to purchase belts of various sizes, the user only needs an adjustable one [42]. However, the major disadvantage of adjustable components is the increase in complexity of a system, which can cause a higher failure rate [43]. In the meantime, an adjustable product frequently involves more part count, which is often a root cause of higher cost [33].

Analysis of anthropometric data has shown that many anthropometric measurements can be approximated as normal distributions, especially length-related ones, with the majority of the data clustering in the middle and the extremity of the data spreading at the tails [2]. In product design, it is neither economical nor realistic to accommodate 100% of the user population due to the large spread of body dimensions. Thus, a design usually aims to accommodate a proportion of the user population [32]. In practice, a target percentage of accommodation is pre-selected, 90% for instance, and serves as an assessment goal for the final product. Sometimes for those who are disaccommodated, they can sometimes still achieve compromised comfort by adjusting their posture.

In other cases, however, disaccommodation may lead to safety hazards. Such phenomenon exists throughout the world, but it is more common in developing countries because resources are more limited. Agriculture plays an important role in northern China's economy, and large machines are used to reduce the amount of manual work [44]. If a worker has a difficulty in operating these machines due to physical limitations, the probability of an injury is much higher. In fact, a study observes a 13.1% prevalence of machinery-related injuries from the surveyed agricultural workers [44]. A similar point can be made in vehicle interior design. Failure to reach or disability to see can cause serious car accidents [17]. Therefore, designers and engineers must ethically investigate the consequences of disaccommodation before making design decisions.

1.5 Postural Preference

Human interaction is not only impacted by the physical dimensions of the human body, but also by a user's postural preference. Postural preference is unique and can be dramatically different from individual to individual [45]. For instance, the purpose of a chair is to provide a sturdy seating surface that supports the user. However, the action of sitting is very complex. Given a standard chair, some like to lean backward, some like to cross their legs. Some prefer to sit high, some never utilize the armrests [46]. Assessment of success is no longer limited to the fundamental purpose of a chair, but rather the capability to accommodate various postures of as many users as possible to provide the most comfort.

Collecting data on postural preference can be a costly process because it requires user's participation which involves experiment design, user testing, data collection, and user feedback. In many cases, the size of a testing group is critical to coming up with an unbiased solution. With a small testing group, extreme behaviors are sometimes magnified and can be over-analyzed which can lead to biases [47]. The testing group must also represent the actual user population in specific demographic descriptors, such as male-female ratio, age, ethnicity composition, etc. Thus, doing market research in preparation for any postural experiment is an essential step [28, 48].

Occasionally, postural preference can be transferable across products when the two products are used in a similar way, but careful consideration needs to be given to the risk of oversimplifying the problem [49]. For example, ice skates and running shoes are comparable in shape and are worn similarly, but they serve different purposes. Ice skates must be stiff enough to protect users from twisting their ankles, but running shoes need to be able to provide shock absorption and comfort, which is why new products usually need to run their own user interaction experiment. Unlike interaction preference, physical dimensions of a human body only need to be measured once. These dimensions can be simulated in space using software to display results in dimensional fitting [50], which will be further discussed later.

1.6 Vehicle Packaging

The knowledge of spatial dimension and postural preference is useful in many fields of design, especially vehicle packaging. As Roe has defined, vehicle packaging is a subject that studies a vehicle's interior spacing and components layout with the purpose of providing safety, spatial accommodation, and comfort to drivers and passengers [2]. Among all the components inside of a vehicle, two are the most critical in this thesis, steering wheel and driver's seat, because they determine the driver's capability to operate the vehicle [14]. By the definition of accommodation, drivers must be able to adjust these two components without encountering any limitations to comfortably turn the steering wheel and step on the accelerator pedal or the brake pedal. One other consideration is driving safety [3]. While operating a vehicle, drivers must maintain awareness of the surrounding traffic to make proper decisions as well [18].

1.7 Research Overview

This thesis examines the essence of human variability and presents a number of methods that have been developed to accommodate such variability, and this knowledge will serve as the basis of vehicle packaging. The goal of this thesis is to investigate bus cab spatial layouts and to simultaneously consider the effect of bus driver's body dimension and postural preference. Following which, the outcomes of this research is to assess existing bus packages for spatial accommodation and driving safety through simulation, and eventually provides recommendations for future designs through software tools.

Chapter 2 Literature Review

Human variability exists in various forms. Such variability is responsible for a broad spectrum of user responses to one solution, and it multiplies the ambiguity in the design process [51]. In some cases, users give dissimilar or even conflicting feedback which pulls the design in opposite directions [48]. In vehicle packaging, for instance, drivers vary in body dimensions and have different driving postures. The ideal situation is to design a vehicle package that allows all of them to safely and comfortably perform all the driving tasks without encountering any limitation; however, such high expectation of accommodation requires large adjustment ranges which are not always achievable due to cost, safety, and the desire to reduce vehicle size [3]. While packaging a vehicle, all these factors must be considered, and compromises always need to be made to find the best possible solution based on the above considerations and accommodation possibilities.

This chapter introduces the concept of vehicle packaging and reviews design objectives that are used to measure success. It also presents a number of approaches that have been developed to design for human variability and discusses the advantages and disadvantages of each.

2.1 Vehicle Packaging

Vehicle packaging is the act of designing the interior layout of a vehicle with the goal of achieving a certain level of accommodation [2]. It involves a broad range of design considerations that determine whether the fundamental driving components, such as the pedals and the steering wheel, are within reach [3]. Further design considerations include button controls, digital displays, and other elements with which the driver interacts. In the automotive industry, designing for vehicle interior layout is one of the first steps, following the body exterior contour design and window openings design [3]. Besides spatial fitting, safety-related vision requirements are also crucial factors to provide accommodation and comfort for drivers [2].

The transportation industry has been evolving, and this trend is not slowing down. Other than daily commute, the demand of vehicles for other uses has increased greatly and the variety of vehicle class divisions has also multiplied [52]. Besides typical four-door sedans, vehicles of different shapes are developed to suit societal needs. Categorizing by interior volume and gross weight, the three major classes are: car class (various sizes of compacts, sedans, and wagons), SUV (various sizes of crossovers and SUVs, and minivan), and trucks (mid/full-size regular/extended/crew) [53].

Although vehicles are different from each other, they all share a similar shape and similar design objectives. While designing the frame, a number of concerns need to be considered. For instance, one of the most important consideration is the field of view. The upper-daylight-opening (UDLO) is a line in the Y-direction (see reference system in Figure 2.1), where the top of the windshield meets the car frame. This line limits the angle that drivers can looking upward. For different categories of vehicles, the up-vision requirements are different. Meanwhile, drivers must also maintain sufficient down-vision. Depending on driver's eye location, the down-vision can be limited by either the hood point (a line in Y-direction that represents the tip of the hood) or the cowl point (a line in Y-direction where the bottom of the windshield meets the hood) [54]. Commonly, these points are all measured from ground in the Z-direction and from Accelerator Heel Point (AHP) in the X-direction (Figure 2.4). Although vehicle packaging is a design task in 3D, only the X-Z plane is studied in this thesis because the adjustable components of interest in this thesis, such as the steering wheel and the seat, are designed on the center line on the driver's side. The design goals in the Y-direction are different and can be their own study.

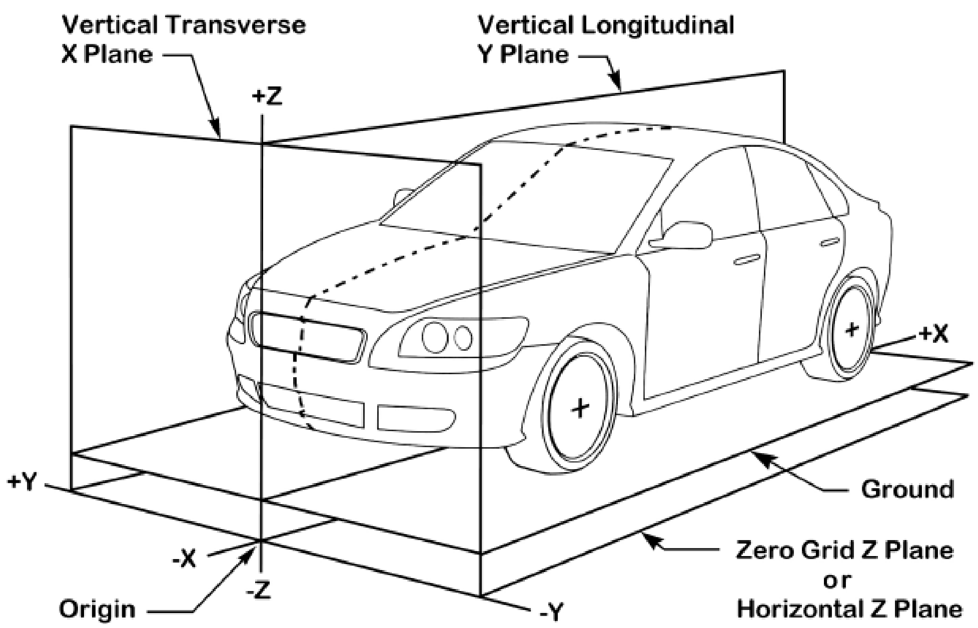

Figure 2.1. 3D Reference System for Vehicle Packaging [1]

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In order to properly and efficiently design a vehicle package, understanding human anthropometric variability is key. In general, there are two categories of data to describe it: conventional static measurements and functional task-oriented measurements. Conventional static measurements are measured when subjects are in standardized and rigid positions, which typically involve lengths, widths, circumferences, and so forth (Figure 2.2). They are the fundamental descriptors of a driver's size and shape, and they do not change due to driver's posture, unlike the functional task-oriented measurements. These descriptors compose the basis of driver-vehicle spatial fitting [2].

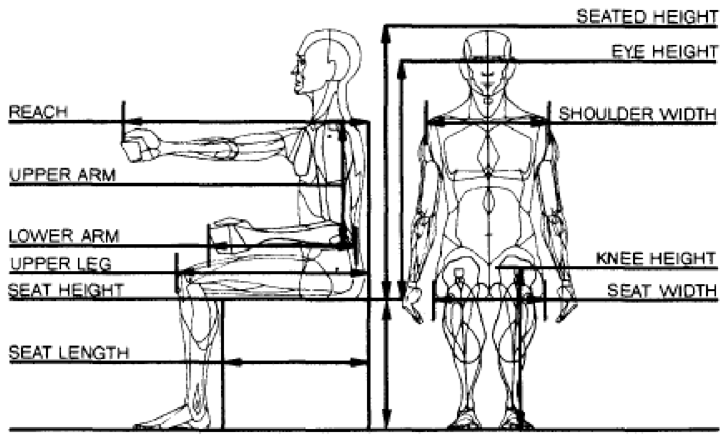

Figure 2.2. Conventional Static Anthropometric Measurements [2]

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Another category of data used in vehicle packaging is functional task-oriented measurements. They are usually measured when drivers are in motion (Figure 2.3). These measurements indicate driver's capability of performing certain tasks, and they can vary among drivers even among those with similar body dimensions. Sometimes, one's ability to reach can compensate for their body dimensions. Vehicle packaging is a complex tasks. A cab needs to designed in a way such that drivers not only need to fit in a cab, but also being able to perform functional tasks, such as turning the steering wheel.

One of the most important reference points is the Accelerator Heel Point (AHP). It is the intersection between the accelerator and the floor. As mentioned earlier, components of vehicle frame geometry (roof, UDLO, cowl point, hood point, etc.) are measured from the ground in Z-direction and from the AHP in X-direction. This reference system works for these components, but it is unsuitable for the interior components, such as the seat and the steering wheel, because there is not a direct way of measuring them from the ground. The difficulty of measuring interior components from the ground causes inaccuracy in these measurements, which should be avoided. Instead, these interior components are measured from the AHP, since the AHP is a fixed distance from the ground [1]. In vehicle packaging research, AHP is commonly referenced as the origin of the system, so this thesis will remain consistent with this convention for the interior components.

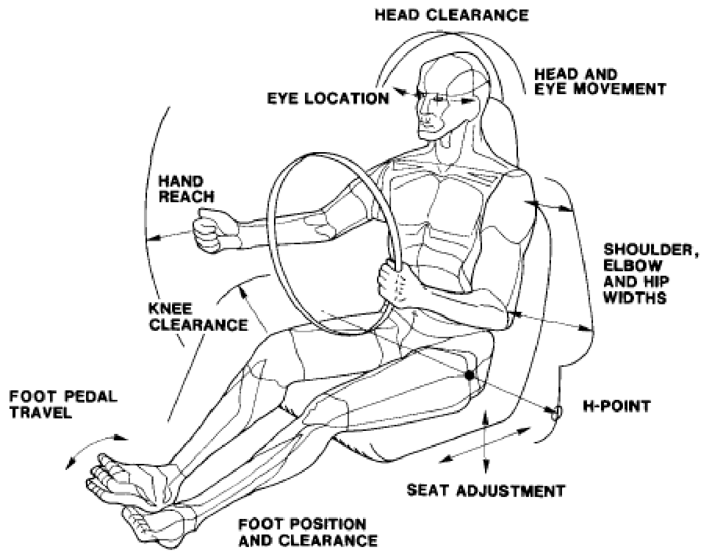

Figure 2.3. Functional Task-oriented Anthropometric Measurements [2]

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While designing the interior layout of a vehicle, it is important to understand each component and its contribution to the overall accommodation. In most vehicles, the steering wheels can tilt about a pivot point, and some can telescope in and out (Figure 2.4). Ideally, a driver's preferred steering wheel location should fall within the adjustment envelope. In that case, that aspect of driver preference is consider to be accommodated. If the preferred location lays outside of the envelope, the location preference is not accommodated, and the driver would compromise by adjusting the steering wheel center to the nearest point on the envelope. Although the driver cannot obtain the most desirable steering wheel location, they can often achieve moderate comfort by adjusting the rest of their body to adapt [14].

Another adjustable component is the seat. Most seats can move in the fore-aft direction. For large vehicles, such as trucks and buses, the seat can also move vertically as well. The adjustment envelope is the shape of a rectangle (Figure 2.4), and the goal is to design a seat adjustment envelope to accommodate the majority of the drivers. If a driver's preferred seat position lays outside of the envelope, they will adjust the seat to the nearest point on the envelope, similar to the steering wheel adjustment [7].

Once the locations of the most critical components, steering wheel and seat, are determined, an assessment on eye location can be conducted. Although eye location is rarely a concern of spatial fitting, it is an important consideration in vehicle packaging because it determines driver's field of view, which is directly related to driving safety [3]. In the past, researchers have found success in estimating drivers' eye locations as an elliptical model [54], which can be a useful tool to assess vehicle layout reference points, such as cowl point, hood point, and UDLO.

In this thesis, eye locations will be explicitly studied, together with steering wheel locations and seat locations.

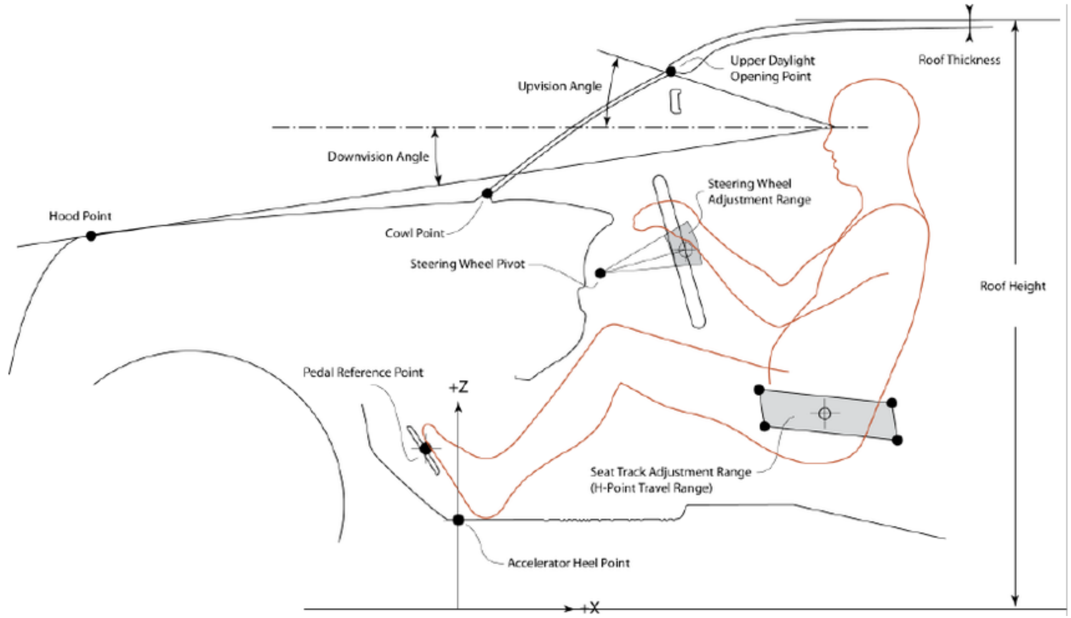

Figure 2.4. Dimensions and Reference Points Used in Vehicle Packaging [3]

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In vehicle packaging, the results of accommodation are usually expressed as a percentage. An accommodation rate can be defined as the proportion of the driver population who is able to meet the spatial fitting requirements and safety requirements [2]. For instance, a seat adjustment envelope can be designed to accommodate 95% of the population, and it implies that 95% of the drivers can move the seat to their desired location without encountering any limits while 5% of them cannot. The assessment of one objective is intuitive, but the design task becomes challenging when more than one component can be adjusted. Therefore, it is important to first distinguish a multivariate problem from a univariate problem [55].

2.2 Univariate and Multivariate

Univariate analysis is a method that analyzes one design objective at a time. It is known to be simple and cost-effective when the design requirements are within its capabilities. A univariate approach analyzes the data that have been collected, describes them without relating other factors, and makes a conclusion of some sort [56]. By directly conducting a univariate analysis without introducing other concerns, a quick and accurate solution can sometimes be reached.

In existing ergonomics practices, the univariate approach can commonly be found in a number of forms. One of the common forms is the estimation of human body. In an univariate approach, body dimensions are assumed to be proportional. By using survey data of U.S. population, a set of proportionality constants can be found to relate a segment of human body to another segment (Figure 2.5). They approximate the length or weight of any body segment of a person by multiplying the proportionality constant by the length or weight of a known segment [4]. This estimation shows a simply way of generating body dimensions of unknown body segments, and it is reliable to a certain extent.

	Absolute Lengths in cm.		Relative Lengths			
			Hand Length = 1,000		Body Height = 1,000	
	G	K	G	K	G	K
Head and neck	21.2	20.2	1.275	1.08	122.7	120.0
Upper trunk	41.0	40.0	1.900	2.14	225.8	238.5
Lower trunk	13.5	17.5	0.690	0.94	81.1	104.5
Upper arm	36.4	30.3	1.792	1.62	211.1	180.7
Forearm	29.9	26.2	1.471	1.40	173.1	156.5
Hand	20.3	18.7	1.000	1.00	117.6	111.7
Thigh	44.9	42.3	2.210	2.26	260.0	252.0
Shank	42.9	38.1	2.111	2.03	248.4	227.0
Foot	6.0	9.7	0.295	0.52	34.7	58.0
Whole body	172.68	167.7	8.500	8.97	1,000	1,000

	Absolute Weights in grams		Relative Weights			
			Hand = 1,000		Body Weight = 1,000.00	
	Cadaver 1	Cadaver 2	Cadaver 1	Cadaver 2	Cadaver 1	Cadaver 2
Head	4,555	3,747	8.435	9.529	71.20	75.11
Upper trunk	23,055	17,779	42.694	45.209	360.40	356.43
Lower trunk	6,553	4,868	12.145	12.380	102.43	97.56
Upper arm	2,070	1,448	3.833	3.682	32.35	29.04
Forearm	1,160	795.5	2.148	2.023	18.13	15.94
Hand	540	383.6	1.000	1.000	8.44	7.69
Thigh	7,165	5,887	13.252	14.972	112.00	118.00
Shank	2,800	2,247.5	5.185	5.716	43.77	45.04
Foot	1,170	985.2	2.167	2.505	18.28	19.74
Both upper extremities	7,540	5,254			117.86	105.34
Both lower extremities	22,270	18,239.4			348.11	365.56
Whole body	63,970	49,895	118.4	126.9	1,000.00	1,000.00

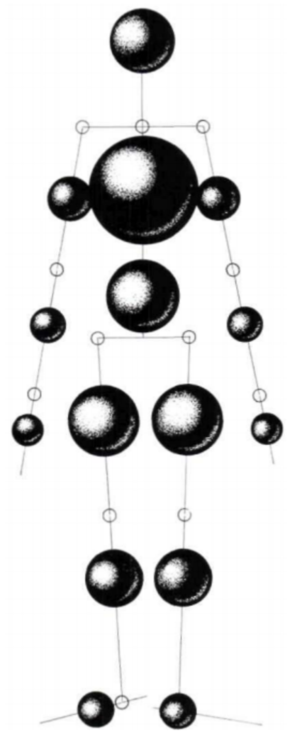

Figure 2.5. Absolute and Relative Lengths of Body Segments (top left) Absolute and Relative Weights of Body Segments (bottom left) and Segment Lengths and Body Mass Distribution Representation (right) [4]

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Although the estimation of proportional body segments has been widely used, unfortunately, it loses its accuracy in high fidelity designs. A group of researchers used 3D scanning to show that human bodies vary in size and shape (Figure 2.6), and this variability is significant. In fact, it is impossible to find two human bodies that have identical dimensions on every measure [5].

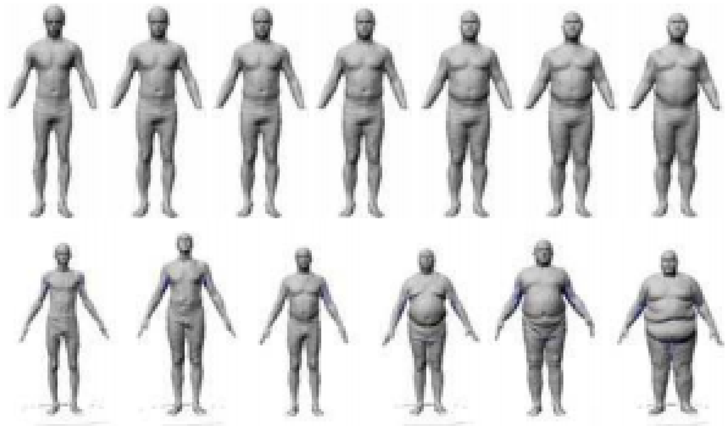

Figure 2.6. Visual Representation of Human Varying in Size and Shape [5]

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Besides human anthropometry studies, the univariate approach can also be found in assessing a design. For instance, while designing a ring, the most critical aspect is the circumference which must provide a comfortable fit to the ring finger. Although other finger-related parameters, such as finger length, exist, the impact is minimal. In this context, a low-cost univariate analysis is more desirable because there is only one design objective to be assessed. When there are more than one design objective, these objectives can be assessed individually. In a study conducted on tractor seats in 2008, several anthropometric measurements, such as popliteal height and hip breadth, were investigated for their contributions to a number of seat-related designs, such as seat height and pan length (Figure 2.7). This study took a univariate approached by separately assessing each characteristic of a tractor seat. At the end of their research, design recommendations were provided to achieve 95% accommodation on each measure individually, wishing the overall accommodation level would be 95%. However, the underlying relationships between different measures remain undiscovered. Being accommodated on one design objective does not guarantee accommodation on another design objective. Were to follow these recomendations in producing an actual tractor seat, the overall accommodation would be much lower than the expected 95% [57].

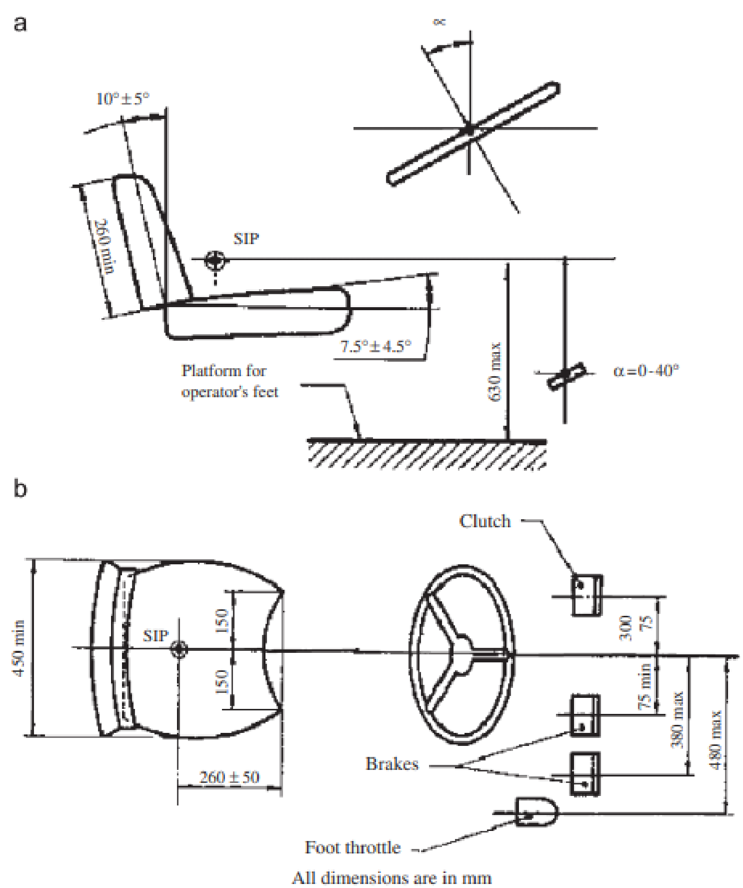

Figure 2.7. Tractor Seat Design in 3D (a) Side View (b) Plane View [5]

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Due to these limitations of the univariate analysis, a multivariate approach is frequently used for these multi-objective design cases. Through multivariate analysis, designers can investigate the accommodation level of a combination of design objectives, which further discovers the underlying relationships between the different objectives [58]. For example, in the tractor seat study above, seat height and pan length are two of the design objectives. A multivariate analysis indicate what percentage of users were accommodated on each design variable individually and what percentage were accommodated on both. The estimated overall accommodation level would be much more accurate.

As previously discussed, vehicle packaging is a multi-objective task. A number of factors need to be considered simultaneously in order to come up with a desirable design. Thus, a multivariate approach is most appropriate and will be used in this thesis.

2.3 Manikin Approach

The variability in human anthropometry is a difficult subject because human bodies vary in size and shape. However, the randomness in most length or width related measures follow a distribution, so statistical tools, such as percentiles, are frequently used. To explain, given a group of people ordered from least to greatest by stature, the 5^{th} percentile is that surpassed by 95% of the group and the 95^{th} percentile is that surpassed by 5% of the group (Figure 2.8). By using percentiles, one can estimate the proportion of a group who meet certain requirement, and further determine design limits [6].

