Automatic Parametric Digital Design of Custom-Fit Bicycle Helmets based on 3D Anthropometry and Novel Clustering Algorithm

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

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In memory of Cathy Ellena
Bicycle helmets can provide valuable protective effects to the wearer’s head in the event of a crash. However, the level of protection that helmets offer varies greatly between the users for similar impacts. Although these discrepancies can be due to many causes, several researchers highlighted the poor fit of helmets experienced by some users as a possible explanation. Poor helmet fit may be attributed to two main causes. First, the helmet could be worn incorrectly, with the helmet either worn back to front, or tilted forward or backward. The chin strap could also be unfastened. Second, helmet sizes and shapes available to the public might not be suitable for the full range of head morphologies observed in the population. Indeed, for some users, there could either be a large gap and/or pressure points between the inner surfaces of the helmet and the head, or a low coverage of the skull area with significant unprotected regions of the head. While the poorly informed usage of bicycle helmets is partly rectifiable through education programs, the mismatch between the head and the helmet’s inside surfaces primarily relates to the conventional design method and manufacturing techniques used in the industry today.

In addition to the safety concerns described above, poorly fitted helmets can cause significant discomfort and may lead people to cycle infrequently or even not cycle altogether. Such a reaction could be somewhat detrimental to the user since the health benefits of regular cycling are significant. Some organisations and institutions even believe that the risks involved in cycling without a helmet (in not-extreme practices such as mountain biking) might be outweighed by the health benefits of consistent physical workout that the activity procures. However, this is impractical in countries such as Australia where mandatory helmet laws (MHL) are in place. Improper helmet fit coupled with MHL might be the reason why Australians cycle less than formerly, despite many initiatives undertaken by the government to grow the activity.

In summary, current commercially available bicycle helmets suffer from the lack of fit accuracy, are uncomfortable, and consequently can discourage riding activities in the community, especially in populations like Australia where MHL exist. Therefore, the main purpose of this research has been to develop an innovative method to produce bicycle helmet models that provide a highly accurate fit to the wearer’s head. To achieve this goal, a mass
customisation (MC) framework was initiated. MC systems enable the association of the small unit costs of mass production with the compliance of individual customisation. Although MC is defined as the use of both computer-aided design and manufacturing systems to produce custom output, it was decided to focus exclusively, in this study, on the design part of the MC framework of bicycle helmets. More specifically, I tried to answer the following central research question: How can one automatically create commercially ready, custom-fit digital 3D models of bicycle helmets based on 3D anthropometric data? One objective was to create certified design models, since helmets must comply with relevant safety regulations to be sold in a country. Safety standards generally determine the amount of energy a helmet must absorb during a crash, which mostly affects the thickness of its foam liner. Since customisation plays a major role in the helmet liner’s thickness, special considerations on how the automatic process should affect the helmet’s shape were provided.

Contrary to conventional helmet production techniques, this method was based on state of the art technologies and techniques, such as three-dimensional (3D) anthropometry, supervised and unsupervised machine-learning methods, and fully parametric design models. Indeed, until today, traditional 1D anthropometric data (e.g., head circumference, head length, and head breath) have been the primary sources of information used by ergonomists for the design of user-centred products such as helmets. Although these data are simple to use and understand, they only provide univariate measures of key dimensions, and these tend to only partially represent the actual shape characteristics of the head. However, 3D anthropometric data can capture the full shape of a scanned surface, thereby providing meaningful information for the design of properly fitted headgear. However, the interpretation of these data can be complicated due to the abundance of information they contain (i.e., a 3D head scan can contain up to several million data points). In recent years, the use of 3D measurements for product design has become more appealing thanks to the advances in mesh parameterization, multivariate analyses, and clustering algorithms. Such analyses and algorithms have been adopted in this project. To the author’s knowledge, this is the first time that these methods have been applied to the design of helmets within a mass customisation framework.

As a result, a novel method has been developed to automatically create a complete, certified custom-fit 3D model of a bicycle helmet based on the 3D head scan of a specific individual. Even though the manufacturing of the generated customised helmets is not discussed in detail in this research, it is envisaged that the models could be fabricated using either advanced subtractive and additive manufacturing technologies (e.g., numerical control machining and 3D
printing, standard moulding techniques, or a combination of both. The proposed design framework was demonstrated using a case study where customised helmet models were created for Australian cyclists. The computed models were evaluated and validated using objective (digital models) fit assessments. Thus, a significant improvement in terms of fit accuracy was observed compared to commercially available helmet models.

More specifically, a set of new techniques and algorithms were developed, which successively: (i) clean, repair, and transform a digitized head scan to a registered state; (ii) compare it to the population of interest and categorize it into a predefined group; and (iii) modify the group’s generic helmet 3D model to precisely follow the head shape considered.

To successfully implement the described steps, a 3D anthropometric database comprising 222 Australian cyclists was first established using a cutting edge handheld white light 3D scanner. Subsequently, a clustering algorithm, called 3D-HEAD-CLUSTERING, was introduced to categorize individuals with similar head shapes into groups. The algorithm successfully classified 95% of the sample into four groups. A new supervised learning method was then developed to classify new customers into one of the four computed groups. It was named the 3D-HEAD-CLASSIFIER. Generic 3D helmet models were then generated for each of the computed groups using the minimum, maximum, and mean shapes of all the participants classified inside a group. The generic models were designed specifically to comply with the relevant safety standard when accounting for all the possible head shape variations within a group.

Furthermore, a novel quantitative method that investigates the fit accuracy of helmets was presented. The creation of the new method was deemed necessary, since the scarce computational methods available in the literature for fit assessment of user-centred products were inadequate for the complex shapes of today’s modern bicycle helmets. The HELMET-FIT-INDEX (HFI) was thus introduced, providing a fit score ranging on a scale from 0 (excessively poor fit) to 100 (perfect fit) for a specific helmet and a specific individual. In-depth analysis of three commercially available helmets and 125 participants demonstrated a consistent correlation between subjective assessment of helmet fit and the index. The HFI provided a detailed understanding of helmet efficiency regarding fit. For example, it was shown that females and Asians experience lower helmet fit accuracy than males and Caucasians, respectively. The index was used during the MC design process to validate the high fit accuracy of the generated customised helmet models. As far as the author is aware, HFI is the first method to successfully demonstrate an ability to evaluate users’ feelings regarding fit using
computational analysis.

The user-centred framework presented in this work for the customisation of bicycle helmet models is proved to be a valuable alternative to the current standard design processes. With the new approach presented in this research study, the fit accuracy of bicycle helmets is optimised, improving both the comfort and the safety characteristics of the headgear. Notwithstanding the fact that the method is easily adjustable to other helmet types (e.g., motorcycle, rock climbing, football, military, and construction), the author believes that the development of similar MC frameworks for user-centred products such as shoes, glasses and gloves could be adapted effortlessly.

Future work should first emphasise the fabrication side of the proposed MC system and describe how customised helmet models can be accommodated in a global supply chain model. Other research projects could focus on adjusting the proposed customisation framework to other user-centred products.
DECLARATIONS

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

Thierry Ellena

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PUBLICATIONS


## Table of Contents

Abstract ............................................................................................................................... iv  
Declarations .................................................................................................................... viii  
Acknowledgements ......................................................................................................... ix  
Publications ..................................................................................................................... x  
Table of Contents ........................................................................................................... xii  
List of Figures .................................................................................................................. xviii  
List of Tables ................................................................................................................... xxvii  
Nomenclature .................................................................................................................. xxix  

1. Introduction ................................................................................................................. 2  
   1.1 Introduction and motivation ..................................................................................... 2  
   1.2 Research Scope and Objectives .............................................................................. 4  
   1.3 Research Questions ................................................................................................. 6  
   1.4 Key Outcomes and Contributions .......................................................................... 7  
   1.5 Thesis Organisation ................................................................................................. 7  

2. Background and Literature Review .............................................................................. 10  
   2.1 Chapter Summary ..................................................................................................... 10  
   2.2 Bicycle Helmet Background .................................................................................. 11  
      2.2.1 History and Design .......................................................................................... 11  
      2.2.2 Helmet Components and Materials ................................................................. 13  
      2.2.3 Bicycle Helmet Safety .................................................................................... 17  
   2.3 Bicycle Helmet Fit ................................................................................................... 21  
      2.3.1 Problems with Current Helmet Sizing Systems .............................................. 21  
      2.3.2 Helmets for ‘outlier’ heads ............................................................................. 23  
      2.3.3 Fit and Safety ................................................................................................. 24  

xii
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.4.5</td>
<td>Head Scan Alignment</td>
<td>58</td>
</tr>
<tr>
<td>3.4.6</td>
<td>Hair Thickness Offset</td>
<td>59</td>
</tr>
<tr>
<td>3.5</td>
<td>Summary of Research Outcomes</td>
<td>62</td>
</tr>
<tr>
<td>4.</td>
<td><strong>Objective Assessment of Helmet Fit</strong></td>
<td>65</td>
</tr>
<tr>
<td>4.1</td>
<td>Chapter Summary</td>
<td>65</td>
</tr>
<tr>
<td>4.2</td>
<td>Introduction</td>
<td>66</td>
</tr>
<tr>
<td>4.3</td>
<td>The HELMET-FIT-INDEX (HFI)</td>
<td>67</td>
</tr>
<tr>
<td>4.3.1</td>
<td>Participants and Sampling Plan</td>
<td>67</td>
</tr>
<tr>
<td>4.3.2</td>
<td>Measurements and Assessments: Qualitative Survey</td>
<td>68</td>
</tr>
<tr>
<td>4.3.3</td>
<td>Measurements and Assessments: Quantitative Survey</td>
<td>69</td>
</tr>
<tr>
<td>4.3.4</td>
<td>Data analysis: Association between qualitative and quantitative data</td>
<td>79</td>
</tr>
<tr>
<td>4.3.5</td>
<td>Discussion on the new method</td>
<td>86</td>
</tr>
<tr>
<td>4.4</td>
<td>Case Study 1: Helmet fit differences between groups</td>
<td>89</td>
</tr>
<tr>
<td>4.4.1</td>
<td>Gender differences</td>
<td>89</td>
</tr>
<tr>
<td>4.4.2</td>
<td>Ethnic Background differences</td>
<td>91</td>
</tr>
<tr>
<td>4.4.3</td>
<td>Discussion of Results</td>
<td>93</td>
</tr>
<tr>
<td>4.5</td>
<td>Case Study 2: Fit improvement of a Bicycle Helmet using the HELMET-FIT-INDEX</td>
<td>94</td>
</tr>
<tr>
<td>4.5.1</td>
<td>Problem Definition</td>
<td>94</td>
</tr>
<tr>
<td>4.5.2</td>
<td>New in-liner design</td>
<td>94</td>
</tr>
<tr>
<td>4.5.3</td>
<td>Fit Analysis</td>
<td>101</td>
</tr>
<tr>
<td>4.5.4</td>
<td>Discussion of Results</td>
<td>103</td>
</tr>
<tr>
<td>4.6</td>
<td>Summary of Research Outcomes</td>
<td>105</td>
</tr>
<tr>
<td>5.</td>
<td><strong>Clustering of the Human Head Based on 3D Anthropometric Data</strong></td>
<td>108</td>
</tr>
<tr>
<td>5.1</td>
<td>Chapter Summary</td>
<td>108</td>
</tr>
<tr>
<td>5.2</td>
<td>Introduction</td>
<td>110</td>
</tr>
<tr>
<td>5.3</td>
<td>Point Set Registration</td>
<td>112</td>
</tr>
<tr>
<td>5.3.1</td>
<td>Registration algorithm definition</td>
<td>112</td>
</tr>
<tr>
<td>5.3.2</td>
<td>Problem Overview</td>
<td>114</td>
</tr>
<tr>
<td>Section</td>
<td>Title</td>
<td>Page</td>
</tr>
<tr>
<td>---------</td>
<td>-------------------------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>5.3.3</td>
<td>Optimization Framework</td>
<td>114</td>
</tr>
<tr>
<td>5.3.4</td>
<td>Linear Least Squares</td>
<td>117</td>
</tr>
<tr>
<td>5.3.5</td>
<td>Hole-Filling and Missing Data</td>
<td>118</td>
</tr>
<tr>
<td>5.3.6</td>
<td>Nearest Neighbour Search for Preliminary Correspondences</td>
<td>125</td>
</tr>
<tr>
<td>5.3.7</td>
<td>Fast algorithm</td>
<td>125</td>
</tr>
<tr>
<td>5.3.8</td>
<td>Rigid Transformation</td>
<td>126</td>
</tr>
<tr>
<td>5.3.9</td>
<td>Complete Algorithm</td>
<td>129</td>
</tr>
<tr>
<td>5.3.10</td>
<td>Results and Verifications</td>
<td>131</td>
</tr>
<tr>
<td>5.4</td>
<td>The 3D-HEAD-CLUSTERING Algorithm</td>
<td>134</td>
</tr>
<tr>
<td>5.4.1</td>
<td>Theoretical Background</td>
<td>134</td>
</tr>
<tr>
<td>5.4.2</td>
<td>The New Algorithm Method</td>
<td>136</td>
</tr>
<tr>
<td>5.5</td>
<td>3D-HEAD-CLUSTERING algorithm applied to the population of Australia</td>
<td>140</td>
</tr>
<tr>
<td>5.5.1</td>
<td>Participants and Data Collection</td>
<td>140</td>
</tr>
<tr>
<td>5.5.2</td>
<td>Results</td>
<td>140</td>
</tr>
<tr>
<td>5.5.3</td>
<td>Algorithm Evaluation</td>
<td>142</td>
</tr>
<tr>
<td>5.5.4</td>
<td>Discussion</td>
<td>142</td>
</tr>
<tr>
<td>5.6</td>
<td>Case study 3: New Australian Headforms for Headgear Design</td>
<td>144</td>
</tr>
<tr>
<td>5.6.1</td>
<td>Design</td>
<td>144</td>
</tr>
<tr>
<td>5.6.2</td>
<td>Shape Evaluations</td>
<td>144</td>
</tr>
<tr>
<td>5.6.3</td>
<td>Discussion</td>
<td>149</td>
</tr>
<tr>
<td>5.7</td>
<td>Summary of Research Outcomes</td>
<td>151</td>
</tr>
<tr>
<td>6.1</td>
<td>Chapter Summary</td>
<td>153</td>
</tr>
<tr>
<td>6.2</td>
<td>Introduction</td>
<td>155</td>
</tr>
<tr>
<td>6.3</td>
<td>Minimum and Maximum Head Shape Representation</td>
<td>156</td>
</tr>
<tr>
<td>6.4</td>
<td>3D-HEAD-CLASSIFIER</td>
<td>158</td>
</tr>
<tr>
<td>6.4.1</td>
<td>Nearest Neighbour Search for Head Covering Points Correspondences</td>
<td>159</td>
</tr>
<tr>
<td></td>
<td>Chapter Title</td>
<td>Page</td>
</tr>
<tr>
<td>---</td>
<td>--------------------------------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>B.</td>
<td>Questionnaire–Grouping Study</td>
<td>223</td>
</tr>
<tr>
<td>C.</td>
<td>Consent Form</td>
<td>224</td>
</tr>
<tr>
<td>D.</td>
<td>Consent Form for Recording of Personal Images</td>
<td>229</td>
</tr>
<tr>
<td>E.</td>
<td>Ordinal Logistic Regression</td>
<td>231</td>
</tr>
<tr>
<td>F.</td>
<td>Friedman Test</td>
<td>234</td>
</tr>
<tr>
<td>G.</td>
<td>One-Way Repeated Measures ANOVA</td>
<td>235</td>
</tr>
<tr>
<td>H.</td>
<td>Hypothesis Test for a Proportion</td>
<td>237</td>
</tr>
<tr>
<td>I.</td>
<td>Independent samples t-test</td>
<td>238</td>
</tr>
<tr>
<td>J.</td>
<td>One-Way ANOVA test with Custom Contrasts</td>
<td>239</td>
</tr>
<tr>
<td>K.</td>
<td>Kruskal-Wallis test</td>
<td>240</td>
</tr>
<tr>
<td>L.</td>
<td>Paired-samples t-test</td>
<td>241</td>
</tr>
</tbody>
</table>

References ........................................................................................................................................ 243
LIST OF FIGURES

Figure 1-1: Overview of the proposed helmet customisation process.............................................. 4
Figure 2-1: The Ariel of the early 1870s [40], man "taking a header" ............................................. 11
Figure 2-2: Rik Van Linden wearing a Hairnet Helmet in the 1970s. ............................................. 12
Figure 2-3: Bell Biker 1975. ........................................................................................................... 12
Figure 2-4: (a) Lil’ bell Shell, (b) Giro all-EPS helmet, (c) Pro-Tec reinforced foam [41] ............ 13
Figure 2-5: (a) Thin shell and liner manufactured separately, (b) in-mould shell design.......... 13
Figure 2-6: Bicycle Helmet standard components. .......................................................................... 14
Figure 2-7: Example of an EPS liner............................................................................................... 15
Figure 2-8: Comfort paddings set for a Giro Helmet....................................................................... 16
Figure 2-9: Dial in Adjustment System. .......................................................................................... 16
Figure 2-10: Side Release Buckle.................................................................................................... 16
Figure 2-11: Peripheral Vision Clearance (AS/NZS 2512.6:2006).................................................. 18
Figure 2-12: Impact Energy Attenuation test (AS/NZS 2512.3.1:2007) ....................................... 18
Figure 2-13: Helmet Stability test (AS/NZS 2512.7.1:2006) ......................................................... 19
Figure 2-14: Retention System test (AS/NZS 2512.5.2:1998) ....................................................... 20
Figure 2-15: The difference between Chinese and Caucasian head shape (source [74]). .......... 23
Figure 2-16: Standard head form definition (AS/NZS 2512.1)..................................................... 25
Figure 2-17: Gilchrist et al. test rig [51]. ......................................................................................... 28
Figure 2-18: Meunier et al. distance analysis [88] ......................................................................... 28
Figure 2-19: Lui et al.’s semi-parametric design tool .................................................................. 36
Figure 2-20: Bell Sports custom-fit program. ................................................................................. 37
Figure 3-1: Netti Lightning, Met Crossover and Met Kaos. ............................................................ 44
Figure 3-2: Participant details. ................................................................. 45
Figure 3-3: Helmet use. ........................................................................... 45
Figure 3-4: Helmet fit requirement. ......................................................... 46
Figure 3-5: Helmet fit assessment.............................................................. 46
Figure 3-6: Artec Eva™. ........................................................................... 47
Figure 3-7: HDI Advance. ........................................................................ 47
Figure 3-8: Bicycle Helmet Reverse Engineering Methodology .................. 48
Figure 3-9: Netti Lightning SM without pads, retention/adjustment systems and visor. .... 48
Figure 3-10: HDI scanner taking a single shot of the Netti helmet. ............... 49
Figure 3-11: Example of three positions of the helmet on the table. ................. 49
Figure 3-12: Left: all single scans aligned, right: final mesh model. .................. 50
Figure 3-13: Close-up on the mesh defects. ................................................. 51
Figure 3-14: Holes filled in the Met Kaos size M helmet. .............................. 51
Figure 3-15: Surface simplification on Met Kaos helmet (adjustment and retention systems, visors attachment). ......................................................... 52
Figure 3-16: Deviation spectrum after a Relax action on Met Kaos. ............... 52
Figure 3-17: Left: Start model of the post-processing step, Right: Final polygon mesh. .............. 53
Figure 3-18: Head Scan with fast alignment ............................................. 56
Figure 3-19: Fused scan from Artec Studio (Watertight option on). .................... 57
Figure 3-20: Deviation Analysis. Green is within the allowed distance variation. . 58
Figure 3-21: Head scan alignment. (a) Sagittal Arc Plane. (b) Head Circumference Plane. (c) Bitragion Coronal Plane............................................................. 59
Figure 3-22: Hair Thickness Offset detection – Vernier calliper method. ........... 60
Figure 3-23: Manual offset procedure for a male with 3.1mm HTO (red regions are the polygons of the mesh selected for modifications)................................. 60
Figure 3-24: Manual offset procedure for a female with 6.2 mm HTO. .............. 61
Figure 3-25: Cross-section showing the head scans of two participants before and after the Hair Thickness Offset.

Figure 4-1: Example of a raw 3D head scan.

Figure 4-2: (a) Left: Met Kaos, inside mesh. (b) Right: Met Kaos regions. green = front, pink = top, blue = right, turquoise = left, yellow = back.

Figure 4-3: The four 3D head scans of the fit assessment analysis. From left to right, the scanned head, the scanned head and the Met Crossover helmet, the scanned head and the Met Kaos helmet, the scanned head and the Netti Lightning.

Figure 4-4: Three scans for alignment. Yellow: head scan. Blue: Intermediate scan. Orange: Helmet scan.

Figure 4-5: Head/intermediate scan alignment. From left to right: Face polygons selection for global registration (red), proper overlapping between the meshes, deviation analysis (green is $< \pm 0.1$mm).

Figure 4-6: Intermediate/helmet scan alignment. From left to right: Helmet polygons selection for global registration (red), proper overlapping between the meshes, deviation analysis (green is $< \pm 0.2$mm).

Figure 4-7: Final Alignment.

Figure 4-8: Gap analysis texture maps before (interferences marked in the red circle) and after the offset. Hair thickness was 0.62mm, and SOD and GU were 5.98mm and 2.92mm, respectively.

Figure 4-9: Gap analysis on the right region. The SOD and GU were 6.11mm and 1.84mm, respectively.

Figure 4-10: (a) Test area in magenta, (b) Actual helmet protection area in green.

Figure 4-11: HFI graph.

Figure 4-12: Mean ranks for subjective assessments of helmet fit.

Figure 4-13: Point Scheme Head Covering Points. Intersections between the 11 Reference Planes and the participant’s head scan.

Figure 4-14: Dendrogram example of the clustering algorithm for the first three permutations.
Figure 4-15: Example of Boolean Operation between two participants. ........................................... 97

Figure 4-16: The 30 participants’ head meshes combined. Each colour represents one of the participants’ head meshes. ........................................................................................................ 97

Figure 4-17: Smoothing steps. The final in-liner mesh is on the right. ........................................... 98

Figure 4-18: Final alignment between the Netti helmet and the combined mesh. ......................... 99

Figure 4-19: Netti liner trimmed. Yellow are the backfacing polygons of the helmet’s shell..... 99

Figure 4-20: Combined mesh trimmed by the helmet’s boundary edges. ................................. 100

Figure 4-21: From left to right: Helmet shell and new in-liner combined, new rough surfaces connecting the two meshes, and the final helmet design with grooves joining the ventilation holes................................................................. 100

Figure 5-1: The head template mesh used, a typical head mesh from the dataset (a target), and the registration result. ................................................................. 113

Figure 5-2: A set of affine transformations $X_i$ is applied to the vertices $v_i$ of the template mesh $S$ that result in a new mesh $S(X)$ that moves towards the target surface $D$, but has not yet reached it. ........................................................................................................ 114

Figure 5-3: The 16 landmarks used in the study. The template mesh (left) and one target mesh (right). ...................................................................................................................... 116

Figure 5-4: Iteration $i$ of the registration process between the target mesh (blue) and the template mesh (orange). Boundary edges are represented in red. Green lines represent examples of correspondence vertices were their weights factor were set to zero. ............... 119

Figure 5-5: First iteration of the registration process. The two correspondences weight factors for the segments shown in green are dropped. $w_{152} = 0$ and $w_{78456} = 0$ for correspondences $(X_0v_{152}, u_{162589})$ and $(X_0v_{78456}, u_{5231})$. The surfaces are too far apart................................................................. 120

Figure 5-6: Iteration number 5 of the registration process. The two correspondences weight factors around the ear for the segments shown in green are dropped. $w_{1239} = 0$ and $w_{25894} = 0$ for correspondences $(X_5v_{1239}, u_{8995})$ and $(X_5v_{25894}, u_{95})$. The surfaces overlay...................................................................................................................... 121

Figure 5-7: segment-triangle intersection problem................................................................. 122

Figure 5-8: Barycentric coordinates of a triangle................................................................. 123
Figure 5-9: Left: The template mesh with the selected vertices weights factors set to zero (red). Middle: One target mesh (the ears are covered by the wig cap). Right: The registered target with the ear positioned and dimensioned correctly for the target. The ear geometry has been reconstructed.

Figure 5-10: The head mesh of one participant before and after the registration process.

Figure 5-11: The Coarse and Fine template mesh models.

Figure 5-12: Alignment examples before rigid transformation. 2\textsuperscript{nd} row shows sections views. Misalignments generate large gaps and/or interferences between the template and the participants meshes.

Figure 5-13: The curve used to define the vertices in correspondence for the rigid transformation.

Figure 5-14: Alignment examples after rigid body transformations.

Figure 5-15: The point set registration process for one of the participants.

Figure 5-16: Deviation Analysis between the scanned data and the registered head mesh for four participants in our database.

Figure 5-17: Dendrogram of a traditional hierarchical clustering algorithm.

Figure 5-18: Dendrogram of the 3D-HEAD-CLUSTERING algorithm, in which the algorithm starts with permutation \{4,6\} (a) and \{1,7\} (b). Clusters merge at step number 4.

Figure 5-19: Example of group dispersion at one of the Head Covering Points.

Figure 5-20: Typical 3D Head Scan from the 3D Anthropometric Database of Australian Cyclists.

Figure 5-21: The four headforms based on the computed clusters.

Figure 5-22: Traditional 1D measurements of the head (shown on headform № 1). Red = HC, purple = HB, orange = HL, green = SA, blue = BA, yellow = proportion of the head that should be under helmet protection.

Figure 5-23: Cross-sections projections of the created headforms. Green = № 1, blue = № 2, orange = № 3, purple = № 4. Left = SA plane, middle = HC, right = BA plane. Grid squares are 10x10mm.

Figure 5-24: Deviation analyses between the most common head shape (№ 1) and the other
three headforms. Left = № 1 and № 2. Middle = № 1 and № 3, right = № 1 and № 4. ........ 146

Figure 5-25: Deviation analyses between headform № 1 and the AS/NZS headforms G (left), J (middle), and K (right). ................................................................. 147

Figure 5-26: Deviation analyses between headform № 2 and the AS/NZS headforms G (left), J (middle), and K (right). ................................................................. 147

Figure 5-27: Deviation analyses between headform № 3 and the AS/NZS headforms K (left), L (middle), and M (right). ................................................................. 148

Figure 5-28: Deviation analyses between headform № 4 and the AS/NZS headforms C (left), D (middle), and E (right). ................................................................. 148

Figure 5-29: Cross-sections projections of D, G, J and L AS/NZS headforms. Left = SA plane, right = BA plane. Grid squares are 10x10mm. A constant offset value is used. ...................... 149

Figure 6-1: Union Boolean operation between the first two participants in cluster № 3. The maximum shape is kept. The MaH is created by combining every individual in a cluster in a similar way. .................................................................................................................. 156

Figure 6-2: Intersect Boolean operation between the first two participants in cluster № 3. The minimum shape is kept. The MiH is created by combining every individual in a cluster in a similar way. .................................................................................................................. 157

Figure 6-3: MaH and MiH for cluster № 3 after the Boolean operations. ...................... 157

Figure 6-4: Final MaH (top row) and MiH (Bottom row) for clusters № 1 to № 4 (from left to right). .................................................................................................................. 157

Figure 6-5: The Head Covering Points (blue dot) for one participant. ....................... 159

Figure 6-6: Example of distance metrics ($d_l$) between two registered meshes at seven Head Covering Points. The smallest distances are not necessarily between the same labelled points (e.g., $d3'$ and $d6'$). .................................................................................................................. 159

Figure 6-7: Point correspondences (grey lines) between the tested head shape and the MaH and MiH of one cluster. .................................................................................................................. 160

Figure 6-8: Example of a $K$-d tree decomposition of 20 data points. $q$ is the query point ...... 161

Figure 6-9: The resulting $K$-d tree. The node in green is called the root, the nodes in red are called the leaves. The $x$ and $y$ values shown are the axes' median for the subtree considered. .................................................................................................................. 161
Figure 6-10: Example of a $K$-d tree decomposition of a polygon mesh. For clarity, only the left child at each node splitting plane is shown. ................................................................. 162

Figure 6-11: $5.3 > 1.1 \rightarrow \text{right}; -0.7 > -1 \rightarrow \text{right}; 5.3 > 4.5 \rightarrow \text{right}; -0.7 < 2 \rightarrow \text{left.}$ [16] is the Current Best.................................................................................................................. 163

Figure 6-12: $k$-d tree decomposition with hyperspheres. .......................................................... 163

Figure 6-13: $r = 2.7 > 5.3 - 4.5 \rightarrow \text{left side is tested.}$ [15] is tested but is not closer than CB. ................................................................................................................................. 164

Figure 6-14: $r = 2.7 > -0.7 + 1 \rightarrow \text{left side is tested.}$ [14] is the new CB......................... 164

Figure 6-15: $r = 1.6 > -0.7 + 1.9 \rightarrow \text{left side is tested.}$ [12] is the new CB. $r = 1.0 < -0.7 + 1.9 \rightarrow \text{left side is not tested.}$ $r = 1.0 < 5.3 - 1.1 \rightarrow \text{left side of the root node is not tested.}$ [12] is the FB................................................................. 164

Figure 6-16: An example of a tested head shape located inside the boundary limit of one of the computed clusters. Grey and green lines are Euclidean distance metrics. ............................................ 166

Figure 6-17: An example of a tested head shape that is considered outside the boundary limit of one of the computed clusters. Grey and green lines are Euclidean distance metrics........... 166

Figure 6-18: Cross-Section view of a participant (blue) sandwiched in between MaH and MiH shapes (orange) of cluster № 3 ........................................................................................................ 167

Figure 6-19: yellow = HCS, blue = HCC, brown = template mesh, green = HPP. On the left, the computed HCS (defined as a B-Spline surface) extends below the HCC (defined as a B-Spline curve) and covers the provided data points from the HPP area. The right image shows the final HPP surface that serves as an input element during the customisation process............................................... 168

Figure 6-20: A third-degree Bézier curve .................................................................................... 171

Figure 6-21: Two five-degree rational Bézier curves. Green curve: the weights $w_1 = 1, 0 \leq i \leq 5$. Blue curve: the weights of $P_1$ and $P_4$ were changed to $w_1 = 3$ and $w_4 = 2$. ......................... 172

Figure 6-22: A B-Spline surface showing its bidirectional net of control points (green grid). .. 174

Figure 6-23: The 50 points selected on the template mesh for the HCC fitting process............ 174

Figure 6-24: The same 50 points on one of the participants using the mesh parameterisation defined in the point set registration method. ................................................................................................. 175

Figure 6-25: HCC in blue using interpolation algorithm for one participant. ......................... 177
Figure 6-26: Porcupine curvature analysis of the interpolating HCC for one participant...... 177

Figure 6-27: Approximation of the HCC. The black circle shows the curvature discontinuity at the closure point. ........................................................................................................................................ 179

Figure 6-28: The HCC of one participant using the approximation method and end derivatives at the closure points. The entire curve is curvature continuous. .................................................. 181

Figure 6-29: The randomly distributed point clouds defining the head mesh of one participant. ...................................................................................................................................................... 184

Figure 6-30: The measured data points used for the surface reconstruction process. They are first defined on the template mesh (left) and then extrapolated to the participant (right). This is made possible since they share the same mesh structure after the point set registration process. ...................................................................................................................................................... 188

Figure 6-31: The HCS of the template mesh used as the base surface during the fitting process. The green lines are the control polygons................................................................. 189

Figure 6-32: The HCC (blue) and HCS (yellow) of five participants from the Australian cyclist database. The right picture is the deviation analysis between the HCS and the participant’s registered head mesh. ........................................................................................................................................ 194

Figure 6-33: Initial outside surface of the generic customised helmet model for cluster № 1. The side view on the right shows the outline profiles of the MaH (red dash) and the MiH (dash blue) surfaces, and the HCC of the MaH (red), the MiH (blue) and the 108 individuals in the cluster (white). The green line is the bottom boundary limit of the generic model. .......... 195

Figure 6-34: The inside design of the generic helmet based on the MiH surface (blue). Right is a section view along the mid-plane. .................................................................................................................. 196

Figure 6-35: The generic bicycle helmet model for group № 1 .................................................. 196

Figure 6-36: The design of the reinforcement features of the generic bicycle helmet model. P1, P2, and P3 are three planes passing through the main aerations of the helmet. The three section views along these planes are represented. The green surfaces are the helmet liner sections intersecting the associated plane. These surfaces can be trimmed down during the customisation process. The yellow surfaces are the opening reinforcements. They are fixed and cannot be changed. The pink contours are the reinforcement sections at the specific cutting plane. Similarly, the red dash lines represent the intersection of the planes with the MaH surface. As shown in the graphics, minimum distance values were kept between the red and
pink elements to allow a slight gap between the top features of the customised helmet and the head of every customer in the group.

Figure 6-37: Customisation process using the computed HPP and HCC shapes of an individual (orange).

Figure 6-38: Shell of the generic helmet model (blue).

Figure 6-39: Examples of customised helmet designs for five individuals included in group № 1.

Figure 6-40: A cross-sectional view of the five customised helmet models Figure 6-39. Each colour represents the cross-section of each participant.

Figure 6-41: Impact locations of the customized helmet: side, front, and top.

Figure 6-42: Peak linear acceleration of five custom-fit helmets (grey), the best-case helmet (green), and the worst-case helmet (red). The simulations were performed at three locations, namely, the front (top graph), the top (middle graph), and the side (bottom graph).

Figure 6-43: Deviation analysis of a participant’s customised helmet. SOD is 1.99mm, GU is 0.87mm, HPP is 0.95 (HFI = 78.1).
LIST OF TABLES

Table 2-1: Sizing Chart for common bicycle helmet brands. ................................................................. 21
Table 3-1: Characteristics of participants.................................................................................................. 55
Table 4-1: Sample expected frequency distribution. .................................................................................. 67
Table 4-2: Sample count and frequency ..................................................................................................... 68
Table 4-3: Qualitative Variables. ................................................................................................................ 69
Table 4-4: Median values (with 95.8% CI) of the qualitative parameters in this study for the three bicycle helmets tested............................................................................................................. 69
Table 4-5: Analysis of \( x \) range for 20 participants. .................................................................................. 76
Table 4-6: Quantitative Variables................................................................................................................ 78
Table 4-7: Mean values (with 95% CI) of the quantitative parameters in this study for the three bicycle helmets tested. .................................................................................................................... 79
Table 4-8: The ordinal dependent variable \( F_{xG} \). .................................................................................. 80
Table 4-9: The cumulative categories of the ordinal dependent variable \( F_{xG} \). ................................. 80
Table 4-10: Assumption of proportional odds - Multiple separate binomial logistic regressions - Odd Ratios. ............................................................................................................................................. 81
Table 4-11: Friedman’s test differences between subjective assessments of helmet fit for different test helmets. ................................................................................................................................. 83
Table 4-12: One way repeated measures ANOVA on the 3 helmets HFIs. .............................................. 84
Table 4-13: HFI capability of finding the best and worst perceived helmet fit out of the three selected models. ........................................................................................................................................ 85
Table 4-14: HFI mean differences between gender (\( N_{male} = 94, N_{female} = 23 \)). ..................... 90
Table 4-15: HFI mean differences between Ethnic groups (\( NAustralasian = 57, NEuropean = 29, NAsian = 21, NOther = 10 \)) (\( A = Helmet A, B = Helmet B, C = Helmet C, KW = Kruskal – Wallis test \)). ................................................................................................................................. 92
Table 4-16: Results for the overall fit parameters of the HFI formula........................................ 101

Table 4-17: Results of the statistical analysis, including Paired-samples t-test and effect size determined by Cohen's d. Significant differences are illustrated by an asterisk (*). ................. 103

Table 5-1: Stiffness and Landmark terms values for the point set registration algorithm in the study................................................................................................................................. 130

Table 5-2: Participants distributions inside the four clusters. ...................................................... 140

Table 5-3: Summary statistics of the best group selection criteria for cluster № 1. ............... 141

Table 5-4: Top 5 groups’ selection criteria values and ranks for cluster № 1. The best performing group is indicated in red font................................................................. 141

Table 5-5: Clusters’ criteria values. ............................................................................................ 141

Table 5-6: Clustering comparison of the 3D head dataset using standards hierarchical methods. ............................................................................................................................... 142

Table 5-7: Traditional 1D measurements of the computed headforms. ....................................... 145

Table 6-1: Group classification for the 15 participants. An “X” means that the head shape belongs to the cluster. The red “X” is the final selection........................................... 166

Table 6-2: Customised helmet liner statistics. Sample size = 116.............................................. 200

Table 6-3: Custom-fit helmets assessment study - Summary Statistics – Data are mean (95% CI) – Sample size is 61............................................................................................... 206
<table>
<thead>
<tr>
<th>Term</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D</td>
<td>Three Dimensional</td>
</tr>
<tr>
<td>ANOVA</td>
<td>Analyse of Variance</td>
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<td>Australasian</td>
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<td>Bitragion Coronal Arc</td>
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<td>Chi Square</td>
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<td>Computer Aided Design</td>
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<td>CAE</td>
<td>Computer Aided Engineering</td>
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<tr>
<td>CI</td>
<td>Confidence Interval</td>
</tr>
<tr>
<td>CP</td>
<td>Control Point</td>
</tr>
<tr>
<td>CP</td>
<td>Control Polygon</td>
</tr>
<tr>
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<td>Coefficient of Variation</td>
</tr>
<tr>
<td>DOE</td>
<td>Design of Experiments</td>
</tr>
<tr>
<td>DV</td>
<td>Dependent Variable</td>
</tr>
<tr>
<td>EC</td>
<td>Evolutionary Computation</td>
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<td>EPS</td>
<td>Expanded polystyrene</td>
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<td>European</td>
</tr>
<tr>
<td>Fid</td>
<td>Helmet fit user ideal</td>
</tr>
<tr>
<td>Fim</td>
<td>Helmet fit user importance</td>
</tr>
<tr>
<td>FXB</td>
<td>Helmet $X'$ Back Fit Assessment</td>
</tr>
<tr>
<td>FXF</td>
<td>Helmet $X'$ Front Fit Assessment</td>
</tr>
<tr>
<td>FXG</td>
<td>Helmet $X'$ Global Fit Assessment</td>
</tr>
<tr>
<td>FXL</td>
<td>Helmet $X'$ Left Fit Assessment</td>
</tr>
<tr>
<td>FXR</td>
<td>Helmet $X'$ Right Fit Assessment</td>
</tr>
<tr>
<td>FXT</td>
<td>Helmet $X'$ Top Fit Assessment</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithm</td>
</tr>
<tr>
<td>GU</td>
<td>Gap Uniformity</td>
</tr>
<tr>
<td>GU$X'$</td>
<td>Helmet $X'$ - Gap Uniformity</td>
</tr>
<tr>
<td>GU$X'B$</td>
<td>Helmet $X'$ - Gap Uniformity Back</td>
</tr>
<tr>
<td>GU$X'F$</td>
<td>Helmet $X'$ - Gap Uniformity Front</td>
</tr>
<tr>
<td>GU$X'L$</td>
<td>Helmet $X'$ - Gap Uniformity Left</td>
</tr>
<tr>
<td>GU$X'R$</td>
<td>Helmet $X'$ - Gap Uniformity Right</td>
</tr>
<tr>
<td>GU$X'T$</td>
<td>Helmet $X'$ - Gap Uniformity Top</td>
</tr>
<tr>
<td>$H_0$</td>
<td>Null Hypothesis</td>
</tr>
<tr>
<td>$H_A$</td>
<td>Alternative Hypothesis</td>
</tr>
<tr>
<td>HC</td>
<td>Head Circumference</td>
</tr>
<tr>
<td>HCC</td>
<td>Head Covering Curve</td>
</tr>
<tr>
<td>HCP</td>
<td>Head Covering Point</td>
</tr>
<tr>
<td>HCS</td>
<td>Head Covering Surface</td>
</tr>
<tr>
<td>HFI</td>
<td>HELMET-FIT-INDEX</td>
</tr>
<tr>
<td>HFI$X'$</td>
<td>Helmet $X'$ - HELMET-FIT-INDEX</td>
</tr>
<tr>
<td>HFI$X'B$</td>
<td>Helmet $X'$ - HELMET-FIT-INDEX Back</td>
</tr>
<tr>
<td>HFI$X'F$</td>
<td>Helmet $X'$ - HELMET-FIT-INDEX Front</td>
</tr>
<tr>
<td>HFI$X'L$</td>
<td>Helmet $X'$ - HELMET-FIT-INDEX Left</td>
</tr>
<tr>
<td>HFI$X'R$</td>
<td>Helmet $X'$ - HELMET-FIT-INDEX Right</td>
</tr>
<tr>
<td>HFI$X'T$</td>
<td>Helmet $X'$ - HELMET-FIT-INDEX Top</td>
</tr>
<tr>
<td>HIC</td>
<td>Head Intersecting Curve</td>
</tr>
</tbody>
</table>

**NOMENCLATURE**
**HPP**  Head Protection Proportion
**HPPx**  Helmet X - Helmet Under Protection
**HTO**  Hair Thickness Offset
**ICP**  Iterative Closest Point
**IV**  Independent Variable
**L**  Large size
**M**  Medium size
**M/L**  Medium Large size
**MaH**  Maximum Head Shape
**MC**  Mass Customisation
**MiH**  Minimum Head Shape
**MSE**  Mean Squared Error
**NNS**  Nearest Neighbour Search
**NURBS**  Non-Uniform Rational Basis Spline
**OR**  Odds Ratio
**PI**  Percentage Increase
**QR**  A matrix decomposition method
**RE**  Reverse Engineering
**S/M**  Small Medium size
**SA**  Sagittal Arc
**SC**  Selection Criterion
**SD**  Standard Deviation
**SOD**  Standoff Distance
**SODx**  Helmet X - Standoff Distance
**SODxB**  Helmet X - Standoff Distance Back
**SODxF**  Helmet X - Standoff Distance Front
**SODxL**  Helmet X - Standoff Distance Left
**SODxR**  Helmet X - Standoff Distance Right
**SODxT**  Helmet X - Standoff Distance Top
**SVD**  Singular Value Decomposition
**UN**  Unisex size
**VIF**  Variance Inflation Factor
**WSE**  Weighted Squared Euclidean distance
**XL**  Extra Large size
1. INTRODUCTION

1.1 Introduction and motivation

The key motivation behind the present study is the improvement of bicycle helmet comfort through customisation.

It is well understood and widely accepted that bicycle helmets play a major role in the cyclist’s safety during a crash [14, 15]. Helmets have been shown to reduce the risk of head injury across the whole cyclist population [16]. However, studies show that a poor helmet fit on the wearer’s head may decrease its safety benefits [17-20]. One example is when the helmet rolls off after a crash and leaves the head of the wearer unprotected for any succeeding impacts with the pavement. Poor helmet fit might be due to improper usage or inappropriate helmet design. Inappropriate design may result in substantial gaps and/or compressed areas between the wearer’s head and the inside surfaces of the helmet.

These issues have been linked to the design processes applied in the industry today. They have remained the same for the past 30 years. For example, the inside surfaces of the helmet are still based on mannequin head models called headforms [21]. In practice, these models should represent and capture the head shape variability of the target population. However, it is difficult to imagine that all adults in a defined population have head shapes so similar that they can be grouped into only one, two or three helmet sizes. Consequently, a large proportion of cyclists who wear helmets may suffer from improper fit to their head sizes and shapes.

The fit issue described above is becoming critical in countries like Australia and New Zealand where compulsory bicycle helmet laws exist. Currently, they are the only two countries in the world that require and enforce the universal use of helmets for cyclists. While there is still no scientific consensus on the effects of compulsory helmet use on head injuries or deaths among cyclists [22-27], it is recognized that this legal obligation [28] has led to a decrease in cycling activities in these countries [29]. This fall in the number of cyclists has been associated with the discomfort experienced by wearing the headgear [30, 31]. This evidence on discomfort raises the question: is there a relationship between helmet fit and helmet comfort?

Helmet comfort has been related to multiple sources. However, most users relate helmet
discomfort to (i) the heat dissipation properties, (ii) the weight and (iii) the fit accuracy. While (i) and (ii) have been improved considerably in recent years through better helmet design techniques (e.g., ventilation, geometry) and material selection [32], (iii) is still problematic [33].

A change in helmet design methodology for a rapid improvement in fit accuracy could, therefore, improve the users’ comfort perception and might help to increase helmet usage and cycling participation.

One obvious solution to the fit problem is to adopt a personalisation strategy through custom-fit designs. Mass customisation, for example, is a production approach that enables the association of the small unit costs of mass production with the benefits of individual customisation [34]. Custom-fit is a sub-strategy of the mass customisation process and emphasises personalised products in relation to shape and size. It has been implemented successfully in some industries such as shoe soles [35], golf clubs [36] and dentistry [37], but has yet to be expanded to bicycle helmets. The reason for this delay is threefold:

1. Design complexity: Over the years, the shapes of bicycle helmets have become extremely complex. This is due to the development of light, well-ventilated and highly aerodynamic designs. Therefore, modifying the complex design of a helmet to fit the head shape of an individual could be difficult due to its design constraints.

2. Safety requirements: Bicycle helmets must comply with safety standards to be sold in a country. Ten or more helmet samples must be tested physically to determine their energy dissipation capabilities before commercialisation [38]. As the energy dissipation capability of a helmet is related to its size and shape, changing the helmet’s thickness to conform to the user’s head shape will certainly compromise the test results. Conducting physical tests on all customised models is impossible as this would increase the lead time and cost significantly.

3. Manufacturing innovation: The manufacture of customised helmet models implies significant changes from traditional production techniques used today. New processes would be required, leading to a high increase in production cost.

It is believed that such limitations can be overcome with the last improvements in parametric design techniques, computational analyses, and advanced manufacturing technologies. The goal of this research is to demonstrate that helmet customisation improves comfort significantly and can be a viable alternative to the current production approaches.
1.2 Research Scope and Objectives

The primary objective of this research project is to develop an automated process to produce a complete, custom-fit 3D model of a bicycle helmet for an individual. The created helmet must comply with the relevant safety standards without being subjected to physical tests.

Figure 1-1 presents an overview of the helmet customisation framework introduced in this work. As shown, the customer’s head shape is first digitized using 3D scanning technology. The recorded data are then modified through a multiple steps process to produce the final customised helmet model. It is first modified and transformed to enable further analysis and simulation on the data. In a second phase, the user’s head shape is classified into a predefined group of users based on head shape similarity. This classification process is deemed necessary to ensure that only small and controlled shape variations are implemented on the design during the customisation procedure (i.e., for certification). This is achieved by performing the customisation step at the group level where head shape similarity is high. Finally, parametric design methods are used to generate the customized model based on the 3D head shape of the user and the grouping classification.

![Diagram of the proposed helmet customisation process.](image)

Figure 1-1: Overview of the proposed helmet customisation process.

From this overview, four main research activities can be formulated in order to achieve the primary objective outlined above:

**Activity #1.** Use a safe and reliable 3D scanning technique to digitize the head and face of the users. This activity is discussed in detail in Section 3.4.

**Activity #2.** Build a post-processing framework where the 3D head scans are transformed
for future use. The basic post-processing processes put in place are presented in Section 3.4. The point set registration algorithm applied during the study is presented in Section 5.4. This transformation enables the comparison of multiple 3D scans on a point-by-point basis. Further alterations on the data are presented in Section 6.5 where the polygon mesh representing the head shape of the user is transformed into a surface model. These surfaces are then used during the design process of the customised helmets.

**Activity #3.** Implement classification procedures where the user’s head shape is categorized into a predefined group of individuals with similar head shapes. This procedure has been named the 3D-HEAD-CLASSIFIER algorithm and is presented in Section 6.4.

**Activity #4.** Automate a 3D design parametric technique, which uses digitized head scans of users to create custom-fit bicycle helmet models. This is achieved by creating generic models for each group size and performing the customisation using these models. This procedure is presented in Chapter 6.

Achieving these activities will create a solid framework for the design of custom-fit helmet models. However, one main problem remains: during the customisation process, predefined groups of users are used for the classification step. These predefined groups need to accurately represent the target population to be most effective. Unfortunately, as shown in the literature review in Chapter 2, such groups do not exist in Australia, which is the population used in the case study in this research. Furthermore, the only few groups available in the literature for other countries were created on 1D anthropometric data (e.g., head circumference, head width, and head length) that tend to not represent perfectly the complex shape of the human head. Therefore, to complement the four core activities outlined above, two more can be formulated in order to achieve the primary objective:

**Activity #5.** Build a database of 3D head scans of Australian cyclists. This is discussed in Chapter 3. Note that Activity #1 is now a sub-task of Activity #5.

**Activity #6.** Create groups of individuals with high head shape similarity. To achieve this objective, a new clustering method is introduced. It has been named the 3D-HEAD-CLUSTERING algorithm and is presented in Chapter 5.

In order to validate the effect on fit of the customization process, a seventh activity is specified:

**Activity #7.** Develop a quantitative index to evaluate the fit accuracy of bicycle helmets in
relation to a person’s head shape and size. The objective method has been named the HELMET-FIT-INDEX (HFI) and was developed based on subjective assessments of helmet fit. The method is introduced in Chapter 4 and applied to the generated customised helmet models in Chapter 6.

Since multiple 3D scans of commercially available bicycle helmets are needed for this analysis, I also present the digitization process of helmets in Section 3.3.

The requirements for helmet certification are generally drafted in standards. The main specifications are often the impact attenuation characteristics of the helmet, which are linked to its material properties and its size and shape. These properties need to be accounted for during the design of the generic helmet models to ensure that all the customised helmets created comply with the relevant safety standard. Simulation analysis like the FEA method (finite element analysis) can be used to replicate crash events and test the shock absorption characteristics of helmets. Consequently, an eighth activity can be formulated:

**Activity #8.** Develop a validated FEA method to test shock absorption characteristics of customised bicycle helmets. The method should follow the requirements of the Australian standard. The method is presented in Chapter 6 in a simplified and concise format since this activity was the main research objective of my fellow Ph.D. colleague Helmy Mustafa at RMIT University [39].

### 1.3 Research Questions

With the scope of the primary research objective and key research activities, a series of more discrete questions are raised. This thesis is guided by the following research questions:

Q1. How can bicycle helmet customisation address fit problems currently reported in the literature? The use of the HFI (Chapter 4) on the generated customised helmets in Chapter 6 will answer this question.

Q2. How to measure quantitatively the fit accuracy of helmet models for individuals? The HFI method in Chapter 4 will answer this question.

Q3. How to group together individuals with similar head shapes using 3D anthropometric data? The 3D-HEAD-CLUSTERING algorithm presented in Chapter 5 will help with this question.

Q4. How to assign new individuals into predefined groups of similar users according to his/her head shape? The 3D-HEAD-CLASSIFIER algorithm will answer this question in Chapter 6.
Q5. How to use parametric design models to automatically modify the generic 3D model of a bicycle helmet in view of customisation? The design procedure describes in Chapter 6 will answer this question.

Q6. In the custom-fit process, how to ensure that all the newly created helmet models comply automatically with the relevant safety standards? Chapter 6 will answer this question.

1.4 Key Outcomes and Contributions

The research will contribute to new methods that can provide detailed information on helmet efficiency regarding fit and novel techniques that are believed to improve fit proficiency through mass customization.

Additionally, the study is considered to be significant in understanding how human head shapes vary across the population and how one can reuse these outcomes to design user-centred products such as bicycle helmets. The presented research methodology introduces a strong framework for future developments on user-centred products, based on 3D anthropometric data.

1.5 Thesis Organisation

This dissertation is organised into seven main Chapters. Chapter 1 introduces the research project and summarises the objectives. Chapter 2 presents a comprehensive review of literature and technology relevant to this research. Specific opportunities for new research outcomes are identified.

Chapter 3 provides a detailed description of the 3D anthropometric database of head scans created for the study. Sampling plan calculations, discussions on 3D scanner technologies, scanning procedures and post-processing methods are provided. Reverse engineering processes developed in this work for three bicycle helmet models are also presented succinctly in this chapter.

Building upon these results, Chapter 4 presents a novel quantitative method to evaluate, objectively, helmet fit between a distinct helmet model and an individual. The method is named the HELMET-FIT-INDEX (HFI). Comprehensive statistical analyses are presented to assess the strength of the correlation between the HFI and the subjective assessments of helmet fit.
Chapter 5 introduces a modified hierarchical clustering algorithm for the grouping of individuals according to their head shape. The database presented in Chapter 3 is used as a case study to validate the algorithm performance. The algorithm was named 3D-HEAD-CLUSTERING. The clustering results are presented in the form of new headforms for the population of Australian cyclists.

Chapter 6 describes the final stages of the bicycle helmet mass customisation framework. A classifier, which categorises new individuals into one of the predefined groups, is presented. It was named 3D-HEAD-CLASSIFIER. Minimum and maximum head shapes within each predefined group are also constructed and used as geometric input during the customisation process. The 3D model of a generic bicycle helmet is created for one of the groups defined in chapter 5. Customisation is then performed for all the participants in this group using parametric design models. The resulting customised 3D models are then validated using objective assessments via the HFI method, which was presented in Chapter 4. Finite Element Analysis is used to validate the design specification of each helmet.

Concluding the thesis is Chapter 7, where the main research contributions are summarised against the research objectives. This chapter provides an overall conclusion that complements the conclusions presented at the end of Chapters 3, 4, 5 and 6, which explicitly address individual research activities. Limitations of the present work are highlighted, as well as recommendations for future research.
2. **BACKGROUND AND LITERATURE REVIEW**

2.1 **Chapter Summary**

This chapter presents a review of literature and technology relevant to the present research work. Specific opportunities for novel research contributions are identified and are further developed in subsequent chapters.

This chapter is divided into two main sections. The first, Section 2.2, sets the background of the research and focuses on the history and evolution of bicycle helmets in terms of their designs, features, and relevant components. The second, from Sections 2.3 to 2.6, focuses on recent active research areas and their limitations in existing methods and knowledge gaps are identified. More specifically, the review identifies problems related to helmet fit, comfort, and safety inherent in the current helmet manufacturing processes (Section 2.3). It then establishes the necessity of objective evaluation of helmet fit, for which the existing methods are inappropriate to the specific requirements (e.g., complex freeform shape, vents design) of bicycle helmet models (Section 2.4). There follows an analysis of previous anthropometric surveys showing that 3D head scans data of the study’s target population (i.e., Australian cyclists) are nonexistent, and that common clustering algorithms for the classification of 3D head shape are not optimal (Section 2.5). Finally, detailed information on mass customisation processes is presented. It is demonstrated that such methods could be applied to bicycle helmets when certain parameters are met (Section 2.6). A summary of the identified research gaps and limitations of the current body of knowledge is presented in Section 2.7. A number of associated research opportunities are discussed.
2.2 Bicycle Helmet Background

For the benefit of the reader, this section provides the history and evolution of bicycle helmet design over time, as well as descriptions of its main components, and information about the specifications of the current helmet safety standards.

2.2.1 History and Design

With the rise of the high wheel bicycle in the 1870s (Figure 2-1), riders realised that some type of head protection was needed. The bicycle’s saddle was so high above the ground that, if its front wheel was stopped by an obstacle on the road, the entire bicycle would rotate around the front wheel axis and the rider would drop head first with his legs trapped under the handlebar. This is when the term “taking a header” came into existence.

![Figure 2-1: The Ariel of the early 1870s [40], man "taking a header"](image)

Consequently, in the 1880s high wheel users began to adopt helmets made from pith—a crushable material that was likely the ideal material available at the time. Although the helmet would probably break into pieces upon impact, the riders’ speed was generally low, and they generally needed protection only against a single impact [41].

Until the 1970s, the principal form of helmets was the “Hairnet” helmet as shown in Figure 2-2. It was made of strips of leather-covered padding, which had a relatively good protection from abrasion and cuts but little to no shock absorption capabilities. The low coefficient of friction of leather allowed the rider’s head to slide along the pavement. By the early 1970s, bicycle clubs started to call for better headgear to protect riders from head injuries, which were the leading cause of death after an accident.
The Mountain Safety Research (MSR) and the Biker helmets were the first two modern bicycle helmets introduced in the mid-1970s (an example in Figure 2-3). They were the first bike helmets with expanded polystyrene (EPS) shock absorption foam on the inside and a hard and stiff polycarbonate shell on the outside. The two models also included small openings to assist with heat ventilation/dissipation around the head. A few years later, Bell refined their design and added the V1-Pro model, the first polystyrene helmet intended for racing. These helmets were able to reduce head injuries significantly. However, they suffered from several design flaws. For instance, they were excessively heavy, making them unpractical for use, and had a poor ventilation system that needed further improvement.