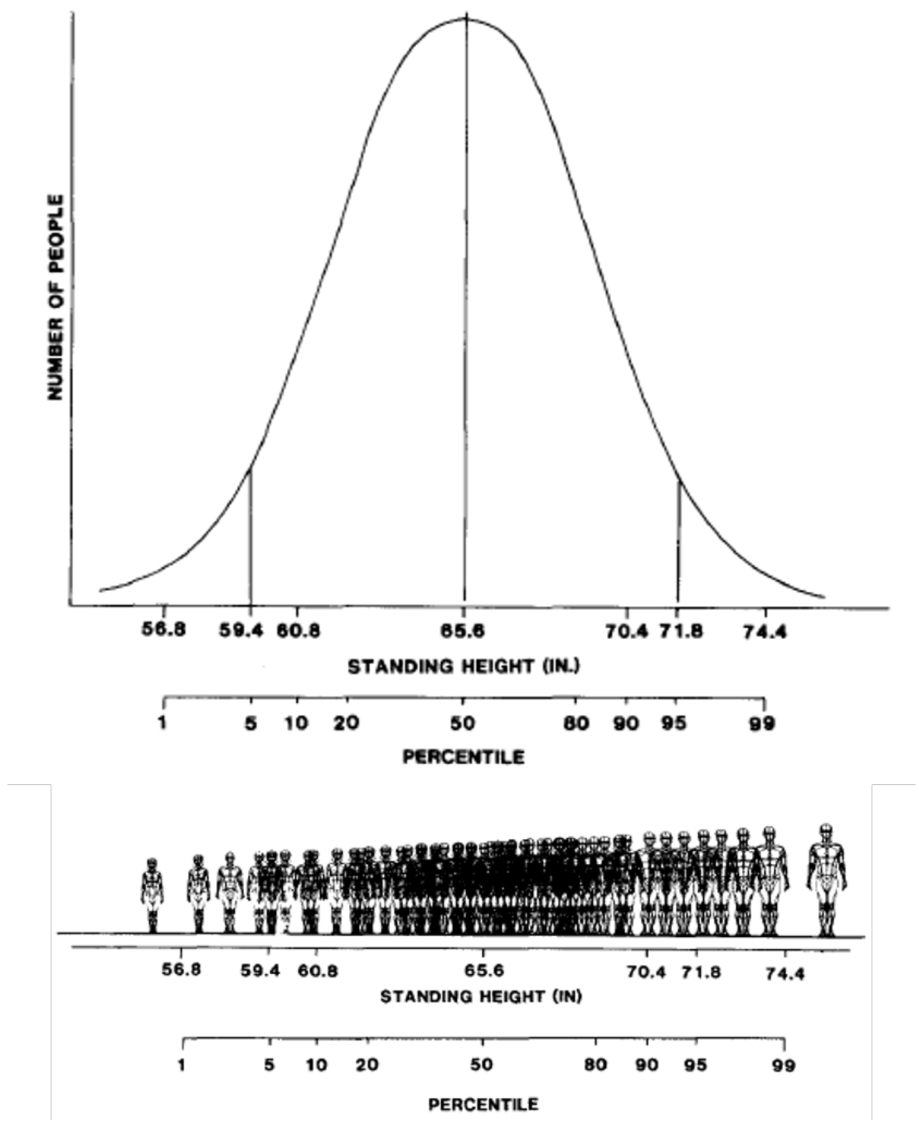

Figure 2.8. Frequency Distribution of Standing Height by Percentile (Top) and Pictorial Representation of Standing Height by Percentile (Down) [6]

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A direct way to apply percentiles is through manikins. Each manikin is built to a unique combination of body dimensions that are suitable for the design project, and it is used to predict human interaction in real life. In order to detect design limits, boundary manikins are frequently used to represent the extremes of the population. A design that can accommodate the extremes is expected to accommodate those with less extreme body dimensions. In many cases, a small female and a large male are used to approximate the extremities of people. For instance, a 2.5^{th} percentile female manikin and a 97.5^{th} percentile male manikin are frequently used to assess a 95% accommodation level, assuming female and male body dimensions are approximately normally distributed and male bodies are bigger than female bodies.

A Gaussian distribution, also known as a normal distribution, contains higher frequency data in the middle and low frequency data at the tails. Providing the same amount of adjustment, more people from the middle can be accommodated by from the tails, which is why it is more cost-effective to design for the central range. Sometimes, when a distribution is skewed, a lower range (i.e. 0^{th}-95^{th} percentile) or an upper range (i.e. 95^{th}-100^{th} percentile) is selected. To demonstrate, the following univariate analysis (Figure 2.9) describes the central location and the travel range of a car seat in fore-aft direction and the associated percentile accommodation [2]. Between 10^{th} percentile and 90^{th} percentile, a near-linear relationship between seat adjustment range and the corresponding accommodation level can be observed. However, a much larger adjustment range is needed to accommodate the tails (below 5^{th} percentile or above 95^{th} percentile).

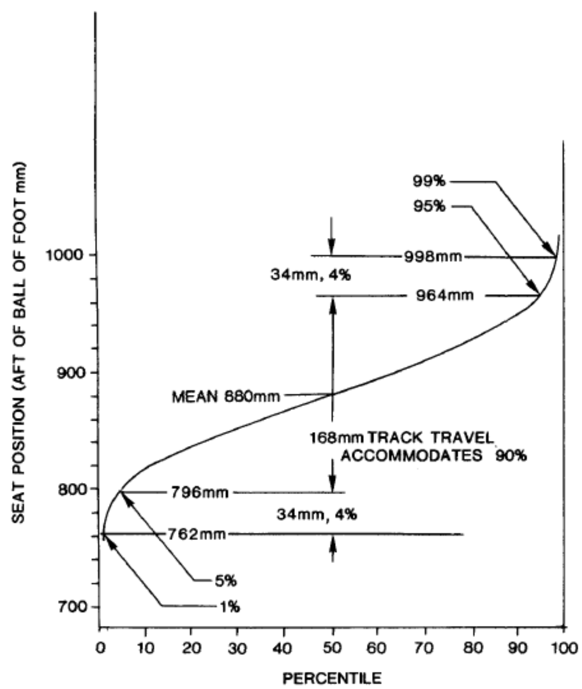

Figure 2.9. Percentile Model of Seat Fore-Aft position with Respect to Ball of Foot [2]

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The manikin approach is relatively easy to understand and is easier. to implement, but it has certain limitations as well. One of those limitations is the reliability of manikins. During the approach, each manikin is a percentile model and represents one user with extreme body dimension. Intuitively, a 90^{th} percentile manikin is expected to be composed of 90^{th} percentile body segments, but in reality these segments would add up to be much taller. By accommodating this 90^{th} percentile manikin, designers assume those with less extreme body dimensions are also accommodated. However, such assumption has major flaws especially in complex design problems. A design that accommodates the users with extreme body dimensions will not necessarily accommodate all the users between the extremes, and an n^{th} percentile individual does not exist [59].

In the past, the manikin approach has been applied in various design fields. For instance, a systematic ergonomics study using manikins was conducted on industrial workstation design in 1996 [60]. Another study was conducted on the optimization of viewing angle for touch-screen displays using a similar approach in 1998 [61]. Manikins have also been used in the automotive industry as early as 1962. Since the late 1950s when the Society of Automotive Engineers (SAE) first proposed the concept of applying standardized procedures and tools in vehicle packaging, the SAE composed J826 that introduced a two-dimensional H-point template to estimate packaging profile and a three-dimensional H-point machine device for defining and measuring occupant seating accommodations (Figure 2.10). This H-point machine, one of the first uses of manikins in the automotive industry, defines the location of the H-point which is specific to a seat [7].

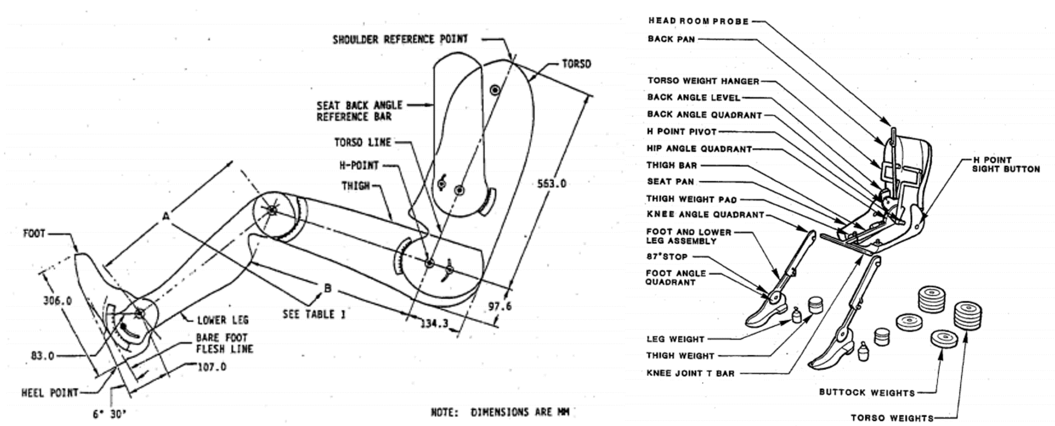

Figure 2.10. 2D H-Point Template (left) and 3D H-Point Machine (right) [7]

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The manikin approach, or the percentile model, is one of the most commonly used approaches in ergonomic design, and it studies the distribution aspect of anthropometric measurements. The investigation of how an individual relates to a population is its core concept. An n^{th} percentile measurement represents precisely n% of the population is more extreme [62]. This simple and intuitive approach remains reliable for most univariate problems. In many design practices, by designing for both the lower extreme user and the upper extreme user, designers assume all the users in the middle are accommodated. This assumption is valid in simple design cases; however, it loses its validity while assessing a full body that consists of multiple measurements. As discussed earlier in the chapter, an n^{th} percentile user does not exist due to human variability. There are countless measurements to define a human body, and it is impossible to find one person that is n^{th} percentile on every single measurement [63].

Manikins are frequently used in vehicle packaging to simulate how an actual user would interact with the main components in a vehicle based on body anthropometry. It is a simple and visual way to assess multivariate accommodate, but it has major flaws. Specifically, driving posture plays a critical role in vehicle packaging, but it is not considered in the manikin approach

[64]. In practice, designers often posture the manikins manually based on either personal intuition or a standardized procedure, which poorly quantifies the postural variability. In order to solve this bias, several methods with a focus on posturing were developed.

2.4 Population Model Approach

The manikin approach provides a visual and intuitive way to estimate user interaction under the assumptions as mentioned in the previous section, and it cannot provide knowledge on human posturing. The population model approach, on the other hand, directly investigates the interaction between users and a design. It first identifies a sample group, then it conducts a human interaction experiment for this group and establishes a model based on the results. This model will then be applied to the user population so that a certain percentage of the population can be accommodated [64].

Dissimilar to the manikin approach, which simulates a percentile-based user who frequently represents an extremity, the population model approach targets the actual users. In order to lower the cost of the design, a sample group, rather than the entire population, is commonly selected for an experiment or a focus study. Although there are advantages in reducing the size of the sample group, the group size must be relatively large to ensure that it can adequately represent the target user. Certain traits could be magnified when the group size is small, which could lead to biases. In addition, a random sampling method must be utilized as well. Such effort is essential to the validity of the results [2].

During the experimental study with the sample group, participants are frequently invited to interact with a robust prototype that provides excessive range of adjustment, and their responses are then recorded and analyzed. Due to the interactive nature of the population model and its use of prototypes, it is frequently used in the product design field. For instance, a research group used a 3D laser scanner to measure standoff distance between the head and the backface of the helmet of a representative sample group of 30 participants. This information was then utilized to guide future ballistic helmet design [65]. Similarly, a study was conducted using a population model approach to determine the optimal grip span with respect to hand anthropometry. During the process, a total of 12 participants were invited to interact with the hand-grip device (Figure **??** [8].

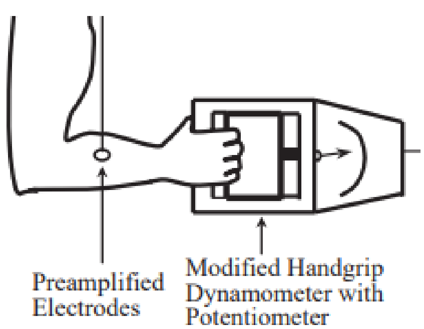

Figure 2.11. Apparatus Setup for Grip Span Measurement [8]

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In order to study postural preferences through a population model approach, participation from a large number of randomly sampled drivers is required. While each participant is in a testing environment, a tracking system can be used to continuously monitor the location of all the critical body landmarks. The relative spatial locations of these landmarks shows the subject's body configuration which indicates their postural preference, and the absolute spatial locations determine whether the subject is accommodated by the vehicle layout or not.

The population model has been applied in the automotive industry, and there are many examples. In a study published by the UMTRI in 2017, a statistical body shape model was used for seated vehicle occupants to study their driving preference. This reliable model used in this research was established from 147 participants. The data of various seating postures was captured with a laser scanner together with manually-measured body landmarks(Figure 2.12) [9]. There are many more applications of the population model approach in the SAE as it serves as one of the fundamentals concepts in the SAE International recommended practices [66].

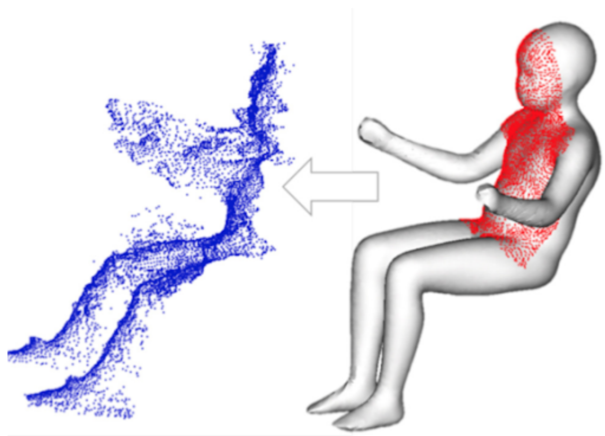

Figure 2.12. Laser Scan of Vehicle Occupant's Normal Driving Posture [9]

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2.5 Hybrid Approach

Even though the population model approach shows improvement from the manikin approach by considering postural preferences, it still has several limitations that cannot be ignored. The most important one being that the population model can only be applied to one single design case. Since the sample group is selected from the user population, this model is limited to that user population and can only be applied in an identical design case, which rarely happens in real life. Even when designing the same product but for a slightly different user population, the entire process will need to be re-done. An adequately large sample group needs to be sampled randomly, and participants will need to participate in the accommodation experiment individually, after which, data will be analyzed. The process of creating a valid model this way is time-consuming and costly. It would be more efficient to be able to utilize the previous efforts.

In order to conquer the issues with the population model, a hybrid approach was developed. The hybrid approach merges the strengths of the postural preference model and the anthropometry-configurable manikins [64]. The goal is to confidently apply the same model to a different user population, so a quantitative relationship must be found that relates the desired outcome to anthropometric measurements. These anthropometric measurements serve as predictors of the model. While applying the model to a different user population, anthropometric measurements can be modified to best match the new user population, and the results from the hybrid model will adjusted accordingly.

By diligently collecting data and interpreting the underlying relationships, researchers have found success in the hybrid model. For example, a group of researchers used an adjustable bicycle simulator to assess comfort level on bicycles and validate commercial bicycle accommodation. To do so, they performed correlation analysis on preferred bicycle dimensions and body anthropometric measurements, and found that saddle-pedal distance is strongly related to crotch height (Figure 2.13) [10]. A similar approach, relating outcome variables with anthropometric measurements, can also be found in Yakao's study on evaluation of cylindrical objects, which examines handle diameter and hand length [67].

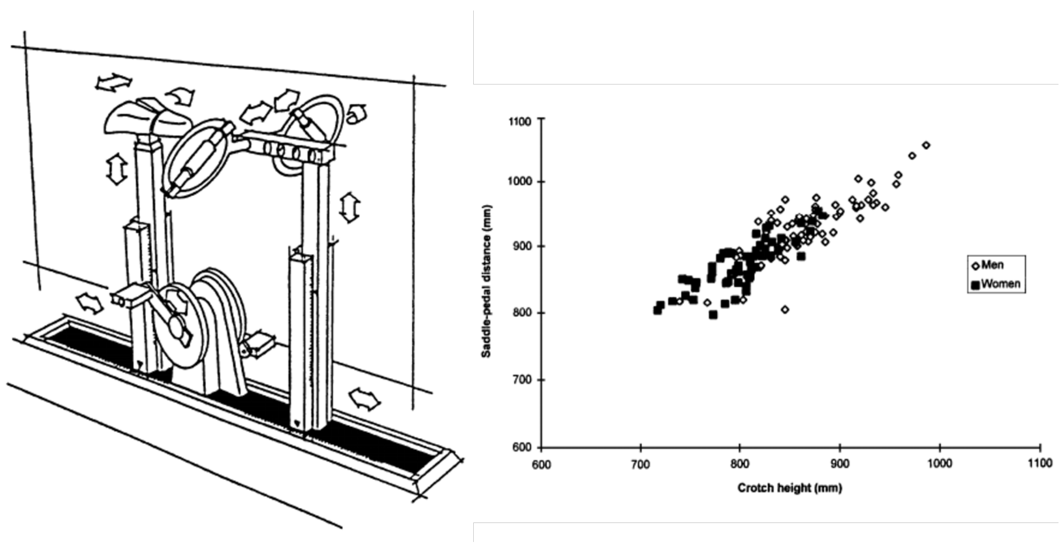

Figure 2.13. Configurable Bike Apparatus (left) and Correlation Between Saddle-pedal Distance and Crotch Height [10]

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2.5.1 Virtual Fitting

For the population model approach and the hybrid approach discussed previously, the reliability of result decreases with the number of participants. Although more participants generally produce more accurate results, they raise the cost significantly as well. The same is true for the percentile approach; in order to better represent the actual population, a large number of manikins with various anthropometric dimensions can be made to represent a variety of user groups. In contrast to boundary manikins, these manikins provide necessary variability in body size and shape.

However, the process of producing these manikins is time-consuming and costly, and this effort is not reusable when designing for a different user population. In order to mitigate this issue, Digital Human Models (DHM), such as RAMSIS, were developed in the 1990s to virtually represent humans as an improvement to the manikin approach. Since then, DHM has been increasingly used for vehicle packaging and other ergonomics design [12].

Since the initial creation of DHM, it has been widely used for task performance simulation. One of the advantages is that it facilitates a quicker design process [50]. With the development of computers, DHM becomes an essential part of product design and provides insights for product usability [68]. Instead of competing on money investment, companies shift their focus to engineering research and computing power. The figure below shows the DHMs generated in four different software tools (Figure 2.14):

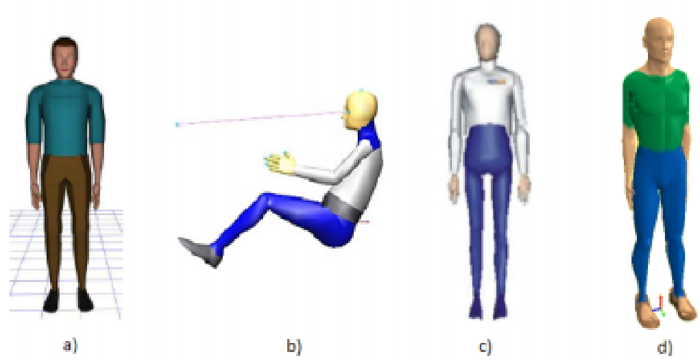

Figure 2.14. Digital Human Models of Jack (a), RAMSIS (b), HumanCAD (c), and 3DSSPP (d) [11]
.

The virtual fitting method not only justifies the cost-effectiveness of using it for vehicle packaging, but also produces more accurate results because of its multivariate nature. Designers can visually assess the fit of all interior components and make appropriate adjustments to improve overall accommodation (Figure 2.15). With the help of software, virtual fitting can be performed repetitively with various body anthropometry which makes it an appealing method in vehicle packaging. The method is especially useful for Class B vehicles, such as trucks and buses because they usually involve more design considerations besides spatial fitting due to the driving tasks. For instance, Class B vehicles commonly use height-adjustable seats so that drivers can maintain adequate vision of the surroundings [69].

Figure 2.15. Digital Human Model Used in Vehicle Packaging (RAMSIS) [12]

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Another significant advantage of applying the virtual fitting method in vehicle packaging is its seamless adaptability to the hybrid model. As discussed earlier, the manikin approach does not usually have a scientific way of posturing the manikins. Commonly, the designers manually posture the manikins which introduces bias. Using a hybrid approach can effectively resolve this issue. The hybrid approach establishes a model relating driver anthropometry to their body landmark locations in space. By creating a large number of virtual driver profiles and feeding their body anthropometric data into the hybrid model, designers can accurately and quantitatively simulate how each of the drivers would posture themselves in a cab. It allows the designers to visually assess the accommodation level of any vehicle layout (Figure 2.16) [3].

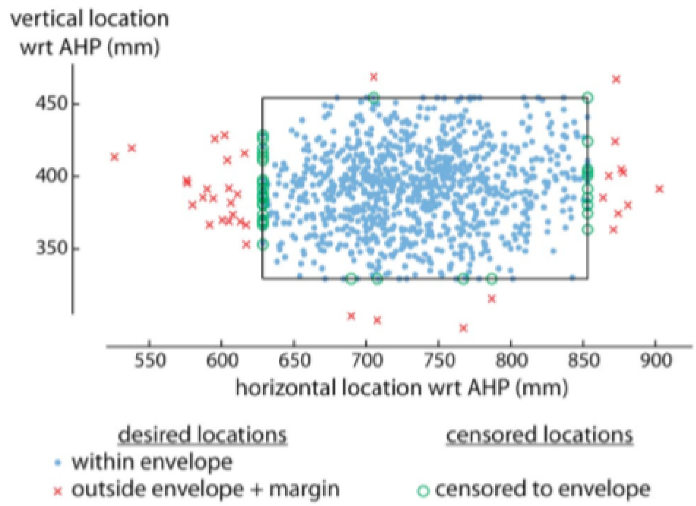

Figure 2.16. Preferred and Censored Seat Locations of Virtual Truck Drivers [3]

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2.5.2 Cascade Prediction Model

The Society of Automotive Engineers (SAE) is an organization of professional engineers, aiming to come up with standards and conduct research to bring safe and innovative design to the world. In the past several decades, many SAE J-tools have been developed and heavily used for vehicle packaging in the automotive industry. For instance, SAE J1517 examines driver seat position, SAE J941 investigates driver eye position, and SAE J1052 specifically studies driver head location (Figure 2.17). These SAE J-tools provide thorough guidelines on each of the components individually. Due to the lack of coherency and its univariate nature, the results can sometimes be less accurate than expected.

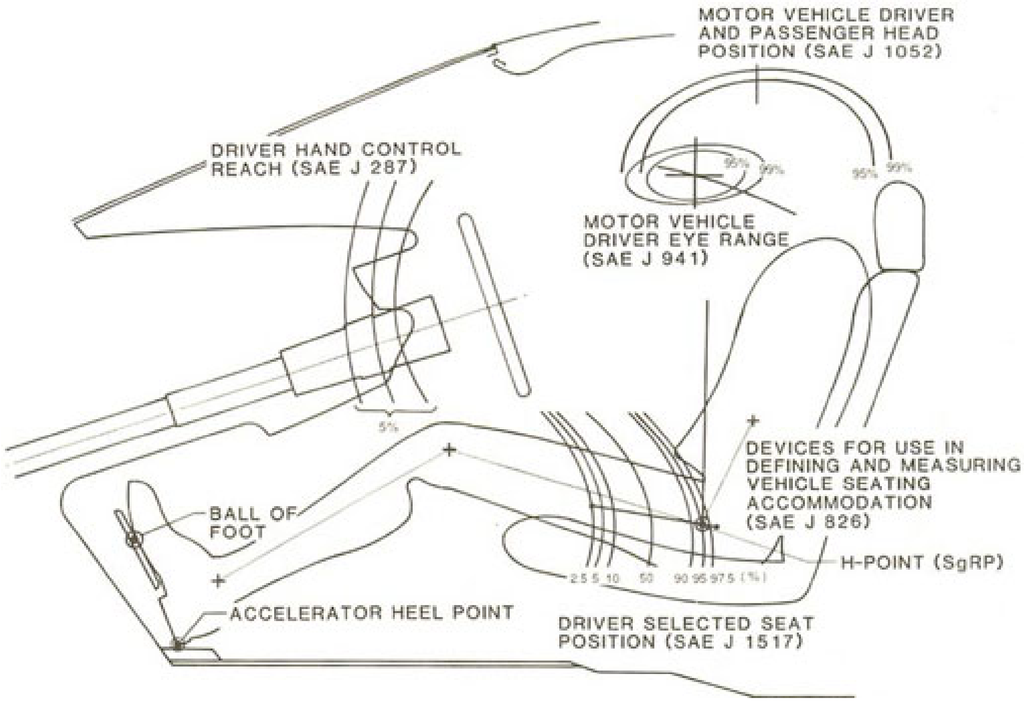

Figure 2.17. SAE Recommended Vehicle Packaging Component Layout Side View [13]

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In the early 2000s, a Cascade Prediction Model (CPM) was developed. From analyzing drivers' postures captured with a sonic digitizer, researchers found that drivers frequently react to the surroundings by moving their limbs while maintaining their torso position still. Since locating the torso is a crucial step that lays the foundation of limb posturing, CPM puts great emphasis on the prediction of hip and eye locations, which are recognized to be the most important measurements in vehicle packaging. Hip location is critical for seat position design and lower limb posturing, while eye location is a direct assessment of driver's vision [70]. With these two critical body landmarks created from the models of experimental data, researchers can establish sub-models and apply inverse kinematics to predict the secondary body landmarks, such as shoulder location, elbow location, and knee location [14].

Even though CPM is relatively recent compared to other vehicle packaging methods, such as the manikin approach, it is proven to be reliable. In a study conducted by the University of Michigan Transportation Research Institute (UMTRI), a group of researchers aimed to estimate driver postures with CPM and compare them to laboratory observations. A total of 63 participants were studied in a laboratory setting to create the CPM while being given 27 vehicle package and seat conditions. The results were found matching with the observed postures of 24 participants from an earlier in-vehicle study. The differences in mean locations of eye and hip were within a few millimeters, and the differences in standard deviation were comparable as well. Although these differences can derive from vehicle layout anthropometric variability, CPM is proven to be an accurate and reliable tool for vehicle packaging [14].

Chapter 3
Methods

The objective of this thesis is to study driving postures of U.S. bus operators and make design recommendations regarding bus cab layout. The previous chapter presented a number of ways to conduct vehicle packaging that have been developed in the past. There are advantages and disadvantages associated with each one, and one method may be more suitable than others for a specific study. While deciding on which method to use, many factors need to be considered regarding existing research, cost investment, fidelity of results, and more. An appropriate approach should be able to provide results of good enough fidelity within a reasonable budget and meet the project expectations.

Besides selecting an appropriate model, another great challenge is to understand the bus operator population as a whole because the work-associated requirements and other considerations make the demographics of U.S. bus operators unique from the general population. The differences can be reflected in descriptors, such as gender ratio, ethnicity composition, and age distribution. In design for human variability, this information is critical to defining the design boundaries and recognizing the actual drivers because it is of interest to design for their characteristics. Without clearly defining the population, drivers will be unsatisfied and the manufacturing cost will increase as well.

The first half of this chapter will explicitly discuss the approach to be used in this thesis and present the models to be applied to predict driver's posture. The second half of this chapter will present the demographics of the U.S. bus drivers.

3.1 Model Selection

Vehicle packaging is a subject that studies spatial definition of components, and any design recommendation is made based on driver sitting or driving behavior. These behaviors are a compound result of the body dimensions and postural preferences. While using an existing model to conduct vehicle packaging, the accuracy in body landmark prediction is a concern. The goal of packaging interior components is for the interior components to provide enough adjustment in order to accommodate a large fraction of drivers.

This thesis aims to provide a toolkit so that the industry users can accurately predict spatial locations of U.S. bus operators and properly design a bus cab to ensure that a large number of U.S. bus operators are capable of reaching the steering wheel and the pedals without any difficulties, and can maintain adequate vision to be alert of the surroundings. To ensure the achievement of meaningful results, it is important to use a model that can accurately predict sitting and driving behaviors given driver anthropometry. The model to be used must also have been verified with experimental data because it is expected to be able to produce accurate results in a consistent manner. From this standpoint, a modern approach, such as cascade modeling, appears to be favorable because of its multivariate nature and its accuracy in successfully predicting driver's postures, although percentile-based or population-based approaches can also provide high enough fidelity when used properly.

Besides accuracy of driving posture prediction, another objective of this thesis is to deliver a toolkit to industry users. Using numbers and tables is a great way to display results, but it lacks the strengths of visuals. As researchers have shown, the usage of visuals increases an individual's patience in learning and understanding [71]. Additionally, 83% on average of what a person learns is through the sense of sight [72]. Therefore, it would significantly reduce the learning curve associated with this new toolkit to include a visual representation of the accommodation results. To be specific, the toolkit should clearly and accurately identify the critical landmarks (preferred steering wheel location, H-point location, and eye location), and display the rest of the landmarks (shoulder location, elbow location, knee location, and ankle location) with moderate accuracy.

The past automotive industry approaches seem incapable of delivering the desired outcomes. As mentioned previously, industry users currently rely heavily on the SAE J tools and conduct mostly univariate analyse by designing interior components independently. They can provide sufficient knowledge on how people react to each design objective and estimate how a driver's interaction varies within a certain population, but they cannot provide a coherent understanding of how individuals adapt to several spatial requirements simultaneously. The correlation between the requirements is disjointed, especially from an individual level. More importantly, the SAE J-tools are incapable of predicting postural adjustments due to disaccommodation.

Current industry standards describe driver posture by estimating the distribution of the preferred locations of each landmark, such as steering wheel, H-point, and eye location. Assuming the distributions are normally distributed, they can be represented with mean and standard deviation. The advantage of such an approach is that distributions are continuous. Without needing an infinite number of drivers, it produces results of infinite resolution. The disadvantages are apparent as well. The main issue is the model cannot adjust accordingly based on bus geometric constraints, because the underlying relationship between meeting multiple design objectives remains uncertain. While designing an adjustment envelope of steering wheel, for instance, a high accommodation rate is desired, but disaccommodated drivers are expected as well. When a driver's preferred steering wheel location is not in the adjustment envelope, they will move the steering wheel to the nearest point on the envelope and adjust the rest of the body to accommodate this change (Figure 3.1).

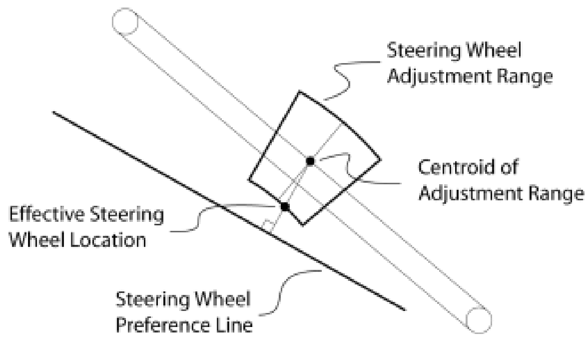

Figure 3.1. Disaccommodated Steering Wheel Locaion Being Adjusted to the Nearest Point on the Envelope [14]

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The purpose of a new design is to minimize these required changes to a driver's preferred posture. In order to visually reflect how adjusting one landmark can impact the location of other landmarks for every virtual bus operator, it is important to approach vehicle packing from an individual level.

Overall, the most appropriate model needs to be able to accomplish the following three objectives: a) predict locations of critical landmarks with high accuracy, b) assess design objectives using a multivariate approach, and c) use visuals to present packaging results. Considering all the available approaches as discussed in Chapter 2, the first two needs can be met by using a Cascade Modeling approach, and data visualization can be achieved through Virtual Fitting.

3.2 Cascade Model for Buses

Previous research has laid a foundation in Class-B vehicle packaging, and a Cascade model for buses and trucks was developed in 2005. Its core concepts can be summaried in a flowchart (Figure 3.2). In this section, the cascading procedure of driving posture prediction will be detailed.

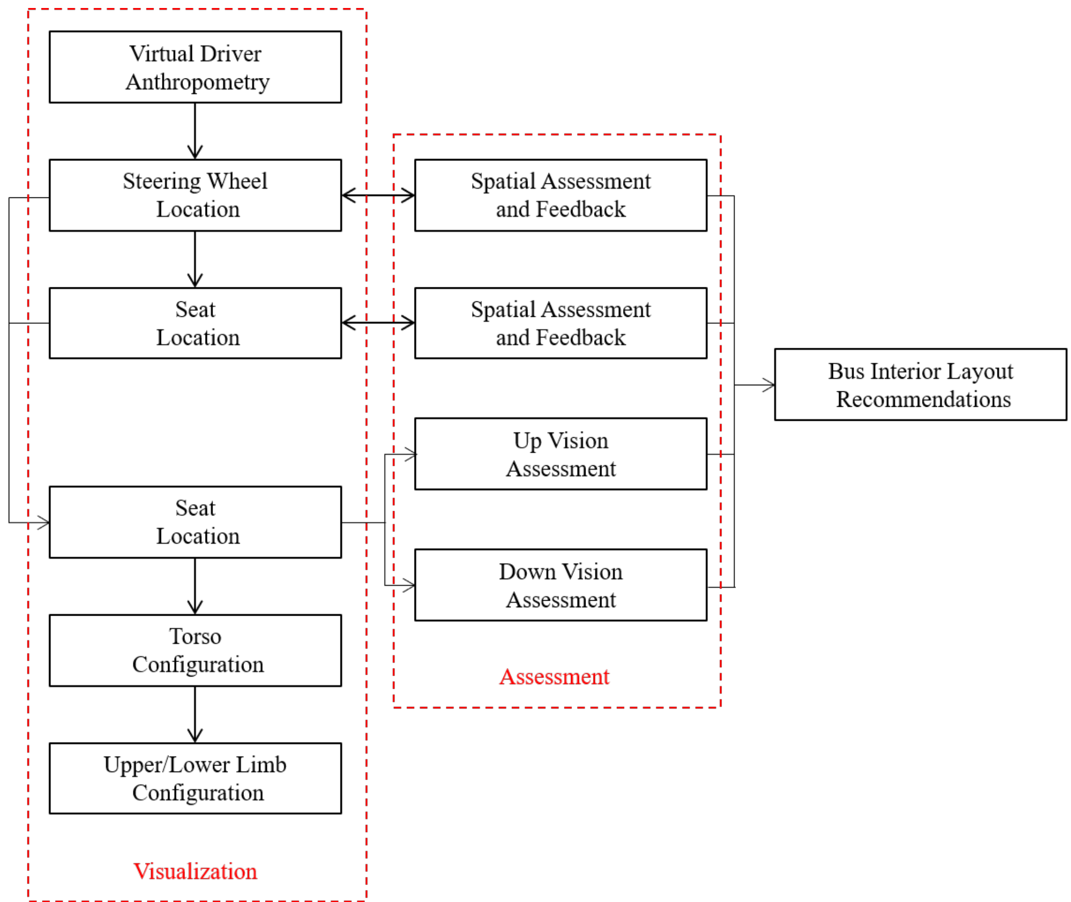

Figure 3.2. Schematic Diagram of Cascade Model

3.2.1 Steering Wheel Location

In posture prediction, locating a preferred steering wheel location is one of the first steps. Most vehicles now include adjustable steering wheels. Due to the spatial demand of the operator cabs among large vehicles, especially buses and trucks, steering wheels need to provide suitable adjustment ranges in order for drivers to maintain sufficient vision while driving. Commonly, there are two modes of adjustments: tilting and telescoping. Tilting is when a steering wheel rotates about its pivot point, located underneath the steering wheel. Telescoping is when a steering wheel moves parallel to the shaft (Figure 3.3). With the two modes of adjustments, the steering wheel can move in both X- and Z- directions.

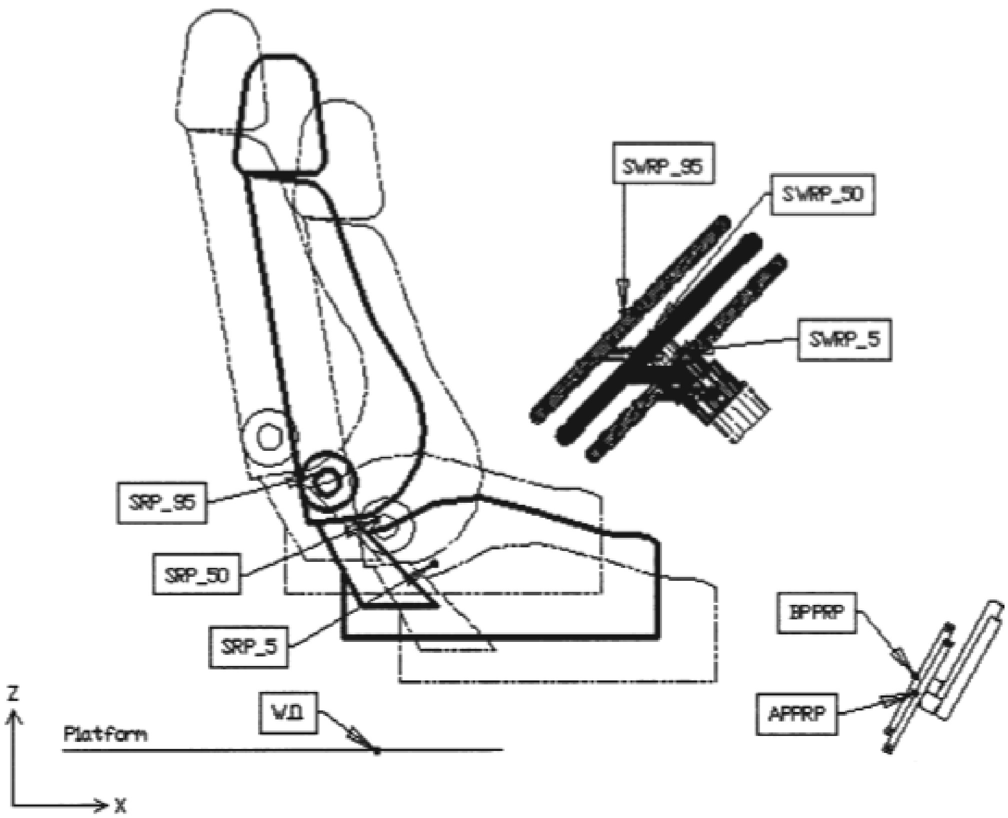

Figure 3.3. Steering Wheel Schematic Diagram in Class B Vehicles [15]

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Drivers tend to place the steering wheel at the most comfortable location for them to perform normal driving tasks. These preferred steering wheel locations vary from person to person, which makes it challenging to comprehend and predict driver preference. In an attempt to understand such variability, a laboratory study has been conducted to investigate preferred steering wheel location for vehicle operators. Participants were asked to sit in a simulated cab and adjust the floor height and the pedals in the X- (fore-aft) and Z- (vertical) direction [14]. Instead of the steering wheel, the origin of the cab (AHP) was adjusted because steering wheels were fixed in space in the experiment setup. It allowed the relative location between the steering wheel and the pedals to vary based on driver preference. After each driver adjusted to their preferred posture, data was collected [14].

The preferred steering wheel location data (measured from the AHP) indicated that the vertical location of the steering wheel is negatively impacted by its horizontal location, and a near-linear relationship was discovered. The average ratio (Mean) was calculated to be -0.559 with a standard deviation (S.D.) of 0.305 [14]. In other words, the vertical location is expected to decrease by an average of 0.559 millimeters as the steering wheel travels back horizontally every 1 millimeter. And, 67% of the drivers will likely choose a ratio between -0.864*(Mean − S.D.)

and -0.254*(Mean + S.D.).

$$SWprefZ \quad -0.559 * SWprefX \tag{3.1}$$

Researchers have also discovered the variance of the ratio was derived from driver's preference, and it was independent of driver anthropometry [14]. However, the preferred total height of the steering wheel is strongly dependent on the driver's vertical size. Stature is known to be the most common way to describe a person's size, and is frequently used in vehicle packaging as a predictor. The preferred vertical location is found to be:

$$SWprefZ@175(mm) = 524 + 0.1613 * Stature, R^2 = 0.32, RMSE = 23.4 \tag{3.2}$$

when the horizontal location is at 175 mm with respect to the AHP. The horizontal location of 175 mm does not hold actual meaning, and is chosen merely for mathematical convenience. In fact, any horizontal location can be chosen because the preferred vertical locations move along a slope of 0.559, as mentioned before. These preferred vertical locations can be found by using the equation below:

$$SWprefZ(mm) = 524 + 0.1613 * Stature - 0.559 * (x - 175) \tag{3.3}$$

This line represents the steering wheel preferred vertical locations. Based on their stature, each driver has their unique preferred steering wheel vertical height line 3.4.

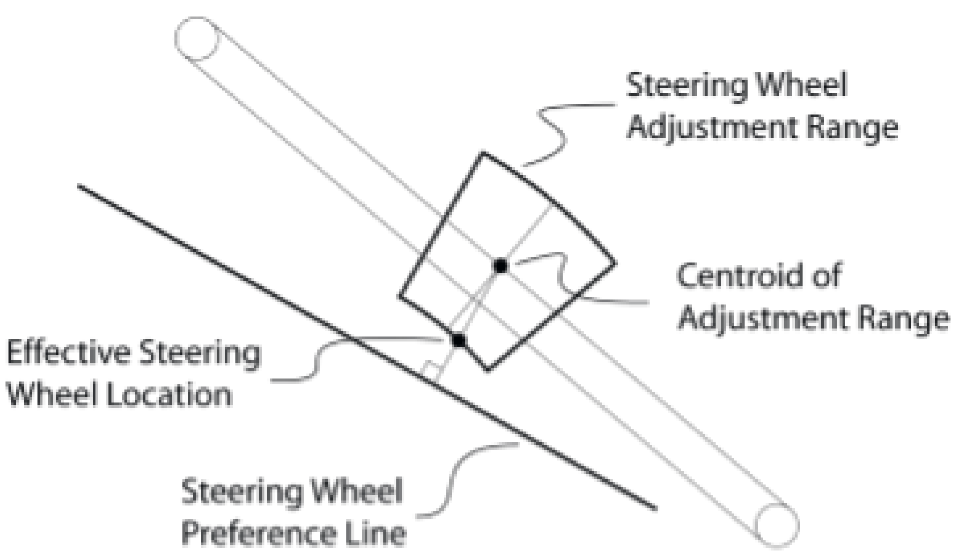

Figure 3.4. Steering Wheel Preferred Line Given Driver's Stature [14]

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One preference line is not enough to locate a preferred steering wheel location in a 2D space because there are two Degrees of Freedom (DoF). Instead, a minimum of two lines are needed.

Besides steering wheel vertical height, human variability can also be reflected in the steering wheel tilt angle [14]. Rotating the steering wheel about the pivot point not only allows drivers to control the face angle of the steering wheel so that it is easier to grab, but also enables the steering wheel to move in the horizontal direction to adapt fore-aft preference. By drawing a line connecting the steering wheel pivot of rotation and the center of the steering wheel, a driver's preferred tilt angle can be found. With these two lines, one can find the intersection that represents the driver's preferred steering wheel location [14].

For a properly designed vehicle, the majority of the preferred steering wheel locations should be accommodated. In fact, the adjustment envelope should be selected after the preferred locations are found. Once the envelope is determined, it can then be used to locate the fore-aft and vertical locations of center of steering wheel with respect to AHP, which are to be used as inputs for the rest of the posture prediction (Figure 3.5) [14]. If the preferred location lies outside of the adjustment envelope, the nearest point to the envelope is used to proceed in the process. Specifically, two measures need to be assessed: tilt angle and telescope distance. Both of them need to be within the vehicle adjustment range. If one exceeds that range, the most extreme location within the range will be selected.

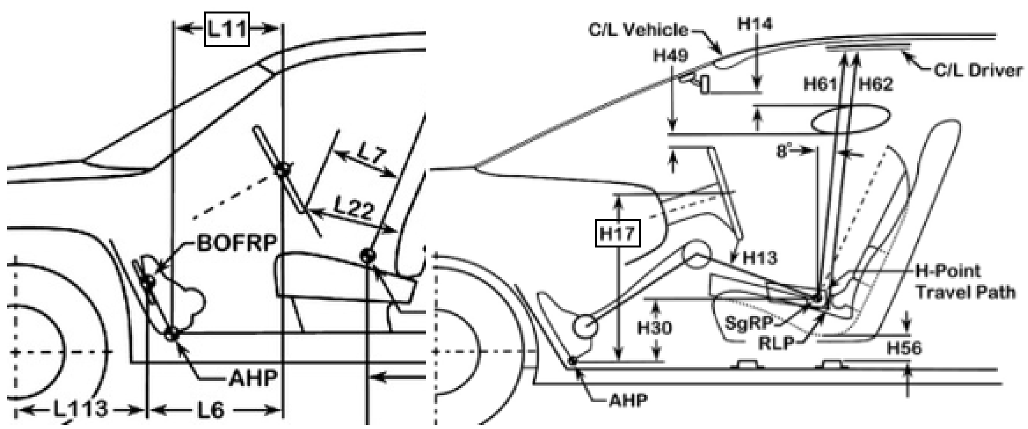

Figure 3.5. L11: fore-aft location of center of steering wheel with respect to AHP; H17: vertical location of center of steering wheel with respect to AHP [1]

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This model provides a mathematical understanding of how drivers would adjust the steering wheel to a preferred location based on their body dimensions and their driving preference. It was developed using laboratory data and has been verified in the field. This model can accurately predict driver's preferred steering wheel location, which lays a solid foundation for upcoming posture studies.

3.2.2 H-point Location

The seat is another adjustable component inside a vehicle. The location of a seat is arguably the most important measure because it has the largest impact on a driver's position in a cab. One of the design concerns of seat location is that drivers must be able to comfortably reach the pedals with their feet. The capability of doing so is a fundamental requirement of vehicle packaging and is an indicator of spatial fitting. Another concern of locating driver's H-point is to provide reasonable relative location between the hand grip and the torso. Similar to reaching the pedals with the driver's feet, reaching the steering wheel with the driver's hands is equally important. Once the steering wheel location and the seat location are chosen, driver eye location will be assessed for safety considerations. A more detailed discussion on driver field of view will be presented in the next section.

The cascade model used for some of the posture prediction was developed based on linear regression, which are in the form of constant coefficients multiplying predictors, as shown below.

$$y = c_0 + c_1 * x_1 + c_2 * x_2 ... \tag{3.4}$$

Y represents the dependent variable, which is the variable of interest. The independent variables (x1, x2, ...) are predictors [73]. In vehicle packaging, two kinds of predictors are common: Driver anthropometry describes size and shape, and plays a major role in spatial fitting, which mostly determines body landmark location. Meanwhile, vehicle geometry can also contribute to the effect because drivers commonly adjust their posture in order to adapt to the vehicle interior component layout. By taking these two predictors into account, one can accurately predict the average location of a desired landmark.

This linear regression is useful for predicting driver's average behavior; however, it is insufficient in expressing their individual preference. In order to do so, an error term is introduced [73]. The error term E(0, SD) is perceived as a randomly generated number from a Gaussian distribution. This distribution has a mean of zero and a standard deviation of SD. By scientifically studying the size of the error and augmenting this error to the linear regression, a complete spectrum of driver preference can be captured through this model.

$$y = c_0 + c_1 * x_1 + c_2 * x_2 ... + E(0, SD) \tag{3.5}$$

As discussed in Chapter 2, an H-point is a fixed point of a car seat near the driver's hip. Unlike a hip point that moves with driver's posture, an H-point is a characteristic of a seat. Given an H-point location with respect to the AHP, one can accurately locate the seat. While performing vehicle packaging, one of the objectives is to design a proper seat adjustment envelope. Thus, the H-point, instead of the hip point, is commonly used.

Instead of measuring H-point location using outdated methods, such as an H-point machine or 2D H-point template as introduced in SAE J826 [7], researchers have created a linear regression model that can predict H-point location with high accuracy [14]. One of the factors that lead to its success is that it uses a stepwise approach in an iterative manner [74]. For instance, there are a number of anthropometric measurements that can describe the length of a human body, including stature, leg length, arm length, erect sitting height, acromial height, and many others. They can all serve as indicators of body length. This introduces more than needed predictors, and can actually lead to more errors because certain body characteristics are over-analyzed. A stepwise approach carries out an automatic process of choosing predictors to fit regression models. During each step, one predictor is analyzed for adding or subtracting from the current list of predictors.

Through an iterative stepwise approach, two predictors regarding vehicle geometry (fore-aft and vertical locations of center of steering wheel with respect to AHP) and five predictors regarding anthropometric measurements (stature, erect sitting height, ratio of erect sitting height to stature, difference between stature and erect sitting height, and natural log of BMI) were identified [14]. As discussed previously, anthropometric measurements are approximately normally distributed, so each measurement of a population can be represented with a mean and a standard deviation. Besides the variation in driver's posture as represented in the error (E) term in the linear regression, the variation in human body size and shape is the other main consideration in design for human variability.

The stepwise regression results indicate that the horizontal location of H-point is largely dependent on the horizontal and vertical location of the steering wheel, which is a sign of drivers adjusting their seating to adapt to vehicle interior components. This is the reason that steering wheel location is predicted first and is used as inputs for seat location prediction, although drivers usually adjust both of them simultaneously in an iterative manner. Driver's functional leg length is estimated by taking the difference between stature and erect sitting height, which is named Diff. A positive coefficient shows that drivers with longer legs tend to adjust the seats backward. BMI (body mass index) is the other predictor that indicates body width. Usually, a wider driver would need more space to operate a vehicle. The purpose of using natural log is to normalize the BMI measurements of the population. The standard deviation of the error term is 37.7mm, which represents driver's postural preference [14].

$$HX(mm) = -53.6 + 0.6081 * SWpivotX - 0.3343 * SWpivotZ$$

+ 0.6394*Diff + 89.07*Ln(BMI) + E(0,37.7) (3.6)

Unlike the horizontal location which uses four predictors, the vertical location of H-point is dependent solely on the vertical location of the steering wheel. Anthropometric measurements regarding body length or width had an ignorable affect. The standard deviation of driver's preferred seat vertical location is 22.9mm, which is smaller than horizontal [14].

$$HZ = -200.3 + 0.8545 * SWpivotZ + E(0, 22.9) \tag{3.7}$$

While designing a seat adjustment envelope for driver's preferred seat location, it is impossible to accommodate 100% of the driver population. In fact, the accommodation goal is commonly set at 95% or lower for economic reasons. When a driver's preferred seat location lies within the adjustment envelope, the cascade model proceeds to the next step. If it is outside of the adjustment envelope, the driver will move the seat to the nearest point on the envelope and adjust their posture to fit inside of a cab.

3.2.3 Eye Location

The Cascade Model received its name from its cascading nature; a sequence of actions need to take place in order to achieve the desired goal. The first step is to predict drivers preferred steering wheel location. Following steering wheel, seat location prediction can be predicted. The Cascade Model can then proceed to driver's eye location prediction. In vehicle packaging, the location of the eye center is represented by the Eye Point (Figure 3.6). Generally, the rotation range is known to be 45° upward, 65° downward, and 30° left and right (Figure 3.7), but for comfort, a 15° turn in all four directions is known as easy eye rotation [17]. In SAE J1050, the Eye Point is defined in 3D space while the left eye and the right eye to be 65 mm apart [17]. Since this thesis studies vehicle packaging in the 2D X-Z plane, only one Eye Point is used which lies on the X-Z plane.

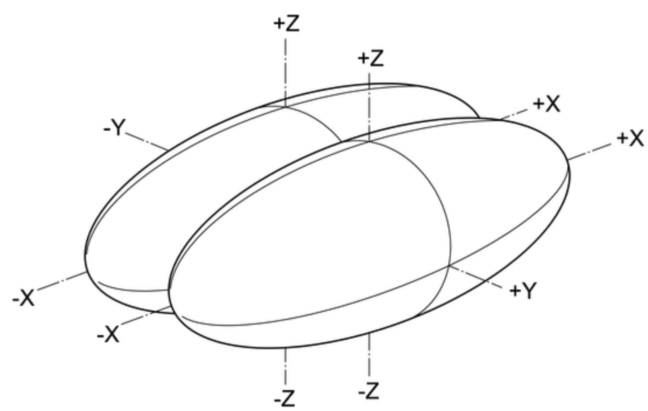

Figure 3.6. Three Dimensional Eyellipse (Left and Right) [16]

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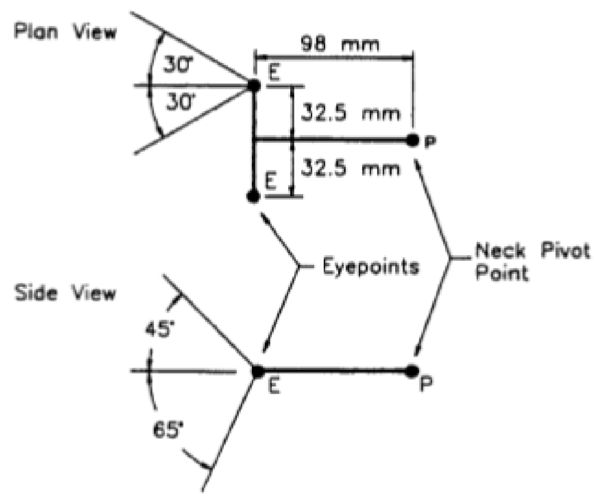

Figure 3.7. Two Dimensional Eyellipse with Range of Vision [17]

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In the referenced Cascade Model, the Eye Point was studied in a similar manner through laboratory data as the H-point, and the same set of predictors are used as well. Both steering wheel location and seat location are predicted from the AHP, the origin of vehicle interior component packaging, because it is most convenient and is also the convention. However, the Eye Point location developed in this model is expressed differently. Due to the limited movement of the driver's neck during driving, the driver's head and driver's torso are relatively static. In other words, the driver's Eye Point is largely dependent on the seat location, and therefore, Eye Points are expressed in terms of H-point [14].

In the horizontal direction, the Eye Point is found to be a function of three predictors: horizontal location of the steering wheel, the ratio of sitting height to stature, and BMI. The standard deviation of driver postural preference is estimated to be 41.0 mm. In the vertical direction, the Eye Point is a function of only one predictor, erect sitting height, and has an error term of 22.3 mm [14]. See formulation below:

$$EyeX = -334.0 + 0.0809 * SWpivotX + 1142 * Ratio - 87.98 * Ln(BMI) + E(0, 41.0) \quad (3.8)$$

$$EyeZ = -47.3 + 0.7812 * SittingHeight + E(0, 22.3) \quad (3.9)$$

Driving requires a number of actions that involve the steering wheel, foot pedals, shifter stick, buttons, and other interior components. They are essential to operating a vehicle as desired, but the ability to see outside of the vehicle is even more important because driver's sight is the main source of information upon which they make decisions. The central vision field, straight through the front windshield, allows drivers to see cars, pedestrians, traffic lights, or signs in the front. Besides central vision, peripheral vision is also important because it captures any cars that are passing. The quality of driver's vision can directly impact driver's safety and performance [75]. Since this thesis is conducted only in the X-Z plane, only central vision is considered.

A driver's central vision in two dimensions is bounded by the driver's ability to look upward and the ability to look downward. An upward vision angle is measured from the horizontal plane to the highest angle the driver can see, and a downward vision angle is measured to the lowest angle. The sum of the two angles makes up the driver's central vision. In most vehicles, the upvision angle is limited by the UDLO, where the top of the windshield meets the frame of the vehicle. An adequate upward vision angle permits the driver to read road signs, respond to traffic lights, and see traffic on uneven roads. According to the American Public Transportation Association (APTA) bus design guideline, the windshield must ensure a minimum of 14° upward vision angle [18].

Besides regulations on upward vision angle, there are requirements on downward vision angle as well because drivers must be able to see traffic near them. But more importantly, because buses are designed to be more elevated from the ground than other vehicles, it is challenging for drivers to see immediately in front of the bus. This issue is especially profound in urban areas where traffic is a primary concern. As will be discussed in a later section, education transportation is one of the main ways buses are utilized, where picking up and dropping off children is the most essential part of the job. Bus drivers must be able to maintain adequate downward vision to ensure clearance in front of the bus. Thus, the APTA requires all bus drivers to detect a 3.5-feet-high object from 2.0-feet in front of the bus (Figure 3.8). The above upward and downward vision regulations agree with SAE practice [17], and they are used as design guidelines in this thesis.

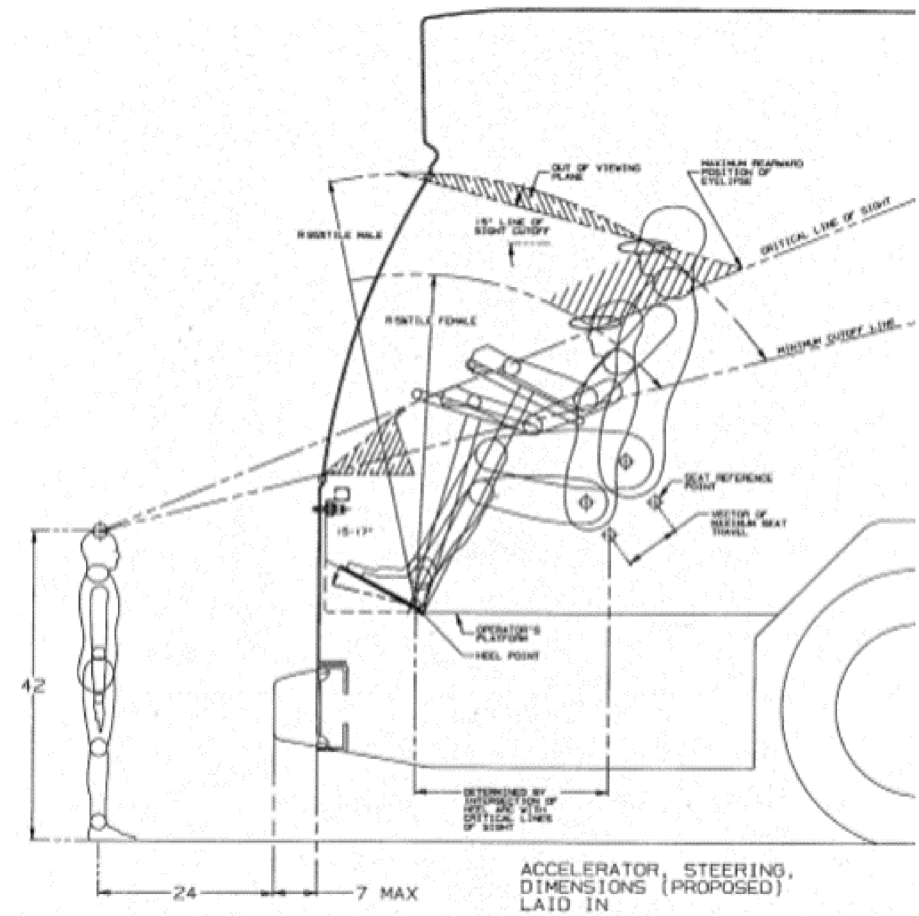

Figure 3.8. Bus Driver Downward Vision Requirement: Must See 2.0-feet Object in 3.5-feet [18]

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Upward vision is usually defined by the location of the UDLO, but downward vision requires more considerations. Depending on the geometric layout, a few interior components could be the limiting factor. Aiming to meet the downward vision requirement, the most common consideration is the location of the cowl point, where the bottom of the windshield meets the body of the bus. If it was designed to be above the line connecting the driver's Eye Point and the tip of the 3.5-feet object, the requirement would be unmet. Besides the cowl point, some buses are equipped with a hood. The hood point, which represents the highest point on the front end of the hood, can also be a limiting factor. Another candidate is the dashboard. As more functionalities are added to buses, the dashboard is growing bigger to fit an increased number of buttons and screens. As designers assess a bus package, all the potential obstacles needs to be considered in order to ensure a safe downward vision angle.