The next significant improvement in helmet design came in the early 1980s when Bell (Figure 2-4.a) and Giant (Figure 2-4.b) introduced new helmets without outer shells. Using an all-EPS helmet reduced the weight significantly and was, therefore, an instant success amongst cyclists. While these helmets had high impact absorption capabilities, they had the tendency to break into pieces after a crash. Three years later, Pro-Tec launched an all-EPS helmet (Figure 2-4.c) with a nylon mesh inserted into the foam to overcome this defect. This innovation improved the overall strength of the helmet significantly. However, the problem was only partially solved, and many helmets still broke after impact.
Plastic shells were reintroduced (Figure 2-5.a) in the 1990s. Their main purpose was to hold the foam together in the event of a crash and to decrease the sliding resistance between the helmet and pavement. Thick and heavy polycarbonate shells from previous designs (e.g., Bell Biker) were replaced with polyethylene terephthalate (PET) and other thin, tough plastics. Initially, the shell and foam were manufactured separately and then glued together during the manufacturing process. To enable the use of thin plastics in the fabrication, a new technique called in-mould shell design was then introduced. The foam was moulded directly into the thin shell (Figure 2-5.b).

The re-introduction of an outer shell has been reported to reduce the risk of head injuries compared to foam only helmets during a crash event [42].

### 2.2.2 Helmet Components and Materials

Customarily, bicycle helmets are made of five main components: the shell, liner, comfort paddings, retention strap, and adjustment system, as shown in Figure 2-6. Some helmets might have additional features, which include a visor, integrated goggles, rear light, and a housing/fixture to attach small video cameras and mirrors. A description of the core attributes of each of the main components is provided in this section.
2.2.2.1 Shell

The outer shell of the helmet serves multiple purposes, and its primary function is to hold the liner structurally together during impacts [43]. It also aims to distribute the impact force to a larger region of the helmet to reduce the localisation of the impact load [44]. Furthermore, it protects users from the direct penetration of sharp and pointed objects [45] and helps to reduce the sliding resistance when the helmet slips on pavement. Shells also absorb a small fraction of impact energy in an accident [46, 47].

2.2.2.2 Liner

The purpose of the helmet liner (Figure 2-7) is to absorb the residual force of the impact that is moderately captured and dispersed by the outer shell. The material properties and thickness of the liner have been recognised as the most important parameters to improve the impact absorption capabilities of the helmet. The foam liner can be classified into two broad categories, crushable and resilient, with different material behaviour during impacts.

Crushable foams, such as EPS, are most effective in single high-energy impacts. Commuting, racing and mountain biking helmets are usually made out of crushable foams. Such foams absorb the energy during an impact due to their mechanical properties to tolerate permanent deformation. However, in the case of a subsequent impact in the same area, the protection level offered by these types of foams is minimal, since the material deforms permanently without elastic recovery.
Resilient foams, however, can sustain mid- to high-impact energy and can recover to their original shape immediately after the impact. Polyurethane (PU) foams are the most common resilient foams for cushioning products but are associated with hydrolytic degradation with long-term moisture. Expanded Polypropylene (EPP) foams introduced by Shuaib et al. [48] are the alternative resilient foams used in bicycle helmets. They were introduced to overcome the single-impact issue of crushable foams and were shown to behave almost equally to EPS (i.e., similar peak accelerations and impact durations for the same helmet with EPS) [48]. However, their weight and cost are higher compared to the same volume of EPS.

Figure 2-7: Example of an EPS liner.

### 2.2.2.3 Comfort paddings

The comfort paddings consist of soft and flexible foams, generally open-cell PU or polyvinyl chloride (PVC) [49, 50], enclosed by a fabric layer. They surround and contact the head to keep a sufficient level of comfort and fit between the cyclist and the helmet (by evenly distributing the static contact force). A uniform distribution of the static force is crucial to avoid headaches [51]. Paddings also enhance sweat absorption that facilitates breathability during activities [52, 53].

The comfort foam does not absorb impact energy in the event of a crash. Its low stiffness attributes make it crushes completely without absorbing any amount of energy [54].

Helmet manufacturers can provide up to two or three different paddings sets for one helmet size. The various thicknesses of the pads can help with the fit of specific users’ head shapes (Figure 2-8).
2.2.2.4 Adjustment System

Bicycle helmets can be adjusted via two different methods. They either (i) use a set of interchangeable pads that match the inside of the liner with the wearer’s head shape, or (ii) use a mix of plastic rings, straps and dial-in wheel (Figure 2-9) that cradle the head when the wheel is tightened. A combination of both methods is also often used.

2.2.2.5 Retention System

The retention system aims at keeping the helmet fixed to the wearer’s head at all time. Most bicycle helmets in the market nowadays use a plastic buckle, made popular by Fastex, called a side release buckle (Figure 2-10). It is formed by two members, the hook end and the catch end, and is made from nylon or PET webbing. It is cheap, light and easy to fasten, but requires the straps to be adjusted properly at all times. The system is mostly reliable, but a number of rolled off helmets with intact and correctly fastened straps have been reported [55].

Figure 2-8: Comfort paddings set for a Giro Helmet.

Figure 2-9: Dial in Adjustment System.

Figure 2-10: Side Release Buckle.
2.2.3 Bicycle Helmet Safety

In the earlier 1970s, bicycle users, race organisers, and government executives realised that bicycle helmets were not effective at protecting the wearer’s head in the event of a crash. It became evident that faster progress was needed in protecting the cyclist from serious head injury. Helmets needed to be tested against standard procedures for certification. The Snell Foundation was the first to publicize a bicycle helmet standard in 1970, but at the time only a light motorcycle helmet could pass it. Since then, standards have been established in many countries around the world to assess the performance of helmets. They are either regulated by governments or issued by private organizations. Most of the standards differ slightly from each other, in terms of requirements for input properties and output measurements. However, they all attempt to assess the effectiveness of the helmet protection by evaluating quantitatively:

- how the helmet absorbs energy during a particular impact and,
- how the helmet remains on the head before, during and after an impact.

Nowadays, all bicycle helmets are designed to meet these specifications. Helmets are not specifically optimized to reduce head injuries during a crash, but to pass the test requirements of a particular safety standard (e.g., decrease headform acceleration in a linear drop test).

Many studies in the literature reported that current helmet standards do not fully replicate the real mechanism of a cyclist’s fall [56-58]. For example, standards assess the ability of the helmet to absorb energy in a free fall, linear impact test. However, it is widely recognised that, during a cyclist’s fall, the impact is generally oblique [59], and the impact force is decomposed into a perpendicular and a tangential component.

These issues are critical and should be dealt with effectively to ensure that bicycling can be practised safely. However, testing new safety procedures is not part of the scope of this research. The main objective is to generate customised helmets that comply with the current helmet standards. It is believed that the customisation framework introduced in this work could be updated easily if new testing methods are introduced (e.g., an oblique impact test). A description of the current safety requirements is provided below for the benefit of the readers.

2.2.3.1 Australian Standards

Bicycle helmet certification in Australia is governed by the AS/NZS 2063:2008 - Bicycle helmets [60] that oversees the series of standards AS/NZS 2512 - Methods of testing protective helmets [61].
The standard tests involve the following:

- Horizontal peripheral vision clearance [62]: “The peripheral vision clearance of the helmet shall be not less than 105° on each side of the mid-sagittal plane.” (Figure 2-11)

![Peripheral Vision Clearance](image)

Figure 2-11: Peripheral Vision Clearance (AS/NZS 2512.6:2006)

- Impact energy attenuation [63]: “Using a flat anvil only and a free-fall height of 1500 +30, -5 mm, the headform acceleration shall not exceed 250 g peak. In addition, the cumulative duration of acceleration shall not exceed: (a) 3.0 ms for acceleration greater than 200g, and (b) 6.0 ms for acceleration greater than 150g.” (Figure 2-12)

![Impact Energy Attenuation Test](image)

Figure 2-12: Impact Energy Attenuation test (AS/NZS 2512.3.1:2007)
- Static helmet stability [64]: “Using a force of 50 ±0.5 N for a period of not less than 15 s and not greater than 30 s, the helmet shall neither completely expose nor completely obscure the test band.” (Figure 2-13)

![Helmet Stability Test](image)

**Figure 2-13: Helmet Stability test (AS/NZS 2512.7.1:2006)**

- Load Distribution [65]: “Using a fall height of 1000 +15, −5 mm, the following conditions shall be met: (a) Loading measured by the force transducer shall not exceed 500 N measured over a circular area of 100 mm², (b) The anvil shall not contact the surface of the headform.”

- Dynamic strength of the retention system [66]: “Using a drop height of 250 −0, +5 mm, the dynamic displacement shall not exceed 30 mm.” (Figure 2-14)
2.2.3.2 International Standards

Many international standards have been developed since 1985. They all share the same primary objective, i.e., to evaluate the ability of the tested helmet to absorb energy during an impact. They all use a linear impact drop test but diverge with the impact conditions (drop height, anvil shape) and the permissible maximum peak acceleration. For example:

- CPSC Standard (Consumer Product Safety Commission) was adopted in 1998 [67] in the U.S. standard. The CPSC standard specifies a lab test drop of 2.0 meters on a flat anvil, and 1.2 meters on a hemispheric and a curbstone anvil. The failure threshold is at 300g.

- Snell Memorial Foundation B-1990 and B-1995 [68] were widely used before the introduction of the CPSC. They required slightly more head coverage and had slightly higher drop heights (i.e., 2.2 meters on the flat anvil and 1.3 meters on the hemispheric anvil for B-19950 with a maximum peak deceleration of 300g).

- EN1078 is the European standard for bicycle helmets and was published in 1997 [69]. It has been criticized for its lower impact characteristics (i.e., 1.5 meters on a flat anvil).
2.3 Bicycle Helmet Fit

Proper helmet fit is of utmost importance for customers. The helmet should be tight enough to sit on the wearer’s head in the event of a crash, but not too tight to avoid discomfort on the head due to high-pressure areas. The optimal fit is usually achieved by leaving small gaps between the head and the helmet. These gaps are then typically filled with multiple sets of comfort paddings (see Section 2.2.2.3) to improve comfort. In practice, it is often difficult to keep these gaps small and uniformly distributed around the head for all users within a population. This is due to very different anthropometrics and physical characteristics between individuals that cannot be represented with the current sizing systems of the head. For example, customers with large, minuscule, rounded, or pointed heads have problems choosing helmets with a comfortable fit.

2.3.1 Problems with Current Helmet Sizing Systems

Today, up to seven helmet sizes can be offered for a given helmet model (from extra-small (XS) to triple extra-large (3XL)). However, most manufacturers do not produce such a broad range of models so as to keep the manufacturing costs as low as possible. Often, the number of sizes offered for a helmet model is between one and three.

Table 2-1 shows examples of different helmet models available on the market, with their sizes and corresponding head circumference. The Table demonstrates that helmet sizes are not consistent across brands and models. For example, a cyclist with a head circumference of 57cm could be classified as Small, Medium, Large or Universal size depending on the brand and model.

Table 2-1: Sizing Chart for common bicycle helmet brands.

<table>
<thead>
<tr>
<th>Brand</th>
<th>Type of Helmet</th>
<th>Available sizes (head circumference scale in cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>dhb</td>
<td>Road</td>
<td><img src="Image1" alt="dhb Road Sizes" /></td>
</tr>
<tr>
<td>Las</td>
<td>Mountain</td>
<td><img src="Image2" alt="Las Mountain Sizes" /></td>
</tr>
<tr>
<td>Bell</td>
<td>Road and Mountain</td>
<td><img src="Image3" alt="Bell Road and Mountain Sizes" /></td>
</tr>
</tbody>
</table>
Numerous anthropometric studies [70-73] have reported that head circumference for adults can vary from ~50cm (1st percentile female) to ~62cm (99th percentile male). By analysing the values in Table 2-1, it is clear that the number of helmet sizes provided by most manufacturers is inadequate to accommodate the vast diversity of head morphologies for a given population.

Furthermore, several surveys and investigations in the literature have reported that the current range of helmet sizes is impractical [21, 71, 72, 74-76]. This is because helmet sizing systems are solely based on one measurement of the head: the head circumference (HC). It has been shown that human head shapes and dimensions are much more complex and diverse and cannot be represented by a single dimension.

For example, a recent field study conducted by Thai et al. [76] demonstrated that head shapes differ according to ethnic groups, age, and gender. The authors studied the factors that influence the size of the helmet worn by cyclists through measuring the head and helmet dimensions of over 200 cyclists. They concluded that helmets worn by commuter cyclists are often the wrong size and that current headforms used in the Australian/New Zealand standard may not be representative of the cyclists’ head shapes in Australia. Similar observations have also been reported by Ball et al. [74] and Zhuang et al. [77]. Both studies have shown that, at equal head circumferences, Chinese heads were rounder, with a flatter back and forehead than Caucasian counterparts (Figure 2-15). These differences have made it difficult to design protective helmets, using only the head circumference as the fitting parameter, that would fit both ethnic groups appropriately.
In this research, the head circumference will not be used for the selection of the helmet size. Instead, thousands of points from the 3D scans defining the head shape will be used. In fact, a helmet size will not be needed at all, since the helmet will be custom-fitted to the head shape of each customer. Although groups of users with similar head shape will be created in the design framework, they will not impact the shape and size of the inside surfaces of the customised helmet.

2.3.2 Helmets for ‘outlier’ heads

As with any physical traits, head shapes and dimensions can vary considerably between individuals. Cyclists’ head sizes can end up being enormous or tiny, while head shapes can tend to have a more pointed or rounded form.

Due to these Individual variations, standard helmet models that are available in the market may not provide adequate fit a considerable variation in customers. For example, with a same helmet size, the area of the head under helmet protection might be decreased significantly for users with large head shapes. Also, the gaps and/or pressure points between the head and the helmet might be increased in some regions of the head and make the helmet very uncomfortable to wear.

Some manufacturers proposed to resolve the inadequate fit issue for ‘outlier’ heads by designing specific models that are suitable for larger heads (e.g., Bell Stoker: fits human heads of up to 65cm HC, Bontrager Quantum: fits human heads of up to 66cm HC, Specialized Max
Adult XXL fits human heads of up to 64cm HC), smaller heads (e.g., Specialized Echelon fits human heads from 50cm HC), rounded heads (e.g., “Asian Fit” helmets, Bell Segment) and pointed heads (e.g., Giro, Specialized, Bell).

However, the costs associated with the fabrication of these specific moulds are enormous and often not economically viable. These high costs have prevented manufacturers from providing a wider range of helmet sizes.

It is envisaged that the manufacturing costs of the Mass-Customization method presented in this study will be independent of the customer’s head shape, and can improve helmet fit for a higher proportion of cyclists.

2.3.3 Fit and Safety

The efficacy of bicycle helmets in preventing head injuries is well-documented in previous published research works [14, 15, 23, 78-81]. However, studies showed that a poor helmet fit on the wearer’s head may decrease its safety benefits during a crash event [17, 18].

In an earlier case-control study, Rivara et al. [18] found that, during crash events, children who wore a helmet with large gaps between the head and the helmet had a higher risk of head injuries compared to those with proper fit.

Similarly, a previous study has also shown a high frequency (about 10 to 30%) [82] of helmet roll off from the cyclist’s head after the first impact. As a result, the head may hit the road unprotected in any succeeding impacts.

In recent years, numerous studies used the finite element method to assess the impact-absorbing characteristics of helmets during a crash [48, 50, 83, 84]. Only a few of these have emphasised the fit effect of the helmeted head. Of these, Chang et al. [85] tested the influence of the helmet size (scaled helmets with the same shell and liner thickness) on the energy absorption capability. Despite their findings indicating no change in peak (de)acceleration in three different impact sites for the helmet that fitted better to the headform, the authors still suggested that a better helmet fit should remain on the wearer’s head during an impact and hence provide better protection against head injury.

Since a better-fitted helmet is less likely to roll off and remain on the user’s head during an impact, one can speculate that custom-fit helmets, like the ones presented in this research, might have better fit on the user’s head and thus minimise the exposure of the unprotected head to direct impact during crashes (especially for multiple impacts accidents).
2.3.4 Helmet Design Methods

Poor helmet fit may be attributed to two main causes: wrong helmet use or inappropriate design. While the misuse of bicycle helmets is rectifiable through school-based education programs, government and helmet manufacturer advertising, and store advice and information, the mismatch between head shapes and helmet liners seems to be related to the design of helmets.

Nowadays, helmets are designed and tested on standard mannequin heads called headforms [21, 86], which aim to represent the full range of head dimensions, geometries, and shapes within a targeted population. Although two headform standards have been proposed in the past (ISO/R1511:1970 and ISO/DIS 6220:1983), neither was adopted as international standards. However, the draft ISO/DIS 6220:1983 has become an international consensus standard for many countries and served as a reference for the development of their standards. For instance, Australia adapted the draft to develop the AS/NZS 2512.1:2009 Methods of testing protective helmets Part 1: Definitions and headforms [38] (Figure 2-16), where five headform sizes are presented, namely, A, E, J, M and O. The ISO draft was itself based on the first set of test headforms produced by the UK Transport Road Research Laboratory in the 1950s’ [87]. One may speculate that designing bicycle helmets on anthropometric measurements from the 1950s British workforce would not adequately encompass the variability of head shapes in today’s population. It might lead to improper helmet fit for a large proportion of cyclists.

![Diagram](image)

Figure 2-16: Standard headform definition (AS/NZS 2512.1).

To account for the shape differences between the current headforms and the variety of head
shapes within the targeted population, designers have created helmet liners with significant offset surfaces from the standard headform geometries. This design approach ensures that the highest proportion of users is captured within the smallest numbers of sizes. As shown in Section 2.3.1, it is common for helmet manufacturers to only provide one or two helmet sizes for both male and female populations. Thick foam pads are then added to fill the gaps between the liners and the wearer’s head. While this approach noticeably improves comfort and allows a minimum gap for air circulation, it does not reduce front-to-back, side-to-side, or rotational movements that are responsible for poor helmet fit. It is apparent that such a design approach may lead to improper helmet fit for an extensive range of consumers.

In the present research, the design of the customised helmets will not be based on standard headforms, thereby eliminating the poor fit issues associated with such design technique. New design methods will be implemented where the inside surfaces of the helmet will be perfectly matched to the head shape and size of the user.
2.4 Fit Analysis

Being able to objectively analyse the fit of wearable products for users can hold significant benefits. For instance, one can use the objective fit analyse method to help with the product design phase for fit surveys and/or for model selection during purchase. Such a method can be greatly beneficial for sports helmets, where fit is strongly associated with comfort. One application of such a method is to use quantitative assessments of helmet fit to validate the fit accuracy of multiple design methods. The validation techniques can be less expensive and less time consuming than traditional subjective assessment process. A quantitative path was chosen for the present research to validate the fit accuracy of the introduced mass customisation design framework.

However, even if the need for the objective fit analyse method is significant, the existing approaches presented in the literature are still tedious and inaccurate, and are not in line with today’s technology.

The first technique introduced by Gilchrist et al. in 1988 [51] attempted to compute the distance between the inside of a helmet and the user’s skull. A test rig, which uses sensors to measure the gap using depth probes inserted in the drilled holes on the helmet, was presented (Figure 2-17). Each sensor was built from a rectilinear potentiometer with a maximum range of 25mm in depth. The sensors were activated through an air pump and a 10ml syringe that forced small plastic discs to contact with the head. Based on a sample of 500 participants, the authors concluded that the helmet fit could be improved through better design techniques, and the retention systems must be revised to avoid the probability of helmet roll-off in an accident.
With the advances in 3D scanning in the early 2000s, Meunier et al. [88] introduced a new method for the fit analysis of ballistic helmets. They measured the spatial relationship between the head and the helmet by digitizing and aligning three different scans, namely, the participant’s head, the helmet, and the helmeted head. They then analysed the gap between the scanned head and the helmet and displayed areas around the head that did not fit their criteria (i.e., interference areas). Figure 2-18 shows an example of their distance analysis on one participant.

The method proposed by Meunier et al. offered a significant improvement over classical fit analysis techniques. However, some limitations existed. Firstly, the 3D scanner used a Cyberware 3030 RGB that was based on laser beam technology. Laser beams could harm a
participant’s eyes over a long exposure time. The scanner also had low resolution and accuracy and was unable to collect data around the top of the head (i.e., the laser scanner is unable to digitize data from surfaces parallel to the laser beam). In addition, large amounts of time were required for post-processing of the 3D scans. Secondly, the authors’ fit criteria only relied on one parameter, i.e., the standoff distance (SOD). This was defined as the distance between the inside of the helmet and the skull of the wearer, and was set to 12.5mm. According to the authors, the helmet was deemed to fit the user if the gap was larger than the 12.5mm limit. No outer limit values were set, and no analyses were carried out on the distribution of the gap over the whole head surface. Lastly, the fit analysis technique was developed for ballistic helmets that have a simple rounded shape with no openings in their shell for air circulation.

In view of these limitations, the adaptation of the Meunier method to complex shapes, such as bicycle helmets, is deemed difficult.

This research will fill the knowledge gap by introducing a new quantitative assessment method of helmet fit called the HELMET-FIT-INDEX. The method will be based on three fit parameters (instead of one from Meunier method) and be able to deal efficiently with the complex shapes of today’s bicycle helmet models. The fit accuracy of the customised helmet models created will then be tested using the HELMET-FIT-INDEX and compared with commercially available helmets.
2.5 Anthropometric Data and Grouping Methods

This section first lists the previous anthropometric studies of the head undertaken worldwide and explains why these studies are impractical to adopt for the present research. Then, a review of current clustering methods of the head based on 3D anthropometric data is presented. Clustering methods are relevant to the present research objective, as one of the main activities was to group individuals together based on head shape similarity (see research objectives in Section 1.2).

2.5.1 Anthropometric survey

Recently, a study was commissioned by Safe Work Australia [89] to investigate the use of anthropometric data in the design of wearable products for the Australian market. The primary objectives were to identify the anthropometric data currently used and to assess whether these data actually reflected the shape diversity of the country’s current population. Results of the study indicated that, when designing a product, most Australian’s designers and engineers still use traditional 1D anthropometric databases [90-94] as their primary source of references. Although these databases are well-documented, they are out-dated and none of them were sourced in Australia. The databases were based on U.S. or U.K. populations and were conducted on their military workforces. Therefore, there is no evidence that these data can accurately represent the contemporary population of Australia, where more than one-quarter of the inhabitants have arrived as migrants, and almost one-eighth have Asian ancestry [95]. Furthermore, previous studies have established that Asian head shapes are significantly different from the Caucasian head shapes [96, 97]. Those differences are not incorporated in the anthropometric data currently used by designers. As a result, Safe Work Australia has recommended the development of a national anthropometric database in order to improve the fit of wearable products for the Australian population.

Likewise, product design specialists have acknowledged the need for an adequate measurements of human anthropometry through the use of 3D scanning technology [89]. Compared with traditional 1D anthropometric measures, which only capture numerical values of single parameters (e.g., head circumference and length), 3D data provide information on the contours and shapes of the person. For example, Robinette et al. [75] have emphasized the need to incorporate 3D anthropometry data when designing head and facial equipment, such as helmets, goggles, and respirator masks, as these objects cannot stretch like garments and other similar products.
In the late 1990s, advances in scanning technology and computational software created new opportunities in the field of anthropometry. Extensive 3D anthropometric studies have been undertaken worldwide: for instance, the CAESAR [98], SizeChina [86] and NIOSH [21] surveys. The CAESAR project began in 1997; researchers collected 1D and 3D data on 2,400 North American and 2,000 European civilians. The researchers used the first ever built 3D full body scanner, which had low accuracy and resolution, limiting its application to head and face studies. In 2006, Ball et al. started the SizeChina project to capture the 3D digital shape of the Chinese head. The heads of 1,600 participants were digitized using an advanced 3D scanner that could capture geometrically complex body parts at high resolution. Finally, Zhuang et al. used similar techniques to capture the facial shape variability of U.S. respiratory users in the NIOSH survey. To the author’s best knowledge, such surveys do not exist for the Australian population.

One of the main limitations when applying 3D scanning for headgear design is the presence of the persons’ hair in the scanned data, which compromises the exact geometric and shape of the skull. Individual hairstyle, length, and thickness limit the use of standard methods to deal with this problem. Most researchers have used wig caps on the head to hide and compress the hair over the skull. However, long or bulky hair styles still produce significant bumps and irregularities on the head’s surface. In particular, the back of the head is commonly associated with large surface deformations due to this issue. The dimensioning of headgear designs based on 3D scans might be skewed if the hair thickness under the wig caps’ compression is not properly accounted for.

The aim of the present research was to introduce a mass customisation design framework of bicycle helmets using 3D anthropometry data. Australian cyclists were chosen as the target population to validate the method. Since no anthropometry survey of the head exists in Australia and none of the ones presented above can be used, a new 3D anthropometric database will be developed in this work using state of the art 3D scanning technologies. The database, presented in Chapter 3, will serve two main purposes: (i) to help with the design of the HELMET-FIT-INDEX method in Chapter 4, and (ii) to assist with the grouping algorithm in Chapter 5. Customised helmets will be created for a subset of individuals in the database and will be presented Chapter 6. A new method called Hair Thickness Offset will be implemented in Section 3.4.6 to account for the person’s hair under the wig cap in the scanned data.

2.5.2 Grouping of the Human Head based on Anthropometric Data

The recent developments in 3D scanning technologies have encouraged the use of 3D
anthropometric measurements for product design [21, 71, 86, 99]. These data provide an in-depth description of the size and shape characteristics of the scanned persons due to the large set of data points they contain. However, it remains difficult to analyse these data efficiently and to present body shape information in a summarised form for the population of interest. As the type of information provided to designers must be simplified, size and shape characteristics are typically presented as a series of generic models, i.e., mannequins and headforms. To create these models, it is necessary to first group participants with similar size and shape attributes into a set of representative clusters.

Multiple methods have been presented in the past to describe how these groups could be created. However, only a few focused on 3D data. For example, researchers have used statistical analyses (Principal Component Analysis (PCA)) and/or data mining methods (clustering algorithms) to outline the shape variation of the human body from 3D anthropometric data [21, 100-106]. These studies were facilitated by Allen et al. [107], who further developed a method called point set registration technique [108, 109] of 3D shapes of human body parts. In such a method, a uniform polygon mesh called the template is warped over the raw 3D scans of numerous participants using regularized transformations and thus enabling shape comparisons on a point-by-point basis.

PCA is a variable reduction technique that aims to decrease the large number of variables (i.e., the number of points in the template mesh) into a smaller set of artificial variables called Principal Components (PCs). Measuring the statistical dispersion of the PCs can provide information about the shape variability of the population. The study of these dispersions has led researchers to the creation of PC-based clusters [21, 103]. However, the inherent characteristics of PCA have made the process of creating these clusters problematic. First, every small change of a PC’s value acts on all the points of the mesh model, often in a confusing and unintelligible manner, making the variations difficult to interpret statistically. Second, the number of PCs to consider in the analysis is often based on subjective assessments, resulting in a non-optimal solution. PCA produces as many components as there are points in the template mesh, accounting for all the variance in the sample. However, compromises must be made, as the purpose of the analysis is to explain as much variance as possible using as few PCs as possible. Third, interpreting and combining the shape variation caused by each selected PC into meaningful clusters have proved to be difficult, especially when three or more components are used. For instance, these limitations caused Meunier et al. [103] to restrict their grouping study to only two PCs, resulting in a statistical model representing only 50% of the sample’s total variance.
The other grouping method is based on Clustering algorithms. These algorithms group objects that are “similar” to each other into clusters. Many clustering methods (e.g., connectivity and density models) have been proposed in the past, and all have some advantages and drawbacks. The selection of clustering algorithms is generally application-dependent. Connectivity models such as hierarchical clustering perform well for the generation of compact clusters, but can be slow when analysing large datasets ($O(N^3)$). They may also suffer from the so-called single-link effect, where apparent distant clusters end up connected due to a thin line of objects between them. Density models like DBSCAN [110] or OPTICS [111], and centroid models like $k$-means [112] and $k$-medoids [113], are faster to solve, but require input parameters that are usually difficult to define efficiently (e.g., $minPts$ and $\varepsilon$ for DBSCAN, $k$ for $k$-means). For example, Niu et al. [101] clustered 3D head scans of Chinese soldiers using a $k$-means algorithm. They set the number of clusters $k$ to seven but did not provide any detailed analysis that justified this selection.

In the present research, a new algorithm that divides and classifies small to medium size samples of 3D head scans into clusters is presented. The algorithm followed a modified hierarchical clustering algorithm where distance metrics between pairs of registered head scans are calculated and implemented in a step-by-step process. The clusters are created one after another (instead of simultaneously) in an optimal manner. As demonstrated in Chapter 5, this new approach generates a smaller number of clusters, while classifying a larger ratio of subjects than conventional hierarchical methods.
2.6 Mass Customisation and Custom-Fit Design

This section defines mass customisation, describes its applications and explains why it could be an excellent alternative production method for bicycle helmets.

2.6.1 Definition

Mass customisation (MC) is a method/process that provides customised products or services to consumers in large volumes and at costs that are reasonably low compared to conventional customisation processes [114-116]. More specifically, MC systems aim to reach customers as in the mass produce market (i.e., standardisation) but try to consider them individually as in the one-on-one production method. The reasons behind the growth of MC systems in the late 1980s and early 1990s were threefold: (i) the development of advanced manufacturing technologies, (ii) the increased demand for diversity in the products range and, (iii) the collapse of many mass industries [115, 117, 118]. These created the need for production methods that focus further on the individual needs.

As summarised by Da Silveira and co-authors in the well-documented MC reviews in [116] and [119], multi degrees of mass customisation exist, from full customer product specifications to simple options selection. Although a fully individualisation (e.g., bespoke tailoring) can hold more value for the consumer, often compromises must be reached on the acceptable level of customisation for a specific product. Therefore, MC should be a good mix between standardisation (i.e., set of common components in a product for all customers) and individualization to be successful [120]. The amount of standardisation and individualization in a MC system can be described in different levels. Multiple generic levels have been proposed in the past [115, 121-123]. Da Silveira et al. [116] condensed the proposed classifications in an eight-level MC scheme, ranging from complete customisation (consumers create the product in collaboration with the designer) to complete standardisation. In between, products might be individualised at the fabrication level (customer-tailored products), the assembly level (modular components), the delivery level (simple addition), the distribution level (different packaging), or the usage level (customers can alter the product during use). However, evaluating the appropriate level of individualisation for a specific product can be difficult. Ideally, preliminary studies should assess the customers’ interest in a level of customisation, measure the feasibility to deliver this level, and determine if achieving such a level holds any comparative advantages. To date, this kind of study to assess the ideal level of customisation for bicycle helmets has not been implemented.
2.6.2 Mass Customisation and Bicycle Helmets

A mass customisation (MC) framework for the design of custom-fit bicycle helmets is introduced in the present study. Custom-fit means being personalised with respect to the person’s shape and size. It is the transparent level in the Gilmore and Pine level of customisation [122], where products are almost fully altered to match the needs of each individual (i.e., need for improved fit accuracy of helmets). This is the level of customisation chosen for the present study. Further to the transparent level, a modular approach is kept in the design process, where only the inside foam liner (see Section 2.2.2.2) of a standard helmet model is altered to fit and match the customer’s head shape. Using a modular approach for MC, where some components remain unchanged, helps to keep the production costs as low as possible.

In the following sections, the justification for the need of custom-fit helmet models is presented. Noted are the successful implementation of MC systems, which are driven by two market-related factors [116, 119] where (i) customer demand for customisation must exist, and (ii) market conditions must be appropriate.

2.6.2.1 i) Customer demand for customisation must exist

Customers must appreciate the added value of MC products to initiate demands. Merle et al. [124, 125] investigated further the work by Addis and Holbrook and Squire et al. [126, 127] to identify the MC characteristic that drives value from the consumers’ perspectives. Merle et al. demonstrated that the consumer’s perceived value of customised products increases due to the products’ intrinsic and extrinsic characteristics. Intrinsic characteristics are related to the utilitarian value (obtaining a product which matches one’s preferences the closest), the uniqueness value (distinguishing oneself from others via the mass customised product) and the self-expressiveness value (obtaining a product that represents oneself). Extrinsic characteristics are related to the user experience provided by MC products. The extrinsic characteristics defined by Merle et al. [125] are the hedonic value (pleasure, fun, inspiration and excitement felt during the MC experience), and the creative fulfilment value (accomplishment related to the creative task of co-designing).

In the proposed MC approach of helmets introduced in the present research, the inside surfaces of a generic bicycle helmet model are automatically redesigned to fit the customer’s head shape. The design is based on 3D anthropometric data recorded using modern technologies. It is envisaged that the proposed design method will improve the helmet fit, and
the MC approach will add value in terms of uniqueness and hedonic values of the customised helmet. Furthermore, as pointed out by Fiore et al. [128], the use of 3D body scanning can contribute to added benefits and may enhance the customers’ willingness to take part in mass customised products. In conclusion, the proposed MC framework of bicycle helmets using a custom-fit approach and 3D anthropometric data should add value to the customer and, therefore, initiate demand.

2.6.2.2 ii) Market conditions must be appropriate

Manufacturers that embark on MC products can achieve significant competitive advantages over competitors, especially when this is the first time such products are customised [118]. From a manufacturer’s perspective, value is added by premium prices for mass customised products, increased customer loyalty and improved brand reputation [129]. All of these could bring significant market share to manufacturers willing to start the MC production method.

While individualisation in the garment industry is now recognised as a valuable alternative to standardisation [130-132], very little work on helmet customisation has been reported in the literature or initiated by industries. Lui et al. [133] first attempted to design custom-fit construction helmets using a semi-parametric surface modelling tool and 1D anthropometric data (e.g., head circumference, head breath, and head length) (Figure 2-19).

Construction helmets are fabricated from a hard shell only (no foam liner) with a simple, rounded egg-shape and only a few design features. They can be designed as simple parametric models with just a handful of parameters. However, contemporary bicycle helmets have complex free-form shapes with ventilation holes that require advanced design models. In
[134], Pandremenos and Chryssoulouris created a custom-fit motorcycle helmet liner (also a simple rounded egg-shape design) using a modular design approach and rapid manufacturing technologies. Although the method proposed could be applicable to many different customised products other than helmets, 3D printing the liner using polyurethane will greatly alter the shock absorption properties of the helmet. The safety performance issue was not addressed by the researchers. In 2013, Bell Sports® (Rantoul, Illinois, USA) launched their Custom-Fit program (Figure 2-20) for two of their motorcycle helmet models. Based on a 3D scan of the head, they claim that the EPS liner is individually redesigned to fill the void between the person’s head shape and the shell. To date, Bell Sports® have not yet applied this technology to their bicycle helmet models which, again, have much more complex shapes than motorcycle helmets.

Figure 2-20: Bell Sports custom-fit program.

Safety and certification are one of the main reasons for the lack of MC systems of helmets. Headgear is tested on standard mannequin heads called headforms, which aim to represent the full range of head dimensions, geometries, and shapes within a specific population. Physical models of the intended helmet design are tested in a set of experiments specified in the relevant standards. For instance, Standards Australia uses the test methods described in AS/NZS 2512:2009 [61] and AS/NZS 2063:2008 [60]. While each customised model presented by Bell Sports’ MC system meets both the DOT standard in the U.S. [135] and the Snell M2015 standard [136], little information on how they achieve these safety requirements is disclosed (although the Snell Memorial Foundation® (North Highlands, California, USA) seems to have new criteria for the certification of customised motorcycle helmets [137]). Certainly, certifying every customised helmet using multiple physical models (e.g., 10 specimens are required in [60]) would not be cost- and time-effective.
In summary, market conditions for customised bicycle helmets are appropriate, but new processes should be initiated to deal with the complex shapes of bicycle helmet models. In addition, new methods such as numerical simulation analysis should be created to ‘certify’ customised helmets without using physical models. Overcoming these limitations is the main objective of this research study. New design and simulation methods will be presented in Chapter 6.
2.7 Conclusions and Opportunities for further work

This chapter has identified the current state-of-the-art knowledge domains associated with the research scope of this work (bicycle helmet fit problem, quantitative fit analysis, anthropometric data, clustering algorithm and mass customisation systems). Using the expanded understanding that resulted from this literature review, a number of limitations in existing methods, as well as gaps in domain knowledge, have been identified. The identified limitations offer several research opportunities, which are stated below.

2.7.1 Helmet Fit Accuracy

Research Gaps and Limitations of previous studies:

- Current helmet sizing systems may not provide a suitable fit for a large proportion of cyclists. Often the number of helmet sizes provided by manufacturers is inadequate and inefficient.
- Head shapes differ according to ethnic groups, age, and gender. These differences are generally not considered during the design of helmets.
- Helmet sizing is only based on one parameter (i.e., the head circumference). However, the human head is a complex freeform shape that cannot be summarised using only one dimension.
- Studies indicate that the current way of sizing people’s head is out-dated and that a contemporary method is necessary.
- Some specific individuals have head shapes that differ significantly from the general population. Some have a tiny or massive head, with an oval, rounded or pointed form. These people cannot be accommodated by the standard helmet sizes and require specific design models. However, making headgear for these ‘outlier’ head shapes is challenging, since current manufacturing costs are driven by standardization.
- Studies show that helmet safety benefits decrease when a poor fit between the helmet liner and the head is attained. However, studies focusing on the improvement of fit accuracy between the head and the headgear are non-existent.

Significance and Original Contribution to New Knowledge

The novel customisation design framework will provide optimised and proper helmet fit for all customers. Although a sizing system will be used for ascertain the fit efficacy, it will be irrelevant to the customer, as the helmet liner will be designed according to his/her head shape.
Chapters 5 and 6 of this work focus on addressing these limitations.

2.7.2 Helmet Fit Analysis

Research Gaps and Limitations of previous studies

- Methods used to assess quantitatively the fit of helmets are out-dated and/or do not account for the specific fit requirements of bicycle helmet models.

Significance and Original Contribution to New Knowledge

The novel HELMET-FIT-INDEX (HFI) will be developed and presented as a new tool for the fit analysis of bicycle helmets. The index will provide fit scores between a helmet and the head shape of a particular individual. This activity is discussed in Chapter 4.

2.7.3 Clustering of Scanned Data

Research Gaps and Limitations of previous studies

- Only a few researchers have classified groups of individuals according to their head shape. Most of them used 1D anthropometric databases. Studies focused on 3D anthropometric data have been presented in the past, but the statistical classification methods and clustering algorithms used might not be the most appropriate techniques for the creation of compact clusters.

Significance and Original Contribution to New Knowledge:

In this research, a novel clustering algorithm will be presented for the classification of 3D anthropometric data. It is presented in Chapter 5.

2.7.4 Custom-fit Design of Bicycle Helmets

Research Gaps and Limitations of previous studies

- Current research on helmet customisation is sparse and not in line with the design and manufacturing requirements of today’s bicycle helmet models.
- There is no reported use of advanced manufacturing technologies and 3D design techniques for automatic customisation of bicycle helmets.

Significance and Original Contribution to New Knowledge

The research will contribute in novel techniques to automatically create digital models of custom-fit bicycle helmets based on the 3D head scan of an individual. These models could
then be used for fabrication using advanced manufacturing technologies. These methods are presented in Chapter 6.
3. DATA COLLECTION

3.1 Chapter Summary

Design specialists have acknowledged the need for more accurate measurements of human anthropometry through the use of 3D data, especially for the design of head and facial equipment. However, 3D anthropometric surveys of the human head are sparse in the literature and practically non-existent in Australia (detailed in Section 2.5.1).

One of the objectives of the present study was to create a 3D head anthropometric database for the Australian cyclist community. Although it is envisaged that the database developed throughout the present work can be used as a reference for the design and testing of helmets in Australia, the main objective of this survey was to generate 3D data that can be used for: (i) the fit evaluation analysis (HELMET-FIT-INDEX) described in Chapter 4, and (ii) the grouping study (3D-HEAD-CLUSTERING algorithms) described in Chapter 5, in relation to the Mass Customisation system of bicycle helmets presented in Chapter 6.

In this chapter, we describe the data collection steps engaged in this work. We first discuss helmet selection, questionnaire design and 3D scanner characteristics in Section 3.2. Then in Section 3.3 a reverse engineering process of bicycle helmets is presented. The digitized helmets are used in Chapter 4 for the creation of the HELMET-FIT-INDEX study. Finally, the anthropometric survey is introduced in Section 3.4.
3.2 Design of Experiment

This section presents the thought process behind this survey, which involved 3D anthropometric data and bicycle helmet digitization.

3.2.1 Bicycle Helmet Selection

One of the primary goals of the experiment design was to keep the survey as short as possible for the participants. This would ensure that the survey would not cause any inconvenience to the participants and avoid or limit non-completion bias. It was therefore decided that three helmet models would be tested in the present research.

The helmet selection was based on price, which is one of the main decision factors when selecting a new helmet. Headgear with a different price ranges is likely to provide different fit characteristics for the users, as different manufacturing techniques and design features are being used. After a pre-selection of a dozen helmets readily available in local stores, three models were selected based on low, middle and high price range categories. The chosen helmets are Netti Lightning, Met Crossover and Met Kaos (presented by increasing price) (Figure 3-1). A total of six helmets was purchased (i.e., S/M and M/L, UN and XL, M and L from low to high range, respectively). Even if the medium and high range products originated from the same manufacturers, the inspection of the liner geometries and shapes revealed that different design techniques were used, resulting in dissimilar fit characteristics.

Figure 3-1: Netti Lightning, Met Crossover and Met Kaos.

3.2.2 Questionnaire Design

Two questionnaires were prepared for the present study, with one being a shorter version of the other. The grouping study required more participants but less personal information than the HELMET-FIT-INDEX study. Copies of both documents are provided in Appendices A and B.

The whole questionnaire was split into five categories, where personal details of the participant as well as specific information about helmet use, helmet fit requirements and
assessments were recorded.

### 3.2.2.1 Participant Details

Personal information such as date of birth, gender, mass and height, and ethnic background were recorded (Figure 3-2). Participants were also asked to provide information about their cycling activities. These parameters were essential to test whether the recruited participants were as equally distributed as those in the general population.

<table>
<thead>
<tr>
<th>a. Date of Birth (DD/MM/YY)</th>
<th>b. Gender: □ Male □ Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>c. Ethnic/Ancestral background:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australian: □ Australian / New-Zealander □ New guinea and Pacific Islands</td>
</tr>
<tr>
<td>European: □ Northern European (UK, Finland, etc.) □ Western European (France, Germany, etc.) □ Southern European (Spain, Italy, etc.)</td>
</tr>
<tr>
<td>Asian: □ Southeast Asian (Indonesia, Malaysia, etc.) □ East Asian (Japan, Korea, China, etc.) □ North Asian (Asian portion of Russia)</td>
</tr>
<tr>
<td>American: □ North American □ South American</td>
</tr>
<tr>
<td>African &amp; Middle Eastern: □ Western, Central and Eastern African □ North African &amp; Middle Eastern</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>d. Cycling Activity:</th>
</tr>
</thead>
<tbody>
<tr>
<td>□ Recreation / Utility / Touring □ Competition / training</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>g. Cyclist mass (kg):</th>
</tr>
</thead>
<tbody>
<tr>
<td>b. Height (cm):</td>
</tr>
</tbody>
</table>

Figure 3-2: Participant details.

### 3.2.2.2 Helmet Use

The survey also assessed how often do the cyclists wear helmet while cycling, and the main reason for not wearing it, if applicable (Figure 3-3).

<table>
<thead>
<tr>
<th>a. When cycling, how often do you wear a helmet?</th>
</tr>
</thead>
<tbody>
<tr>
<td>□ always □ half the time □ never □ most of the time □ rarely</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>b. Main reason for not wearing a helmet (if applicable)?</th>
</tr>
</thead>
<tbody>
<tr>
<td>□ inconvenience □ discomfort □ vision □ other</td>
</tr>
</tbody>
</table>

Figure 3-3: Helmet use.

### 3.2.2.3 Helmet Fit Requirement

The helmet fit requirement was assessed through two questions: the ‘fit ideal’ and the ‘fit importance’ parameters. A ten point rating scale was used to evaluate the qualitative response
of cyclists regarding fit (Figure 3-4). Qualitative descriptions of the categories were proposed to improve the readiness of the rating scale.

![Helmet fit user ideal. In a scale from 1 to 10, please rate your ideal degree of pressure on your head when wearing a bicycle helmet. If 1 was a very loose feeling and 10 very tight, what value would best describe your fit requirement?](image1)

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
</table>

![Helmet fit user importance. In a scale from 1 to 10, please rate the importance to achieve your ideal fit in a bicycle helmet model. When purchasing a new helmet, is it essential that it match your ideal degree of pressure on your head (10) or you can buy one which doesn’t (1) but satisfied others parameters?](image2)

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
</table>

Figure 3-4: Helmet fit requirement.

### 3.2.2.4 Helmet Fit Assessment

Similarly, volunteers were asked to complete the fit assessment form on a ten point rating scale (Figure 3-5). The aim was to record the subjective rating of fit for the three bicycle helmets, both globally and locally (five local regions were defined).

![In a scale from 1 to 10, please rate how fit and comfort are achieved in the provided helmets. 1 being very bad comfort and fit feeling, and 10 being excellent fit and comfort. Please rate for the overall helmet model and for the 5 described regions. Pick the best size for you first.](image3)

<table>
<thead>
<tr>
<th>Helmet A Met Kaos</th>
<th>Helmet B Met Crossover</th>
<th>Helmet C Notl Lightning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size: M or L</td>
<td>Size: UN or XL</td>
<td>Size: S/M or M/L</td>
</tr>
<tr>
<td>Overall Fit Assessment value</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Top region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Front region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Back region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Right region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Left region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
</tbody>
</table>

Figure 3-5: Helmet fit assessment.

### 3.2.3 3D Scanner

The Artec Eva™ (Figure 3-6) was selected as the 3D scanner for the anthropometric study. As a handheld white light scanner, it can produce accurate point clouds up to 100 micrometres at a half a millimetre resolution. It is completely portable and can scan the whole head of a person in less than 40 seconds. The scanning rate can be adjusted from 5 to 15 frames per second, representing, on average, 600 single scans per participant. These frames are then aligned
(global registration) and merged in order to create a smooth polygon mesh.

The studied helmets were digitised with a more advanced 3D scanner, i.e., the HDI Advance from LMI Technologies (Figure 3-7), which had a high level of scan accuracy and quality when dealing with more complex geometries. The average point-to-point resolution is 75µm with an accuracy of up to 45µm. It is a fixed white light scanner that can take a single shot of the scanned object every 2 seconds. It was combined with a rotating table for an improved quality of the digitization process. The table (with the helmet on top) rotates at a fix angle rate after every shot, while the software performs automatic alignment of the scans.

Figure 3-6: Artec Eva™.

Figure 3-7: HDI Advance.
3.3 Reverse Engineering of Bicycle Helmets

Reverse engineering (RE) techniques were implemented to digitize the six selected helmet models. RE is the process of extracting knowledge or design information from anything man-made [138], and more specifically to gather reusable CAD data regarding geometry and form of an existing product. The RE process consists of a 3D scanning component, a data processing step, and a CAD model construction stage. The implemented RE methodology for the six bicycle helmets studied is shown in Figure 3-8. In this section, we only present the steps relevant to the present study, which are helmet preparation, 3D scanning and Data Post Processing.

3.3.1 Step 1: Helmet preparation

Comfort paddings, adjustment systems, and retentions straps were physically removed from the helmets in preparation for the 3D scans (Figure 3-9). These flexible components could have moved their position during the scanning procedure and made the alignment between the multiple shots more complicated. Visors were also detached from the helmets because they often hide a good portion of the shell during the scanning process.

Figure 3-8: Bicycle Helmet Reverse Engineering Methodology.

Figure 3-9: Netti Lightning SM without pads, retention/adjustment systems and visor.
3.3.2 Step 2: 3D Scanning

The HDI Advance 3D scanner was used for the digitization of the bicycle helmet models (Figure 3-10). The hardware works in combination with the FlexScan3D® software in order to create a polygon mesh of the digitized object.

![HDi scanner taking a single shot of the Netti helmet.](image)

On average, 70 single shots were recorded for each helmet. The scanning procedure was to position the helmets on top of the rotating table and to record a shot every 30 degrees increment of the driving motor. Five unique positions of the helmets were used to capture the entire object (three positions are shown in Figure 3-11). Distinct shots were then added in order to increase the coverage of the small geometric surfaces of the air ventilation holes.

![Example of three positions of the helmet on the table.](image)

The software was set to generate a medium density mesh model from the scans (~1.2 million polygons per shot). For every revolution of the table, 12 scans were captured, resulting in an average mesh size of 16 million polygons. The five revolutions scans and single shots were then aligned altogether using the fine alignment algorithm in the software. The scans were then joined into a single combined mesh and finally merged into one final scan using the smoothed merge option. The final mesh was also decimated, while tiny holes on the geometry were filled.
automatically. The final mesh consists of around 1.7 million polygons. Undesirable scanned surfaces (rotating table, rig supports) were approximately trimmed from the mesh as displayed on the two pictures on the right of Figure 3-12. The final scan was exported as a polygon mesh using the .ply extension file.

Figure 3-12: Left: all single scans aligned, right: final mesh model.

3.3.3 Step 3: Post-Processing

The resulting scan was then imported into Geomagic Studio 12® for further processing. This is a more powerful software for data processing that provides enhanced point cloud and mesh editing tools, as well as advanced surfacing functions.

In the Polygon toolbar of the software, a set of actions was implemented to repair the imperfections of the polygon mesh. First, non-manifold triangles (i.e., triangles not connected to the mesh on three sides) and small components (i.e., sets of freestanding triangles that are so few in number that they probably represent noise) were deleted, self-intersection triangles were repaired (i.e., triangles that intertwined with neighbours), and spikes were removed (i.e., sets of three or more triangles that form a pyramid with a single point at the top on a mostly-smooth mesh). Figure 3-13 shows the detected defects (red elements) of the imported Netti Lightning helmet scan.
Next, *Fill* tools were applied to detect and close openings of the polygon object. The implemented procedure used automated fill tools for tiny holes and manual geometric reconstructions for larger openings. Three filling options (i.e., *Flat*, *Tangent* and *Curvature*) were employed, depending on the continuity properties of the surface area being treated. The *Flat* button specified that the new mesh was generally flat, while the *Curvature* and *Tangent* buttons specified that the newly generated mesh must match the curvature continuity of the surrounding mesh (more tapering for the *Tangent* option). Figure 3-14 shows the post-processing work performed on the Met Kaos size M. The left picture shows the holes of the imported mesh in yellow (with red contours) and the right picture, the repaired polygon object. The ability to fill holes in a polygon mesh is essential when preparing the object for surfacing.

In addition to the *Fill* tools, the *Defeature* function was used to simplify the geometry around some parts of the helmet. For instance, the attachment points of the retention straps and adjustment systems were flattened as shown in Figure 3-15.
Next, an array of smooth commands was applied to minimize the surface deviation of the polygon mesh. The *Relax* tool was executed to lessen the angles between individual polygons. The maximum deviation tolerance was set to 0.5mm, and a deviation spectrum was created to indicate the degree of change in the mesh (Figure 3-16).
Noise Reduction techniques were also implemented to compensate for noise data (such as scanner error) by moving points to statistically correct locations.

Finally, the mesh was reconstructed by creating new vertices. The existing mesh was removed, underlying points were generated, and a new polygon mesh was created laying on those new points. The process was optimized for a mesh that was regular and uniform in size. The final polygon count for all helmet models was set to 2 million. The value ensured that the six helmets had a similar mesh density and resolution when the fit analysis was performed in the HELMET-FIT-INDEX study (Chapter 4).

Figure 3-17 shows the final model of the Met Kaos size M after all the tools and procedures described above were implemented.

![Figure 3-17: Left: Start model of the post-processing step, Right: Final polygon mesh.](image)
3.4 Anthropometric Database of Australian Cyclists

This section aims to achieve the following: (i) to construct a 3D head scan database of Australian cyclists’ population for headgear design; (ii) to develop a method for alignment of all scans to a common standard axis system; and (iii) to introduce a new method to account for the hair’s thickness on scanned data.

3.4.1 Sampling Plan

The sample size was determined according to the procedures outlined in the ISO 15535: General requirements for establishing anthropometric databases [139]. The standard estimates the sample size based on the true population 5th and 95th percentiles of a parameter with 95% confidence, and a percentage of relative accuracy:

\[ n = (1.96 \times CV/a)^2 \times 1.534^2 \]  \hspace{1cm} (1)

\[ CV = 100 \times SD/\bar{x} \]  \hspace{1cm} (2)

\[ a = 100 \times \bar{x} / \text{precision level} \]  \hspace{1cm} (3)

where \( CV \) is the Coefficient of Variation and is the ratio between the Standard Deviation (SD) and the mean of a population (\( \bar{x} \)) (multiplied by 100), \( a \) is the percentage of relative accuracy desired, and \( n \) is the estimated sample size. In the present study, the calculations were based on the head circumference dimension. This dimension, along with head breadth and head length, is the most common dimension used in helmet design. Furthermore, because the head circumference is associated with the largest variability of these three dimensions, it provides a worst case sample size (\( n \) increases when \( SD \) increases). The ISO 7250-1: Basic human body measurements for technological design [140] defines the head circumference as the maximum horizontal circumference above the glabella, crossing the rearmost point of the skull (occipital bone). However, these landmarks are usually not aligned horizontally. In addition, the standard does not indicate whether the hair should be compressed under the tape measure. In view of the above, a measurement precision level of 3.5 mm was deemed adequate for this study. Replacing Eqs. (2) and (3) in (1) gave a sample size estimator that relies only on the precision level and the \( SD \) of the dimension considered:

\[ n = (1.96 \times SD / \text{precision level})^2 \times 1.534^2 \]  \hspace{1cm} (4)

The expected \( SD \) was predicted to be around 17 mm, corresponding to a sample size estimate of 214 participants. This estimation was based on a combination of anthropometric surveys of
the European and U.S. populations [71, 73, 97, 141, 142].

A total of 222 cyclists were recruited for the 3D anthropometric survey, slightly more than the targeted sample size of 214. Table 3-1 provides a summary of the demographic characteristics of the recruited participants.

Table 3-1: Characteristics of participants.

<table>
<thead>
<tr>
<th>Ethnic Group</th>
<th>Male</th>
<th>Female</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
<td>AU</td>
<td>EU</td>
<td>Asian</td>
</tr>
<tr>
<td></td>
<td>88</td>
<td>46</td>
<td>28</td>
</tr>
<tr>
<td>Proportion of Total (%)</td>
<td>39.6</td>
<td>20.7</td>
<td>12.6</td>
</tr>
<tr>
<td></td>
<td>28</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>12.6</td>
<td>3.6</td>
<td>3.6</td>
</tr>
</tbody>
</table>

AU = Australasian, EU = European. Data are mean ± Standard Deviation

3.4.2 Participants and Locations

The survey took place at multiple sites around the metropolitan area of Melbourne, Australia, and spanned a 9-month period throughout 2014 (April to December). Interview venues included five local bicycle shops and a university research laboratory. Recreational and commuter cyclists were recruited through advertisement (e.g., online forums and Melbourne bicycle and triathlon clubs) or directly at the survey site. Cyclists had to be of 18 years of age or above to participate. All participants volunteered for the study and provided written informed consent.

A successful ethic application was lodged with the relevant university committee at RMIT University. The application included a project brochure, a flyer, and a consent forms (Appendices C and D) that needed to be signed by all the volunteers involved in the project.

Bicycle clubs, stores, and racing events were contacted prior to the start of the experiment to seek venues where the survey could be conducted.

3.4.3 3D Scanning

The Artec Eva™ 3D scanner was used for the head anthropometric study. During the scanning process, participants were invited to sit straight and look at a fixed point on a wall with his/her usual facial expression. The posture position and scanning techniques were in accordance with the requirements of ISO 20685:2010(E) 3D scanning methodologies for internationally compatible anthropometric databases [143]. All participants wore standard wig caps over their heads to avoid hair irregularities on the scanned geometry.
The Artec Studio’s hardware and software package recorded multiple single shots of the head and face during the scanning process. The frame rate of up to 15 shots was recorded every second. A high frame rate ensured a fast and efficient 3D scan and minimized the slight movements of the neck that could arise during the scanning process. Investigators were trained to capture the head and face of a participant within 40 seconds, resulting in an average of 600 frames per head scan.

Scans were first coarsely aligned in real time using a position tracking algorithm, which is available in the Geometry + Texture tracker option. This option helped during the scanning to locate the regions of the head with missing data. Figure 3-18 shows an example of the rough alignment of hundreds of single shots during the 3D scan of a participant’s head and face.

![Figure 3-18: Head Scan with fast alignment.](image)

A scan revision (or pre-processing) was executed on each head scan, where large misalignments of frames in relation to one another were verified. Individual errors were removed, and parts of the scans under the thyroid gland were deleted.

The next step was to convert all one-frame surfaces into a single scan model using the Global Registration algorithm. In order to achieve this goal, unique geometry points were selected and matched on each of the frames. Upon successful global registration, all the processed data were then fused into a single polygonal 3D model. The Smooth Fusion tool was used for this operation. The tool provided the option to create a final watertight mesh (all the holes are filled) and was used whenever possible during the procedure (Figure 3-19).
3.4.4 Post-Processing of the 3D scan

The post-processing of the 3D scan head images was executed in Geomagic Studio 12\. Hair bumps and fabric folds were removed (Fill Holes and Defeature tools), while the scan was smoothed out by minimising angles between individual polygons (Smooth and Noise Reduction tools). The polygon mesh was also re-wrapped to generate a more uniform spacing and resolution between each point. Finally, the mesh was decimated to exactly one million polygons.