3.2.4 Secondary Body Landmarks

The purpose of vehicle packaging is to apply an understanding of driver behavior inside of a vehicle and make design decisions on the layout of the interior components to best accommodate them. In this thesis, most of the essential components in the X-Z plane are included: steering wheel, seat, and vision-related components. They are assessed with driver's preferred steering wheel location, H-point, and Eye Point. With the knowledge provided above, one can successfully package many elements of a bus layout. As discussed in the beginning of this chapter, besides accurately predicting drive postures, virtually presenting these postures is significantly useful for industry users. Therefore, this section will briefly discuss how secondary body landmarks (hip point, shoulder point, grip point, elbow point, ankle point, and knee point) are predicted.

In the study of biomechanics, a human body can be presented using body landmarks. To properly configure a human body in a vehicle package model, it is much more comprehensive to describe and define each driver by the make-up of their body landmarks as joints and links than to use only height (Figure 3.9) [19, 22, 76]. This approach not only gives us visual representation of the drivers, but works seamlessly with the Cascade model. As a continuation of the Cascade model, the next step is to use reverse kinematics to estimate the locations of other body landmarks, which is useful to assess accommodation and visualize the driver.

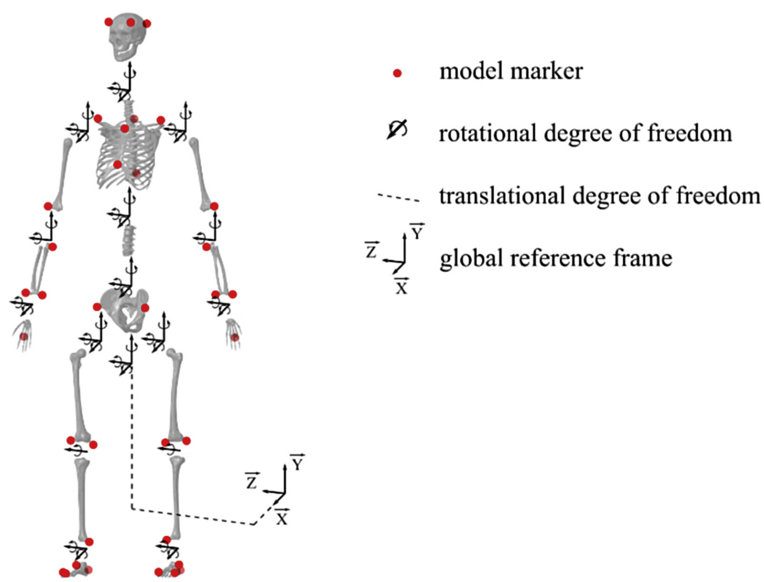

Figure 3.9. Biomechanical Model and Markers location for the Inverse Kinematics Configuration [19]

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In previous sections, linear models of finding the preferred H-point were presented. The H-point is a fixed location of a seat and does not move relatively to the seat based on driver preference. A hip point, however, is the joint center of a driver's hip (Figure 3.10). It is a commonly used body landmark while configuring driver posture, because it is not only a main part of one's torso, but also the axis of one's lower body.

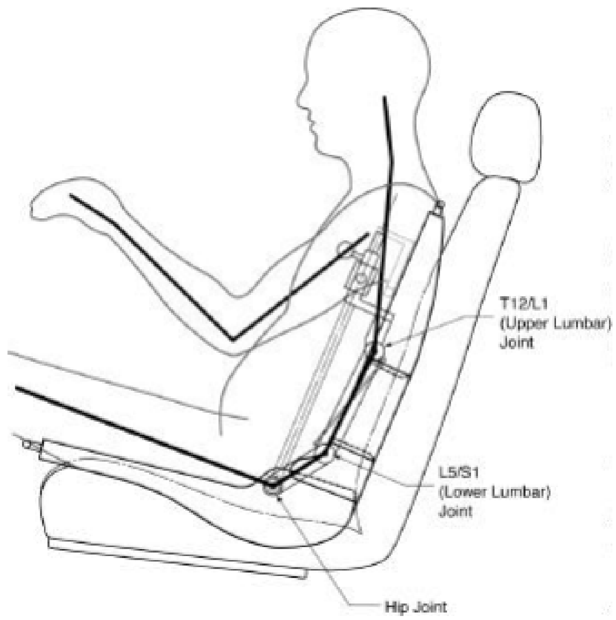

Figure 3.10. Sideview Schematic of A Driver Kinematic Model, Showing Hip Point [20]

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Although the hip point is different from the H-point, it can be estimated using linear regression. Researchers have found that the offset vector from the H-point to the hip point is a function of driver's body dimensions [14]. Specifically, the horizontal offset distance is negatively proportional to driver's BMI, and the vertical offset distance is positively proportional to both driver's BMI and erect sitting height. By adding these offset distances to the H-point location, the hip point location can be found. Since the following body landmarks are mainly used for visualization and have minimal impact on vehicle interior layout, simple linear regression models are used without variance. Hip point location are shown below:

$$HipX = 90.2 - 5.27 * BMI + HX \tag{3.10}$$

$$HipZ = -109.9 + 1.51 * BMI + 0.0813 * SittingHeight + HZ \tag{3.11}$$

For consistency of terminology in this thesis, shoulder joint center, elbow joint center, and knee joint center are referred to as shoulder point, elbow point, and knee point. Once the hip point is located, the next nearby joint center can be predicted, which is the shoulder joint center. While driving, the shoulder point and the hip point together represent driver's torso. Commonly, drivers lean their torso against the back of the seat to reduce stress. Taking this slouching factor into consideration, researchers have found the distance between the hip point and the shoulder point to be a function of driver's erect sitting height. As the formulation indicates, the distance is solely impacted by the driver's length. However, the angle between the two is largely dependent on the driver's width. The formulation below shows how this angle can be predicted, with the angle being measured from the vertical direction:

$$HipShoulderDist = 0.49 * SittingHeight \tag{3.12}$$

$$HipShoulderAngle = -25.1 + 0.297 * BMI + 67.6 * Ratio \tag{3.13}$$

With the distance and angle between the two points, the X- and Z- offsets can be calculated using trigonometry. The location of shoulder point can be obtained by augmenting the offsets to the hip location, as shown below:

$$ShoulderX = HipX + HipShoulderDist * sin(HipShoulderAngle) \tag{3.14}$$

$$ShoulderZ = HipZ + HipShoulderDist * cos(HipShoulderAngle) \tag{3.15}$$

After successfully configuring the driver's torso, predicting the driver's limbs is the next step. Starting with the upper body, it can be modeled as a combination of three joints (grip center, elbow joint center, and shoulder joint center) and two links (forearm and upper arm). Through laboratory observation and road driving verification, researchers found that driver hand placement varies tremendously while driving. DUsing a large number of photos collected by three independent observers, researchers discovered several positions where drivers place their hands [21]. Interestingly, the driver's left hand tends to be placed higher than the right hand. This is because some drivers utilize the left door panel to rest their elbow. Thus, the right hand position more accurately represents a normal driving posture. Data shows that the majority of drivers (78% of male and 70 % of female) tend to place their hands at Position 0 (Figure 3.11), which is estimated to be 3/4 of the steering wheel in the X-Z plane [77]. This finding agrees with what has been used in other vehicle packaging studies [78], so this thesis will be consistent with previous studies.

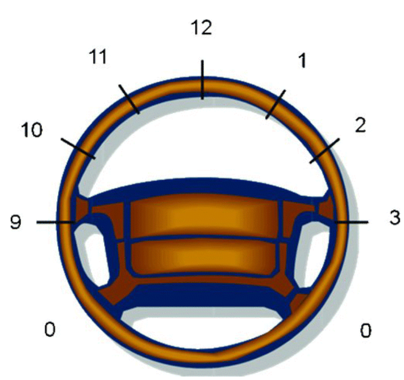

Figure 3.11. Common Hand Placement on A Steering Wheel [21]

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The next step is locating the center of the steering wheel. In addition, the preferred steering wheel angle was also calculated through the process, which was measured from the vertical direction by convention. This angle is the same as the angle formed between the wheel face and the horizontal direction. Knowing the steering wheel diameter (SWD), once again, the X- and Z- offsets can be found using trigonometry and can then be added to the steering wheel location, which indicates the driver's grip point.

$$GripX = SWX + SWdiameter/4 * cos(SWangle) \tag{3.16}$$

$$GripZ = SWZ - SWdiameter/4 * sin(SWangle) \tag{3.17}$$

The grip point, the shoulder point, and the elbow point form a triangle (Figure 3.12). With two of the vertices and one side being known, the third vertex can be positioned by knowing the lengths of the other two sides. One of the sides is the upper arm length, which is measured from the shoulder center joint to the elbow center joint, and this length can be estimated using the Acromial Radial Length from an anthropometry database, such as the US Army Anthropometric Survey (ANSUR II) [23] which will be discussed in a later section. In the survey, distances are measured from landmarks to landmarks, such as the acromion and the radiale. Although these landmarks are different from the joint centers, researchers have quantified the offset between them. For instance, the offset between the acromion and the shoulder joint center is found to be 34.5 mm, and the offset between the radiale and the elbow joint center is found to be 34.5 mm [79]. Likewise, the length between the elbow joint center and the grip center can also be estimated to represent forearm length. After knowing both upper arm length and forearm length, the elbow joint center can be estimated.

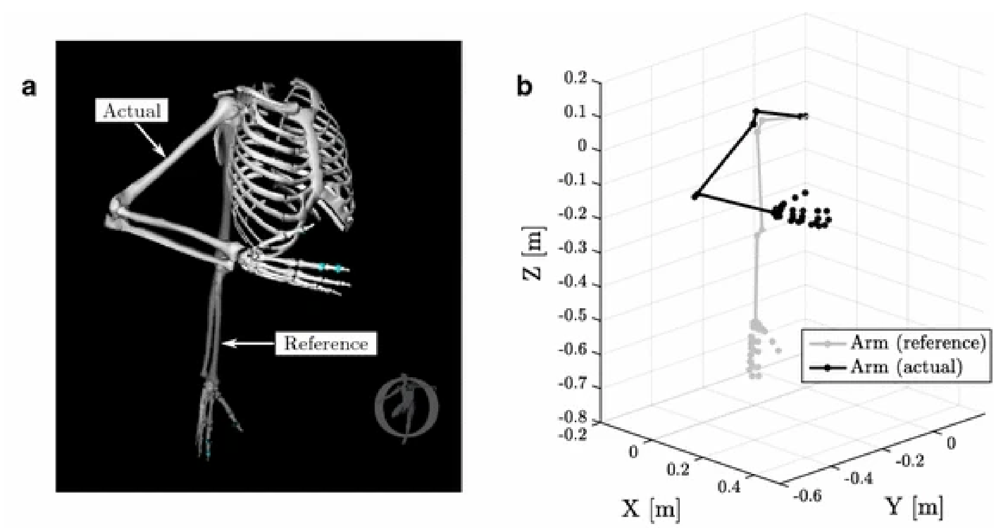

Figure 3.12. Representations of Upper Limb Modeled As Links and Joints [22]

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Due to the similarities between the upper limbs and the lower limbs, the same procedure of study can also be applied to lower body configuration. Instead of the grip point, an ankle joint center is used. Relative to the AHP, researchers estimated the ankle to be 32 mm in the X-direction and 128 mm in the Z-direction [78]. Besides the ankle point, leg lengths are needed as well. One of them is the thigh length, which represents the distance between the hip joint center and the knee joint center. The other one is the shank length, which represents the distance between the knee joint center and the ankle joint center. After knowing the lengths and the locations of two vertices, the third vertex can be configured using the fundamentals of trigonometry, which represents the knee joint center.

3.2.5 Estimation of Accommodation

The Cascade Model used in this thesis advocates the principle of letting information flow down from experts through layers of customized treatment to obtain desired outcomes [80]. In vehicle packaging, the Cascade Model applies a similar concept. Driver's anthropometric dimensions and vehicle geometry are the high-level data. With these data, preferred steering wheel location is predicted. Using it as an input, preferred seat location is then predicted. Although these two steps usually take place iteratively in a laboratory setting or in real life, a sequential order of the two steps are carried out in vehicle packaging because the model was developed based on final locations of these reference points. From here, Eye point is predicted, and field of vision is assessed. Once these primary locations are predicted, secondary body landmarks can be estimated afterwards, starting with hip point and the shoulder point. Following which, grip point, ankle point, elbow point, and knee point can be calculated.

Throughout the process of cascade posture prediction, a total of four design objectives were assessed. They are (in order of prediction):

- Steering wheel adjustment envelope accommodation
- Seat adjustment envelope accommodation
- Upward vision (minimum of 14°)
- Downward vision must (see a 1067 mm object 610 mm in front of vehicle)

The multivariate approach of assessing the accommodation condition of each driver is a significant component of this thesis. With a large population of drivers as inputs, it provides high resolution and allows designers to study bus drivers individually. For each driver, designers can directly assess how they are accommodated on each of the four objectives. It facilitates on understanding of the underlying relationship between the objectives. While calculating overall accommodation, which is the proportion of drivers who have met all four design objectives, an accurate result can be given. Otherwise, assumptions would need to be made on who is disaccommodated on more than one design objective.

As researchers have stated, anthropometric accommodation is described as the proportion of the intended users who are within the range of desired objectives [81]. Frequently, a percentile method is only suitable for univariate accommodation models. With multiple objectives, adding and subtracting cannot accurately combine accommodation results [82].

One common approach to assess multivariate accommodation is through the intersections of sets because of the comparable nature of the two mechanism [83]. While performing set intersection, set correlation is considered. For a pair of positively related variables, the intersection can be calculated as:

$$P(A \cap B) = r_{AB} * (SD_A * SD_B) + P(A)P(B) \tag{3.18}$$

where r_{AB} is the correlation between the two variables, and SD_A and SD_B are the standard deviations. For negatively related (disjoint) variables, the correlation is zero, which simplifies the calculation to:

$$P(A \cap B) = P(A) * P(B) \tag{3.19}$$

Intersection of sets is a well-known method and has been validated with simulation data [83]. However, the effort of studying variable correlations is costly. Since this thesis conducts design assessments for each individual in the population, a sequence of "True/False" indicators can be assigned to them instead. To explain, the outcome of assessing each design objective is either True or False. For such binary assessment, an indicator function assigns a value of 0 or 1 to each event based on the accommodation condition [83]. In this thesis, a total of four design objectives are being assessed, so each virtual driver will be assigned four binary digits to indicate their accommodation. For instance, if the indicator functions generate 1-1-1-1 for a driver, the driver is expected to be accommodated on all four objectives. Similarly, a 1-1-1-0 indicates that the driver failed the downward vision requirement (the 4^{th} test) but is accommodated on all others.

3.3 Bus Driver Population

The Cascade Model used in this thesis passes information through a sequence of models. The outputs from the previous model become the input to the next model. In order to improve the reliability of the final results, one can not only choose the most appropriate model, but also increase the fidelity of the source data, which is driver's anthropometry. Therefore, the rest of the chapter will explicitly discuss the U.S. bus driver population and the available information that can be utilized in this thesis.

3.3.1 Anthropometric Database

Conventionally, military studies have been the main source where anthropometric data can be found and used in industrial applications. Due to its large quantity of measurements and rigorous methodology, the 1988 United States Army Anthropometry Survey (ANSUR) has been arguably the most frequently used anthropometric database. ANSUR reported 132 directly measured dimensions and derived an additional 60 dimensions from each of the 3,982 U.S. military personnel (1,774 men and 2,208 women). It also included the demographic information, such as age and ethnicity, to make it possible to sample from the most appropriate population [84]. However, they do not represent the general U.S. civilian population, especially dimensional extremities. For instance, obesity is under-presented in the military. Because of military's strict selection requirements, ANSUR data reflect a young, healthy, and athletic population. If a design for the civilian population uses ANSUR data to simulate user interaction, the result will not be reliable [85].

Over time, army leaders noticed secular trends in increased body size and felt the need to carry out a follow up study. They used a broader sampling strategy and with the addition of whole-body scans. In ANSUR II they collected measurements from a total of 6,068 participants (4,082 men and 1,986 women) and found that weight, circumferences and breadths had all increased. They found that the variation in these measurements had increased as well (Figure 3.13). ANSUR II replaced ANSUR and was made available publicly in 2017 [23]. Even though it is not an accurate approximation of the U.S. civilian population, it still contains useful information and can be used in the early phases of research.

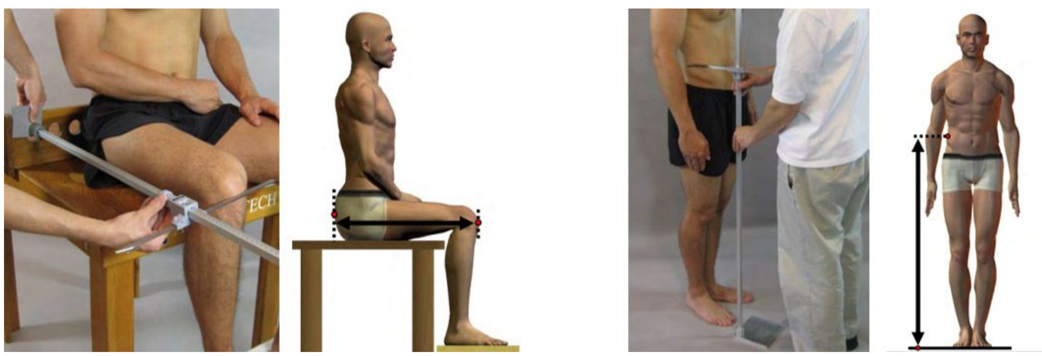

Figure 3.13. Examples of How Anthropometric Data Being Collected in ANSUR II [23]

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The results from ANSUR II reflected that secular trends over the previous thirty years are noticeable and significant. Unlike ANSUR and ANSUR II, the National Health and Nutrition Examination Survey (NHANES) is conducted continuously in the U.S. since 1999 [86]. This periodic sampling methodology makes it a suitable tool to analyze secular trends. The most important observation is that mean stature and weight both have been increasing, especially weight, which agrees with ANSUR II [87]. One of the biggest advantages of NHANES is the oversampling strategy. By oversampling the tails of the anthropometric distribution, the underrepresented groups are included at a higher frequency, which ensures plenty of data to be revealed regarding these groups. Thus, each measured individual has an associated weight that indicates the size of the population they represent. Since the objective of NHANES is to monitor U.S. civilian health condition, NHANES is capable of representing U.S. civilian population, which is the biggest advantage of using this database. In the 1980s, University of Michigan Transportation Research Institute designed dummies of various sizes by combining NHANES anthropometric data and stereo-photogrammetry. This knowledge was then applied in automobile design [88–90]. One distinct disadvantage of the NHANES data is that it only collects a limited number of measurements, such as stature, mass, and BMI. However, researchers can sometimes make predictions on the desired body dimensions by establishing relationships between known measurements and unknown measurements.

All the anthropometry data resources discussed above have strengths and weaknesses, which is expected. In order to make them useful, it is important to build a deep understanding of the desired user population and discover the characteristics of this population. Following that, any of the anthropometry data resource can be modified accordingly, using a method to be discussed later, to match these characteristics. Once a U.S. bus driver anthropometry data is generated, it can be applied to the Cascade model.

3.3.2 Bus Driver Demographics

The main four types of bus drivers in the United States are school bus drivers, local transit bus drivers, intercity bus drivers, and charter bus drivers. Data from the Bureau of Labor Statistics show that in 2018, among all 681,400 bus driver jobs, 497,500 (73.0%) of them were provided by schools and special clients. Transit and intercity bus held about 183,800 (27.0%) jobs (Table 3.1). Many bus drivers operate through heavy traffic or bad weather, and sometimes deal with unruly passengers. Because of the road hazards and mental stress, bus drivers have one of the highest rates of injuries and illnesses of all occupations [91]. Unlike many other jobs, bus drivers have a spatially limited workstation. While driving, they frequently maintain a driving posture for hours before taking a break. Thus, a well-designed bus cab can significantly improve the working conditions for a bus driver.

While designing a bus cab, proper driver demographics must be defined. Otherwise, the final design would be inappropriate and ineffective. In 1987, a study on urban transit buses used in Hong Kong discovered that many buses were designed based on European anthropometric data and were built in the United Kingdom, which were not suitable for the Cantonese workforce [92]. This study showed that the designs for one ethnic group do not accommodate another ethnic group. This fact raises the challenge in the U.S. because the U.S. workforce has become more diverse not only in ethnic composition, but also in gender composition, age, and other aspects. In the next few sections, a study on bus driver demographics is conducted with the aim of understanding the driver population and providing important design guidelines.

Table 3.1. Industry Composition of U.S. Bus Drivers 2018

Type	Count	Total	Percentage
School and Client	497500	681400	73.01%
Intercity and Transit	183800	681400	26.97%
Others	100	681400	0.015%

3.3.3 Gender Composition

In the past several decades, many occupations were dominated by either male or female. It was true especially before World War II. For instance, the secretary workforce was limited to females, and the commercial driver workforce was limited to males [93]. However, the demographics have shifted in the U.S. significantly in recent years. In 2020, the U.S. Department of Labor published that women comprised 47% of the total U.S. labor force [94]. Such trend can also be found in the commercial driver workforce where males drivers were most prevalent for decades.

According to the American Community Survey (ACS) provided by the Census Bureau, the male and female ratio of commercial driver workforce has been consistent over the past few years (2014-2017), with males and females taking up 54.7% and 45.3% of the workforce, respectively [95]. As the years go by, a small fluctuation is observed in the total number of drivers and the gender composition, but overall they remain about the same (Table 3.2). Thus, this ratio should be used as default for driver demographics, posture prediction, and accommodation assessment. However, this ratio only represents the national average, and it could vary in different regions or due to specific driving responsibilities. In order to maintain reliability of the bus design, industry designers must conduct driver demographics study and modify the male-to-female ratio to best represent the driver population. Gender summary table is presented below. More detailed information on gender composition can be found in Appendix C.

3.3.4 Race and Ethnicity

The U.S. is the third largest country in the world by population, and it is known for its diversity. As of 2018, the white population constituted the majority with 76.4%, which had been slowly but steadily decreasing in the previous eight years, and the black or African American population stood as second with 13.4% [96]. Unsurprisingly, such ethnic composition is reflected in the employment market. In 2018, the white and black population took up 73.6% and 12.0% of the total employments in the U.S., respectively, which matches closely with the ethnic composition in the society.

Similar to most of the occupations, ethnic diversity can be found in the bus driver workforce.

Table 3.2. U.S. Bus Driver Gender Composition 2014 - 2017

Year	Male	Female	Total	Male Ratio	Female Ratio
2014	401946	331576	733522	54.8%	45.2%
2015	424168	347898	772066	54.9%	45.1%
2016	406475	333660	740135	54.9%	45.1%
2017	393972	334603	728575	54.1%	45.9%
Average	1626561	1347737	2974298	54.7%	45.3%

ACS showed that the workforce consists of 62.9% white drivers, 27.7% black drivers, 2.2% Asian drivers, and 7.2% other drivers in 2017. Clearly, white drivers represent the majority of the workforce, followed by black drivers. While comparing the ethnic composition in the bus driver workforce to that of the U.S. workforce, the white population (62.9%) and the black population (27.7%) dominated with a total of 90.6% of the workforce, which is expected. Not only in 2017, this dominance can also be found in previous years as well (Table 3.3). Detailed data of ethinic composition in the bus driver workforce and the entire U.S. job market from 2014 to 2017 consecutively, can be found in Appendix C. The percentage of white bus drivers fluctuated between 62.0% and 64.4%, and the percentage of black bus drivers fluctuated between 27.0% and 28.0% within these four years. This fact indicates that white and black dominance is likely to continue for the next several years, and thus should be used as default values in bus packaging unless designing for a target user group.

Besides the ethnic dominance, an interesting observation is that the bus driving industry is more common in some ethnic group than others. To explain, 12.0% of the U.S. workforce was constituted by black employees in 2017, but 27.7% of the bus drivers were black. Using ethnic composition in the general society as a reference, there were proportionally more black drivers than white drivers or Asian drivers by a large margin. Not only in 2017, this phenomenon exists in previous four years as well, as shown in Appendix C. This is strong evidence that the proportion of black bus drivers in the workforce is about twice of the proportion of black people in the society. Even though the previous observation shows that ethnic diversity in bus drivers mostly match with the ethnic diversity in the general society, proper adjustments still need to be made to certain ethnic groups for more accurate simulation results. This topic will be further discussed.

3.3.5 Age

Besides male-to-female ratio and ethnic composition, age is another important descriptor of the U.S. bus driver demographics. In the U.S., most states require their bus drives to be at least 18 years old and those who drive across states to be 21 years of age or older. By enforcing a minimum age requirement, these states expect their bus drivers to be physical capable for the

Table 3.3. U.S. Bus Driver Ethnicity Composition 2014 - 2017

Year	White	Black	Asian	Other
2014	64.4%	27.0%	1.9%	6.7%
2015	63.1%	27.5%	2.3%	7.1%
2016	62.0%	28.0%	2.5%	7.5%
2017	62.9%	27.7%	2.2%	7.2%
Average	63.1%	27.6%	2.2%	7.1%

job. Since people age differently, a maximum age limit does not exist. Instead, interstate bus drivers must successfully finish a physical exam every two years, per federal regulations [95].

As discussed previously, gender composition varies in bus driver workforce with males constituting 54% of the workforce while females constituting 46%. Surprisingly, data analysts have discovered a noticeable age difference in the two genders as well. According to the ACS, with 95% level of confidence, the average age is 54.5 ± 0.60 for male bus driver and 49.7 ± 0.58 for female bus drivers in 2017 (Table 3.4). This made up an age difference of 4.8 years. In the previous three years, 2014 to 2016, a similar age difference was noticeable at 4.6, 4.1 and 4.8, respectively. This trend is plotted in the average age chart in Appendix C. Such consistent trend indicates that a 4-to 5-year age difference describes the bus driver demographics, and it will likely last for the next several years without any major age requirements.

The age distribution charts from 2014 to 2017, which are shown in Appendix C, not only indicate an age difference between the two genders, but also visually showed how age impacts the bus driver workforce. One of the observations is that the age distribution is skewed left. In other words, the number of drivers gradually increase with age until it reaches the average age. Once past the average age, the number of drivers decrease with age at a faster rate. This observation is likely to be the result of a combination of experience requirement and physical capabilities. Another observation is that the majority of the bus driver workforce is between 45 and 70 years of age for males and between 40 and 65 years of age for females. In general, male drivers are older than female drivers. Thus, designers must make proper adjustments while using any of the anthropometry database to represent the bus drivers to best represent the bus driver demographics.