As for the post-processing of bicycle helmets, non-manifold triangles and small components were deleted, self-intersection triangles were repaired, and spikes were removed.

The deviation analysis tool was used to ensure that the modification to the mesh had not excessively distorted the original scanned head shape. The maximum deviation distance for non-hair bumps or fabric fold was set to ±50µm. Figure 3-20 shows the deviation analysis computed after the post-processing had been completed. The green areas are deviations from the threshold value. Higher deviation values (highlighted in red and blue) arose from folds in the wig cap fabric and uneven surfaces due to hair irregularities.
3.4.5 Head Scan Alignment

An alignment procedure was developed to obtain comparable positions and orientations of head meshes. It was based on the creation of a generic axis system for each individual scan. The procedure began with the creation of three planes associated with key dimensions of the head, i.e., the (a) Sagittal Arc, (b) Head Circumference, and (c) Bitragion Coronal Arc (Figure 3-21). Firstly, the plane spanning the Sagittal Arc (SA plane) was created as symmetrical with respect to the head (Figure 3-21(a)). Secondly, the plane spanning the Head Circumference (HC plane) was established (Figure 3-21(b)) by using the outer corners of the eye sockets to make the plane approximately horizontal, and subsequently moving the plane to a position spanning the area slightly above the glabella and near the top of the occipital bone. The plane was adjusted visually in order to obtain the position of the head circumference. Thirdly, the plane spanning the Bitragion Coronal Arc (BCA plane) was created perpendicular to the two existing planes, positioned according to the Tragions (Figure 3-21(c)). An orthogonal axis system was created using the position of the three planes, which was subsequently aligned to a standard axis system incorporated in the software.
3.4.6 Hair Thickness Offset

To date, published research studies have not proposed concrete methods that can accurately address the hair thickness responsible for inaccurate representation of the head’s shape. In order to evaluate the exact head shape of the participants, the hair thickness under the wig cap compression was measured and considered during the processing stage. Initially, The Hair Thickness Offset (HTO) value was detected through either the computational method (Chapter 4) or manually using a Vernier calliper. In the computational method, the HTO was determined as the maximum negative deviation from the alignment of the participant’s head and a bicycle helmet scan (Section 4.3.3.4). The calliper measurement was performed with the depth measuring blade of the apparatus (Figure 3-22) pointed at three locations around the head, i.e., the top, back, and side. The bottom edge of the Vernier Body was kept adjacent to the upper part of the wig cap (Figure 3-22) during the measurement. Cross-checked comparisons between the two proposed methods were performed for 10 participants, displaying similar HTO values (up to 1 mm differences).
Figure 3-22: Hair Thickness Offset detection – Vernier calliper method.

Subsequently, a manual offset was performed on the head scan. Figure 3-23 and Figure 3-24 show the five-step procedures for a male and female participant with a 3.1 mm and 6.2 mm HTO value, respectively. The procedure steps are described as follows:

1. The region of the head covered by the hair is defined, starting from the forehead hairline (detectable in the scan), spanning over the ears and through the neckline.
2. The selected set of polygons is lowered by the HTO value. Additional triangles are created in a narrow surrounding band in order to keep the overall surface intact.
3. The polygons around the narrow band are selected.
4. The polygons around the narrow band are deleted.
5. The surface reconstruction is performed to create a smooth transition between the offset region and the surrounding mesh.

Figure 3-23: Manual offset procedure for a male with 3.1mm HTO (red regions are the polygons of the mesh selected for modifications).
Figure 3-24: Manual offset procedure for a female with 6.2 mm HTO.

Figure 3-25 displays the head shape differences for two participants before and after the HTO process. The transparent contours in blue inside the “zoom in” areas represent the scanned head shape, while the solid blue contours represent the true head shape of the participants after the HTO method has been applied.

Figure 3-25: Cross-section showing the head scans of two participants before and after the Hair Thickness Offset.
3.5 Summary of Research Outcomes

The main objective of this chapter was to develop a database of 3D head scans for the Australian population that could be used during the next phases of the present research study. A total of 222 Australian residents volunteered for the survey in 2014, covering a wide range of the population, aged from 18 to 80+, of both genders. Results were presented in Table 3-1.

A simple random sampling plan was adopted and the sample size was measured in accordance with ISO 15535: General requirements for establishing anthropometric databases [139]. The ISO standard was adapted to meet the design specifications of 3D anthropometric data, as previously described in the SizeChina and NIOSH projects [21, 144]. The head circumference dimension was used for the estimation. Since no formal anthropometric study of the Australian population has been published previously, a combination of anthropometric surveys of the European and U.S. populations was used to determine the expected standard deviation value of the head circumference.

A handheld 3D scanner was used to digitize the participants’ heads. The resulting scans were then post-processed, and aligned to a common axis system defined using three planes spanning the Sagittal Arc, the Head Circumference, and the Bitragion Coronal Arc.

Furthermore, a Hair Thickness Offset (HTO) was applied to the polygon mesh within the region of the hairline (Figure 3-23) to provide a better estimation of the true head shape of each participant. This is in opposition to other 3D anthropometric databases that might overestimate the size of the head in their study.

The created database of head shapes will be used in the next three chapters where:

- The HELMET-FIT-INDEX study is developed (Chapter 4). The index will provide a quantitative mean to assess the fit accuracy of bicycle helmets for the wearer.
- The 3D-HEAD-CLUSTERING algorithm is established (Chapter 5). When applied to the database, the algorithm will generate groups of participants with high head shape similarity. Using these results, new headform models representing the variability of head shapes in Australia will be generated.
- The proposed mass customisation framework is demonstrated (Chapter 6). Based on the computed groups, customised helmets will be created for a large subsample of the head database.

In addition to the head database, reverse engineering (RE) techniques were also implemented.
on three commercially available helmets. The digitized helmets will be used in Chapter 4 for the index development. The selection of the helmets was based on price, which is the main buying criterion when choosing a new helmet. A more sophisticated 3D white light (i.e., HDI Advance) scanner was used for the headgear in order to capture the full geometry of such complicated geometric forms.
4. **OBJECTIVE ASSESSMENT OF HELMET FIT**

4.1 **Chapter Summary**

This segment is built on the 3D anthropometric database of head shapes introduced in Chapter 3, where the development phases of a novel quantitative assessment method of helmet fit are presented. As shown in Section 2.4, such a method was required to evaluate the fit improvement of the mass customisation framework introduced in the study for bicycle helmets. To achieve this goal, a fit index is developed in Section 4.3. It is then applied to two case-studies in Sections 4.4 and 4.5 to demonstrate the benefits associated with such quantitative assessment method. The index is applied later in Chapter 6 to assess the fit accuracy of the generated customised helmet models.

This chapter answers the following key research question related to the present research (Section 1.3):

Q2. How to measure quantitatively the fit accuracy of helmet models for individuals?
4.2 Introduction

Helmet safety benefits are reduced if the headgear is poorly fitted on the wearer’s head (Section 2.3.3). However, no industry standards are currently available to assess objectively how a specific protective helmet fits a person’s head (Section 2.4).

Typically, a proper fit is defined as a small and uniform distance between the helmet liner and the wearer’s head shape, with a broad coverage of the head area. Taking into account these considerations, the novel HELMET-FIT-INDEX (HFI) method, which estimates the ‘fit score’ of bicycle helmets on a scale from 0 (excessively poor fit) to 100 (perfect fit) is developed in this chapter based on subjective fit assessments of surveyed cyclists. As opposed to Meunier et al. in [88] (Section 2.4), the HFI method sets the Standoff Distance SOD (distance between a person’s head and the inside surface of a helmet) as optimum when spanning between 4 and 8 mm. In further contrast to Meunier et al.’s study, two additional parameters are included in the index: (i) the Gap Uniformity GU, which is the standard deviation of the gap distribution; and (ii) the Head Protection Proportion HPP, which is calculated as the proportion of the head under helmet protection. GU and HPP are defined as optimum when they get close to 0 and 1, respectively. As shown in the subsequent sections in this chapter, a set of reverse engineering tools and computational techniques are also developed to deal with the complex shapes of today’s bicycle helmets models. Again, this is in contrast with Meunier et al.’s paper, which only tested the simple, rounded egg-shape models of ballistic helmets.

Two case-studies demonstrate that the HFI could be a valuable tool for statistical analysis of fit for a defined population, and for the comparison of different headgear models with respect to fit.
4.3 The HELMET-FIT-INDEX (HFI)

This section presents the research and development steps undertaken for the creation of the fit index. A four-step procedure was developed:

1. First, the study required a set of volunteers (section 4.3.1), as the index was developed based on subjective assessments of helmet fit. These individuals took part in the 3D anthropometric survey described in Chapter 3.

2. Second, a series of qualitative questions was recorded for each participant regarding fit requirement and fit assessment for three commercially available helmets (section 4.3.2). The selection and digitization steps of these three helmets are discussed in Sections 3.2.1 and 3.3, respectively.

3. Third, a series of quantitative data was calculated numerically for each participant and each helmet tested. The formulae of the HELMET-FIT-INDEX are introduced in this section (Section 4.3.3).

4. Finally, various parametric and non-parametric statistical analyses were applied to determine if the quantitative data (HFI) were appropriate estimates of the qualitative data for helmet fit assessment (section 4.3.4). The results are discussed in 4.3.5.

4.3.1 Participants and Sampling Plan

The sampling distribution plan for the study was primarily drawn from the Australian Cycling Participation report [29]. The report estimates the cycling activity (measured in the past week, month and year) across Australia according to gender and age groups. For each stratum in the report, data were presented as “population proportion who rode in the past seven days.” Expected frequency distributions for the study were then calculated based on these proportions and the 2011 Australian census data [95]. The planned frequency for each group is shown in Table 4-1 below.

<table>
<thead>
<tr>
<th>Age Groups</th>
<th>Male</th>
<th>Female</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>18-29</td>
<td>18.29</td>
<td>18.29</td>
<td>16.239</td>
</tr>
<tr>
<td>30-49</td>
<td>30.49</td>
<td>30.49</td>
<td>30.49</td>
</tr>
<tr>
<td>50+</td>
<td>50+</td>
<td>50+</td>
<td>50+</td>
</tr>
</tbody>
</table>

Table 4-1: Sample expected frequency distribution.
A total of 117 cyclists were recruited for this study over an 8-month period (2014). Twenty-two percent were recruited at RMIT University (staff and students), while the remainder were recruited at local bike shops. The sample included the following participants (Table 4-2):

Table 4-2: Sample count and frequency

<table>
<thead>
<tr>
<th>Age Groups</th>
<th>Male</th>
<th>Female</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>18-29</td>
<td>31</td>
<td>11</td>
<td>42</td>
</tr>
<tr>
<td>30-49</td>
<td>48</td>
<td>10</td>
<td>58</td>
</tr>
<tr>
<td>50+</td>
<td>15</td>
<td>2</td>
<td>17</td>
</tr>
<tr>
<td>Total</td>
<td>94</td>
<td>23</td>
<td>117</td>
</tr>
</tbody>
</table>

A chi-square goodness-of-fit test was conducted to determine if the sample followed the expected distribution from Table 4-1. The minimum expected frequency was 8.9. The chi-square goodness-of-fit test indicated that the sample distribution was statistically significantly different ($\chi^2(5) = 23.135, p < .01$). The study’s sample was biased in terms of gender and age, with too many males over females, and too many young people over older adults (the middle-age men category was also over-represented). The consequences of these biases on the study’s results are discussed in Section 4.3.5.

The cyclists surveyed were self-classified as Australasian (48.7%), European (24.8%), Asian (17.9%) or Other (8.6%). Australasians were considered as Caucasians if they did not specify an ethnic background from Asia, Africa, America or a Middle East country. Ninety-five percent of the volunteers claimed to always wear a helmet while cycling.

4.3.2 Measurements and Assessments: Qualitative Survey

Participants were asked to complete a self-administered questionnaire, including demographics (gender, age and ethnicity, mass and height), cycling type (recreational, competition, commuter), helmet use, helmet fit requirements (helmet fit user ideal and helmet fit user importance) and helmet fit assessments. Full descriptions of the survey questions are provided in Section 3.2.2 and Appendix A. Questions regarding helmet fit requirements and assessments were recorded on a 10-point scale for the Helmet Fit User Ideal (Fid), the Helmet Fit User Importance (Fim), and the Fit Assessments Scores ($F_X$). The $F_X$ was recorded on the global and local regions of the head for the three selected helmets.

Table 4-3 below lists the 20 qualitative variables recorded for each individual participant on a 10-point scale.
Table 4-3: Qualitative Variables.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Helmet fit user ideal</td>
<td>Fid</td>
</tr>
<tr>
<td>Helmet fit user importance</td>
<td>Fim</td>
</tr>
<tr>
<td>Helmet X&quot; Global Fit Assessment</td>
<td>FxG</td>
</tr>
<tr>
<td>Helmet X&quot; Front Fit Assessment</td>
<td>FxF</td>
</tr>
<tr>
<td>Helmet X&quot; Top Fit Assessment</td>
<td>FxT</td>
</tr>
<tr>
<td>Helmet X&quot; Right Fit Assessment</td>
<td>FxR</td>
</tr>
<tr>
<td>Helmet X&quot; Left Fit Assessment</td>
<td>FxL</td>
</tr>
<tr>
<td>Helmet X&quot; Back Fit Assessment</td>
<td>FxB</td>
</tr>
</tbody>
</table>

"X takes the value A, B and C for the three helmets studied.

Table 4-4 shows the median values (with 95.8% CI) for these qualitative parameters. In general, helmets A and B provided a better-perceived fit than helmet C. The medians for helmet fit ideal (Fid) and helmet fit importance (Fim) were 7 and 8, respectively.

Table 4-4: Median values (with 95.8% CI) of the qualitative parameters in this study for the three bicycle helmets tested.

<table>
<thead>
<tr>
<th>Region</th>
<th>Parameters</th>
<th>Helmet A</th>
<th>Helmet B</th>
<th>Helmet C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>FxG</td>
<td>6 (5, 6)</td>
<td>6 (5, 7)</td>
<td>4 (4, 5)</td>
</tr>
<tr>
<td>Front</td>
<td>FxF</td>
<td>6 (5, 6)</td>
<td>6 (5, 7)</td>
<td>4 (4, 5)</td>
</tr>
<tr>
<td>Top</td>
<td>FxT</td>
<td>6 (5, 7)</td>
<td>7 (6, 7)</td>
<td>5 (4, 6)</td>
</tr>
<tr>
<td>Right</td>
<td>FxR</td>
<td>5 (4, 6)</td>
<td>6 (5, 7)</td>
<td>4 (3, 4)</td>
</tr>
<tr>
<td>Left</td>
<td>FxL</td>
<td>5 (4, 6)</td>
<td>6 (5, 7)</td>
<td>4 (3, 4)</td>
</tr>
<tr>
<td>Back</td>
<td>FxB</td>
<td>5 (5, 6)</td>
<td>6 (5, 7)</td>
<td>4 (4, 5)</td>
</tr>
<tr>
<td></td>
<td>Fid</td>
<td></td>
<td>7 (7, 7)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Fim</td>
<td></td>
<td>8 (8, 9)</td>
<td></td>
</tr>
</tbody>
</table>

4.3.3 Measurements and Assessments: Quantitative Survey

4.3.3.1 3D Anthropometry: Data Collection and Processing

A description of how the 3D anthropometric data were collected and processed for the present study was provided in Section 3.4. Figure 4-1 shows an example of a participant 3D head scan after the post-processing procedures were applied.
4.3.3.2 Bicycle Helmet Reverse Engineering and Data Preparation

The reverse engineering process of the three selected helmets is presented in Section 3.3. Further to this work, a simplified 3D representation of the models was created to only retain the inside surfaces of the helmet liner for the analysis. Figure 4-2(a) shows the final inside surface of the Met Kaos helmet after careful trim and accurate area selection.

The fit analysis was performed both globally and locally to assess if the fit was similar throughout the whole head shape. Consequently, the inside mesh of the helmet liner was further divided into five regions, namely, front, top, right, left, and back, as shown in Figure 4-2(b).

4.3.3.3 Scans Alignment

Each participant took part in four 3D scans of their head and face. The first scan was with a wig.
cap only, as shown in Figure 4-1, and three scans were with each of the selected helmets on their head. Participants were asked to reproduce the same seating posture and facial expression for the four scans. Foam pads, chin strap, and the adjusting system were excluded during the fit analysis process, as the objective of the study was to investigate how well the helmet liner matched with the head shape of the participant. Figure 4-3 shows an example of the four recorded 3D scans of a participant.

Figure 4-3: The four 3D head scans of the fit assessment analysis. From left to right, the scanned head, the scanned head and the Met Crossover helmet, the scanned head and the Met Kaos helmet, the scanned head and the Netti Lightning.

For each selected helmet, the three scans (Figure 4-4) were then aligned using the n-points manual registration and the global registration algorithms within Geomagic Studio 12®. The alignment process was split into two stages: (i) aligning the head scan and the intermediate scan (Figure 4-5) using the face polygons of the participant; and (ii) aligning the helmet scan with the intermediate scan (Figure 4-6) using the helmet surfaces.

Figure 4-4: Three scans for alignment. Yellow: head scan. Blue: Intermediate scan. Orange: Helmet scan.
Figure 4-5: Head/intermediate scan alignment. From left to right: Face polygons selection for global registration (red), proper overlapping between the meshes, deviation analysis (green is < to ±0.1mm).

Figure 4-6: Intermediate/helmet scan alignment. From left to right: Helmet polygons selection for global registration (red), proper overlapping between the meshes, deviation analysis (green is < to ±0.2mm).

After the two-stages alignment process had been completed, the intermediate scan was then removed, and the head and helmet scans were now aligned accurately (Figure 4-7). This alignment method permitted the clean inspection of the gap between the head and helmet liner.

Figure 4-7: Final Alignment
4.3.3.4 Gap Analysis

4.3.3.4.1 Standoff Distance and Gap Uniformity

In this analysis, the gap distribution between the head mesh and the inside of the helmet was calculated. Two parameters were determined: (i) the Standoff Distance (SOD), which was defined as the average minimal distance between the head shape and all the points that defined the inside mesh of the liner; and (ii) the Gap Uniformity (GU), which was the standard deviation of the gap distribution defined as the dispersion from the average.

A distance analysis tool available in CATIA V5R21 (Dassault Système, Vélizy-Villacoublay, France) was used to measure the gap between the head and the inside liner meshes. The gap was first analyzed for any negative values that would indicate interference between the two meshes. Interference can be caused either by inaccurate alignment between the meshes or by the hair thickness of the participant. The participant’s hair was likely to be compressed under the helmet’s weight during fitting. Extra hair thickness, which was assumed to be uniform across the whole head, was considered during the gap analysis. Artifact points were removed from the gap analysis result, and the head scan was offset by the maximum negative deviation. Distance analysis was then recalculated, and the SOD and GU were recorded. Figure 4-8 shows the gap analysis with colour texture maps before and after the hair thickness was offset.

Figure 4-8: Gap analysis texture maps before (interferences marked in the red circle) and after the offset. Hair thickness was 0.62mm, and SOD and GU were 5.98mm and 2.92mm, respectively.
In addition, similar deviation analyses were conducted in the five local regions, where the SOD and GU were recorded. Figure 4-9 shows the gap analysis of the right region.

Figure 4-9: Gap analysis on the right region. The SOD and GU were 6.11mm and 1.84mm, respectively.

4.3.3.4.2 Proportion of Head under Helmet Protection

The helmet should cover as much skull area as possible to provide maximum protection to the wearer. However, for some human head shapes, commercially available helmet models might provide only minimal total coverage area and reduce intended protection capability. The AS/NZS 2512.1:2009 Methods of testing protective helmets Part 1: Definitions and headforms [38] defines a test line around the head to which the helmet is supposed to extend. Dimensions for the test line were based on the Bitragion coronal and inion arcs, and the mid-Sagittal arc. In this analysis, the dimensions of the head length, breadth and circumference were added to define an area that should be under the helmet protection for each participant (magenta area in Figure 4-10(a)).

The proportion of the head mesh under helmet protection was determined by projecting the boundary edges of the inside liner onto the test area (green area in Figure 4-10(b)). This fit parameter was named the Head Protection Proportion (HPP). Its value ranged between 0 and 1.
4.3.3.4.3 Formulae of the HELMET-FIT-INDEX (HFI)

The HELMET-FIT-INDEX (HFI) provides a fit score for a particular helmet model and a human head. The index was defined on a scale from 0 (excessively poor fit) to 100 (perfect fit). The probability density function, \( f \), of an exponential distribution was used to generate the index and is described as follows:

\[
    f(x; \lambda) = \begin{cases} 
    \lambda \exp(-\lambda x) & x \geq 0, \\
    0 & x < 0. 
    \end{cases}
\]  \( (5) \)

where \( \lambda > 0 \) is the parameter of the distribution called the rate parameter; \( x \) is defined as a function of the SOD, GU, and HPP (it tends to approach 0 when the fit is improved).

The probability density function was established on the exponential distribution, as its right tail is relatively short and may be considered as having moderate skew (i.e., few outliers). A distribution with fewer outliers will produce more statistically significant results [145].

The SOD optimal value should be greater than zero to allow for a gap for thermal ventilation control throughout the helmet and the addition of thin foam paddings for comfort. However, previous research showed that an excessive standoff distance would decrease the helmet protective function during a crash [18]. For this reason, the SOD was considered to be optimum when it was in the range between 4 and 8 mm.

GU is a critical parameter when analysing the dispersion of the distance distribution. Seemingly, the fit is optimal when the standoff distance is uniformly distributed over the whole liner surface, which is equivalent to a lower deviation from the mean. Hence, the gap
becomes more uniform when GU approaches zero. Likewise, fit improves when the HPP approaches 1, which corresponds to a higher coverage area of the head provided by the helmet.

The fit parameter $x$, was defined as:

$$x = \begin{cases} 
  a \ast (|SOD - 6| - 2) + b \ast \frac{GU}{HPP} & \text{for } 4 > SOD > 8 \\
  b \ast \frac{GU}{HPP} & \text{for } 4 \leq SOD \leq 8 
\end{cases}$$

(6)

Where $a$ and $b$ are calculated as coefficient parameters. $a = \frac{2}{3}$ and $b = \frac{6}{5}$, respectively.

The value for $\lambda$ was based on two short observational studies. The range of $x$ was first analysed for 20 participants of the survey’s sample. Figure 4-5 summarises the results for the parameters included in the HFI equation. The global $x$ distributions show two extreme poor fit for participants No. 2 and No. 7 ($x = 20.1$ and 16.1 respectively) with large SODs and GUs. Only 60.7% of the head test area for participant No. 2 was protected by the helmet. The $x$ value for the other 18 participants ranged from 4.5 to 11.5 and with a mean value of 8.0.

Table 4-5: Analysis of $x$ range for 20 participants.

<table>
<thead>
<tr>
<th>No.</th>
<th>Gender</th>
<th>Helmet Size</th>
<th>Hair Thickness (mm)</th>
<th>SOD (mm)</th>
<th>GU (mm)</th>
<th>Test Area (mm$^2$)</th>
<th>Actual Helmet Protection Area (mm$^2$)</th>
<th>HPP</th>
<th>$x$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Male</td>
<td>Medium</td>
<td>3.35</td>
<td>6.76</td>
<td>3.40</td>
<td>66190</td>
<td>56610</td>
<td>0.855</td>
<td>4.8</td>
</tr>
<tr>
<td>2</td>
<td>Male</td>
<td>Large</td>
<td>0.11</td>
<td>15.61</td>
<td>7.60</td>
<td>76670</td>
<td>46530</td>
<td>0.607</td>
<td>20.1</td>
</tr>
<tr>
<td>3</td>
<td>Female</td>
<td>Medium</td>
<td>3.36</td>
<td>11.06</td>
<td>4.34</td>
<td>62150</td>
<td>50680</td>
<td>0.815</td>
<td>8.5</td>
</tr>
<tr>
<td>4</td>
<td>Male</td>
<td>Large</td>
<td>3.22</td>
<td>10.50</td>
<td>4.36</td>
<td>70400</td>
<td>56350</td>
<td>0.800</td>
<td>8.2</td>
</tr>
<tr>
<td>5</td>
<td>Male</td>
<td>Medium</td>
<td>3.79</td>
<td>9.17</td>
<td>4.11</td>
<td>66820</td>
<td>52570</td>
<td>0.787</td>
<td>7.1</td>
</tr>
<tr>
<td>6</td>
<td>Male</td>
<td>Medium</td>
<td>4.46</td>
<td>8.11</td>
<td>2.98</td>
<td>68840</td>
<td>54830</td>
<td>0.796</td>
<td>4.6</td>
</tr>
<tr>
<td>7</td>
<td>Female</td>
<td>Large</td>
<td>9.22</td>
<td>16.94</td>
<td>7.34</td>
<td>63640</td>
<td>55320</td>
<td>0.869</td>
<td>16.1</td>
</tr>
<tr>
<td>8</td>
<td>Male</td>
<td>Large</td>
<td>1.44</td>
<td>9.58</td>
<td>4.68</td>
<td>63240</td>
<td>53980</td>
<td>0.854</td>
<td>7.7</td>
</tr>
<tr>
<td>9</td>
<td>Male</td>
<td>Large</td>
<td>3.74</td>
<td>12.02</td>
<td>4.64</td>
<td>63140</td>
<td>54920</td>
<td>0.870</td>
<td>9.1</td>
</tr>
<tr>
<td>10</td>
<td>Male</td>
<td>Medium</td>
<td>4.36</td>
<td>7.73</td>
<td>3.31</td>
<td>62430</td>
<td>54680</td>
<td>0.876</td>
<td>4.5</td>
</tr>
<tr>
<td>11</td>
<td>Male</td>
<td>Large</td>
<td>2.88</td>
<td>9.28</td>
<td>3.67</td>
<td>72060</td>
<td>56265</td>
<td>0.781</td>
<td>6.5</td>
</tr>
<tr>
<td>12</td>
<td>Female</td>
<td>Medium</td>
<td>4.41</td>
<td>8.97</td>
<td>3.48</td>
<td>63170</td>
<td>54340</td>
<td>0.860</td>
<td>5.5</td>
</tr>
<tr>
<td>13</td>
<td>Male</td>
<td>Large</td>
<td>1.22</td>
<td>9.07</td>
<td>3.70</td>
<td>62740</td>
<td>54590</td>
<td>0.870</td>
<td>5.8</td>
</tr>
<tr>
<td>14</td>
<td>Male</td>
<td>Medium</td>
<td>2.04</td>
<td>7.41</td>
<td>3.33</td>
<td>67190</td>
<td>53700</td>
<td>0.799</td>
<td>5.0</td>
</tr>
<tr>
<td>15</td>
<td>Male</td>
<td>Large</td>
<td>7.62</td>
<td>14.17</td>
<td>5.18</td>
<td>67420</td>
<td>56733</td>
<td>0.841</td>
<td>11.5</td>
</tr>
<tr>
<td>16</td>
<td>Female</td>
<td>Medium</td>
<td>2.98</td>
<td>10.37</td>
<td>5.55</td>
<td>50403</td>
<td>51140</td>
<td>0.947</td>
<td>8.6</td>
</tr>
<tr>
<td>17</td>
<td>Male</td>
<td>Medium</td>
<td>2.88</td>
<td>7.12</td>
<td>3.59</td>
<td>75030</td>
<td>53415</td>
<td>0.712</td>
<td>6.1</td>
</tr>
<tr>
<td>18</td>
<td>Female</td>
<td>Medium</td>
<td>7.35</td>
<td>10.17</td>
<td>3.74</td>
<td>64680</td>
<td>57100</td>
<td>0.883</td>
<td>6.6</td>
</tr>
</tbody>
</table>

76
The expected $x$ value was also analysed from previously published 1D anthropometric studies using 1st and 99th percentile head measurements of males and females [71, 73]. Based on these observations, it was predicted that $x$ would rarely exceed the 30-point mark. Such a high value for $x$ would represent an exceptionally low fit. Therefore, it was decided to assign 0.1 to $\lambda$ and multiply the function by 1000 to define the HFI equation. The HFI function is shown in Figure 4-11 (e.g., with $x = 30$, $HFI = 5$).

\[
HFI: \quad [0; \infty) \rightarrow (0; 100) \\
x \mapsto 100 \times \exp(-0.1x)
\]  

Figure 4-11: HFI graph.