Table 3.4. U.S. Bus Driver Age Distribution 2014 - 2017

Year/Gender	30 or lower	30 to 40	40 to 50	50 to 60	60 to 70	70 or older
2014/Male	6.8%	10.0%	17.8%	30.7%	25.9%	8.9%
2014/Female	5.7%	15.4%	29.5%	34.2%	13.4%	1.7%
2015/Male	7.1%	10.2%	19.3%	28.7%	25.4%	9.3%
2015/Female	6.8%	13.9%	29.3%	32.2%	16.0%	1.9%
2016/Male	7.2%	10.8%	17.5%	28.3%	26.8%	9.5%
2016/Female	7.3%	16.3%	26.8%	32.8%	14.8%	2.1%
2017/Male	6.5%	10.5%	17.8%	27.9%	27.6%	9.8%
2017/Female	6.5%	16.8%	26.5%	31.6%	15.9%	2.8%
Male Average	6.9%	10.4%	18.1%	28.9%	26.4%	9.4%
Female Average	6.6%	15.6%	28.5%	32.7%	15.0%	2.1%

3.3.6 Weighted Population Approach

In the previous sections, descriptors (gender ratio, ethnic composition, and age distribution) regarding bus driver demographics was drawn from the ACS. Clearly, many similarities exist between the U.S. bus driver population and the U.S. civilian population, but there are noticeable differences as well regarding gender ratio, ethnicity composition, and age distribution. One of the solutions to address this issue is to start over and conduct a new survey that is specifically designed for the U.S. bus driver population. This solution is intuitive and direct, but the disadvantages outweigh the advantages. In order to capture the majority of the characteristics of the desired demographics without biases, the sample size must be large enough so that the data is reliable. In addition, the participants must be recruited from all over the nation to avoid regional bias. After collecting the data from this large sample group, it would be equally challenging to sync and analyze the data. Because of these reasons, the new survey solution is not suitable for this research due to its costly and time-consuming nature.

As discussed previously, many surveys, such as ANSUR I, ANSUR II, and NHANES, have already been conducted to gather detailed anthropometric data from the military population and the civilian population, so it will be much more efficient to modify these databases that are available, to make them represent the target population. Fortunately, researchers have studied this subject and have come up with a number of methods. Among all of them, Down-sampling and Weighting are the most effective.

Down-sampling is the easier method of the two. Given an unmodified database, designers can down-sample it by constructing a sub-database whose composition matches the characteristics of the target population. The core idea is to eliminate the data that is not desired, and to only keep the useful data for further studies. This method is simple and intuitive, but it has its limitations. One of the associated weaknesses is that the down-sampling wastes a lot of information. Depending on how well the unmodified database matches the target population, a significant amount of data can be lost [97]. Without adequate data, there is high risk of introducing bias. Another challenge is the difficulty in maintaining flexibility in its data. As mentioned earlier, industry users may need to adjust the driver demographics to suit a specific need. Once the database is down-sampled, the change is irreversible. There may not be enough data to produce accurate results for a specific driver group. For the reasoning above, down-sampling is not suitable for this thesis.

Unlike down-sampling truncating the database, the weighting method utilizes all the data under the assumption that each individual is randomly selected. The weighting method assigns a sampling weight to each person, which indicates the proportion of the target population who have a similar characteristics [97]. In other words, the weighting method manipulates the demographic composition of the database by modifying how much each person matters. Designers are usually responsible for adjusting the weights. For example, if a database contains 500 males an 100 females, designers can make this 5:1 male-to-female ratio behave as 1:1 by assigning a weight of 1 to all males and assigning a weight of 5 to all females. The weighting method is a common method of modifying a database to meet the requirements. An example can be found in the National Automotive Sampling System (NASS) where they modified a civilian database into a desired vehicle crash population using the weighting approach [98].

Chapter 4
Results

When packaging a bus, several design parameters need to be considered. This thesis exclusively discusses driver's accommodation in the X-Z plane and explicitly addresses the concerns regarding spatial fitting of components and driver's vision safety. In order to provide meaningful feedback to the automobile industry users, the following design parameters are being assessed:

- Steering wheel pivot location
- Steering wheel tilt angle adjustment
- Steering wheel telescope distance adjustment
- Steering wheel diameter
- Seat fore-aft adjustment
- Seat vertical adjustment
- Upper Daylight Opening (UDLO) location
- Cowl point location
- Tip of dashboard location
- Tip of front bumper location
- Accelerator Heel Point (AHP) location

While packaging a bus, the industry users must carefully design the above parameters to ensure the majority of the driver population are accommodation on all four design objectives, as discussed in Chapter 3.

Apart from bus geometry, driver population profile is also a critical contributor to the success of a design because a bus package made for one population may not suit for another population. In fact, the wrong match could cause driver's fatigue and other safety hazards [99]. As previously mentioned, the U.S. is known for its diversified population, and this diversity is reflected in the bus driver workforce. To fulfill the purpose of representing the U.S. bus drivers, this chapter utilizes a 55:45 male-to-female ratio.

This chapter will present the outcomes of the Cascade Model by visually showing the predicted reference points and body landmarks in a virtual bus cab. It is important to be aware that the location of these points are dependent on bus cab geometry. The virtual bus cab shown in this chapter only serves the purpose of visual representation and can be altered to meet specific needs of the industry user.

4.1 Steering Wheel

Steering wheel location prediction is the first step of Cascade Modeling, and it will become the input for the following steps. Each preferred location is described with an angle and a distance from the pivot. With a total of 1000 virtual drivers, 1000 steering wheel locations are generated, and they form an annular fan-shaped cluster of points where purple represents male and gold represents female (Figure 4.1).

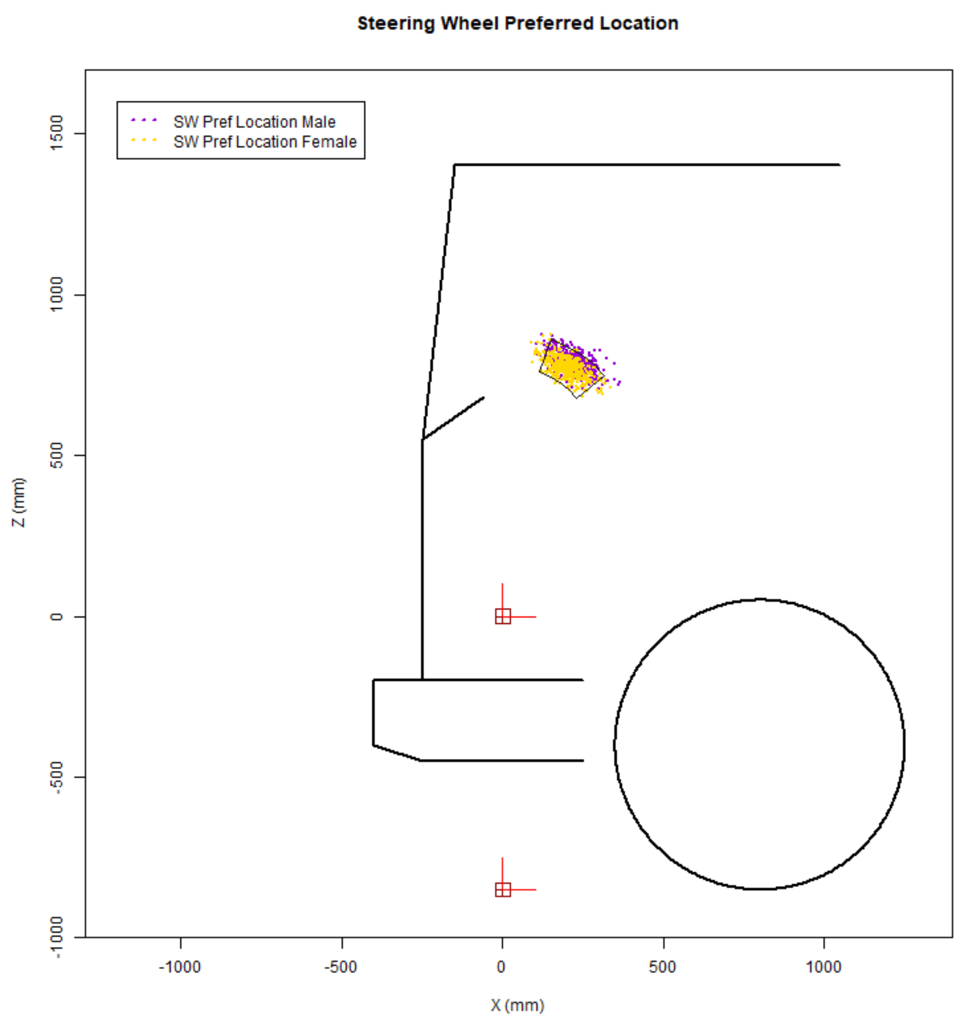

Figure 4.1. Steering Wheel Preferred Location of Both Males and Females

Through calculation, the preferred steering wheel locations of male are found to be farther away from the pivot than of female by 20 mm on average, which is expected given that male drivers are generally taller than female drivers. It is a reflection of drivers' body dimensions. In the meantime, the steering wheel tilt angles are almost identical between the two genders. This outcome indicates that driver's postural preference is independent of gender when controlled for stature.

In some cases, a large enough adjustment envelope may be constructed to accommodate all the virtual drivers, but for the purpose of demonstration, a smaller adjustment envelope is chosen, and the disaccommodated drivers are marked in red (Figure 4.2). Similar to how steering wheel locations are described, the adjustment is provided through a combination of telescoping and tilting about the pivot point.

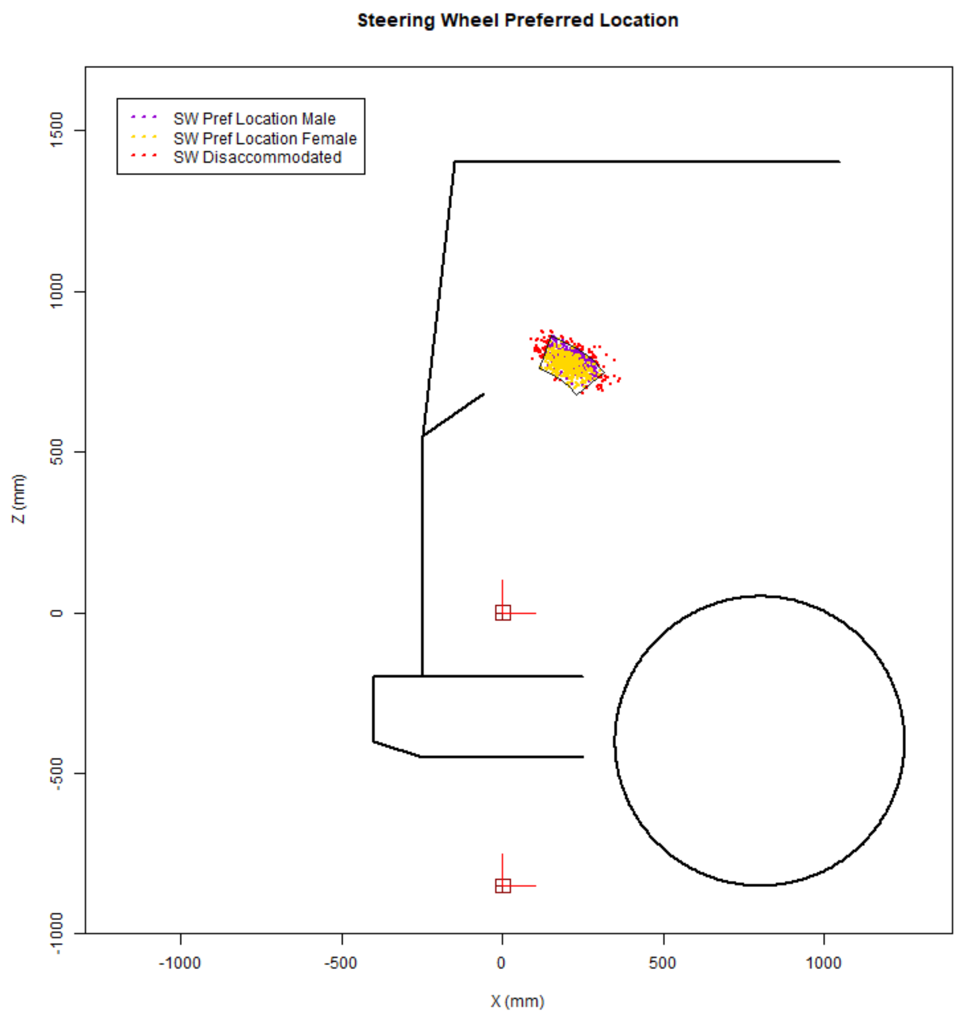

Figure 4.2. Disaccommidated Steering Wheel Location of Both Males and Females

For this specific bus layout, the pivot of the steering wheel is at (20 mm, 500 mm) with respect to the AHP. It has a telescoping range of 275 mm to 385 mm and a tilt angle of 20° to 50° from the vertical direction. Among the 1000 virtual drivers, a total of 100 were disaccommodated with 52 of them being male and 48 being female, which means 89.6% and 90.4% accommodation rate for male and female, respectively. Considering gender ratio, the total accommodation is 90.0%. When a driver is disaccommodated, they would adjust the steering wheel to the nearest point on the envelope and adjust the rest of their body to adapt to the change. After applying such adjustment to all 100 disaccommodated drivers, the following steering wheel locations are achieved (Figure 4.3):

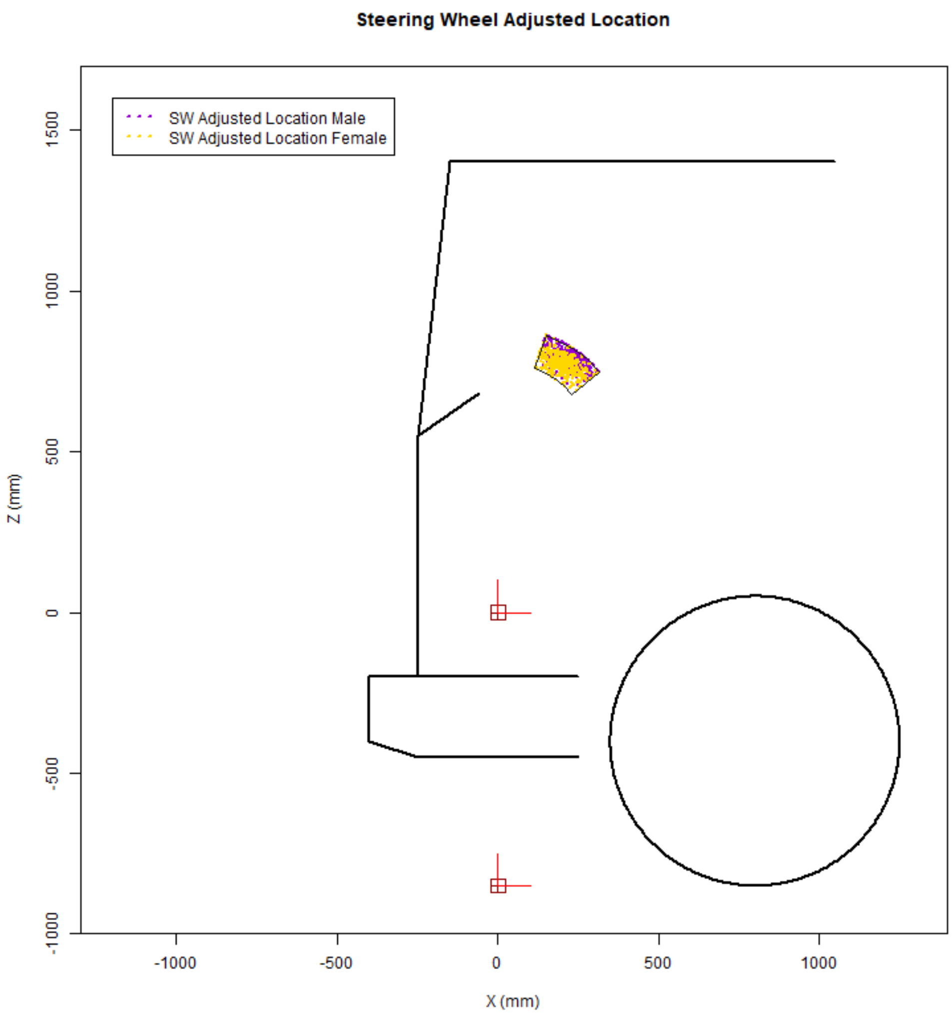

Figure 4.3. Steering Wheel Adjusted Location of Both Males and Females

4.2 H-point

Once the steering wheel locations are predicted and adjusted, the Cascade Model can proceed to seat position. Again, 1000 preferred seat locations are generated, and the cluster of these points is ellipse-shaped. Due to the variation in average size across gender, the preferred seat locations of male drivers are expected to be further away from the AHP, and such expectation is supported by data. On average, male drivers move the seat 54 mm more in the X-direction and 15 mm more in the Z-direction than female drivers (Figure 4.4):

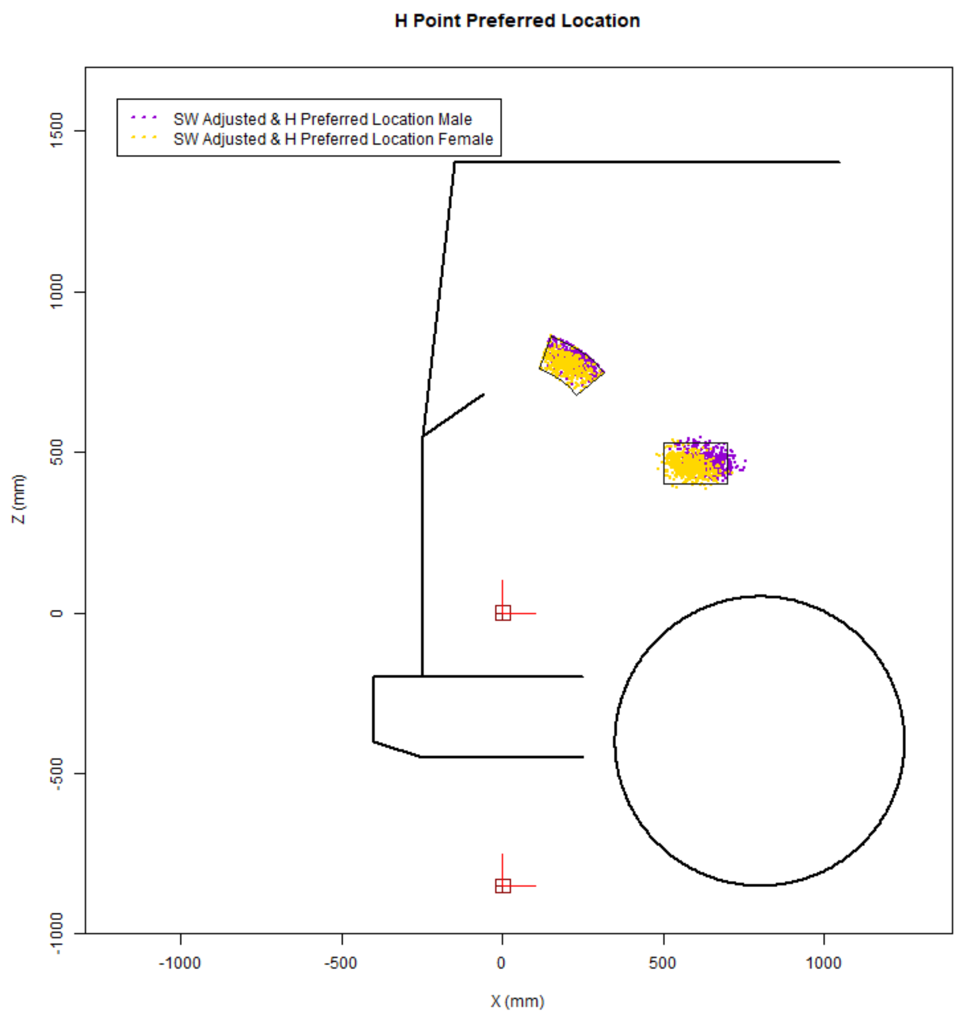

Figure 4.4. H-point Preferred Location of Both Males and Females

In this thesis, a limited adjustment range of the seat, 500 mm to 700 mm in the X-direction and 400 mm to 530 mm in Z-direction, is used to demonstrate disaccommodation. This adjustment envelope leads to a 90.6% accommodation rate for male drivers and a 96.6% for female drivers, with a combined rate of 93.6%. Among all the disaccommodated drivers, 47 of them are male, and 17 of them are female. The disaccommodated drivers are shown in red (Figure 4.5).

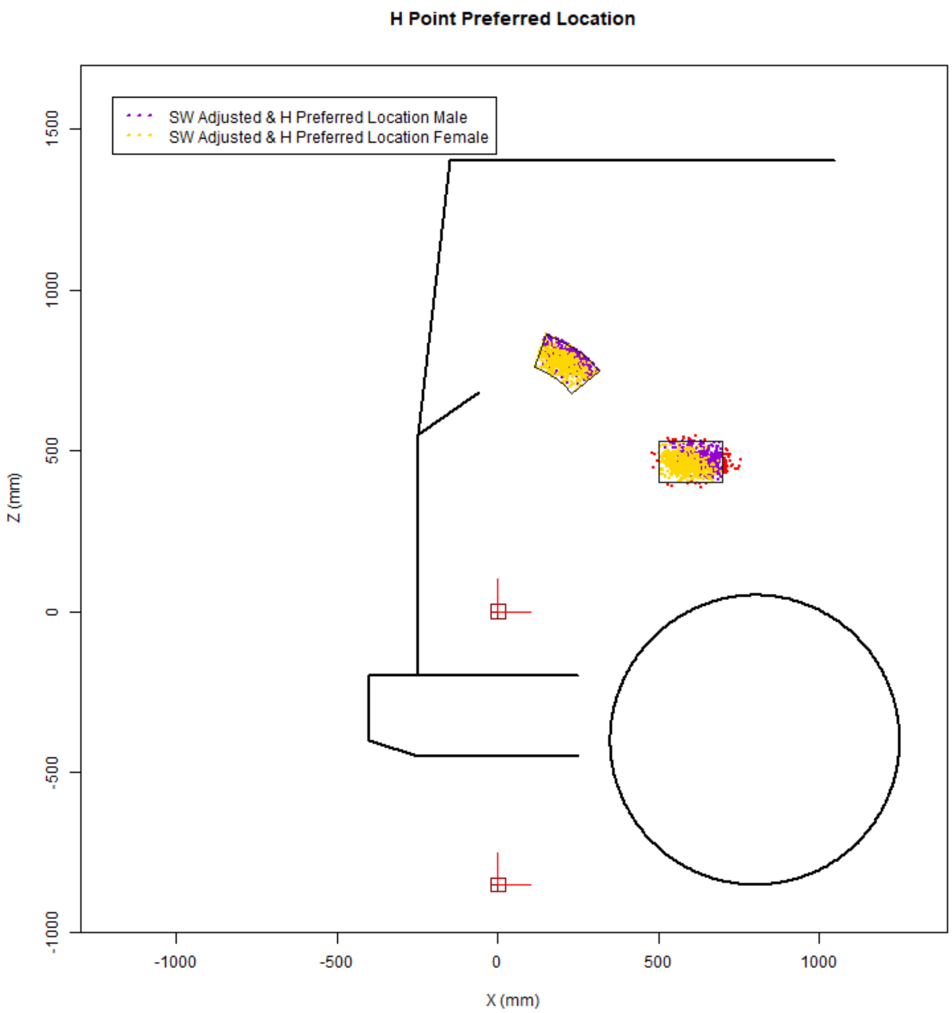

Figure 4.5. Disaccommodated H-point Location of Both Males and Females

Similar to disaccommodated steering wheel locations, disaccommodated seat locations are moved to the nearest point on the envelope, and the drivers are expected to adjust their posture to adapt this change. Although such adjustment is not ideal, it takes place frequently in people's daily lives and the discomfort is rarely noticeable. The effect of driver self-adjustment is shown (in Figure 4.6).

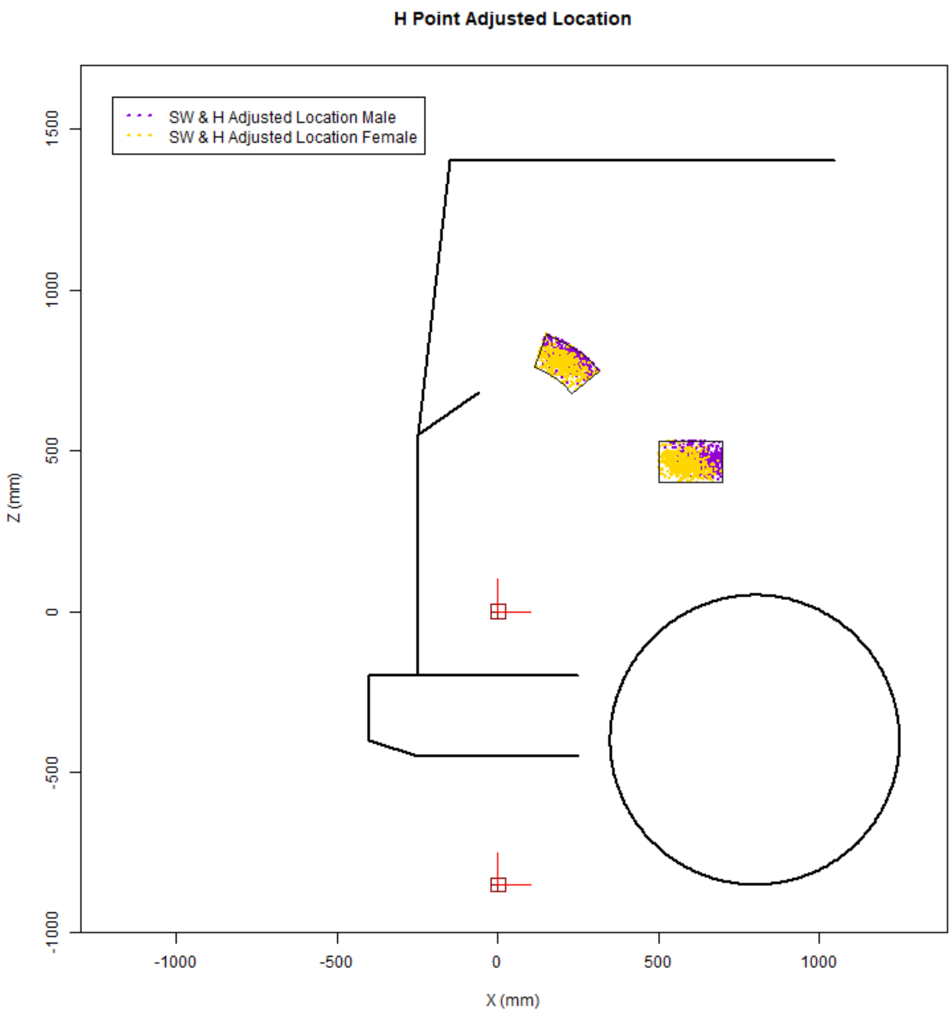

Figure 4.6. H-point Adjusted Location of Both Males and Females

4.3 Eye Point

After having both steering wheel locations and seat locations successfully predicted, eye locations can be found using both as inputs. For both male and female, the clusters of points are both ellipse-shaped. Similar to seat position, male drivers' eye locations are farther away from the AHP than female drivers' eye location, by an average of 49 mm and 66 mm in the X- and Z-direction, respectively (Figure 4.7).

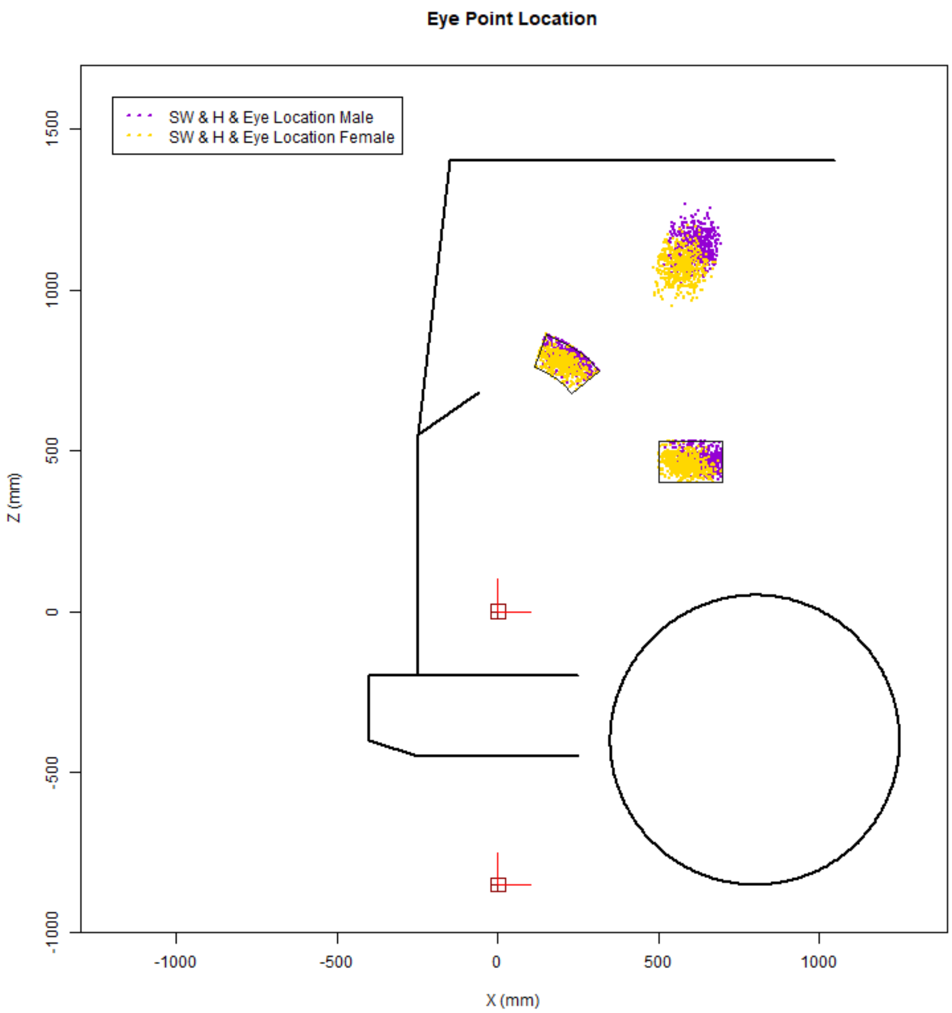

Figure 4.7. Eye Location of Both Males and Females

As mentioned in Chapter 3, one of the safety requirements is that drivers must be able to see 14° above the horizontal plane, and the UDLO is usually the limiting factor. Due to the large size of most buses, the UDLO is usually very high, and the upward vision requirement is never a concern. In this thesis, the UDLO is significantly lowered comparing to other transit buses in order to demonstrate the contrary situation. For this specific bus layout, 95.4% of the male drivers and 100% of the female drivers, 97.7% combined, meet the upward vision requirement. Disaccommodated drivers are shown in red (in Figure 4.8).

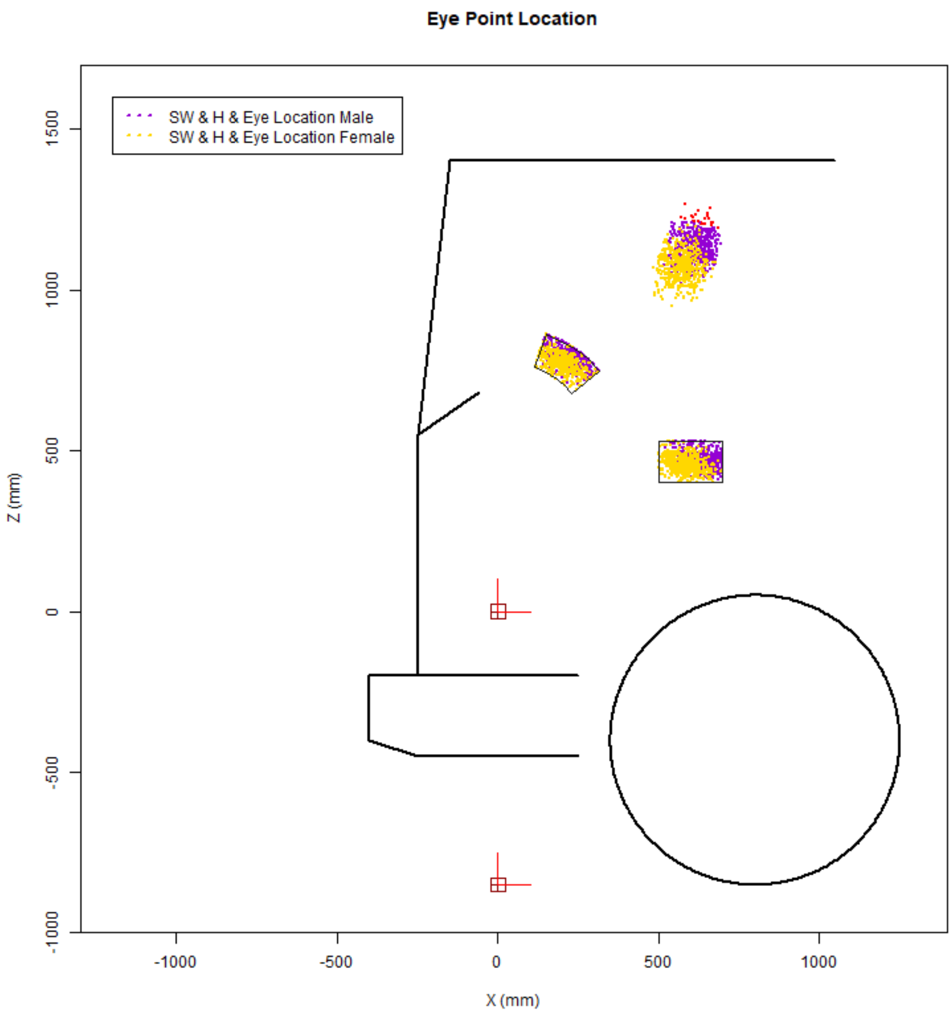

Figure 4.8. Upward Vision Assessment for Both Males and Females

Besides a 14° upward vision angle, the APTA requires all bus drivers to be able to see a 3.5-ft tall object 2.0-ft in front of the bus to ensure road safety. In the picture below, the vertical line in maroon represents the object. When a driver looks downward, two components could block their vision: the cowl point and the tip of the dashboard. Depending on driver eye location, either one could be the limiting factor. Only when neither of them blocks driver vision, is the requirement met. Given the location of these components (Figure 4.9), 100% of the male drivers and 96.4% of the female drivers are accommodated on this requirement, which makes a 98.2% combined accommodation.

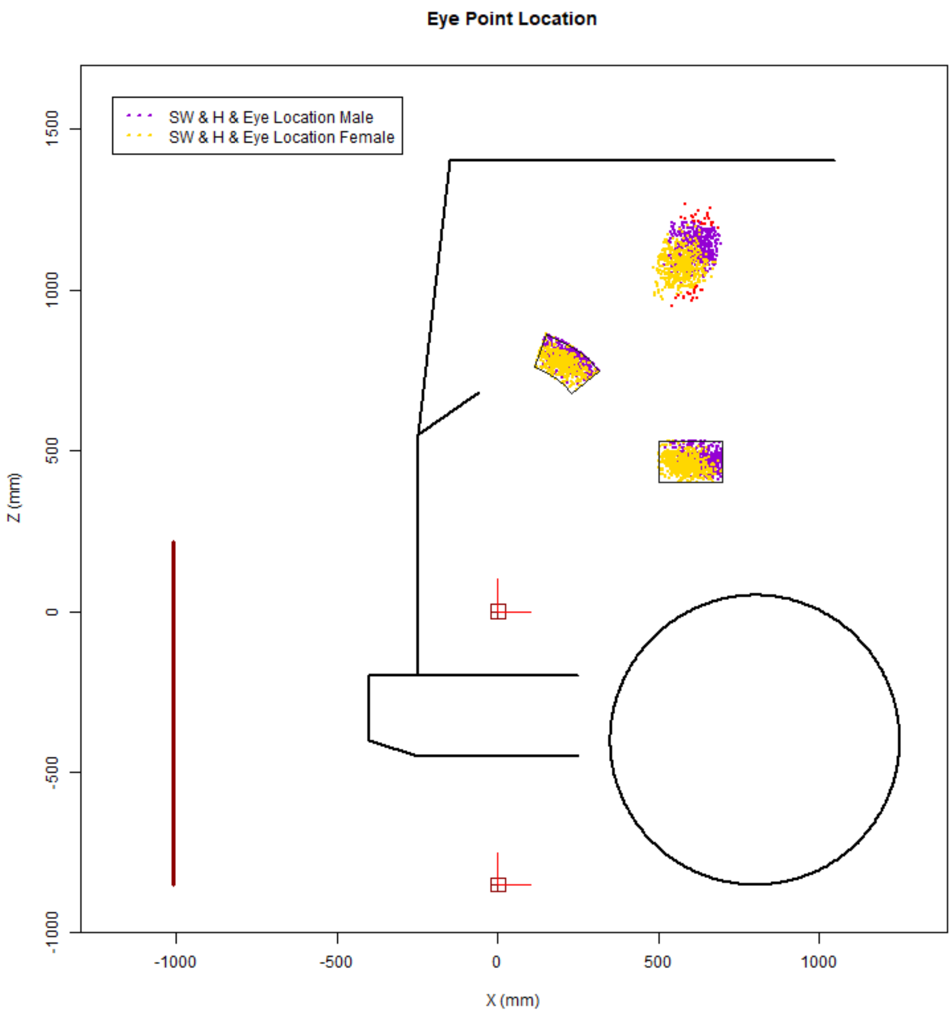

Figure 4.9. Downward Vision Assessment for Both Males and Females

4.4 Overall Accommodation

Steering wheel location, seat location, and eye location are the three primary considerations in vehicle packaging, and these locations are used to assess all four requirements regarding spatial fit and vision safety (steering wheel, seat, up vision, and down vision). Through previous efforts, the accommodation rate of each requirement can be calculated, but it is of interest to study the overall accommodation. As discussed in Chapter 3, this thesis applies indicator functions to each virtual driver to gain a thorough understanding of what limitations they are encountering, and from there, the overall accommodation rate can be calculated for the 1000 drivers (Table 4.1).

As shown in the accommodation table above, the difference between male drivers and female drivers is noticeable. In general, male drivers tend to sit farther back and higher with respect to the AHP. This observation is expected because of the variation in body size across gender. In this thesis, a small bus with limited adjustment ranges is used in order to effectively illustrate disaccommodation. With this specific layout, a combined population of 83.8% is accommodated; however, the accommodation rate can improve dramatically by 1) raising the UDLO, 2) lowering the cowl point and the dashboard, and 3) increasing the adjustment ranges of the steering wheel and the seat.

4.5 Other Body Landmarks

The results produced from the Cascade Model demonstrate its usefulness while packaging a bus as the model delivers instantaneous and quantitative feedback for a design. This thesis aims to establish a bridge between bus layout and accommodation so that designers can effectively make proper changes to their current bus designs, which will ultimately improve drivers' overall well-being.

Besides an accurate and reliable model to predict drivers' interaction with the vehicle, another goal of this thesis is to provide visualization to the industry users to make vehicle packaging a more intuitive process. Specifically, a full body kinematics diagram that represents a human figure would be beneficial. In order to do so, more body landmarks need to be predicted to indicate the location of body joints. The first step is to locate shoulder joints using linear regressions so driver's torso can be oriented (Figure 4.10).

Table 4.1. Univariate and Multivariate Accommodation Rates of 1000 Virtual Bus Drivers

Gender	Steering Wheel	Seat (H-point)	Up Vision	Down Vision	Overall
Male	89.6%	90.6%	95.4%	100.0%	80.6%
Female	90.4%	96.6%	100.0%	96.4%	97.0%
Combined	90.0%	93.6%	97.7%	98.2%	83.8%

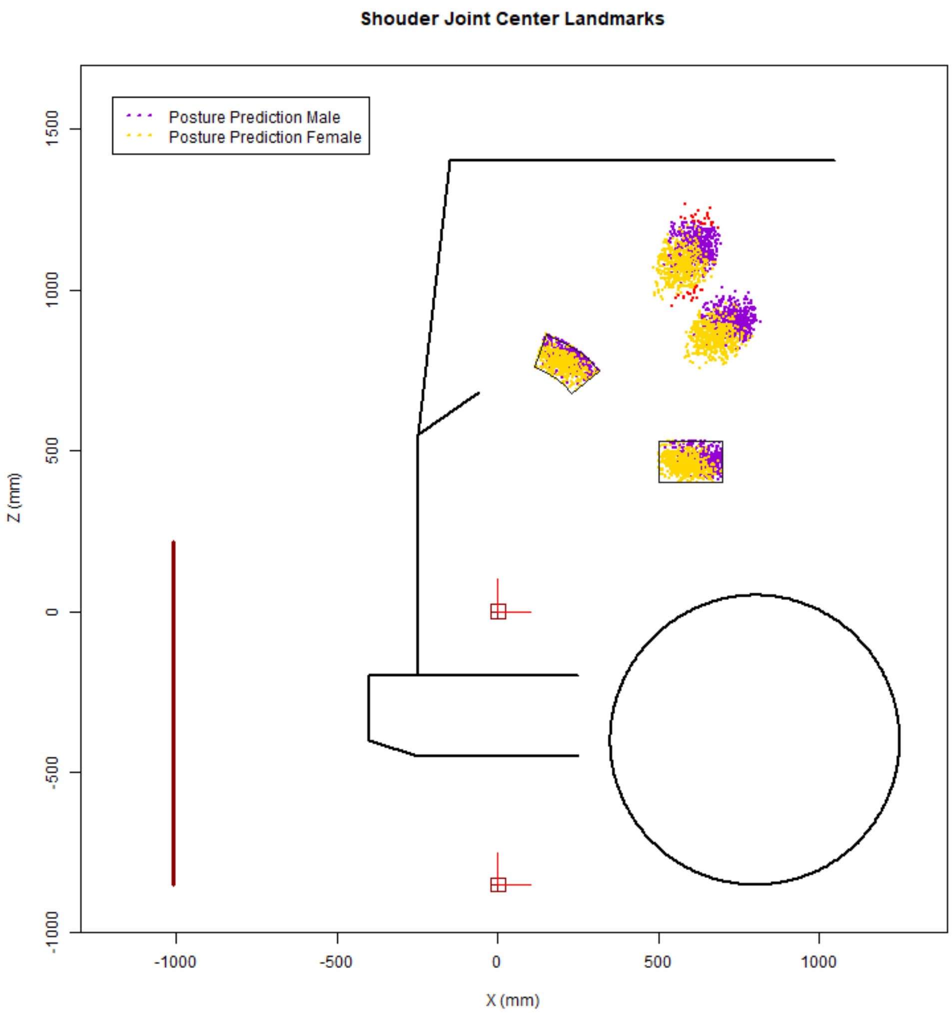

Figure 4.10. Male and Female Driver Shoulder Joint Location Prediction

A normal driving posture is when a driver is operating a vehicle without taking additional actions, such as spinning the steering wheel or braking. While drivers are maintaining a normal driving posture, their hands are expected to be placed at the lower quarter of the steering wheel. With hand location, shoulder location, and body dimensions being known, driver's upper limbs can be configured using inverse kinematics. Similarly, driver's foot tends to gently tap on the accelerator pedal while driving, so their ankle joint is relatively static to the AHP. With information on their leg lengths, driver's lower limbs can also be configured (Figure 4.11)

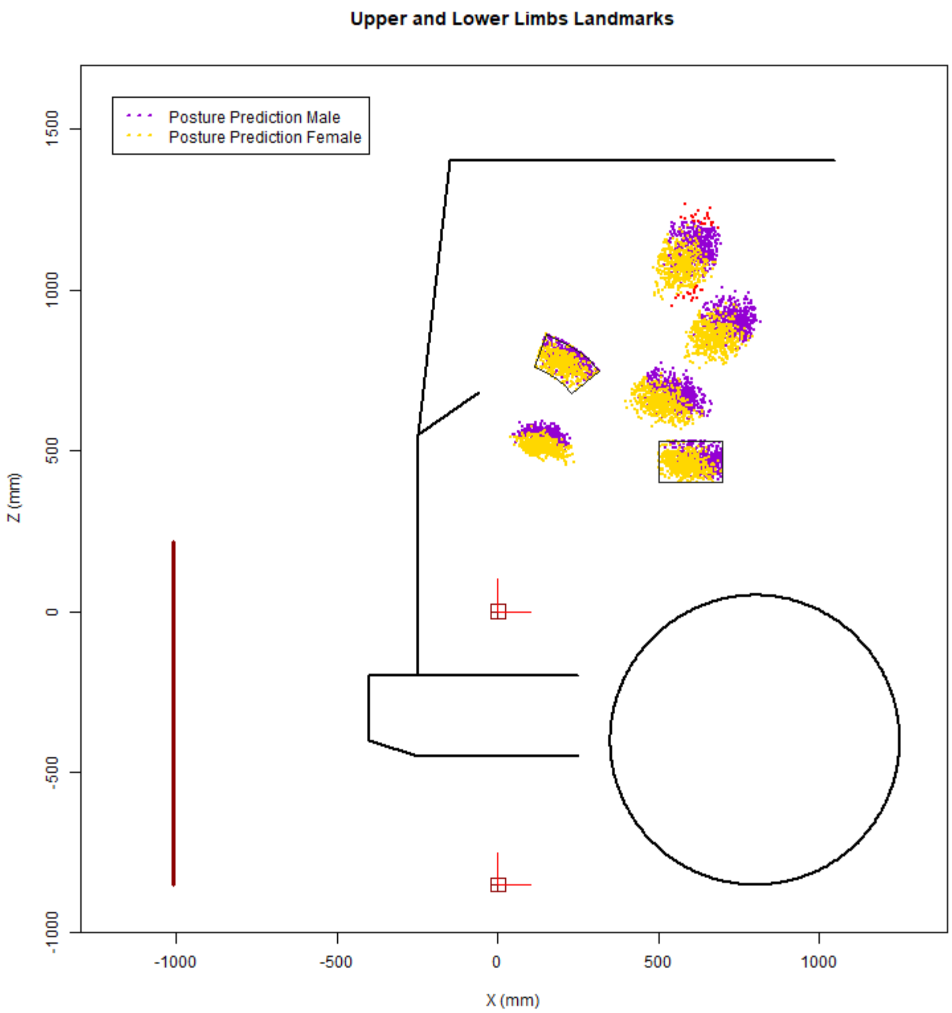

Figure 4.11. Male and Female Driver Elbow Joint and Knee Joint Configuration

4.6 "Average" Driver

In Chapter 2, a detailed discussion on the percentile model is carried out, and it is obvious that the percentile approach was incapable of consistently producing accurate posture prediction. One of the arguments being that an n-th percentile person does not exist due to human variability. In spite of that weaknesses, the model can be utilized as a visualization tool to show driving postures because an n^{th} percentile person can certainly exist in a virtual world. The green lines represent an "average" male driver with average body dimensions throughout, and the orange lines represent an "average" female (Figure 4.12).

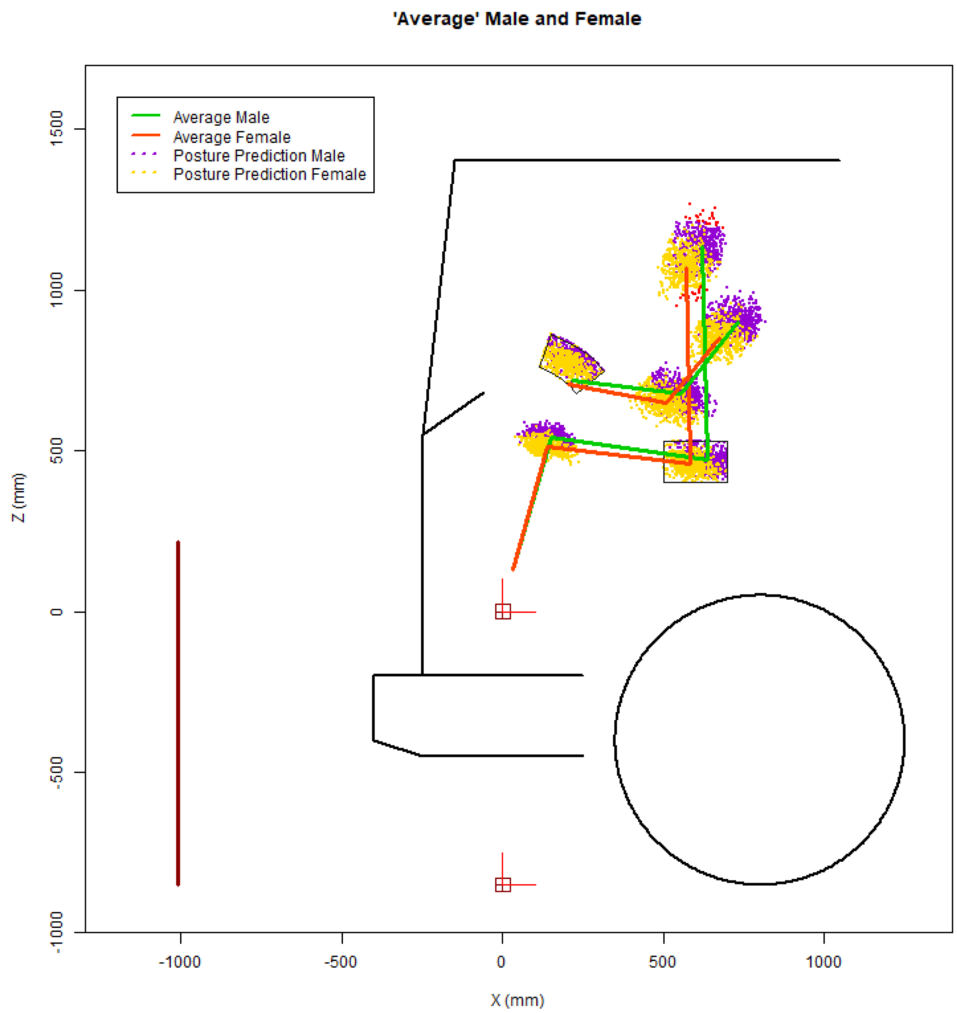

Figure 4.12. "Average" Male Driver and Female Driver

Although these two body configurations are great visual tools to describe the average driving posture, they cannot represent actual drivers since an n-th percentile person does not exist in the real world. In order to demonstrate this, 500 virtual male drivers are used, and a male driver, who is 50th percentile in stature, is configured and plotted against the "average" male driver (Figure 4.13). Clearly, the two drivers have significantly different postures, and it would be inaccurate to assume a driver with 50th percentile stature would be 50th percentile on other body dimensions. In fact, this is never true.

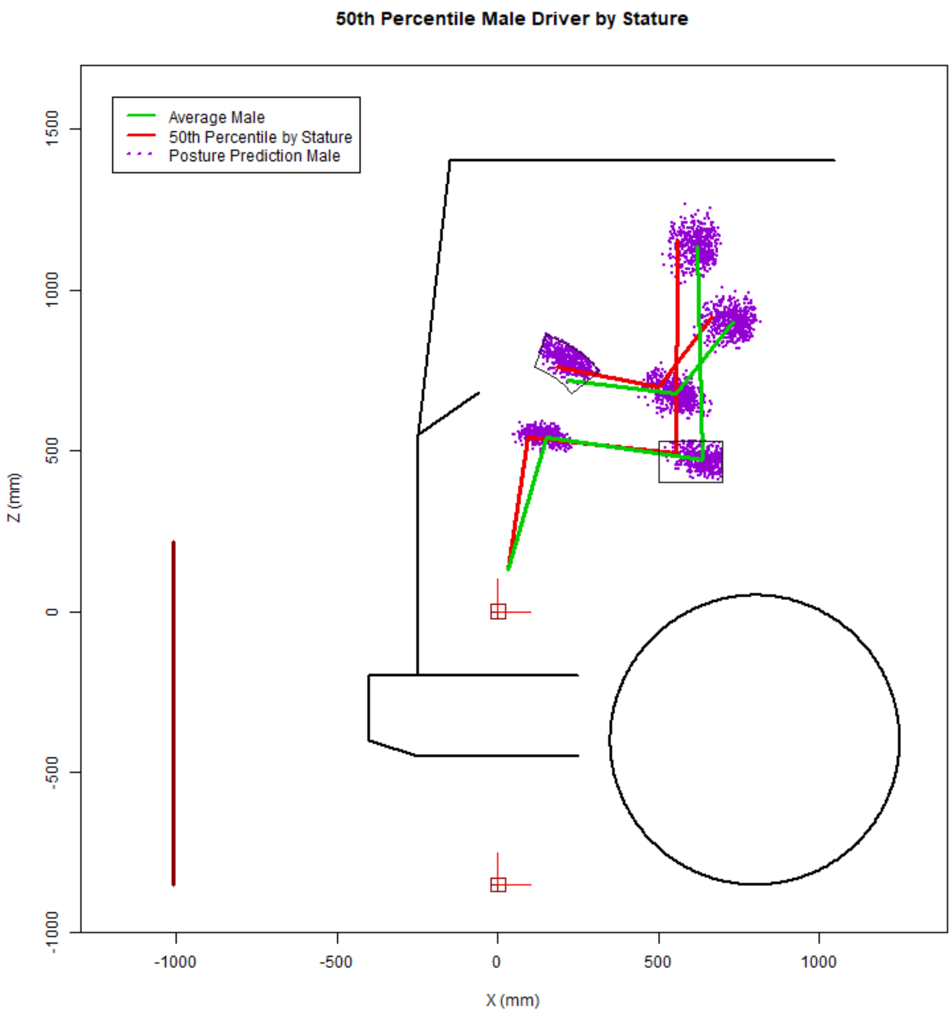

Figure 4.13. Male Driver with 50th Percentile Stature vs. "Average" Male Driver

4.7 RULA

This thesis dedicates a large amount of effort into driver's posture prediction and configuration of each driver's posture as joints and links. With this effort, it is of interest to utilize this information to investigate into their musculoskeletal health because bus drivers are known for their critical work environment. As discussed in Chapter 3, they operate the vehicle within a spatial-limited workstation and are expected to maintain the same posture for hours. Under such circumstance, they are likely to develop fatigue and musculoskeletal symptoms, which not only deteriorate driver's health but also increase the likelihood of an accident. In fact, this is one of the reasons bus drivers leave the bus transportation industry [100].

Aiming to quantitatively study driver's posture-related fatigue, a Rapid Upper Limb Assessment (RULA) is used. RULA is a method of estimating the risks of upper limb fatigue and disorders through work-related postures. It receives inputs such as body angles and force requirements to predict individual worker's ergonomic risk factor [101]. In recent years, RULA has been widely used for assembly workers who repetitively perform certain tasks, and RULA's success has proved itself to be a valuable tool to evaluate workers' risk factors [102]. Although RULA puts a great emphasis on the upper limb, factors such as leg support and torso angle are also considered, which makes it a suitable method to assess bus drivers' work conditions. The RULA worksheet is shown (in Figure 4.14).