Replacing $x$ in Eq. (7) and rounding up to two decimal points gives:

\[
HFI = \begin{cases} 
100 \times \exp \left(0.13 - \frac{|SOD - 6|}{15} - 0.12\frac{GU}{HPP}\right) & \text{for } 4 > SOD > 8 \\
100 \times \exp \left(-\frac{0.12GU}{HPP}\right) & \text{for } 4 \leq SOD \leq 8 
\end{cases}
\]  

Similarly, an HFI score was developed for local regions based only on the local SOD and GU values. The proposed equation is expressed as follows:
$$HFI_{local} = \begin{cases} 
100 \times \exp \left( 0.13 - \frac{|SOD - 6|}{15} - 0.12GU \right) & \text{for } 4 > SOD > 8 \\
100 \times \exp(-0.12GU) & \text{for } 4 \leq SOD \leq 8 
\end{cases}$$

(9)

4.3.3.5 Quantitative Survey Summary

Table 4-6 summarizes all 57 quantitative variables generated for each participant. HFI was defined for six regions (one global and five locals) based on two or three parameters (SOD, GU and HPP (only for global)) and for three different helmet models.

Table 4-6: Quantitative Variables.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Helmet X - Standoff Distance</td>
<td>SODx</td>
</tr>
<tr>
<td>Helmet X - Gap Uniformity</td>
<td>GUx</td>
</tr>
<tr>
<td>Helmet X - Helmet Under Protection</td>
<td>HPPx</td>
</tr>
<tr>
<td>Helmet X - HELMET-FIT-INDEX</td>
<td>HFIx</td>
</tr>
<tr>
<td>Helmet X - Standoff Distance Front</td>
<td>SODxF</td>
</tr>
<tr>
<td>Helmet X - Gap Uniformity Front</td>
<td>GUxF</td>
</tr>
<tr>
<td>Helmet X - HELMET-FIT-INDEX Front</td>
<td>HFIxF</td>
</tr>
<tr>
<td>Helmet X - Standoff Distance Top</td>
<td>SODxT</td>
</tr>
<tr>
<td>Helmet X - Gap Uniformity Top</td>
<td>GUxT</td>
</tr>
<tr>
<td>Helmet X - HELMET-FIT-INDEX Top</td>
<td>HFIxT</td>
</tr>
<tr>
<td>Helmet X - Standoff Distance Right</td>
<td>SODxR</td>
</tr>
<tr>
<td>Helmet X - Gap Uniformity Right</td>
<td>GUxR</td>
</tr>
<tr>
<td>Helmet X - HELMET-FIT-INDEX Right</td>
<td>HFIxR</td>
</tr>
<tr>
<td>Helmet X - Standoff Distance Left</td>
<td>SODxL</td>
</tr>
<tr>
<td>Helmet X - Gap Uniformity Left</td>
<td>GUxL</td>
</tr>
<tr>
<td>Helmet X - HELMET-FIT-INDEX Left</td>
<td>HFIxL</td>
</tr>
<tr>
<td>Helmet X - Standoff Distance Back</td>
<td>SODxB</td>
</tr>
<tr>
<td>Helmet X - Gap Uniformity Back</td>
<td>GUxB</td>
</tr>
<tr>
<td>Helmet X - HELMET-FIT-INDEX Back</td>
<td>HFIxB</td>
</tr>
</tbody>
</table>

*X takes the value A, B and C for the three helmets studied.

Table 4-7 lists the mean values of the quantitative parameters created in this study for the three selected helmets. Overall, helmet B provides a better quantitative fit than A and C. However, the top region of the head was better fitted by helmet C, and the sides and back regions by helmet A.
Table 4-7: Mean values (with 95% CI) of the quantitative parameters in this study for the three bicycle helmets tested.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Parameters</th>
<th>Helmet A</th>
<th>Helmet B</th>
<th>Helmet C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SODx</td>
<td>9.1 (8.79.57)</td>
<td>8.3 (7.9.87)</td>
<td>10.0 (9.5.10.5)</td>
</tr>
<tr>
<td></td>
<td>GUx</td>
<td>3.9 (3.7.4.0)</td>
<td>3.8 (3.6.4.0)</td>
<td>4.2 (4.1.4.4)</td>
</tr>
<tr>
<td></td>
<td>HPPx</td>
<td>.829 (.819.838)</td>
<td>.850 (.841.859)</td>
<td>.826 (.817.834)</td>
</tr>
<tr>
<td></td>
<td>HFIx (/100)</td>
<td>52.9 (51.0.54.7)</td>
<td>55.7 (53.6.57.7)</td>
<td>48.3 (46.1.50.5)</td>
</tr>
<tr>
<td>Front</td>
<td>SODxF</td>
<td>10.0 (9.4.10.6)</td>
<td>9.8 (9.2.10.4)</td>
<td>12.4 (11.8.13.0)</td>
</tr>
<tr>
<td></td>
<td>GUxF</td>
<td>3.2 (3.1.3.4)</td>
<td>2.4 (2.2.2.5)</td>
<td>4.1 (4.0.4.3)</td>
</tr>
<tr>
<td></td>
<td>HFIxF (/100)</td>
<td>58.9 (56.7.61.1)</td>
<td>65.3 (62.9.67.7)</td>
<td>47.1 (44.9.49.3)</td>
</tr>
<tr>
<td>Top</td>
<td>SODxT</td>
<td>9.1 (8.7.9.6)</td>
<td>5.9 (5.6.6.3)</td>
<td>4.9 (4.7.5.2)</td>
</tr>
<tr>
<td></td>
<td>GUxT</td>
<td>4.2 (4.1.4.3)</td>
<td>2.7 (2.6.2.9)</td>
<td>2.4 (2.2.2.5)</td>
</tr>
<tr>
<td></td>
<td>HFIxT (/100)</td>
<td>55.8 (54.2.57.4)</td>
<td>71.7 (70.6.72.9)</td>
<td>74.4 (73.5.75.3)</td>
</tr>
<tr>
<td>Right</td>
<td>SODxR</td>
<td>9.0 (8.5.9.5)</td>
<td>10.4 (9.8.11.0)</td>
<td>10.9 (10.4.11.5)</td>
</tr>
<tr>
<td></td>
<td>GUxR</td>
<td>2.7 (2.6.2.9)</td>
<td>2.7 (2.5.2.9)</td>
<td>2.9 (2.7.3.0)</td>
</tr>
<tr>
<td></td>
<td>HFIxR (/100)</td>
<td>66.1 (64.1.68.0)</td>
<td>61.8 (59.4.64.3)</td>
<td>59.2 (56.8.61.6)</td>
</tr>
<tr>
<td>Left</td>
<td>SODxL</td>
<td>8.9 (8.4.9.4)</td>
<td>8.9 (8.3.9.4)</td>
<td>10.6 (9.9.11.2)</td>
</tr>
<tr>
<td></td>
<td>GUxL</td>
<td>2.8 (2.6.2.9)</td>
<td>3.0 (2.8.3.2)</td>
<td>3.0 (2.8.3.1)</td>
</tr>
<tr>
<td></td>
<td>HFIxL (/100)</td>
<td>65.8 (63.8.67.8)</td>
<td>63.6 (61.2.66.0)</td>
<td>59.6 (57.0.62.2)</td>
</tr>
<tr>
<td>Back</td>
<td>SODxB</td>
<td>8.9 (8.4.9.4)</td>
<td>8.9 (8.3.9.4)</td>
<td>10.6 (9.9.11.2)</td>
</tr>
<tr>
<td></td>
<td>GUxB</td>
<td>2.8 (2.6.2.9)</td>
<td>3.0 (2.8.3.2)</td>
<td>3.0 (2.8.3.1)</td>
</tr>
<tr>
<td></td>
<td>HFIxB (/100)</td>
<td>64.2 (61.8.66.6)</td>
<td>61.7 (59.2.64.2)</td>
<td>61.1 (58.1.64.1)</td>
</tr>
</tbody>
</table>

4.3.4 Data analysis: Association between qualitative and quantitative data

The main objective of this section is to determine if the quantitative data (HFIs) are appropriate estimates of the qualitative data (Fit assessment scores FxG) for helmet fit assessment. Three ordinal Logistic Regression model are used as well as a Friedman test, a one-way repeated measure ANOVA, and a hypothesis test for proportions to assess the strength of this association. The detailed description of the statistical analysis is available in Appendices E to L.

4.3.4.1 Prediction of Helmet fit assessment using the HFI

Data for each helmet were first analysed independently using ordered logistic regression where relationships between the independent variables (age, gender, Fim, Fid and HFIs) and dependent variables (FxG) were assessed. Odds ratios (OR) for a higher score in perceived helmets fit for the three helmets, given the independent variables, were determined when suitable. (See Appendix E for a short description of the Ordinal Logistic Regression test.)
Three cumulative odds ordinal logistic regression with proportional odds were performed (one per helmet to keep the assumption of independence of observations correct) to determine if the level of perceived helmet fit could be predicted based on age, HFI, Fid and Fim scores. The 10 ordinal levels of the fit assessment score were grouped together (2 by 2) to decrease the number of cells with zero frequencies in the model. The five values of the ordinal dependent variable (FxG) are listed in Table 4-8 and a description of its four cumulative categories is given in Table 4-9.

Table 4-8: The ordinal dependent variable FxG.

<table>
<thead>
<tr>
<th>FxG scores</th>
<th>[1-2]</th>
<th>[3-4]</th>
<th>[5-6]</th>
<th>[7-8]</th>
<th>[9-10]</th>
</tr>
</thead>
<tbody>
<tr>
<td>FxG values</td>
<td>“Very Low”</td>
<td>“Low”</td>
<td>“Neutral”</td>
<td>“High”</td>
<td>“Very High”</td>
</tr>
</tbody>
</table>

Table 4-9: The cumulative categories of the ordinal dependent variable FxG.

<table>
<thead>
<tr>
<th>Cumulative category</th>
<th>Target Category</th>
<th>Other categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cat. 1</td>
<td>( \text{Prob(cat.} \leq 1 ) i.e., “Very Low” )</td>
<td>( \text{Prob(cat.} &gt; 1 ) i.e., “Low”, “Neutral”, “High” and “Very High” )</td>
</tr>
<tr>
<td>Cat. 2</td>
<td>( \text{Prob(cat.} \leq 2 ) i.e., “Very Low” and “Low” )</td>
<td>( \text{Prob(cat.} &gt; 2 ) i.e., “Neutral”, “High” and “Very High” )</td>
</tr>
<tr>
<td>Cat. 3</td>
<td>( \text{Prob(cat.} \leq 3 ) i.e., “Very Low”, “Low” and “Neutral” )</td>
<td>( \text{Prob(cat.} &gt; 3 ) i.e., “High” and “Very High” )</td>
</tr>
<tr>
<td>Cat. 4</td>
<td>( \text{Prob(cat.} \leq 4 ) i.e., “Very Low”, “Low”, “Neutral” and “High” )</td>
<td>( \text{Prob(cat.} &gt; 4 ) i.e., “Very High” )</td>
</tr>
</tbody>
</table>

*No Multicollinearity*

The assumption of no multicollinearity was met, as assessed by the VIF (Appendix E) values being inferior to 10 for each of the independent variables (including dummy variables). Similar results were shown for the three tested helmets.

*Proportional odds*

The assumption of proportional odds was also met, as assessed by comparing the similarities between odds ratios of multiple separate binomial logistic regressions run on the four cumulative categories of the dichotomous dependent variables. Table 4-10 shows the Odds Ratio (OR) for two of the independent variables (i.e., age and HFI scores) for each of the cumulative categories and for the three studied helmets.
Table 4-10: Assumption of proportional odds - Multiple separate binomial logistic regressions - Odd Ratios.

<table>
<thead>
<tr>
<th>Cumulative category</th>
<th>HFI Odds Ratios</th>
<th>Age Odds Ratios</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Cat. 1</td>
<td>0.980</td>
<td>0.971</td>
</tr>
<tr>
<td>Cat. 2</td>
<td>0.969</td>
<td>0.932</td>
</tr>
<tr>
<td>Cat. 3</td>
<td>0.970</td>
<td>0.919</td>
</tr>
<tr>
<td>Cat. 4</td>
<td>0.890</td>
<td>0.963</td>
</tr>
</tbody>
</table>

**Model Fit**

The deviance goodness-of-fit test indicated that the models were of excellent fit to the observed data ($\chi^2(460) = 326.280, p = 1.000$, $\chi^2(460) = 318.165, p = 1.000$ and $\chi^2(460) = 331.100, p = 1.000$ for helmets A, B and C, respectively), but most cells were sparse with zero frequencies in 80.0% of cells. However, for helmets A and B, the final models statistically significantly predicted the dependent variable over and above the intercept-only model ($\chi^2(4) = 12.151, p < .05$ for A, and $\chi^2(4) = 16.855, p < .005$ for B).

**Results of the regression models**

An increase in one unit of HFI score was associated with an increase in the odds of a higher score in the perceived helmet fit, with an OR of 1.041 (95% CI, 1.006 to 1.078), $Wald \chi^2(1) = 5.170, p < .05$ for helmet A, and 1.063 (95% CI, 1.030 to 1.098), $Wald \chi^2(1) = 13.845, p < .0005$ for helmet B.

A change in HFI score for helmet C was not associated with a change in how participants scored the fit of the helmet.

An increase in age (expressed in years) was associated with a decrease in the odds of a higher score in the perceived fit of helmet A, with an OR of 1.040 (95% CI, 1.008 to 1.073), $Wald \chi^2(1) = 6.056, p < .05$. A change in Fid or Fim score was not associated with how participants perceived helmet fit for the three helmets studied.

**4.3.4.2 Differences in the subjective assessment of helmet fit**

A Friedman test (Appendix F) was run to determine if there were differences in the subjective assessment of helmet fit for the global and local regions of the three selected helmet models. Pairwise comparisons were performed (SPSS, 2012) with a Bonferroni correction for multiple comparisons.
**Global region**

The test statistic Q was estimated by a chi-squared distribution due to the large number of participants in the study ($n = 117 > 15$). The chi-square test was statistically significant ($\chi^2(2) = 38.429, p < .0005$), leading to the conviction of differences for the fit assessment scores of the three selected helmet models.

Mean Ranks were 2.11, 2.31 and 1.59 for helmets A, B and C, respectively (Figure 4-12). Generally, helmet B had been ranked by participants to have a better fit than helmets A and C, and helmet C had been ranked the worst as compared with helmets A and B. Post hoc analysis revealed statistically significant differences in terms of perceived fit for helmets A ($Mdn = 6$) and C ($Mdn = 4$) ($p < .0005$), and helmet B ($Mdn = 6$) and C ($Mdn = 4$) ($p < .0005$), but not for helmets A and B.

![Figure 4-12: Mean ranks for subjective assessments of helmet fit.](image)

**Local regions of the head**

The comparative results are presented in Table 4-11. Fit assessments were statistically different for the three helmet models at the local regions, and post hoc analysis revealed statistically significant differences for all regions between helmet A and C, (A higher ranking than C) and B and C (B higher ranking than C), but not A and B.
Table 4-11: Friedman’s test differences between subjective assessments of helmet fit for different test helmets.

<table>
<thead>
<tr>
<th></th>
<th>Median A</th>
<th>Median B</th>
<th>Median C</th>
<th>Mean Ranking A</th>
<th>Mean Ranking B</th>
<th>Mean Ranking C</th>
<th>Friedman’s test</th>
<th>Post Hoc Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>6</td>
<td>6</td>
<td>4</td>
<td>2.11</td>
<td>2.31</td>
<td>1.59</td>
<td>( \chi^2(2) = 38.429^* )</td>
<td>* *</td>
</tr>
<tr>
<td>Front</td>
<td>6</td>
<td>6</td>
<td>4</td>
<td>2.14</td>
<td>2.26</td>
<td>1.59</td>
<td>( \chi^2(2) = 37.522^* )</td>
<td>* *</td>
</tr>
<tr>
<td>Top</td>
<td>6</td>
<td>7</td>
<td>5</td>
<td>2.12</td>
<td>2.24</td>
<td>1.63</td>
<td>( \chi^2(2) = 29.376^* )</td>
<td>** *</td>
</tr>
<tr>
<td>Right</td>
<td>5</td>
<td>6</td>
<td>4</td>
<td>2.06</td>
<td>2.30</td>
<td>1.65</td>
<td>( \chi^2(2) = 32.319^* )</td>
<td>** *</td>
</tr>
<tr>
<td>Left</td>
<td>5</td>
<td>6</td>
<td>4</td>
<td>2.05</td>
<td>2.30</td>
<td>1.65</td>
<td>( \chi^2(2) = 31.381^* )</td>
<td>** *</td>
</tr>
<tr>
<td>Back</td>
<td>5</td>
<td>6</td>
<td>4</td>
<td>2.11</td>
<td>2.27</td>
<td>1.62</td>
<td>( \chi^2(2) = 34.234^* )</td>
<td>* *</td>
</tr>
</tbody>
</table>

* = statistically significant at \( p < .0005 \) level, ** = statistically significant at \( p < .001 \) level

4.3.4.3 Differences in HFIs

A one-way repeated measures ANOVA (Appendix G) was conducted to determine whether there were statistically significant differences in the global HFI scores for the three selected bicycle helmet models. Data are presented as mean ± standard deviation unless otherwise specified.

Outliers

Two outliers in the HFI distribution of helmet A were detected (\( HFI_A = 13.4 \) and 19.9). It was decided to keep them for the analysis after discovering no differences in the final result when running the same test with and without these two points.

Distributions

The distribution of the three within-factor levels was assessed. The three distributions were not normally distributed with a slight negative skewness (skewness = −1.013, −0.753, −0.501 with standard error = 0.224 and kurtosis = 1.648, −0.004, −0.457 with standard error = 0.444 for helmets A, B and C, respectively). However, the test was conducted because the levels of the within-subjects factor were similarly skewed.

Sphericity

The assumption of sphericity was violated, as assessed by Mauchly’s test of sphericity, \( \chi^2(2) = 24.973, p < .0005 \). Therefore, a Greenhouse-Geisser correction was applied (\( \varepsilon = 0.837 \)).

One-way repeated measures ANOVA results

The HFIs scores showed statistically significant differences for the three helmet models \( (F(1.673,194.111) = 45.289, p < .0005, \text{ partial } \eta^2 = 0.281) \), with HFI means equal to

83
52.9 ± 10.0, 55.7 ± 11.4 and 48.3 ± 12.0 for helmets A, B and C, respectively.

Post Hoc Tests

Post hoc analysis with a Bonferroni adjustment revealed that HFI means were statistically significant between all helmet combinations. Differences were −2.8 (95% CI, −4.6 to −1.0, \( p < .001 \)) for helmets A and B, 4.6 (95% CI, 2.3 to 6.9, \( p < .0005 \)) for helmets A and C, and 7.4 (95% CI, 5.8 to 9.0, \( p < .0005 \)) for helmets B and C. On average, helmet B provided the highest HFI score, followed by helmets A and C.

Local regions of the head

Similar tests on local regions were computed and are summarised in Table 4-12. Helmet A performed better in the right, left and back regions, helmet B performed better in the front region, and helmet C performed better in the top region.

In the post-hoc analysis, a difference of 3 HFI units (close to the measurement error for the design steps used in the HFI computation) or greater was required to indicate practical importance.

Table 4-12: One way repeated measures ANOVA on the 3 helmets HFIs.

<table>
<thead>
<tr>
<th></th>
<th>HFI means</th>
<th>Sphericity</th>
<th>Repeat ANOVA</th>
<th>Post Hoc Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td></td>
</tr>
<tr>
<td>Global</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>52.9 ± 10.0</td>
<td>55.7 ± 11.4</td>
<td>48.3 ± 12.0</td>
<td>F (1.673,194.111) = 45.289*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Front</td>
<td>58.9 ± 12.2</td>
<td>65.3 ± 13.4</td>
<td>47.1 ± 12.3</td>
<td>F (1.836,213.014) = 244.358*</td>
</tr>
<tr>
<td>Top</td>
<td>55.8 ± 8.7</td>
<td>71.7 ± 6.4</td>
<td>74.4 ± 5.0</td>
<td>F (1.512,175.372) = 405.109*</td>
</tr>
<tr>
<td>Right</td>
<td>66.1 ± 10.6</td>
<td>61.8 ± 13.6</td>
<td>59.2 ± 13.0</td>
<td>F (2.232) = 32.264*</td>
</tr>
<tr>
<td>Left</td>
<td>65.8 ± 11.1</td>
<td>63.6 ± 13.2</td>
<td>59.6 ± 14.2</td>
<td>F (2.232) = 18.668*</td>
</tr>
<tr>
<td>Back</td>
<td>64.2 ± 13.7</td>
<td>61.7 ± 13.7</td>
<td>61.1 ± 16.5</td>
<td>F (1.798,208.614) = 6.159**</td>
</tr>
</tbody>
</table>
4.3.4.4 HFI capability of finding the best and worst perceived helmet fit

A hypothesis test for a proportion (Appendix H) was run to establish the capability of the HFI to select the best and worst perceived fitted helmet for each participant, given the three distinct models.

The probability $p_0$ of identifying the best helmet fit was 0.427 (95% CI, 0.338 to 0.517). It was determined as follows:

$$p_0 = \frac{x \cdot \frac{1}{3} + y \cdot \frac{2}{3} + z \cdot (1)}{n}$$  \hspace{1cm} (10)

where $x (= 93)$ is the number of participants with dissimilar ratings for the three helmets fit, $y (= 15)$ is the number of participants with two helmets tied at the highest score, and $z (= 9)$ is the number of participants with the same rating for the three models. The observations were independent, and the success-failure condition was achieved ($np_0 = 50$ and $n(1 - p_0) = 67$).

A HFI prediction was considered a success when the highest helmet fit recorded by a participant was also the helmet with the highest calculated HFI score. The HFI had a success rate of 61.5%, providing statistically significant difference with $p_0$ ($p < .0005$).

Likewise, the $p_0$ probability of identifying the worst helmet fit was 0.444 (95% CI, 0.354 to 0.534), while the HFI had a success rate of 65.8%, providing statistically significant difference with $p_0$ ($p < .0005$).

**Local regions of the head**

Similar tests were run on the local regions and are presented in Table 4-13. The HFI had a higher OR of finding the best and worst fitted helmet than $p_0$ for the front, right and left regions.

Table 4-13: HFI capability of finding the best and worst perceived helmet fit out of the three selected models.

<table>
<thead>
<tr>
<th></th>
<th>Best Helmet Fit</th>
<th></th>
<th>Worst Helmet Fit</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$p_0$ probability</td>
<td>HFI success ratio</td>
<td>$p_0$ probability</td>
<td>HFI success ratio</td>
</tr>
<tr>
<td>Global</td>
<td>0.427</td>
<td>0.615*</td>
<td>0.444</td>
<td>0.658*</td>
</tr>
<tr>
<td>Front</td>
<td>0.484</td>
<td>0.684*</td>
<td>0.456</td>
<td>0.701*</td>
</tr>
<tr>
<td>Top</td>
<td>0.456</td>
<td>0.385</td>
<td>0.430</td>
<td>0.342</td>
</tr>
</tbody>
</table>
4.3.5 Discussion on the new method

A new fit method, named the HELMET-FIT-INDEX (HFI), was introduced based on a field survey of 117 cyclists. Statistical analyses were conducted to determine the ability of the Index to predict subjective assessment of helmet fit. Participants were asked to rate their perceived feel of fit for three nominated bicycle helmets, where HFIs had been calculated. Analyses of local regions of the head were also included.

The conducted regressions on each helmet model demonstrated that perceived feel relating to helmet fit and HFIs were moderately correlated. An increase in HFI scores resulted in a slight increase in helmet fit assessment for two out of the three helmets (A and B). However, associations were fairly small. Comparing how users perceive fit on an ordinal psychometric scale appeared to be a challenging task. Attitudes of the population toward a particular sensation may lie in a large, multi-dimensional continuum that can be problematic to capture in a single parameter. In addition, expectations and perception of helmet fit could be entirely different from one cyclist to another, even with similar head shapes. A superior approach is to allow individuals to compare individual’s sensation in a within-subject design explicitly (e.g., Friedman test, one-way repeated ANOVA), where differences in the within-subject factor (helmet model) can be estimated objectively. For example, two cyclists with similar head shapes may have different fit requirements, and hence different fit assessments of the same helmet, but may react similarly when comparing multiple helmet models. The fit assessment scales become an important objective measure to determine which helmet fits the best or the worst on a user’s head.

Following this approach in the current study, within-subject studies (Sections 4.3.4.2 and 4.3.4.3) of subjective (fit assessment) and objective (HFI) data revealed a good correlation between the HFI formulae and the participants’ perceived feel associated with fit. Both analyses showed that helmet B, in general, provided the best fit, followed by helmets A and C. Although the differences in terms of fit assessment between helmets A and B were statistically non-significant, analysis of mean ranks a preference for helmet B (Table 4-11).

The comparisons for local regions were slightly different. Helmet C was consistently ranked as
the worst helmet in the five predefined regions, even if it performed better than helmets A
and B at the top region, and almost equivalently to helmet B at the right, left and back regions.
Helmet A was ranked below helmet B at the right, left and back regions, but performed better
in terms of HFI in these regions. These differences can be attributed to participants either
losing interest in answering the fit assessments in local regions due to time constraint or
having difficulties understanding what was required. A fair proportion of participants had just
copied and pasted the same scores for the global and local regions for each helmet. This may
indicate that cyclists had trouble assessing helmet fit at a local level, but rather rely on their
global or overall feel.

The HFI ranking had a success rate of 61.5% and 65.8% (Table 4-13) in estimating the best and
worst fitted helmets, respectively. Results were statistically significant compared with a simple
random selection process. However, the results indicate that the HFI could not explain the full
variety of fit assessment scores. Several possible reasons might explain these disparities. The
global HFI formula includes a safety component through the HPP parameter that is probably
not estimated in personal ratings. In addition, other parameters, such as the helmet’s design,
weight, material properties (surface roughness), adjustment system and retention straps, and
the brand reputation (which probably influence the perceived sensory perception of fit), were
not incorporated in the index.

Overall, the proposed index correlated reasonably well with the participants’ subjective
assessment data. The fit is indeed related to the distribution of the gap between the head and
the inside surfaces of the helmet liner (SOD and GU). The HFI incorporates another parameter,
i.e., the helmet safety, by integrating the proportion of the head area under helmet protection
in its formula (HPP). The formula was developed based on previous work of Meunier et al. [88].
The present HFI has considered maximum distances for SOD, the dispersion around the SOD
responsible for non-uniform distribution of the gap, and details on how to deal with openings
for air circulation that are not present in Meunier et al.’s ballistic helmets. The HFI can be used
to compare fit between cyclists’ head shapes as well as between helmet models.

The broad range of HFI scores and the presence of outliers and extreme outliers recorded in
the present study have indicated that the current standard headforms used in the design of
bicycle helmets might not capture the full variety of cyclists’ head shapes. The conventional
two or three helmet sizes offered by most manufacturers should be reviewed to account for
the variability of head shapes in the population. In addition, current sizing labels do not inform
users how the helmets are shaped. Using the head circumference as the only size criterion is
probably not satisfactory. Shapes description such as roundness values (oval or round) could be a useful addition. Cyclists acknowledged this shortcoming by evaluating the fit of the three selected helmets with low median assessment scores (6/10, 6/10 and 4/10 for helmets A, B and C, respectively). The importance of achieving a suitable fit was rated with a median score of 8/10, suggesting a need for better-fitted helmets.

There are however some limitations in the present study. Firstly, it was assumed that the participants’ hair was fully flattened under the helmet compression and did not affect the fit score. However, HFI for people with very thick, bulky and curly hair will produce erroneous results. Also, a uniform hair thickness across the participant’s head might not be an accurate assumption. People with partial baldness may only have hair on the side of the head, while others may have asymmetric haircuts with non-uniform hair distribution. Regarding the survey sample, a gender and age bias was unintentionally introduced compared to the targeted population (Australian cyclists that cycle at least once in the past week [29]), resulting in under-representation of females and older adults. Secondly, the site selections for the study are the possible reason for this non-sampling error. For example, in the University’s engineering laboratory young males were more likely to be selected than females. Also, young and middle-age males were more likely to be present in bicycle shops during interview due to their high interest in cycling equipment, compared with older males and females. Thirdly, participants had difficulties in assessing fit scores for the defined local regions, resulting in high percentage of statistically non-significant results. Implications of these biases in the results are threefold: (i) HFI means reported are likely to be higher than the true population mean for the three selected helmets (more females in the sample would decrease the mean), (ii) helmet C assessment scores might be lower than the true population median (participants with high interest in bicycle gears are more likely to be sensitive to the cost of bicycle helmets when estimating fit assessment; helmet C was the cheapest and the lowest rated helmet), and (iii) fit assessment in local regions might be completely overestimated or underestimated, as assessed by low association between subjective and objective data in the local regions compared with the global region. Despite these limitations, the findings showed that the HFI method did provide accurate and efficient data to analyse, compare and improve bicycle helmet fit amongst the targeted cyclist population.
4.4 Case Study 1: Helmet fit differences between groups

The goal of this case study is to use the HFI method to assess whether there are differences in terms of helmet fit for diverse groups of users (gender and ethnic background). The qualitative and quantitative data computed from the 117 individuals selected for the development of the fit index (Section 4.3.1) were used in this study.

Independent samples t-tests were first run to assess gender disparity. In addition, one-way ANOVA tests with custom contrasts or Kruskal-Wallis tests were run to investigate if any significant inequalities regarding helmet fit existed between Caucasians (Australasian and European) and Asians.

4.4.1 Gender differences

Independent samples t-tests (Appendix I) were run to assess the differences in HFI scores between males and females for the three selected helmet models.

Outliers

A total of four outliers were identified in the HFI distributions, one male and one female for helmet A, and two males for helmet B (HFI’s too low). HFI’s values were increased to just one unit smaller than the second (or third) lowest value in their particular distribution.

Distributions

HFI’s followed a normal distribution for the three helmets for males and females, as assessed by the Shapiro-Wilk’s test ($p > .05$).

Homogeneity of Variances

There was homogeneity of variances, as evaluated by Levene’s test for equality of variances ($p = 0.629, 0.339\text{ and } 0.519$ for helmet A, B and C, respectively).

Independent samples t-tests results

HFI means were significantly higher for males than females for the three helmets studied. Differences in HFI means were $7.5 (95\% CI 3.5 to 11.6), t(115) = 3.684$ for helmet A, $13.6 (95\% CI 9.1 to 18.0), t(115) = 6.061$ for helmet B, and $15.7 (95\% CI 10.9 to 20.5), t(115) = 6.530$ for helmet C ($p < .0005$).

Effect Size
Cohen’s d values were 0.85, 1.41 and 1.51 for helmets A, B and C, respectively. These values suggest large practical differences between the two groups according to Cohen’s table [146] (\(d > 0.8\)).

**Local regions of the head**

Similar tests were run on the five local regions of the head. HFI means were significantly higher for males as compared with females in the front, right, left and back regions, where large differences were observed. Differences in the top regions were either not significant or not practical. Table 4-14 below summarizes the test results (presented data are mean ± standard deviation).

Table 4-14: HFI mean differences between gender (\(N_{\text{male}} = 94, N_{\text{female}} = 23\)).

<table>
<thead>
<tr>
<th></th>
<th><strong>Helmet A</strong></th>
<th></th>
<th><strong>Helmet B</strong></th>
<th></th>
<th><strong>Helmet C</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HFI</td>
<td>HFI</td>
<td>Differences</td>
<td>HFI</td>
<td>HFI</td>
</tr>
<tr>
<td></td>
<td>male</td>
<td>fem.</td>
<td></td>
<td>male</td>
<td>fem.</td>
</tr>
<tr>
<td>Glo.</td>
<td>54.6 ± 8.7</td>
<td>47.1  ± 9.3</td>
<td>7.5 (95% CI 3.5 to 11.6), (t=3.684^*), (d=0.85)</td>
<td>58.5 ± 9.3</td>
<td>44.9 ± 11.1</td>
</tr>
<tr>
<td>Front</td>
<td>61.8 ± 10.2</td>
<td>47.1  ± 12.7</td>
<td>14.6 (95% CI 9.6 to 19.5), (t=5.839^*), (d=1.37)</td>
<td>68.0 ± 12.2</td>
<td>54.3 ± 12.4</td>
</tr>
<tr>
<td>Top</td>
<td>56.1 ± 8.9</td>
<td>54.7  ± 8.3</td>
<td>1.4 (95% CI -2.6 to 5.4), (t=0.694^*)</td>
<td>72.4 ± 6.1</td>
<td>69.0 ± 6.7</td>
</tr>
<tr>
<td>Right</td>
<td>68.3 ± 9.3</td>
<td>57.1  ± 10.9</td>
<td>11.1 (95% CI 6.7 to 15.6), (t=4.969^*), (d=1.16)</td>
<td>64.9 ± 12.1</td>
<td>49.4 ± 12.2</td>
</tr>
<tr>
<td>Left</td>
<td>67.9 ± 9.7</td>
<td>57.2  ± 12.5</td>
<td>10.6 (95% CI 5.9 to 15.4), (t=4.438^*), (d=1.04)</td>
<td>66.5 ± 12.0</td>
<td>51.5 ± 10.8</td>
</tr>
<tr>
<td>Back</td>
<td>66.0 ± 12.2</td>
<td>56.8  ± 14.6</td>
<td>9.2 (95% CI 3.4 to 15.1), (t=4.272^{***}), (d=0.72)</td>
<td>64.2 ± 12.1</td>
<td>51.4 ± 15.5</td>
</tr>
</tbody>
</table>

\(* = \text{statistically significant at} \ p < .0005 \text{ level,} \ ** = \text{statistically significant at} \ p < .001 \text{ level,} \ *** = \text{statistically significant at} \ p < .005 \text{ level,} \ **** = \text{statistically significant at} \ p < .05 \text{ level,} \ ^* = \text{non statistically significant.}\)
4.4.2 Ethnic Background differences

One-way ANOVA tests with custom contrasts (Appendix J) were conducted to determine if there were any significant differences in terms of helmet fit (HFI) between the four ethnic groups represented in the present study (Australasian, European, Asian and Other).

Outliers

One outlier in helmet A and one outlier in helmet B were detected (HFIs too low). HFIs values were increased to just one unit smaller than the second lowest value in their particular distribution.

Distributions

HFIs were normally distributed for the three helmets within each ethnic group, as assessed by Shapiro-Wilk’s test ($p < .05$).

Homogeneity of Variances

There was homogeneity of variances, as assessed by Levene’s test for equality of variances ($p = 0.660, 0.194 \text{ and } 0.936$ for Helmets A, B and C, respectively).

Custom Contrasts results

The HFI scores increased from the Asian, to Other, to Australasian/European groups for the three helmets, in that order. Two simple and one complex contrasts between the mean HFI scores of the Australasian and European groups (assessed individually and combined) compared with the Asian group showed that the mean differences were statistically non-significant for helmets A and B. Differences were only significant for helmet C (Table 4-15).

Local regions of the head

Similar tests were run on the local regions of the head and results are shown in Table 4-15 (95% CI for differences mean score between groups are only indicated for the global region). Differences between ethnic background for the front, right and left regions were statistically non-significant.

However, when the assumptions of normal distribution for the HFIs were not met, and/or the number of outliers was too high, the Kruskal-Wallis test (Appendix K) was used. This was the case for the top and back regions where the distributions of the HFIs for the four ethnic groups were similarly shaped (the Kruskal-Wallis test assumes similarly shaped distributions). Differences were statistically non-significant for the top region. The differences for median HFI
scores between the four ethnic groups for the back region were statistically significant.

Subsequently, pairwise comparisons were performed using Dunn’s procedure with a Bonferroni correction for multiple comparisons. Adjusted p-values are presented. This post-hoc analysis of the back area of the head revealed statistically significant differences in median HFI scores between Asian and Caucasian (Australasian/European) participants.

Measures of central tendency are mean ± standard deviation for custom contrast tests and median for Kruskal-Wallis tests.

Table 4-15: HFI mean differences between Ethnic groups ($N_{Australasian} = 57$, $N_{European} = 29$, $N_{Asian} = 21$, $N_{Other} = 10$) ($A = Helmet A, B = Helmet B, C = Helmet C, KW = Kruskal–Wallis test$).

<table>
<thead>
<tr>
<th>Statistical Test</th>
<th>HFI central tendency</th>
<th>Differences between groups</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AU±     EU±     Asian Other</td>
<td>AU± - Asian EU± - Asian U( AU±, EU±) - Asian</td>
</tr>
<tr>
<td><strong>Global</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simple and Complex Contrast</td>
<td>54.0 ± 9.1 54.5 ± 8.5 49.6 ± 10.9 50.1 ± 11.4</td>
<td>4.3 (95%CI - 1.6 to 10.1) p=0.246 4.7 (95%CI - 1.9 to 11.3) p=0.258 4.5 (95%CI - 1.2 to 10.2) p=0.174</td>
</tr>
<tr>
<td>B Simple and Complex Contrast</td>
<td>57.2 ± 11.2 57.5 ± 9.6 51.1 ± 13.2 52.6 ± 9.3</td>
<td>6.0 (95%CI - 0.8 to 12.9) p=0.105 6.4 (95%CI - 1.3 to 14.1) p=0.141 6.2 (95%CI - 0.4 to 12.8) p=0.075</td>
</tr>
<tr>
<td>C Simple and Complex Contrast</td>
<td>49.8 ± 12.3 50.9 ± 11.0 42.5 ± 11.6 44.4 ± 10.9</td>
<td>7.3 (95%CI 0.0 to 14.6)* 8.4 (95%CI 0.2 to 16.6)* 7.9 (95%CI 0.8 to 14.9)*</td>
</tr>
<tr>
<td><strong>Front</strong></td>
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<td></td>
</tr>
<tr>
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<td>3.9* 5.4* 4.7*</td>
</tr>
<tr>
<td>B Simple and Complex Contrast</td>
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<td>-0.9* 0.7* -0.1*</td>
</tr>
<tr>
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<td>6.0* 7.6* 6.8*</td>
</tr>
<tr>
<td><strong>Top</strong></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>54.3 57.4 62.3 57.9</td>
<td>NA</td>
</tr>
<tr>
<td>B K W $\chi^2(3) = 5.512$</td>
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<td>NA</td>
</tr>
<tr>
<td>C K W $\chi^2(3) = 1.434$</td>
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<td>NA</td>
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<td><strong>Right</strong></td>
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<td></td>
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<tr>
<td>Simple and Complex Contrast</td>
<td>67.3 ± 9.4 67.5 ± 8.8 64.6 ± 9.4 61.5 ± 14.0</td>
<td>2.6* 2.8* 2.7*</td>
</tr>
<tr>
<td>B Simple and Complex Contrast</td>
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<td>7.3* 7.8* 7.5*</td>
</tr>
<tr>
<td>C Simple and Complex Contrast</td>
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<td>5.2* 4.8* 5.0*</td>
</tr>
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<td><strong>Left</strong></td>
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<td></td>
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<tr>
<td>Simple and Complex Contrast</td>
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<td>4.2* 1.5* 2.9*</td>
</tr>
<tr>
<td>B Simple and Complex Contrast</td>
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<td>5.1* 4.5* 4.8*</td>
</tr>
<tr>
<td></td>
<td>Simple and Complex Contrast</td>
<td>60.0 ± 14.4</td>
</tr>
<tr>
<td>------------------</td>
<td>-----------------------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Back</td>
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<td>68.9</td>
</tr>
<tr>
<td></td>
<td>B K W ( \chi^2(3) = 10.048^* )</td>
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</tr>
<tr>
<td></td>
<td>C K W ( \chi^2(3) = 9.047^* )</td>
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* = statistically significant at \( p < 0.05 \) level, ° = statistically non significant. AU = Australasian, EU = European.

### 4.4.3 Discussion of Results

This case study highlighted the differences in terms of fit between genders and ethnic groups for three commercially available helmets.

Females presented much lower HFI scores than males in all the selected helmets, as well as for both global and local regions of the head. Differences were predominantly in the front, back and side regions, indicating that females, in general, have smaller head shapes than males. The need for better-designed headforms for females has been previously highlighted in the literature [21, 71, 72, 76, 100], but standards remain unchanged.

Similarly, ethnic differences were observed between Caucasian and Asian groups (Table 4-15). Differences in HFI scores were observed in the front, back and sides regions. However, only the difference at the back of the head was statistically significant. The lack of statistical power for other regions might be due to gender bias, where only 14% of the participants in the Asian group were females, compared to 23% of the Caucasian group. Results could not be adjusted for gender as the sample size was too small for the Asian group. The outcomes from this study agreed with literature findings that Asian heads are rounder than Caucasian counterparts, with a flatter back and forehead [74]. Specific helmet models should be designed to accommodate the Asian population (especially relevant for Australia, where one eighth of the population has Asian ancestry [95]). Helmet shapes must be rounder and should be based on Asian-specific headforms. For example, Ball et al. [86, 147] introduced Chinese headforms in 2009 by scanning thousands of Chinese people across multiple regions of the country. Recent developments of Asian-specific products, such as helmets, sunglasses, and respiratory masks, indicated that the industry has started to recognize this shortcoming.

The results in this study support earlier findings of helmet fit differences between genders and ethnic groups and provide evidences that the HFI is a good indicator of helmet fit accuracy.
4.5 Case Study 2: Fit improvement of a Bicycle Helmet using the HELMET-FIT-INDEX

4.5.1 Problem Definition

This present case study is related to product design intent. It describes how the basic definitions of the HELMET-FIT-INDEX (HFI) can be used to improve the fit of a bicycle helmet for a small group of participants with similar head shapes. The liner’s design of an existing helmet is modified in order to match better the three main parameters described in the index’s formulae:

- An average gap distribution SOD (Standoff Distance) between the head and the inside surfaces of the liner spanning between 4 and 8mm → $4 < SOD < 8$.
- A uniform distribution of this gap throughout the head shape. Gap Uniformity (GU) → GU close to 0.
- A high coverage of the head area under helmet protection. Head Protection Proportion (HPP) → HPP closer to 1.

The experiment method consists of the following five steps:

1. Select a subgroup of 30 participants from the 3D anthropometric database of Australian cyclists. The participants were grouped together based on their head shape similarity.
2. Merge the polygon meshes of each participant together to form one 3D model representing the outer shell of the group’s head shapes. This mesh would serve as a foundation for the design of the new liner.
3. Align the combined mesh of head shapes with the selected bicycle helmet.
4. Modify the inside surfaces of the helmet’s liner based on the computed mesh model.
5. Compute and compare the HFI values for the 30 participants before and after the shape modifications have been applied.

4.5.2 New in-liner design

4.5.2.1 Group Selection and Participants

Participants were selected from the 3D anthropometric database of Australian cyclists (Chapter 3) and had their head mesh post-processed according to the methods described in Sections 3.4.4 to 3.4.6 (i.e., holes filled and mesh repaired, mesh aligned to generic axis system, and Hair Thickness Offset applied).
The objective was to select 30 participants with similar head shapes, i.e., that belong to the same sizing system. Using 30 participants was deemed acceptable to meet the sample size assumption of the Central Limit Theorem for the paired t-test analysis [145]. This is the minimum sample size required for normally distributed or moderately skewed distribution of the dependent variable (HFI) and with no outliers.

The selection process was based on the 3D-HEAD-CLUSTERING algorithm, introduced and described in detail in Chapter 5. The method is based on the hierarchical clustering procedure, which groups objects together into clusters on the basis that close-by objects are more related to each other than objects further apart. A Squared Euclidean metric is used to compute the head shape similarity between pairs of participants. Only 37 Head Covering Points (HCP) were defined to describe the spatial dimension of the head.

The point scheme (Figure 4-13) was primarily based on three reference planes spanning the Sagittal arc, the Head Circumference, and the Bitragion Coronal arc. In addition, four planes (planes 4 to 7) were offset by 31mm, 62mm, −71.5mm and −35.7mm from the Bitragion Coronal plane, and four planes (planes 8 to 11) were offset angularly by 30°, 60°, −30° and −60° from the Sagittal arc plane. The offset values for planes 4 through 7 were determined using (i) one third and two thirds of the full sample average distances between the origin of the generic axis system, and (ii) two points located at the front and back of the head. The intersections between the 11 planes and the scanned mesh were used to determine the location of 37 Head Covering Points (HCP).

The distance function was adapted by weighting single points, considering the low density of points in the front and back regions of the head. As a result, a weight factor of 2 was applied to the two farthest points from the origin of the generic axis system on the y-axis.

The algorithm loop was run only once in order to select the group with the most common head shape (Figure 4-14). (See Chapter 5 and the 3D-HEAD-CLUSTERING algorithm for more detail on the method applied for this selection.)

The resulting group consisted of 26 males (86.7%) and 4 females (13.3%), among which 27, 1 and 2 had a Caucasian (Australasian and European), Asian and “Other” ethnic background, respectively.
Figure 4-13: Point Scheme Head Covering Points. Intersections between the 11 Reference Planes and the participant's head scan.

Figure 4-14: Dendrogram example of the clustering algorithm for the first three permutations.
4.5.2.2 Combination of Head Meshes

The aligned polygon meshes of the 30 participants were combined in Geomagic Studio 12® by multiple solicitations of the Boolean tool. The operation generates new objects that are the union of two existing meshes. The aim was to generate the outer shell of the group’s head shapes. This ensured that the newly created helmet liner would not intersect with any of the participants’ heads. Figure 4-15 shows an example of the Boolean operation between two participants, and Figure 4-16 shows the finalised outer shell for the selected group.

The outer surface of the combined head shapes was repaired, smoothed out and cleaned in order to achieve a steady and even in-liner surface, suitable for the design of the modified helmet. The following steps were applied (Figure 4-17):

a. The face and neck geometry were trimmed away from the reference mesh.
b. The angles between individual polygons were minimized to reduce the occurrence of sharp edges on the final geometry.
c. The resulting mesh was offset by 1 mm on the outer side of the geometry to create a minimum gap distance between the liner and the participants’ head shapes.

Figure 4-15: Example of Boolean Operation between two participants.

Figure 4-16: The 30 participants' head meshes combined. Each colour represents one of the participants’ head meshes.
4.5.2.3 Helmet Liner Alignment

The Netti Lightning helmet was selected for this experiment. Over the three helmets studied (Section 3.2.1), the Netti was the only one where the 30 participants included in the cluster had all selected the same helmet size (i.e., S/M).

The objective of this step was to align the in-liner mesh (Figure 4-17, right) with the polygon mesh of the Netti helmet. This was achieved by computing the average head location of each participant along the three directions of the generic axis system. The combined mesh was then positioned on the average location of the x and y axis. Furthermore, the mesh was slightly translated along the z+ direction in order to increase the value of the Head Protection Proportion parameter (HPP) in the HFI formula. (See HFI formula Section 4.3.3.4.3).

Figure 4-18 shows the final alignment between the two meshes. According to the image on the right, the combined mesh in blue intercepted the helmet’s liner in pink spanning from the top to the back of the head. However, on the sides there were regions with large gaps between the two surfaces. The prediction was that the gap distance (SOD) between the new liner and the head shapes would be decreased significantly for the HFI calculation, leading to an improved overall fit score for the group.
4.5.2.4 In-liner design

The design of the new user centred-liner followed a three-step procedure. The first step involved trimming away the polygon mesh of the current Netti liner. Figure 4-19 shows the trimmed mesh on the right, where the yellow colour represents the backfacing polygons of the helmet’s shell. The ventilation holes in the shell were left open and used in the remaining design steps.

Figure 4-19: Netti liner trimmed. Yellow are the backfacing polygons of the helmet’s shell.

The second step involved trimming the combined mesh according to the helmet limit and ventilation holes by projecting the boundary edges of each features (Figure 4-20).
The third step involved combining the outside surface of the helmet and the in-liner by creating new surfaces connecting the two meshes (Figure 4-21). In this third step, polygon bridges were first created between the boundaries of the meshes, which could then be filled without excessively distorting the curvature of the new surfaces. After all the boundaries had been connected, sharp edges and slightly distorted surfaces were repaired and smoothed in order to improve the curvature uniformity of the in-liner. Then grooves were added to the in-liner to mimic the ventilation characteristics of the original Netti design.

When the final helmet design was completed, 22.7 % (8497 mm²) of the Netti Lightning in-liner surface experienced a decrease of its foam thickness (mean reduction was $-1.6 \pm 1.2$ mm), and 77.3 % (37378 mm²) of the surface experienced an increase of foam thickness, corresponding to a mean enlargement of $3.2 \pm 1.8$ mm.
4.5.3 Fit Analysis

The HELMET-FIT-INDEX (HFI) (Section 4.3.3.4.3) was computed for the participants on both helmet models (i.e., the original Netti Lightning and the modified in-liner design). Results are presented in Table 4-16 for the overall fit for all 30 participants.

Overall, 28 of the 30 participants (93%) obtained a higher HFI after the design modifications of the helmet liner. Similar results were observed in the local regions of the head.

Table 4-16: Results for the overall fit parameters of the HFI formula.

<table>
<thead>
<tr>
<th>Participant No.</th>
<th>Hair Thickness (mm)</th>
<th>Helmet</th>
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<th>SOD (mm)</th>
<th>GU (mm)</th>
<th>HFI</th>
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Paired-samples t-tests (Appendix L) were used to determine whether the HFI mean differences between the original and modified helmets were statistically different from zero.

**Outliers**

Inspection of computed boxplots established that no outliers were present in the difference scores, except for participant No. 10 with respect to the back region. In order to ensure that the single outlier did not significantly influence the results, the paired t-test was performed with and without the outlier. No notable differences were observed in the resulting statistical calculations, and the outlier was, therefore, included in the analysis.

**Distributions**

The Shapiro-Wilks Test of normality established that the HFI difference scores were normally distributed with respect to the global in-liner inside surface ($p = 0.204$), and the front ($p = 0.831$), top ($p = 0.392$), right ($p = 0.113$), left ($p = 0.877$) and back ($p = 0.288$) regions.

**Paired-samples t-tests results**

Significant increases in the HFI scores were observed both global region and with respect to all

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<td>0.84</td>
<td>10.7</td>
<td>3.97</td>
<td>47.25</td>
</tr>
<tr>
<td>30</td>
<td>4.2</td>
<td>0.80</td>
<td>9.54</td>
<td>4.3</td>
<td>47.34</td>
</tr>
</tbody>
</table>

Paired-samples t-tests (Appendix L) were used to determine whether the HFI mean differences between the original and modified helmets were statistically different from zero.
of the defined regions. Values are mean ± Standard Deviation. Globally, the HFI was significantly increased by 11.32 ± 7.82, corresponding to a percentage increase (PI) of 20.06%. For the defined regions, the largest increases were established for the front, right and left, corresponding to 19.50 ± 8.04 (PI = 31.38%), 11.66 ± 8.13 (PI = 17.99%) and 10.35 ± 6.41 (PI = 15.56%), respectively. The HFI for the back region showed a slightly small increase of 7.46 ± 6.48 (PI = 11.08%), while the top region showed the smallest increase, corresponding to 3.66 ± 5.78 (PI = 4.83%). All mean differences were statistically significant.

**Effect size**

Cohen’s d values were superior to 1.15, except for the top region of the head, which was equal to 0.63. These values suggest large and medium practical differences between the two helmets according to Cohen’s table [146] (i.e., large: d > 0.8, medium: d > 0.5).

Table 4-17: Results of the statistical analysis, including Paired-samples t-test and effect size determined by Cohen’s d. Significant differences are illustrated by an asterisk (*).

<table>
<thead>
<tr>
<th>Helmet</th>
<th>Global</th>
<th>Front</th>
<th>Top</th>
<th>Right</th>
<th>Left</th>
<th>Back</th>
</tr>
</thead>
<tbody>
<tr>
<td>HFI (µ)</td>
<td>Old</td>
<td>New</td>
<td>Old</td>
<td>New</td>
<td>Old</td>
<td>New</td>
</tr>
<tr>
<td>HFI (SD)</td>
<td>9.6</td>
<td>6.0</td>
<td>8.3</td>
<td>5.6</td>
<td>3.9</td>
<td>4.8</td>
</tr>
<tr>
<td>Mean differences</td>
<td>11.32</td>
<td>19.50</td>
<td>3.66</td>
<td>11.66</td>
<td>10.35</td>
<td>7.46</td>
</tr>
<tr>
<td>Paired t-tests</td>
<td>p &lt; 0.0005*</td>
<td>p &lt; 0.0005*</td>
<td>p = 0.002*</td>
<td>p &lt; 0.0005*</td>
<td>p &lt; 0.0005*</td>
<td>p &lt; 0.0005*</td>
</tr>
<tr>
<td>Cohen’s d</td>
<td>1.45</td>
<td>2.43</td>
<td>0.63</td>
<td>1.43</td>
<td>1.61</td>
<td>1.15</td>
</tr>
</tbody>
</table>

### 4.5.4 Discussion of Results

The main purpose of the second case study was to demonstrate new procedures for the modified in-liner design of bicycle helmets, incorporating 3D anthropometric data of the head. The basic parameters of the HELMET-FIT-INDEX were used as new guidelines in the re-design of a commercially available helmet.

A group of 30 participants with similar head shapes was first selected from the anthropometric database (introduced in Chapter 3). The selection was made on the basic definitions of the 3D-HEAD-CLUSTERING algorithm (presented in Chapter 5). The participants’ head meshes were then merged together using Boolean operations. The resulting head shape was extracted and served as the foundation for the new helmet in-liner. The fit of both helmets (old and new) was analysed and compared by computing the HFI for each participant.
Paired-samples t-tests show large practical improvement of the fit index scores for the majority of the cyclists in the cluster. These results were significant at the global and local regions of the head. This study demonstrated the key benefits of the HELMET-FIT-INDEX method for fit accuracy when designing bicycle helmet models.
4.6 Summary of Research Outcomes

The objective assessment of fit can provide in-depth understanding of how a wearable product performs for a targeted population. This is especially true for helmets, where fit plays a significant role in both the cyclist’s safety during crashes, and his/her perceived feelings about comfort (Section 2.3.3).

To date, only sparse methods have been developed for the objective assessment of helmet fit accuracy. Meunier et al. [88] demonstrated that 3D anthropometric data could be used for this assessment but did not provide specific requirements for particular parameters that could quantitatively estimate the fit characteristics.

In the present research, a novel quantitative method was developed to compute the HELMET-FIT-INDEX (HFI) for a specific person and a specific helmet (Section 4.3). The approach combined (i) 3D scanning techniques and (ii) analyses of the gap distribution between the head and the inside surfaces of the helmet, to determine the three fundamental parameters used in the HFI formula, namely, the Standoff Distance SOD (average distance between the head and the helmet), the Gap Uniformity GU (measure of SOD dispersion), and the Head Protection Proportion HPP (measure of the head surface area percentage under helmet protection). The HFI was defined by an exponential distribution and provided a fit score on a scale from 0 (excessively poor fit) to 100 (perfect fit). The HFI formula was then adapted for the evaluation of the global and local regions of the head, namely, the front, top, right, left, and back.

A correlation study between quantitative (HFIs) and qualitative (subjective assessment) data was implemented for 117 Australian cyclists. Three commercially available helmets were selected and evaluated numerically by both techniques. Regression analyses and within-subjects’ studies were computed (Section 4.3.4). Results showed that the index is a useful and suitable indicator of bicycle helmet fit, especially when comparing multiple helmets.

Furthermore, in Case Study 1, statistical analyses of helmet fit were conducted to determine the differences between groups to highlight gender and ethnic background disparities (Section 4.4). Results showed that females and Asian people experienced lower fit scores than males and Caucasians, respectively.

A second case study related to design intent was presented where a new fit design approach was introduced for bicycle helmets (Section 4.5). The study used the HFI as the main tool for both, setting up the design requirements for an improved helmet fit, and for evaluating and comparing the fit accuracy of the two helmets studied (i.e., the original and modified helmets).
The above was made possible by first combining the polygon meshes of 30 participants with similar head shapes and then designing a new helmet’s liner originated from the existing Netti Lightning model. Overall, this design approach resulted in significant improvement of helmet fit accuracy for the global and local regions of the head.

The possible applications of the HELMET-FIT-INDEX are listed below:

- Helmet design for standardization: Designers could test the fit accuracy of their new models against the population of concern (e.g., country, gender, ethnic group, child/adult). A sample of 3D head scans from the population would be tested against all the sizes proposed, where the highest HFIs for each individual would be kept. Measures of good fit would be the average HFIs (both global and local) and the dispersion around the average using percentiles. Furthermore, HFIs could be directly calculated for all headform sizes of a specific standard, but only if they have been shown to truly represent the population of interest (e.g., [86]). Requirements for minimum HFI values might be included in relevant standards. Although further research studies are necessary to determine what these threshold values might be.

- Helmet design for customisation: The design of custom-fit bicycle helmets could be concentrated on the fit requirements conveyed in the HFI formulae, which are high coverage of the head area, standoff distance between 4 and 8mm, and low dispersion from the average gap distribution. This would achieve an optimum fit in terms of comfort and safety for the customer.