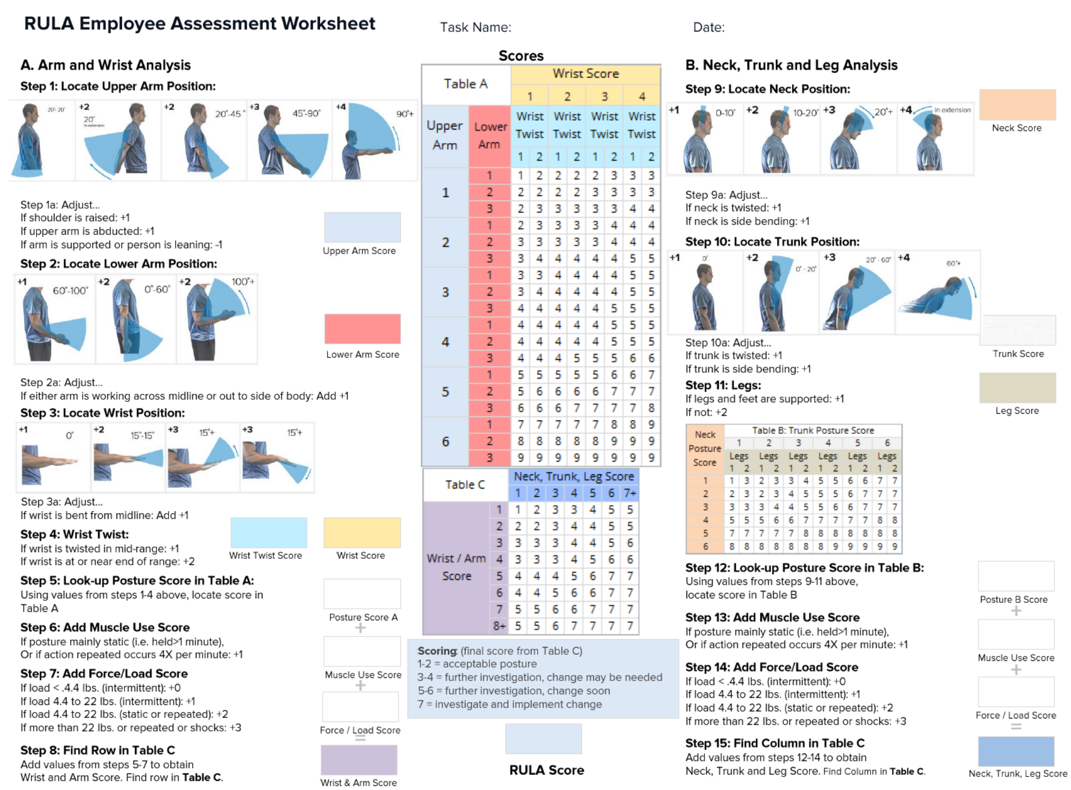

Table A		Wrist Score 1		Wrist Score 2		Wrist Score 3		Wrist Score 4	
Upper Arm	Lower Arm	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2	Wrist Twist 1	Wrist Twist 2
1	1	1	2	2	2	2	3	3	3
	2	2	2	2	2	3	3	3	3
	3	2	3	3	3	3	3	4	4
2	1	2	3	3	3	3	4	4	4
	2	3	3	3	3	3	4	4	4
	3	3	4	4	4	4	4	5	5
3	1	3	3	4	4	4	4	5	5
	2	3	4	4	4	4	4	5	5
	3	4	4	4	4	4	5	5	5
4	1	4	4	4	4	4	5	5	5
	2	4	4	4	4	4	5	5	5
	3	4	4	4	5	5	5	6	6
5	1	5	5	5	5	5	6	6	7
	2	5	6	6	6	6	7	7	7
	3	6	6	6	7	7	7	7	8
6	1	7	7	7	7	7	8	8	9
	2	8	8	8	8	8	9	9	9
	3	9	9	9	9	9	9	9	9

Table C		Neck, Trunk, Leg Score 1	2	3	4	5	6	7+
Wrist / Arm Score	1	1	2	3	3	4	5	5
	2	2	2	3	4	4	5	5
	3	3	3	3	4	4	5	6
	4	3	3	3	4	5	6	6
	5	4	4	4	5	6	7	7
	6	4	4	5	6	6	7	7
	7	5	5	6	6	7	7	7
	8+	5	5	6	7	7	7	7

Neck Posture Score	Table B: Trunk Posture Score 1		2		3		4		5		6	
	Legs 1	Legs 2	Legs 1	Legs 2	Legs 1	Legs 2	Legs 1	Legs 2	Legs 1	Legs 2	Legs 1	Legs 2
1	1	3	2	3	3	4	5	5	6	6	7	7
2	2	3	2	3	4	5	5	5	6	7	7	7
3	3	3	3	4	4	5	5	6	6	7	7	7
4	5	5	5	6	6	7	7	7	7	7	8	8
5	7	7	7	7	7	8	8	8	8	8	8	8
6	8	8	8	8	8	8	8	9	9	9	9	9

Figure 4.14. RULA Worksheet Example [24]

After carefully estimating the force loads in the upper body and the lower body while driving with a normal posture, a RULA is carried out for each driver. The final score of RULA, indicating the ergonomics risk factor, is the outcome of the assessment. Given in a scale of 1 to 7, the associated actions to be taken are shown as following:

- 1-2: acceptable posture
- 3-4: further investigation, change may be needed
- 5-6: further investigation, change soon
- 7: investigate and implement change

The results show that all 1000 virtual drivers scored a 3, which indicates that their driving postures put them at low ergonomics risk, and the need for a posture change is minimal. Although drivers may experience discomfort at times, especially when driving for too long, ergonomics risk is not likely to become a major concern. In addition, drivers' postures vary from each other, but the variation is not large enough to dramatically impact drivers' ergonomics risk factors. Therefore, it is unnecessary to repetitively conduct RULA for each virtual driver after conducting it once.

Chapter 5
Discussion and Software Tools

This thesis aims to provide increased understanding of anthropometric variability of U.S. bus drivers and their postural preferences while driving. In order to achieve this, a cascade approach is utilized with linear regression models that have been verified in the past for posture prediction. Using this method, a total of 1000 virtual drivers are successfully postured in a given bus cab. Based on the accommodation conditions shown in the model, proper design recommendations can be made. In this chapter, the recommendations will be discussed. Following which, an overview of the Cascade Model and its software applications will be presented.

5.1 Observation and Reflection

As discussed previously, the driver's body landmarks and vehicle interior components, such as the steering wheel and the seat, are all measured from the AHP. Intuitively, smaller drivers tend to posture themselves closer to the AHP for comfort and task-oriented considerations as a result of body dimensions. However, this observation is not always true due to human variability. Variability comes from two sources: body dimensions and postural preferences. As research has shown, an n^{th} percentile person, who has all n^{th} percentile body dimensions, does not exist. In fact, people vary tremendously from each other, and anthropometric variability and preference are expected to contribute largely to the final driving posture of a driver. Even among people with similar body dimensions, a large degree of variation still exists, as shown in the "average"-male and 50^{th}-percentile-stature-male comparison in Chapter 4. This observation indicates that human variability in preference plays a critical role in how drivers posture themselves in a bus, which is evidence that Percentile Model is incapable of producing reliable results.

Although there has been a lot of literature on the H-point and the eyellipse, research on steering wheel location is very limited. In small vehicles, steering wheels have only one mode of adjustment (tilting), and the drivers are expected to achieve a comfortable driving posture by moving the seat. In the case of buses and most other large vehicles however, the steering wheels are designed to move in two dimensions by implementing telescoping mechanisms due to their vertical spacing. In the Cascade Model developed for buses and trucks, the steering wheel location prediction is the first step, and it serves as an input for seat location prediction and eye location prediction. Therefore, it is critical to select a proper pivot location and provide an adequate adjustment range for the steering wheel. It not only improves driver's hand grip comfort, but also makes it easier to accommodate the preferred seat location and eye location.

In this thesis, a spatially limited bus cab is chosen on purpose to demonstrate disaccommodated conditions. The cab layout accommodates the majority of the preferred body configurations, which are the centers of the cluster of points, as shown in Chapter 4. In other words, for each body landmark, being indicated as a cluster of points, the highest frequency of occurrence is at the center. As extending outward, the frequency of occurrence decreases. The farther the distance, the larger the decrease. Previously, researchers have found that body dimensions can be approximated as Gaussian distributions. Since driver's posture is predicted using linear regression models with variance, it is implied that driver's posture is also normally distributed.

5.2 Cascade Model Overview

This thesis utilizes estimated anthropometry of U.S. bus drivers. This data passes through a sequence of posture prediction models and becomes an invaluable part of representing preferred driving posture. Two critical design concerns, spatial fitting and driving safety, are analyzed for accommodation during each step of the prediction process. Spatial fitting is usually limited by the adjustment envelope, and drivers can sometimes compromise on a less desirable posture and achieve comfort by adjusting the rest of their bodies to adapt. Driving safety is assessed by a driver's ability to maintain adequate vision during driving in two dimensions. The outcomes of the analysis indicate the overall quality of a bus package, and they recommend directions to improve the design.

The posture prediction models are carried out in a cascading manner such that the output of the previous step becomes the input of the next step. Starting with steering wheel location prediction, the cascading process then directs its focus to seat location and eye location, which are the critical reference points in vehicle packaging. Following that, other body landmarks can be configured, such as shoulder joint, elbow joint, knee joint, and ankle joint. A schematic diagram of the cascading approach is shown (in Figure 5.1):

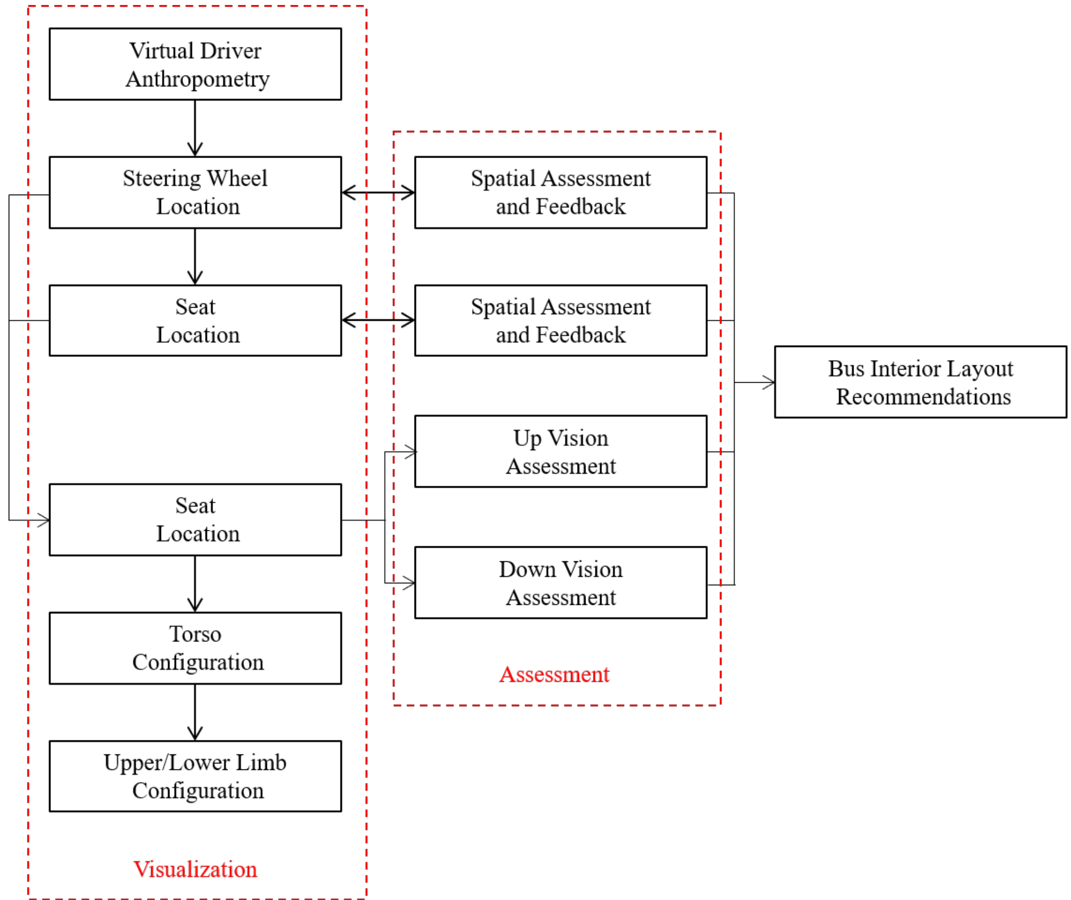

Figure 5.1. Schematic Diagram of Cascade Model

5.3 Applications

The objective of this thesis is to investigate the effect of human variability in the vehicle packaging subject, and deliver software tools to design interior bus layouts for U.S. bus drivers. The goals are met by applying the fundamental principles of cascading throughout this research, utilizing the linear regression with variance to predict landmark locations for each virtual driver, and using reverse kinematics to configure body posture. The outcomes of the research are delivered in two forms: a web application using R Shiny and an Excel spreadsheet.

These software tools are to be used by automobile industry users who are in positions of packaging buses. Due to the complexity of the subject and the learning curve of using a new tool, an intuitive software tool with visuals is highly desirable. Within the tool, users are given the access to change the bus geometry, adjustment range of the components, and driver demographics. The tool automatically performs posture prediction for each virtual driver and assesses the design. Results are presented in two forms: one is a table that summarizes the accommodation rates of each of the four design objectives (steering wheel location, seat location, upward vision, and downward vision), together with the overall accommodation rate. The other is a pictorial representation of the bus layout and the body landmarks. It allows users to visually see how the drivers are accommodated so they can make proper adjustments to the design.

In the Excel spreadsheet and the web application, the inputs are used to construct a frontal layout of a bus, a seat track adjustment envelope, and a steering wheel adjustment envelope (Figure 5.2) and (Figure 5.6). The table outputs that display univariate and multivariate accommodation rates are shown (in Figure 5.3 and Figure 5.7), and the pictorial outputs are shown (in Figure 5.4 and Figure 5.5).

Bus Geometry (mm)	
ST_X1	475
ST_X2	700
ST_Z1	400
ST_Z2	550
SW_Pivot_X	20
SW_Pivot_Z	500
SW_Diameter	450
SW_Telescop_min	275
SW_Telescop_max	400
SW_Angle_min	20
SW_Angle_max	50
AHP_X	0
AHP_Z	850
Cowl_X	-250
Cowl_Z	1400
Db_X	-60
Db_Z	1550
Bumper_X	-450
Bumper_Z	650
UDLO_X	-150
UDLO_Z	2400

ST	Seat Track
SW	Steering Wheel
Rf	Roof
Db	Dashboard

Figure 5.2. Bus Packaging Software Tool - Excel Input Box

	Up Vision	Down Vision	H point	SW	Total	RULA
Male	100.0%	99.8%	91.8%	94.4%	87.6%	3.0
Female	100.0%	90.2%	98.0%	90.6%	83.0%	3.0
Total	100.0%	97.9%	93.0%	93.6%	86.7%	3.0

Figure 5.3. Bus Packaging Software Tool - Excel Output Table

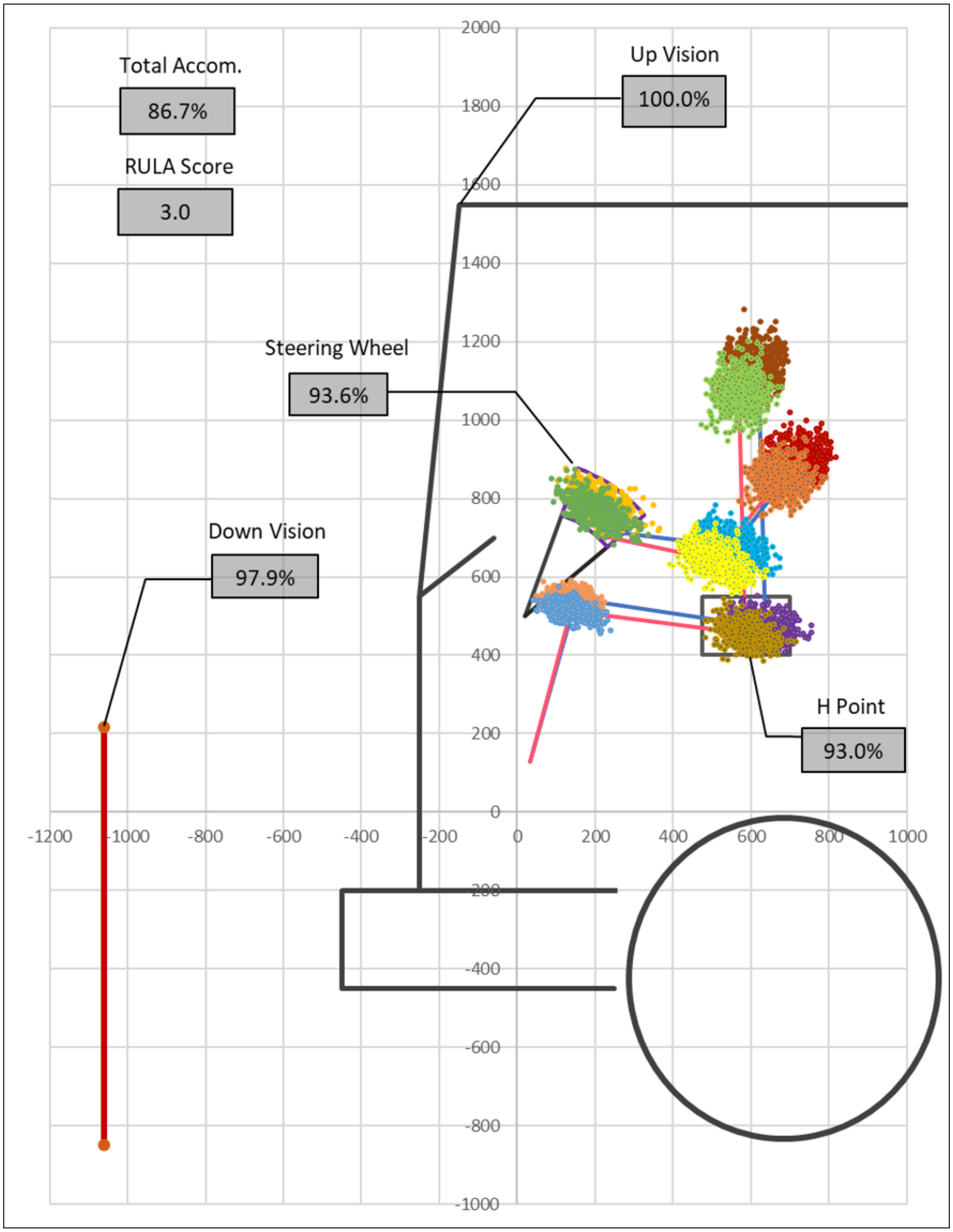

Figure 5.4. Bus Packaging Software Tool - Excel Output Picture

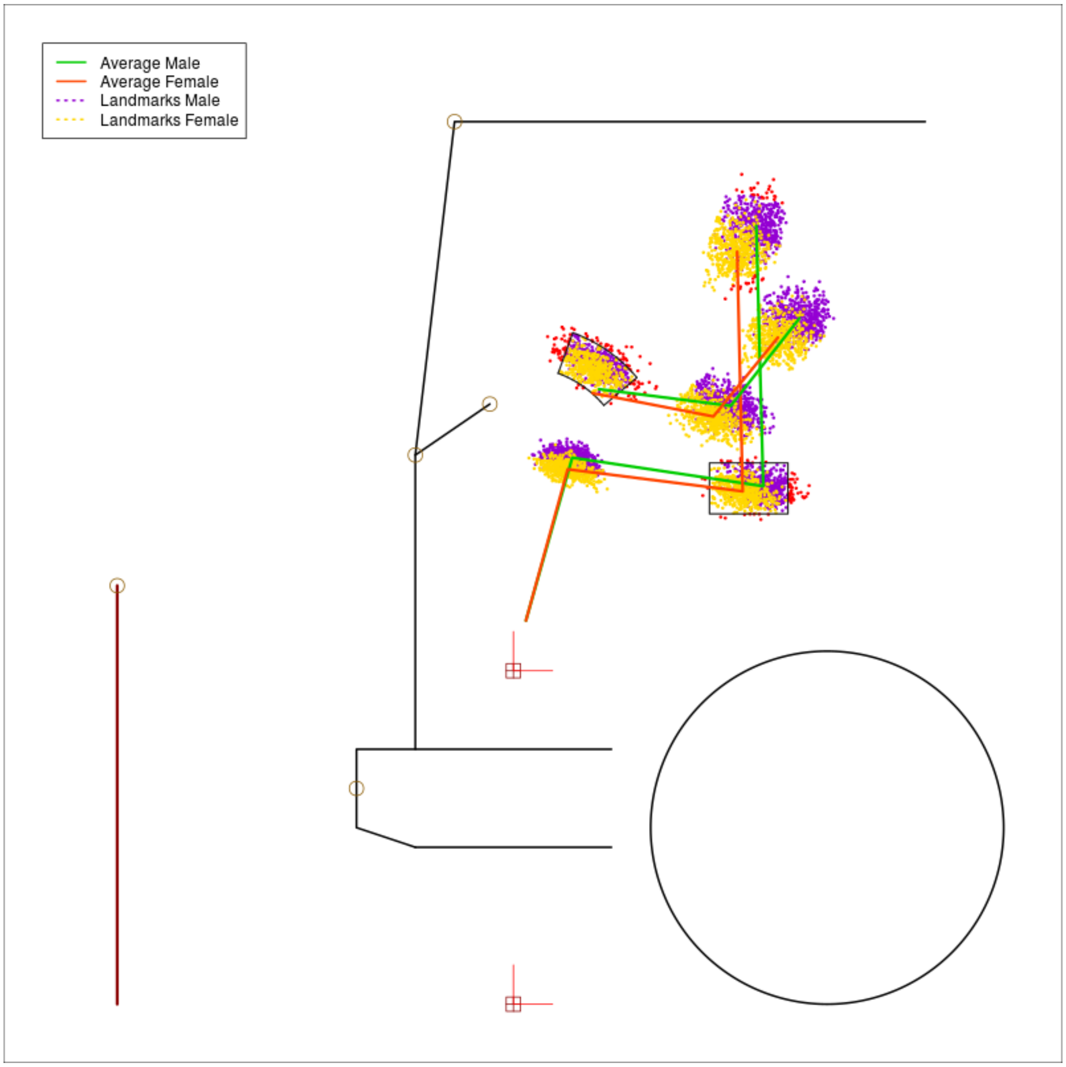

Figure 5.5. Bus Packaging Software Tool - R Shiny Output Picture

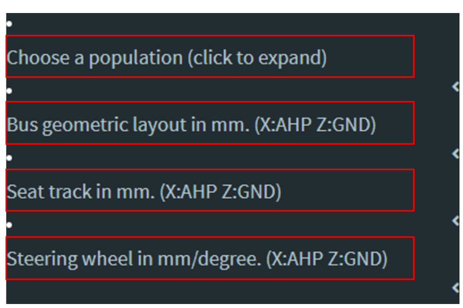

Figure 5.6. Bus Packaging Software Tool - R Shiny Input Box

Gender	Steering_Wheel	H_Point	Up_Vision	Down_Vision	Total_Accom
Male	89.6%	90.6%	95.4%	100.0%	80.6%
Female	90.4%	96.6%	100.0%	96.4%	86.4%
Combo	90.0%	93.6%	97.7%	98.2%	83.5%

Figure 5.7. Bus Packaging Software Tool - R Shiny Output Table

5.4 Limitation and Future Work

This thesis primarily studies bus driver's posture and uses it to assess bus packages in the X-Z plane because most of the packaging components are designed to be only adjustable in this plane. For example, the steering wheel and the seat are two of the most important design considerations while packaging a bus. They are fixed in the Y-direction but are adjustable in the X-Z plane. By default, they are expected to reside in the center plane on the driver's side so the distance from the driver's left hand to the components is the same as from their right hand. In addition to spatial fitting, a driver's central vision is also mainly determined in the X-Z plane due to the windshield setup. By analyzing the two-dimensional accommodation, the majority of the design questions can be answered. The software presented in thesis is able to consistently provide accurate and reliable results. However, with additional time and resource, a three-dimensional analysis can be performed by augmenting the spatial fitting assessment and the vision safety assessment in the Y-direction. For instance, the A-pillar creates a blind spot behind it while driving. By knowing driver's eye point in three dimensions, designers can identify the effective range of driver's peripheral vision make design the A-pillar accordingly. With a three-dimensional analysis, parameters such as seat width can also be assessed.

Through the effort of this thesis, a web application tool and an Excel spreadsheet are developed to assist industry users to package a bus. The output summary table quantitatively estimates the percentage of people to be accommodated, and the graphic indicates how to modify the bus layout to improve the accommodation rate. Currently, users are responsible to make the modifications which may introduce bias, since people all interpret pictorial results differently. In addition, an iterative process of finding a desired overall accommodation rate is expected due to the multivariate nature of this subject. For instance, if a user wants to improve the accommodation rate of the upward vision, they can raise the ceiling or lower the seat adjustment envelope. It will be the user's decision to do one of the two or both. In order to minimize this ambiguity, future research can investigate into the cost factors of the components to be packaged so the design decisions can be logically made. Once the cost factors are quantitatively studied, an overall cost calculation method can be developed and utilized as an objective function in an optimization study. By setting a target overall accommodation rate and an objective of minimizing cost, the "best" vehicle layout can be found.

Appendix A
Data Processing in Excel

Stature	ESH	BMI	UpperLeg	LowerLeg	UpperArm	LowerArm	ESH/Stature	Stature-ESH
1740.0	931.1	23.18	447.2	429.8	281.9	335.8	0.535	809.0
1675.3	863.4	22.85	430.5	413.8	271.4	323.3	0.515	811.9
1665.6	902.1	29.96	428.1	411.4	269.8	321.5	0.542	763.5
1683.0	860.7	23.35	432.5	415.7	272.6	324.8	0.511	822.4
1833.0	936.8	24.51	471.1	452.8	297.0	353.8	0.511	896.3
1804.5	908.0	25.84	463.7	445.7	292.3	348.3	0.503	896.5
1719.1	894.4	23.34	441.8	424.6	278.5	331.8	0.520	824.7
1834.6	939.0	25.93	471.5	453.1	297.2	354.1	0.512	895.6
1653.2	856.9	26.30	424.9	408.4	267.8	319.1	0.518	796.4
1782.4	921.2	23.11	458.1	440.3	288.8	344.0	0.517	861.3
1842.9	946.4	26.53	473.6	455.2	298.6	355.7	0.514	896.5
1762.9	919.9	25.60	453.1	435.4	285.6	340.2	0.522	843.0
1643.9	845.6	24.81	422.5	406.0	266.3	317.3	0.514	798.4
1711.8	881.7	18.61	439.9	422.8	277.3	330.4	0.515	830.1
1839.1	957.0	21.60	472.7	454.3	297.9	355.0	0.520	882.1
1817.6	955.5	29.10	467.1	449.0	294.5	350.8	0.526	862.1
1869.5	994.6	26.53	480.5	461.8	302.9	360.8	0.532	874.9
1899.8	961.2	21.37	488.2	469.2	307.8	366.7	0.506	938.6
1739.1	912.7	31.28	447.0	429.6	281.7	335.7	0.525	826.4
1765.4	879.9	20.34	453.7	436.0	286.0	340.7	0.498	885.5
1747.2	897.9	27.87	449.0	431.6	283.1	337.2	0.514	849.3

Figure A.1. Virtual U.S. Bus Driver Body Dimensions

.

SW_pref_X	SW_pref_Z	SW_X	SW_Z	H_pref_X	H_pref_Z	H_X	H_Z	Eye_X	Eye_Z
276.5	749.8	276.5	749.8	656.9	441.6	656.9	441.6	655.1	1117.8
182.7	814.0	182.7	814.0	579.0	496.7	579.0	496.7	561.1	1118.4
164.1	803.9	164.1	803.9	563.4	479.1	563.4	479.1	552.9	1140.4
194.0	774.7	194.0	774.7	605.6	463.8	605.6	463.8	583.7	1084.0
187.2	845.6	187.2	845.6	631.2	529.6	631.2	529.6	608.0	1213.0
186.2	820.5	186.2	820.5	642.2	507.4	642.2	507.4	609.9	1169.6
187.6	779.9	187.6	779.9	601.4	468.5	601.4	468.5	586.8	1115.8
104.8	846.0	141.8	834.8	609.3	519.4	609.3	519.4	584.2	1206.6
180.6	738.9	180.6	738.9	600.7	429.2	600.7	429.2	577.8	1050.4
238.3	756.8	238.3	756.8	662.7	452.0	662.7	452.0	646.3	1120.7
167.8	830.4	167.8	830.4	629.9	515.4	629.9	515.4	605.4	1209.3
273.0	782.4	273.0	782.4	674.8	470.6	674.8	470.6	657.8	1141.6
187.4	770.0	187.4	770.0	592.6	456.8	592.6	456.8	569.5	1066.9
198.8	798.4	198.8	798.4	591.0	487.8	591.0	487.8	581.4	1118.0
221.7	747.1	221.7	747.1	662.8	446.6	662.8	446.6	652.4	1142.0
210.6	791.0	210.6	791.0	655.7	477.1	655.7	477.1	637.0	1181.3
185.6	786.0	185.6	786.0	640.4	475.8	640.4	475.8	632.9	1207.8
237.5	817.6	237.5	817.6	687.5	511.5	687.5	511.5	665.7	1210.0
240.9	805.1	240.9	805.1	656.2	484.6	656.2	484.6	630.9	1157.1
147.6	827.8	147.6	827.8	590.0	516.4	590.0	516.4	564.5	1147.6
215.4	809.0	215.4	809.0	641.6	492.3	641.6	492.3	613.5	1148.9

Figure A.2. Virtual U.S. Bus Driver Primary Reference Points

.

Grip X	Grip Z	Hip X	Hip Z	Shoulder X	Shoulder Z	Elbow X	Elbow Z	Elbow Angle	Knee X	Knee Z	Knee Angle
276.5	669.2	625.0	442.4	765.5	876.4	611.1	640.6	118.4	186.3	529.2	99.9
182.7	762.3	548.8	491.5	669.1	897.1	497.2	687.1	115.9	120.1	532.3	96.9
164.1	755.7	495.7	487.8	649.8	902.1	479.4	692.9	118.0	70.5	537.6	88.7
194.0	714.5	572.7	459.1	691.8	863.7	513.7	657.2	120.7	145.7	527.9	96.8
187.2	796.6	592.3	532.9	724.3	972.5	536.8	742.2	120.4	122.8	571.6	96.9
186.2	768.7	596.3	510.3	723.2	936.8	530.6	716.9	122.7	135.3	561.6	97.1
187.6	722.2	568.6	466.5	696.7	885.6	515.8	673.9	122.2	133.0	540.4	94.2
141.8	808.0	562.8	525.0	698.8	964.5	491.4	751.7	125.2	94.2	576.9	91.6
180.6	676.2	552.3	428.6	680.2	828.5	496.8	633.4	125.6	137.9	522.4	92.3
238.3	683.9	631.1	451.9	760.8	884.3	581.3	658.1	124.2	182.0	541.9	98.6
167.8	784.5	580.3	522.5	719.6	964.8	521.0	741.9	124.9	109.7	576.5	93.3
273.0	707.3	630.1	474.1	767.6	903.4	610.6	664.8	116.2	181.4	537.0	102.1
187.4	710.8	552.0	453.1	673.3	849.3	498.5	648.4	119.8	134.9	520.8	95.5
198.8	740.6	583.1	477.7	696.7	894.5	523.3	678.2	117.9	146.9	534.9	98.4
221.7	675.9	639.1	447.1	772.2	896.8	576.7	672.0	130.4	179.6	557.6	95.5
210.6	729.3	592.5	488.8	745.5	931.3	560.3	702.4	124.6	131.8	565.7	93.4
185.6	729.7	590.8	486.8	747.3	948.3	546.3	721.8	130.4	119.7	581.3	89.6
237.5	754.0	665.1	512.1	790.5	966.0	602.8	722.1	122.7	180.7	573.1	101.3
240.9	739.1	581.6	496.2	732.0	917.3	572.2	685.3	115.4	137.2	544.5	98.0
147.6	787.0	573.0	508.7	681.9	925.9	481.9	721.4	123.3	121.6	554.7	96.1
215.4	748.9	584.9	497.4	720.2	916.1	547.7	691.7	117.8	138.5	546.2	98.1

Figure A.3. Virtual U.S. Bus Driver Secondary Body Landmarks

.

Up_Vision	Down_Vision	H_point	SW	Total	RULA
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	0	0	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3
1	1	1	1	1	3

Figure A.4. Virtual U.S. Bus Driver Accommodation Assessment

.

Appendix B
Web Application Visualization

B.1 Data Input: Bus Package and Drive Demographics

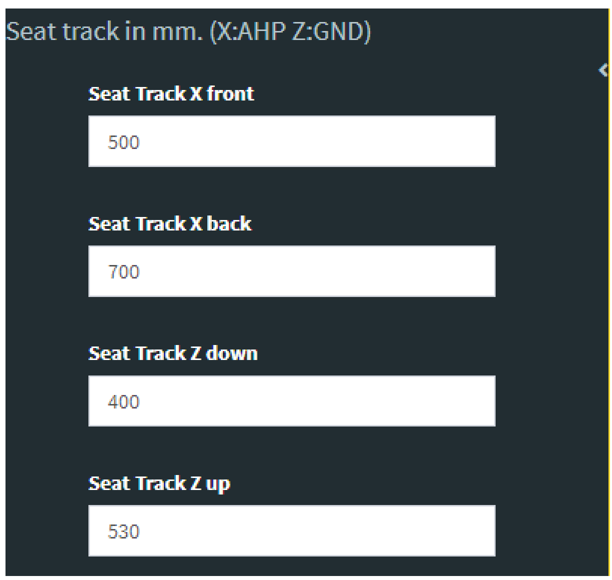

Figure B.1. Bus Seat Design

.

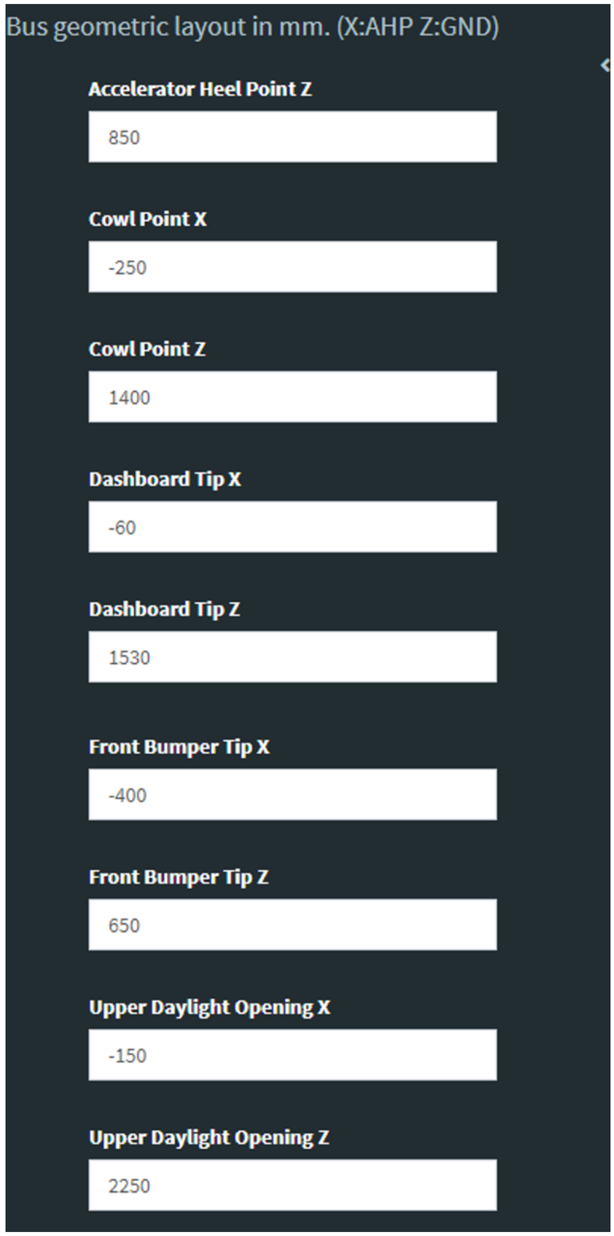

Figure B.2. Bus Layout Design

.

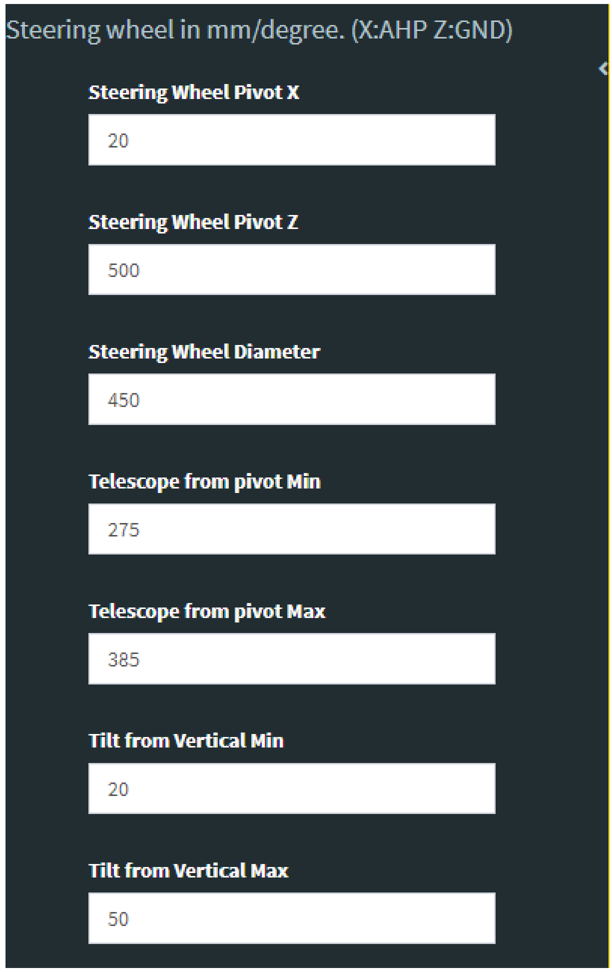

Figure B.3. Bus Steering Wheel Design

.

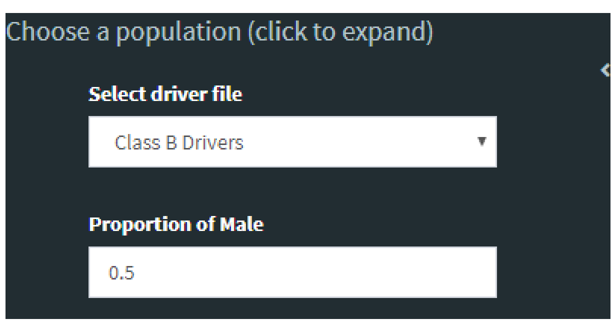

Figure B.4. U.S. Bus Driver Demographics

.

B.2 Data Output: Table Summary and Visualization

Gender	Steering_Wheel	H_Point	Up_Vision	Down_Vision	Total_Accom
Male	89.6%	90.6%	95.4%	100.0%	80.6%
Female	90.4%	96.6%	100.0%	96.4%	86.4%
Combo	90.0%	93.6%	97.7%	98.2%	83.5%

Figure B.5. Accommodation Summary Table

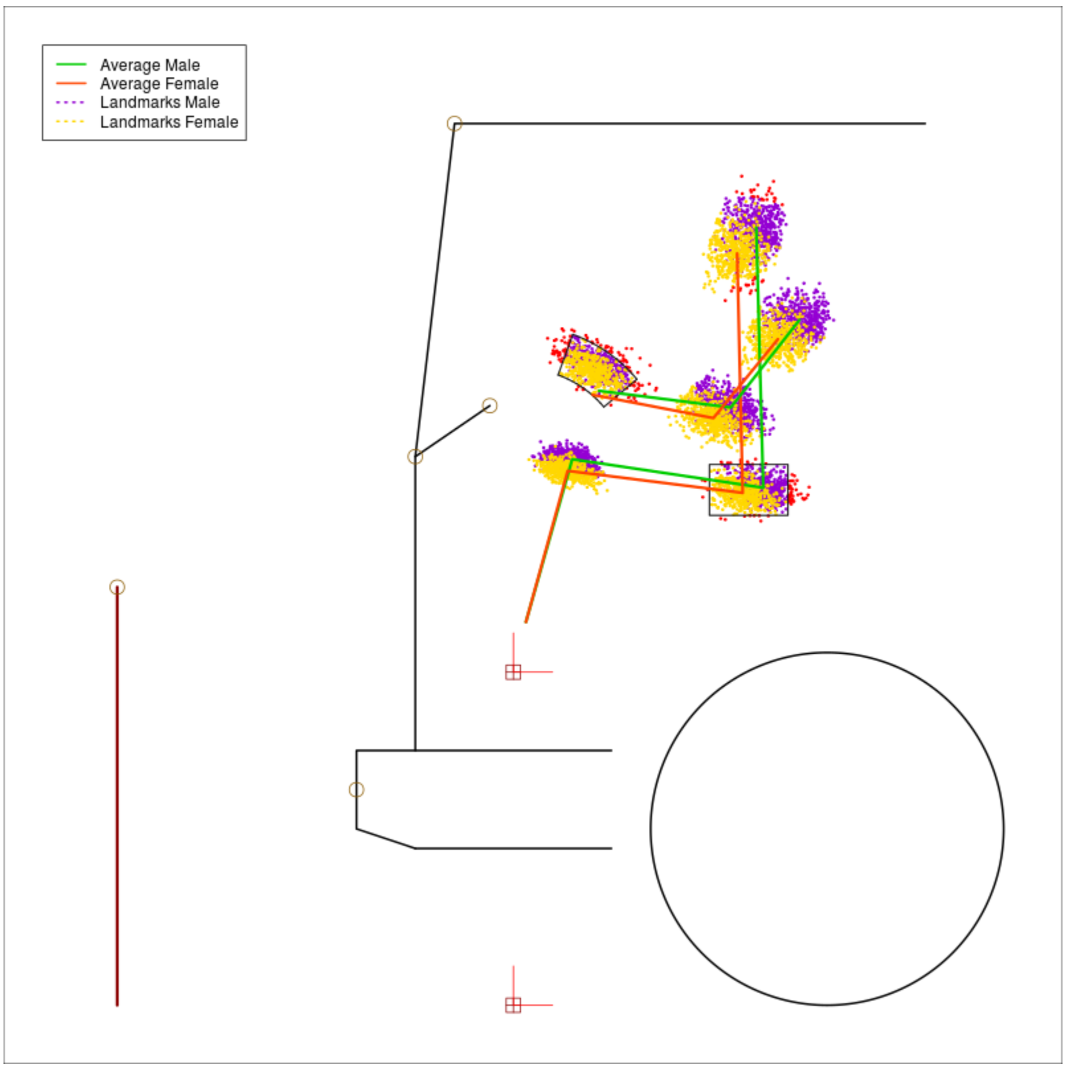

Figure B.6. Design Visualization

Appendix C
U.S. Bus Driver Demographics

C.1 Bus Driver Demographics: Gender

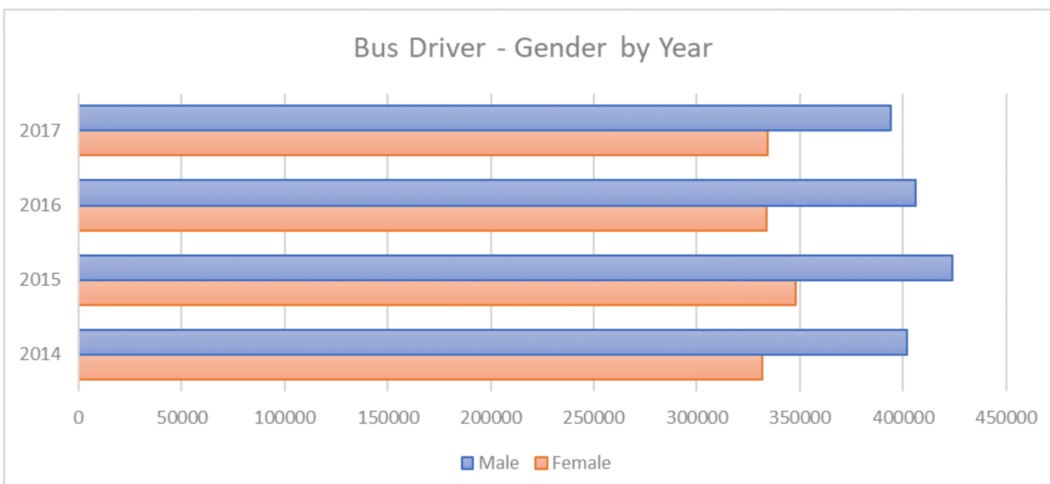

Figure C.1. U.S. Bus Driver: Male and Female Ratio (2014 2017)

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C.2 Bus Driver Demographics: Ethnicity

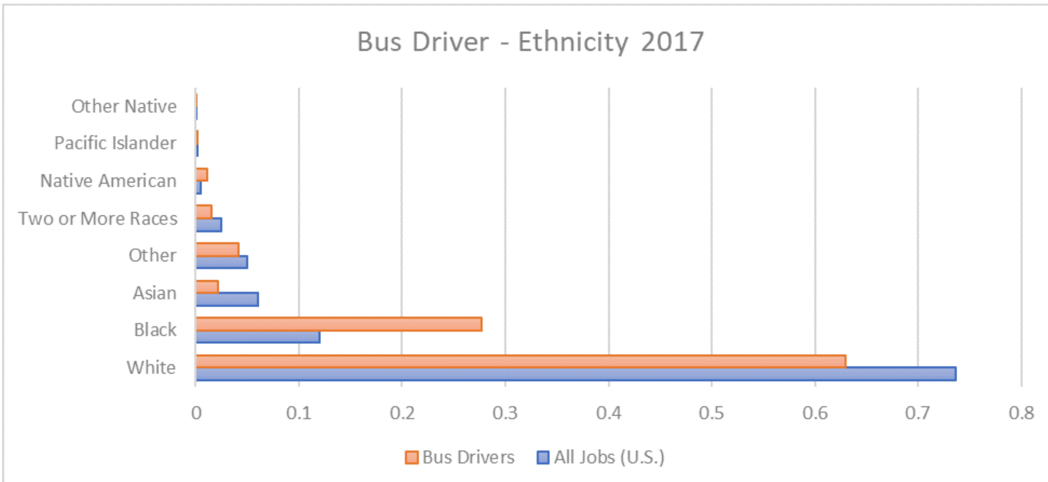

Figure C.2. U.S. Bus Driver: Ethnicity Diversity (2017)

.

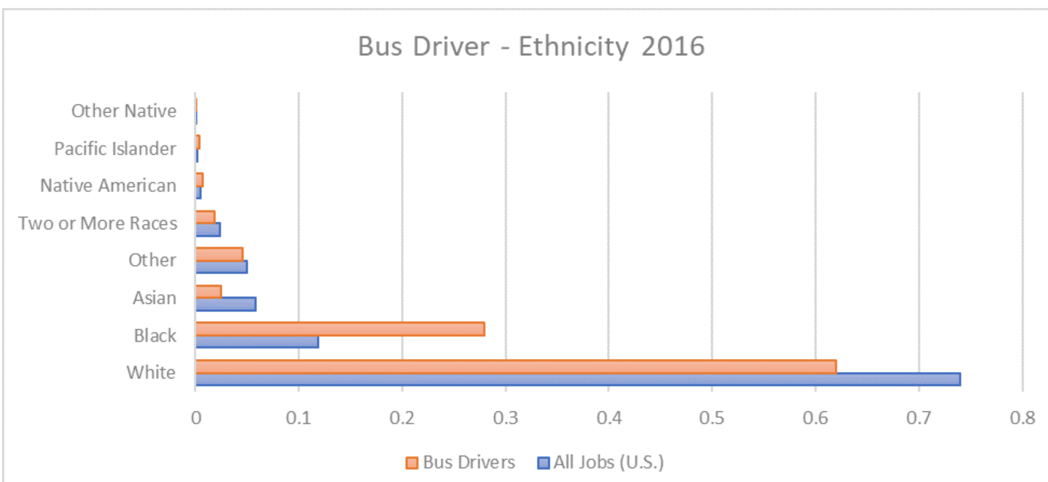

Figure C.3. U.S. Bus Driver: Ethnicity Diversity (2016)

.

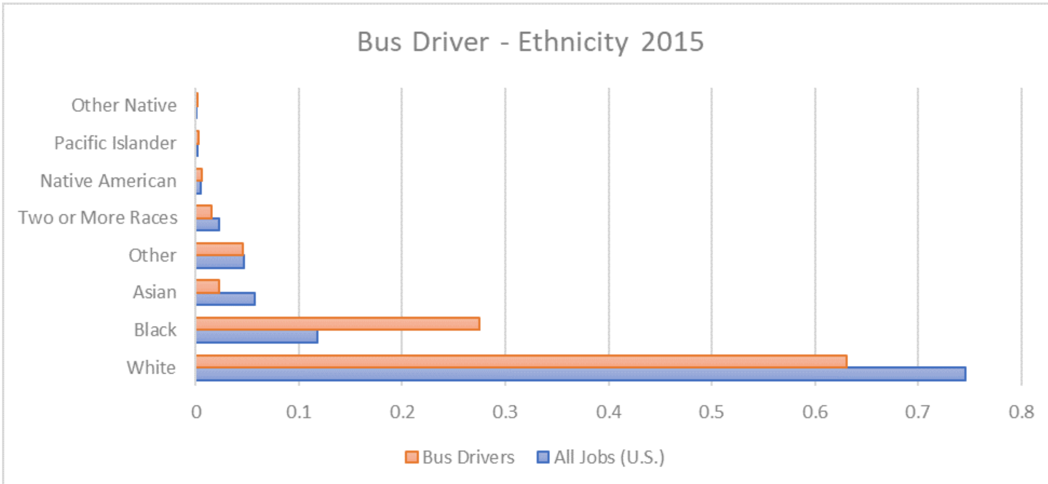

Figure C.4. U.S. Bus Driver: Ethnicity Diversity (2015)

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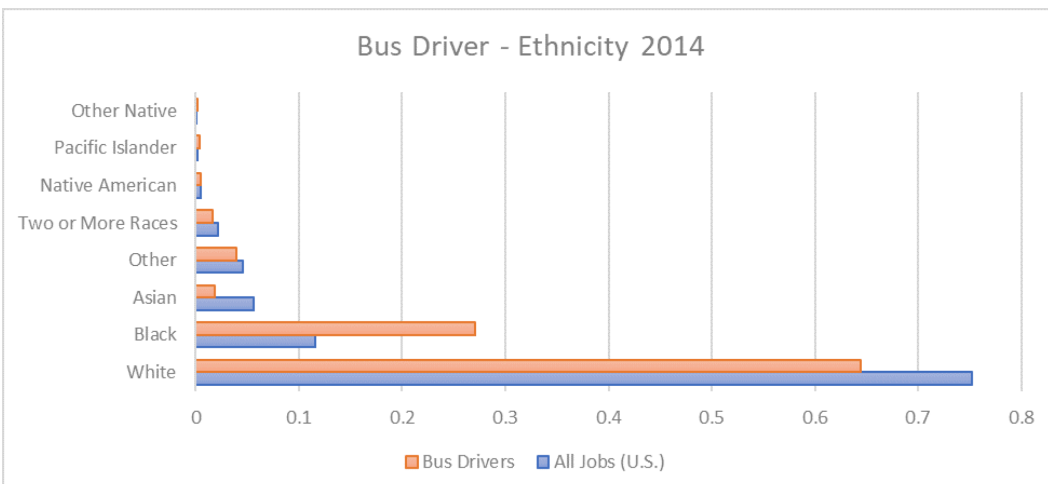

Figure C.5. U.S. Bus Driver: Ethnicity Diversity (2014)

.

C.3 Bus Driver Demographics: Age

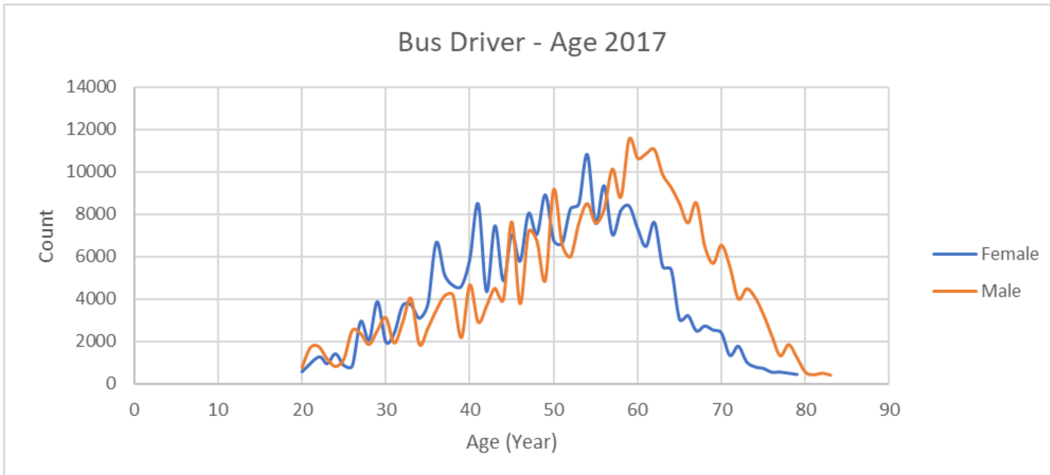

Figure C.6. U.S. Bus Driver: Male and Female Age Distribution (2017)

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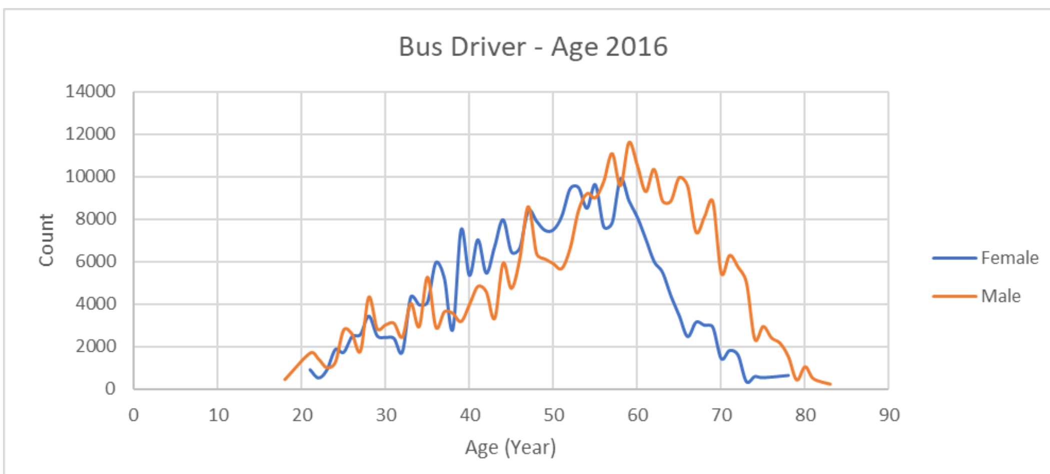

Figure C.7. U.S. Bus Driver: Male and Female Age Distribution (2016)

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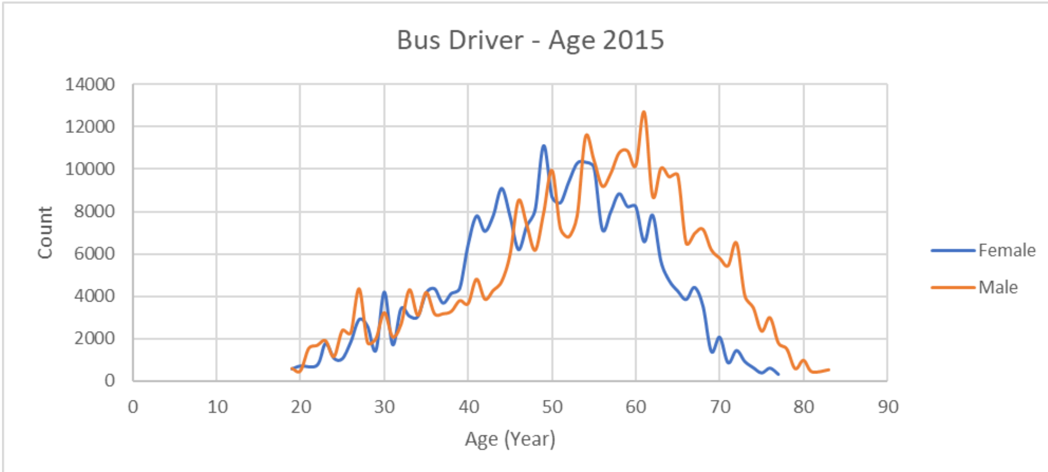

Figure C.8. U.S. Bus Driver: Male and Female Age Distribution (2015)

.

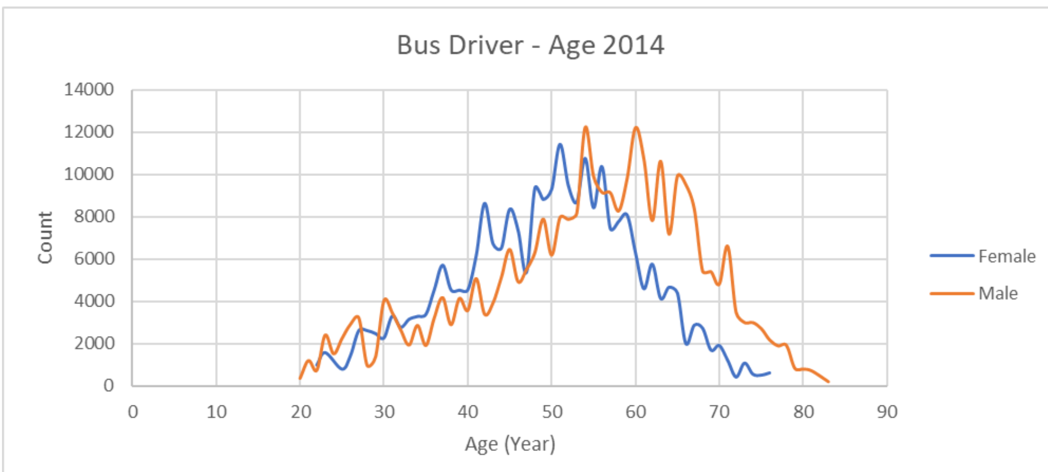

Figure C.9. U.S. Bus Driver: Male and Female Age Distribution (2014)

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