- Online helmet purchase: 3D digital fitting rooms have started to emerge on the Internet, where customers can virtually experience garments or glasses that fit their morphology. Similar developments are expected in the helmet industry, and the HFI could provide useful information on how a specific helmet fits a customer’s head.

Now that the HELMET-FIT-INDEX method has been introduced and validated, it will be used in Chapter 6 to highlight the significant improvement of fit accuracy of the generated customised helmets compared with today’s commercially available models.
5. CLUSTERING OF THE HUMAN HEAD BASED ON 3D ANTHROPOMETRIC DATA

5.1 Chapter Summary

This chapter presents a novel algorithm that groups individuals, based on head shape similarity. This process was required in the present research to ensure that only small and controlled shape variations were implemented on the helmet design during the customisation procedure.

The grouping algorithm is built upon the results presented in Chapter 3, where an anthropometric database of Australian cyclists was developed.

Before one can apply the algorithm to the anthropometric data, all the 3D scans in the database need to be transformed to a “registered” state. It is important to make this transformation beforehand to ensure that the 3D scans can be compared and analysed collectively. Multiple registration algorithms exist in the literature. The one applied in the present study is called point registration and is presented in Section 5.3.

The theoretical foundations behind the new algorithm, called the 3D-HEAD-CLUSTERING, are then presented in detail in Section 5.4. It is built upon the results of the point registration process and based on a standard hierarchical clustering algorithm with modified initialisation steps and stopping criteria. The algorithm is finally applied to the Australian database of 3D head shape (developed in Chapter 3) and presented in Section 5.5. Four groups are generated. These groups are used for the design of the custom-fit bicycle helmets in Chapter 6. The results are finally compared to standard clustering algorithms (i.e., hierarchical methods) to validate the benefits new method.

A case study is presented at the end of the chapter (Section 5.6) to demonstrate one of the possible utilisations of the 3D-HEAD-CLUSTERING algorithm. In the presented study, new headform models are created and compared with the current standard headforms in Australia. It is demonstrated that these new headforms more accurately represent the population of Australia today and could be used during design and testing of helmet models.

This chapter answers the following key research question related to the present research
(Section 1.3):

Q3. How to group together individuals with similar head shapes using 3D anthropometric data?
5.2 Introduction

One of the core objectives of human factors, when applied to engineering and industrial design, is to conceive equipment and devices that closely “fit” the people who use them. This is accomplished by collecting and processing anthropometric data of a particular group of users that describe their body dimensions relevant for the specific design. These data need to be described in a simplified and useful manner in order to be used efficiently by the products designers.

For decades, traditional 1D anthropometric measurements have been used as the main source of anthropometric data in a multitude of applications and disciplines, such as epidemiology, the study of human physical variation, forensics, and ergonomics. 1D anthropometric data have been extensively used in product design in the past due to their capability to provide, economically, broad information on the size dispersion of specific parameters (e.g., head circumference and head length). However, 1D measurements do not capture shape attributes, which are essential in the design of close-fitting head and facial equipment [75], such as respirator masks, glasses, and helmets.

The recent growth of 3D scanning technology has encouraged the development and use of 3D anthropometric measurements for product design [21, 71, 86, 99]. These data provide an in-depth description of the size and shape characteristics of the scanned persons, thanks to the large set of data points they contain. However, it remains difficult to manipulate the data efficiently and to present easily the summarised shape information of the population of interest. Indeed, as the type of information provided to designers must be simplified, size and shape characteristics are typically presented as a series of generic models: for instance, in the form of mannequins and headforms. In order to create these generic models, it is necessary to first group the persons with similar head or body shapes into clusters.

In recent years, researchers have used statistical analyses or clustering algorithms to generate these clusters based exclusively on 3D anthropometric data. All these methods start with a common transformation process, called point set registration, that enables comparisons of participants on a point-by-point basis. The transformation involves using a generic template model made from a uniform polygon mesh that is warped over the raw 3D scans [107, 148]. Once the transformations are applied on all the individuals in the database, multivariate analyses (e.g., Principal Component Analysis (PCA)) or data mining methods (i.e., clustering algorithm) are then used on the modified data to investigate the shape variation within the
Certain requirements should be satisfied when creating clusters of individuals for 3D-sizing systems. The requirements are:

1. the generated clusters should be as compact as possible to favour better-fitted designs of ergonomic products such as helmets (for 3D head scans, the whole geometry of the head should be similarly shaped for all participants in a cluster);
2. the method should be robust against outliers to avoid the creation of too many clusters (very dissimilar objects could belong to no clusters), but should also aim to accommodate a large proportion of people from the studied population;
3. the method should be able to capture clusters with various densities and shapes in order to represent the full spectrum of the 3D shapes considered; indeed, while it is envisaged that a large proportion of the data could be clustered in a couple of very dense clusters, it is important that less frequent shapes are also detected; and
4. the algorithm’s complexity should be in line with the size of the dataset considered (i.e., the larger the dataset, the more efficient the algorithm).

This study introduces an algorithm called 3D-HEAD-CLUSTERING that divide and classify small to medium size samples of 3D head scans into clusters. The algorithm is based on a modified hierarchical algorithm where distance metrics between pairs of subjects are calculated and implemented in a step-by-step process and where clusters are created one after another in an optimised and enhanced approach.

The new algorithm is then applied to the 3D head dataset of Australian cyclists. In addition, new headform models are generated and compared with the current Australian standard in a case study. This is to demonstrate the benefits of the new clustering method. The clustering results presented in this chapter will be used in the next chapter, where the mass customisation framework of bicycle helmets will be introduced.
5.3 Point Set Registration

This section presents the transformations methods implemented to the 3D head scans in our database. These steps are often applied to 3D anthropometric data to simplify their analysis via statistical or clustering methods. This is also the aim in the present research study.

5.3.1 Registration algorithm definition

The point set registration method was first employed in computer vision and pattern recognition fields to align two point sets together using a regularized transformation. Researchers started to adapt this registration algorithm method to full body scans in the late 1990s to analyze and compare more efficiently 3D anthropometric data. The method consists of iteratively transforming a high-resolution mesh, called the template, to match a person’s mesh (i.e., the scanned head), called the target. This entire transformation cycle is called the registration process. The process has also been described as warping the template onto the target.

Once the registration process is completed for multiple targets (i.e., they share the same registration), shape variation can be studied more easily using statistical or clustering techniques. For example, a point $i$ on the left eye socket of the template mesh should be located on everybody’s left eye socket, when they share the same registration. Two main registration process methods exist: (i) the sparse registration methods, which only work for selected feature points, and (ii) the dense registration methods, which map each point of the template mesh onto the target mesh. For dense registration methods, the transformation is either rigid, where distances between points in the template mesh are not changed, or non-rigid, where the distances between points can be changed. Affine transformations such as scaling and shearing can be described as non-rigid. A dense registration method with non-rigid transformations was required in this work.

Since several dense registration algorithms exist, the review of current methods focused on techniques that take advantage of the similarity of the shapes being registered (i.e., the head), and the ability to deal with missing data in the target geometry. It was important to account for this limitation, since some of the scans in the database contained missing regions that needed to be filled in a practical way. One solution to the missing data problem is to fill these regions using the shape curvature information encrypted in the template model during the transformation process. For example, if a small region around the nose of a person’s scan is
missing, the algorithm will fill the missing data by extrapolating the curvature continuity of the template mesh around this area.

In 2003, Allen et al. [107] were the first to take into account these considerations for the registration of human body parts. Their method combined dense and non-rigid registrations processes that propagate the transformation along the template surface using locally affine transformations (i.e., one affine transformation per vertex). This was further developed by Amberg et al. [148] four years later in their Optimal Step Nonrigid Iterative Closest Point (ICP) algorithm (N-ICP-A). This is the point set registration process that was applied in the present study.

The N-ICP-A extends ICP methods to non-rigid deformations. The ICP method [146] assumes that every point in the template model corresponds to the closest point to it on the target model. It then aims to minimize the error between these points by finding the least squares rigid transformation. The process is replicated until a threshold error value is reached. The N-ICP-A works with the addition of a stiffness term, which can manage the amount of rigid and non-rigid deformation that can be applied at each iteration. The process starts with a high stiffness value, to force nearly rigid transformations, and then release the stiffness gradually as the iterations progress to let more non-rigid transformations to be applied. The algorithm improves upon the method in [107] that proposed to use a Newton-type optimiser to solve the cost function, which is subject to numerical instabilities when used with a localised stiffness term. Figure 5-1 shows an example of a point set registration transformation for a subject head scan using the N-ICP-A.

Figure 5-1: The head template mesh used, a typical head mesh from the dataset (a target), and the registration result.
5.3.2 Problem Overview

The point set registration problem may be summarized as follows. The template $S = (V, E)$ is defined as a set of $n$ vertices, $V$, and a set of $m$ edges, $E$. In Amberg’s [148] and Allen’s [107] method, the target can be described as any representation of the surface $D$, which allows us to find the closest point on the surface for any query point $i$. However, for simplicity, a polygon mesh similar to $S$ is used for the target $D$ in the present study. The method’s objective is to find a set of affine transformations $X_i$ to be applied to $S$ such that the difference between $S$ and $D$ is minimized iteratively. Figure 5-2 shows a detailed step of the registration process where $S$ is moving towards $D$. The minimisation process is shown in Section 5.3.3 below.

![Figure 5-2: A set of affine transformations $X_i$ is applied to the vertices $v_i$ of the template mesh $S$ that result in a new mesh $S(X)$ that moves towards the target surface $D$, but has not yet reached it.](image)

5.3.3 Optimization Framework

An optimization framework is used to complete the match of the two polygon meshes. Each vertex of the template mesh is modified iteratively by a $3 \times 4$ affine transformation matrix $X_i$. Such transformations include scaling, shear mapping, rotation, and translation in any combination and sequence. Twelve parameters are therefore generated for each template vertex as follows:

$$X_i = \begin{bmatrix} a_i & b_i & c_i & d_i \\ e_i & f_i & g_i & h_i \\ k_i & p_i & q_i & r_i \end{bmatrix}$$  \hspace{1cm} (11)

The unknowns’ parameters are organised in a $4n \times 3$ matrix $X$.

$$X = [X_1 \ldots X_n]^T$$  \hspace{1cm} (12)

The optimization problem consists of minimizing a cost function $E(X)$, which is defined by
three error terms, i.e., $E_d$, $E_s$ and $E_l$ such that:

$$E(X) = E_d(X) + \alpha E_s(X) + \beta E_l(X)$$  \hspace{1cm} (13)

The data error, $E_d$, is a weighted sum of the squared distances between the transformed template mesh $S(X)$ and the target mesh $D$. The aim is to ensure that the two surfaces are as close as possible toward the end of the registration process. $E_d$ is defined as:

$$E_d(X) = \sum_{v \in V} w_i \text{dist}^2(D, X_i v_i)$$  \hspace{1cm} (14)

where $w_i$ is a weighted term that controls how the data in the target mesh influence the error term (see 5.3.5 for more details), and the $\text{dist}(\cdot)$ function computes the closest distance from $S(X)$ to $D$. Since we work with affine transformations matrices, the template vertices are defined by homogeneous coordinates $v_i = [x_i, y_i, z_i, 1]^{T}$.

The stiffness error, $E_s$, penalises the weighted difference of the transformations of neighbouring vertices. More specifically, this term ensures that similar deformations apply within triangles located in the same region of the head. $E_s$ is defined as:

$$E_s(X) = \sum_{(i,j) \in E} \|X_i - X_j\|_F^2$$  \hspace{1cm} (15)

where $\|\cdot\|_F$ is the Frobenius norm. The term is used to regularise the deformation.

Finally, a landmark term, $E_l$, is added to guide the start of the transformation, especially when the two meshes are too far from each other at the start of the registration process. Given a set of landmarks $L = \{(v_{i1}, l_1), \ldots, (v_{il}, l_l)\}$, $E_l$ is defined as:

$$E_l(X) = \sum_{(v_i, l) \in L} \|X_i v_i - l\|^2$$  \hspace{1cm} (16)

Figure 5-2 shows the landmarks $l_1$ and $l_2$ of the target mesh corresponding to points $v_2$ and $v_7$ of the template mesh, respectively. Sixteen landmarks were used in this study (Figure 5-3).
\( \alpha \) (see eq. 13) is the stiffness weight that influences how much rigid and non-rigid deformation is performed at a given iteration, and \( \beta \) (see eq. 13) is the landmark weight that dissipates the effect of the landmarks term toward the end of the registration algorithm.

As shown in Section 5.3.2, the N-ICP-A aims to find the optimal deformation at a given stiffness for specific correspondences between the template and target vertices: see section 5.3.6, where we explain how these correspondences vertices are calculated between the target and the template. According to Amberg et al., ‘When correspondences are fixed, the cost function becomes a sparse quadratic system which can be minimized exactly’ [148]. With fixed correspondences, the data error term becomes:

\[
E_d(X) = \sum_{v_i \in V} w_i \| X_i v_i - u_i \|^2 = \| W (CX - U) \|^2_F \tag{17}
\]

where \( W = \text{diag}(w_1, \ldots, w_n) \) is the weight matrix, \( U = [u_1, \ldots, u_n]^T \) is a matrix arranging the target correspondence points, and

\[
C = \begin{bmatrix}
v_1^T \\
v_2^T \\
\vdots \\
v_n^T
\end{bmatrix} \tag{18}
\]

is a sparse matrix mapping the \( 4n \times 3 \) matrix of unknows \( X \) onto the displaced source vertices.

In order to write the cost function in matrix notation, the stiffness term can be rewritten as:

\[
E_s(X) = \| (M \otimes I_d) X \|^2_F \tag{19}
\]

where \( M \) is the node-arc incidence matrix (sparse) of the template mesh topology that contain
one row for each edge and one column for each vertex. For each row, $-1$ is assigned to the first vertex connecting the edge and $1$ is assigned to the second row; $\otimes$ is the Kronecker product; $I$ is the identity matrix.

Similar to the data error term, the landmark term can be rewritten as:

$$E_l(X) = \sum_{(v_l) \in L} \|X_i v_l - l\|^2 = \|C_l X - U_l\|_F^2$$  \hspace{1cm} (20)

Therefore, the complete cost function becomes a general linear least squares problem of the form:

$$E(X) = E_d(X) + \alpha E_s(X) + \beta E_l(X)$$

$$= \left\| \begin{bmatrix} \alpha M \otimes I_4 \\ WD \\ \beta C_l \end{bmatrix} X - \begin{bmatrix} 0 \\ WU \\ \beta U_l \end{bmatrix} \right\|_F^2$$  \hspace{1cm} (22)

$$= \|AX - B\|_F^2$$  \hspace{1cm} (23)

### 5.3.4 Linear Least Squares

In numerical analysis, least squares problems imply solving non-square systems where the number of equations and unknowns differ. Because such system may not necessarily have a solution, we seek to minimize some norm of the residual. The Euclidean norm is generally the most common, but other norms like the Frobenius in eq. (23) are sometimes used.

For a matrix $A \in \mathbb{R}^{m \times n}$ and $m > n$, we want to minimize the norm of the residual $r$ of the linear system $AX = B$. If $\text{rank}(A) = n$, then one way to solve the problem is to set the derivatives to zero and solve the resulting system of linear equation. Such operations give us the normal equations:

$$A^T AX = A^T B.$$  \hspace{1cm} (24)

Rearranging eq. (24), we have

$$X = (A^T A)^{-1} A^T B = A^\dagger B,$$  \hspace{1cm} (25)

where $A^\dagger$ is the Moore-Penrose pseudoinverse of $A$ that can be solved directly. However, for large (and sparse) linear systems, computing directly the inverse of the Gramian matrix $A^T A$ is never pursued, since the computational efforts for this operation can be tremendous. Instead, numerous numerical methods have been developed in the past century to solve efficiently least squares problems. The methods mainly fall into two categories: direct methods (used in the present study) and iterative methods. Directs methods theoretically give the exact solution.
in a finite number of steps. This is sometimes not true in computational practice due to rounding errors: see [149] for an extensive description of direct solver methods for sparse linear systems. Iterative methods are less sensitive to numerical difficulties like rounding errors. They construct a series of solutions approximations that converge to the exact solution: see [150] and [151] for an in-depth survey of current iterative methods.

One of the most used direct methods in linear problems is the Cholesky Factorization, which decomposes a Hermitian positive-definite matrix in the form of \( A = R^T R \) with \( R \) upper triangular. The system of linear equation is then solved by forward and backward substitution. For linear least squares problems, if \( A \) has full rank, \( A^T A \) is positive-definite, and the method can be applied to solve the normal equations with \( A^T A = R^T R \). The solving process consists of:

(i) creating the matrices \( A^T A \) and \( A^T B \);
(ii) computing the factorization \( A^T A = R^T R \); 
(iii) solving the lower-triangular system \( R^T W = A^T B \) for \( W \); and
(iv) solving the upper-triangular system \( RX = W \) for \( X \). The method is easy to use and understand, but roundoff errors can cause \( A^T A \) to no longer appear as positive-definite and fail the factorization.

An alternative to the Cholesky factorization is to use orthogonal methods such as the QR factorization. With \( m > n \), an orthogonal matrix \( Q \) of order \( m \) is computed and reduces \( A \) and \( B \) to the form

\[
QA = \begin{bmatrix} R \\ 0 \end{bmatrix}, \quad QB = \begin{bmatrix} C \\ D \end{bmatrix}, \tag{26}
\]

where \( R \) is an upper triangular matrix. The solution to the linear least squares problem may be obtained by solving the triangular system \( RX = C \). Three methods exist for computing the factorization: Gram-Schmidt orthogonalization, Householder reflections, and Givens rotations.

Amberg et al. [148] showed that \( A \) has full rank, so \( A^T A \) is a positive-definite matrix, and Cholesky factorization can be used to solve the normal equations. It was decided to use Cholesky as the default solver in the registration problem because it is faster than QR. However, when numerical instability failed the factorization, QR with Gram-Schmidt orthogonalization was used. The Apache Commons Mathematics Library (Apache Commons Math™) in Java programming was used for both methods. (See section 5.3.10 for a complete example of the registration process for an individual where linear least squares was used.)

### 5.3.5 Hole-Filling and Missing Data

In this section, we explain in detail how missing data in the target mesh are filled in a practical way during the point registration algorithm. The idea is to assign a zero value to the weight
factors $w_i$ from eq. (14) when the template vertices $v_i$ are put in correspondence with unsuitable vertices in the target mesh. The effect of this operation is the dissipation of the error term $E_D$ for the regions of the scanned head where bad data have been recorded.

5.3.5.1 Data missing due to scanning errors

For example, in the case of missing data, if the closest point from $S$ to $D$ is located on one of the boundary edges of $D$, then setting its weight factor to zero in eq. (14) will have the effect of only transforming the vertex based on the stiffness error term. As a result, holes in the target mesh will be filled by using the shape curvature information encoded in the template. For example, in Figure 5-2, template vertex $v_4$ corresponding to the target vertex $u_4$ has its weight set to zero. In Figure 5-4 below, the red curves of the target surface (in blue) represent boundary edges where scanning data are missing. All vertices that correspond to one of these edges have their weight factor set to zero (i.e., the data error term for these points does not contribute to the cost function). These vertices will be transformed using the stiffness term, meaning only that their deformations will be similar to the triangles located in the same region of the head.

Figure 5-4: Iteration $i$ of the registration process between the target mesh (blue) and the template mesh (orange). Boundary edges are represented in red. Green lines represent examples of correspondence vertices that were set to zero.

5.3.5.2 Angle between vertex normals

In addition to setting the vertex correspondence weight factor to zero for missing data, we also want to lessen the importance of poor scanned data, such as spikes, self-intersection triangles, and highly creased edges. We also try to avoid the mismatching of front-facing surfaces with
back-facing surfaces. Hence, we drop the weight factors to zero at a correspondence \((X_i v_i, u_i)\) if the angle between the vertex normals of the meshes is larger than 90 degrees.

**5.3.5.3 Intersections between correspondence segments and mesh**

Furthermore, weight factors are also dropped to zero if the line segments \(X_i v_i\) to \(u_i\) intersect the template mesh. This test removes abnormal correspondences when the surfaces are too far apart (Figure 5-5), and where multiple layers of the scanned geometry are overlaid (Figure 5-6) (e.g., ear). Transformations are therefore only affected by the stiffness and landmark terms.

![Figure 5-5: First iteration of the registration process. The two correspondences weight factors for the segments shown in green are dropped. \(w_{152} = 0\) and \(w_{78456} = 0\) for correspondences \((X_0 v_{152}, u_{162589})\) and \((X_0 v_{78456}, u_{5231})\). The surfaces are too far apart.](image)
Figure 5-6: Iteration number 5 of the registration process. The two correspondences weight factors around the ear for the segments shown in green are dropped. $w_{1239} = 0$ and $w_{25894} = 0$ for correspondences $(X_5 V_{1239}, u_{8995})$ and $(X_5 V_{25894}, u_{95})$. The surfaces overlay.

In order to detect these abnormal correspondences, a technique widely used in computer graphics for image generation, called Ray Tracing, was adopted. Such a technique produces a high degree of visual accuracy of images by tracing the path of light and mimicking the effects of its encounters with virtual objects.

The Ray Tracing method relies on solving the ray-triangle intersections problem. Such a simple problem can become complicated when there is a multitude of different triangles that need to be accounted for during the detection. Efficient and robust algorithms to solve this problem of multiple triangles have been widely studied by the community of computer graphics scientists. The Möller-Trumbore algorithm [152] is still recognized today as one of the most efficient and robust algorithms. It was therefore adapted to segment-triangle intersections in the present study to detect the abnormal vertices correspondences described above.

The segment-intersection method can be divided into two main steps. First, we test if the segment intersects the plane defined by the triangle, and then, if that is the case, we test if the intersection point is located inside the triangle (Figure 5-7).
Figure 5-7: segment-triangle intersection problem.

Given $P$, the intersection between the segment and the triangle, defined by its segment origin $O$ and its direction $R$, the segment parametric equation is:

$$P = O + tR$$  \hspace{1cm} (27)

where $t$ is the distance from the origin $O$ to $P$. The plane equation is given by:

$$Ax + By + Cz + D = 0$$ \hspace{1cm} (28)

where $A$, $B$ and $C$ are the components of the normal to the plane $N$, and $D$ is the distance from the axis system origin to the plane (parallel to the plane’s normal). These components are computed using the triangle vertices $v_0$, $v_1$ and $v_2$. Since $P$ should be located in the plane, we can substitute eq. (27) and eq. (28) and solve for $t$ as follows:

$$t = -\frac{N(A, B, C) \cdot O + D}{N(A, B, C) \cdot R}$$ \hspace{1cm} (29)

Based on eq. (29), we test if the triangle’s normal and the segment are perpendicular (i.e., they are not intersecting ($N \cdot R \neq 0$)) and if the triangle is located behind or in front of the segment ($0 \leq t \leq \text{dist}(OE)$).

Then, we test if $P$ is inside or outside the triangle. Barycentric Coordinates are used to solve the Möller-Trumbore algorithm. These coordinates express the position of a point located
inside the triangle with three scalars \( i, j \) and \( k \). The position of point \( P \) is computed using:

\[
P = i v_0 + j v_1 + k v_2
\]

where \( i + j + k = 1 \).

![Figure 5-8: Barycentric coordinates of a triangle]

The Barycentric coordinates are proportional to the area of the three sub-triangles defined by \( P \) and the triangle's vertices \( (v_0, v_1, v_2) \), denoted by \( v_0v_1P, v_1v_2P \) and \( v_2v_0P \). Hence:

\[
i = \frac{\text{Triangle } v_2v_0P_{\text{area}}}{\text{Triangle } v_0v_1v_2_{\text{area}}}
\]

\[
j = \frac{\text{Triangle } v_0v_1P_{\text{area}}}{\text{Triangle } v_0v_1v_2_{\text{area}}}
\]

\[
k = \frac{\text{Triangle } v_1v_2P_{\text{area}}}{\text{Triangle } v_0v_1v_2_{\text{area}}}
\]

Developing \( P = O + tR \) and \( P = i v_0 + j v_1 + k v_2 \) with \( i + j + k = 1 \) gives:

\[
[ -R (v_1 - v_0) (v_2 - v_0)]
\]

\[
\begin{bmatrix} i \\ j \end{bmatrix} = O - v_0.
\]

The above formula can be solved using Cramer’s rule and the determinant. For the segment to intersect the triangle, \( i \) and \( j \) cannot be greater than 1 nor lower than 0 \((0 \leq i \leq 1 \text{ and } 0 \leq j \leq 1)\), and neither can their sum be greater than 1 \((i + j \leq 1)\).

5.3.5.4 Synthesizing details not digitized in the scan

In the present study, we scanned the participants’ heads with a wig cap covering their ears. Therefore, only the overall shape of the ears was acquired during the digitization process. In this section, we were able to digitally reconstruct the ears (Figure 5-9) by again setting the weight factors of the vertices near the ears to zero (eq. (14)). This technique had the effect of positioning and dimensioning the ear using the stiffness and landmark terms only, without
comprising the geometric details of the organ.

Figure 5-9: Left: The template mesh with the selected vertices weights factors set to zero (red). Middle: One target mesh (the ears are covered by the wig cap). Right: The registered target with the ear positioned and dimensioned correctly for the target. The ear geometry has been reconstructed.

5.3.5.5 Hole-Filling Example

Figure 5-10 shows the hole-filling capability of the algorithm for one female participant when all the techniques explained above are implemented.

The method was very helpful in handling participants with long hair, where the bulk of hair on top of the neck was first manually removed before the registration and then filled in an intelligent way during the registration.

Figure 5-10: The head mesh of one participant before and after the registration process.
5.3.6 Nearest Neighbour Search for Preliminary Correspondences

Preliminary correspondences between every vertex of the template and the vertices of the target are found using Nearest Neighbour Search (NNS). Formally, the NNS problem is stated thus: given a set of points \( u \in U \) (i.e., the target), and a set of query points \( v \in V \) (i.e., the template), find for all \( v \) the closest point to \( U \). The simplest solution is to compute the distance for each query point to all the points in the target mesh and keep track of the closest point. However, for each NNS, this linear search has a running time of \( O(3n) \) where \( n \) is the number of target vertices.

Instead, we used a space-partitioning method called \( k \)-d tree (\( k \)-dimensional tree) to solve the NNS problem. The algorithm has a \( O(\log n) \) average complexity in the case of randomly distributed points [153]. (See Section 6.4.1 for detailed description of the NNS problem.)

5.3.7 Fast algorithm

Solving eq. (23) for a large number of points proved to be an expensive computational task in terms of CPU time for the solver. Two models (Figure 5-11) for the template mesh were used in order to decrease the total running time of the point set registration algorithm. A coarse mesh model of 1291 vertices and 2578 triangles was first used to calculate the transformations at each step of the N-ICPA. The results were then extrapolated to a finer mesh model after every iteration by determining the five closest points to the coarse mesh model. A Nearest Neighbour Search and a weighted distribution based on the Euclidean distance were used to compute the transformations matrices for each vertex of the fine template. The fine model was defined by 48962 vertices and 97920 triangles.
The method showed a significant increase in the algorithm speed. However, the fitting accuracy of the transformations was reduced for features of the face with high curvatures. For example, the nose, the lips, and the eyes were noticeably impacted (see Section 5.3.10 and Figure 5-16 for examples of deformation). This problem was not important for the present study, where only high accuracy of some parts of the head shape was deemed necessary. These important parts included the frontal, the parietal, the occipital, and the temporal regions. As shown in Section 5.3.10, the accuracy of the head in these regions was high using this method.

### 5.3.8 Rigid Transformation

#### Problem

After careful analysis of the first transformed head, it appeared that the alignment of the registered meshes was inadequate for future investigations. For example, the head shape comparison on a point-by-point basis used in the clustering algorithm (Section 5.4) using this alignment would not provide significant results, since the distance metrics for each pair of points would be either underestimated or overestimated. Figure 5-12 shows the misalignment.
of two participants’ heads and the template mesh after the registration process. For instance, participant 1 was positioned too high compared to the template mesh, creating large gaps at the back of the head and interferences at the front and top. A better alignment procedure than the one presented in Section 3.4.5 was therefore required in this stage of the study.

![Alignment examples before rigid transformation. 2nd row shows sections views. Misalignments generate large gaps and/or interferences between the template and the participants meshes.](image)

The solution was to apply a rigid transformation process on top of the point set registration algorithm. Rigid transformation methods include rotations and translations, in that order. The Iterative Closest Point (ICP) method [146] is an example of such method and was used in the present study.

In the N-ICP-A, the target was fixed and the template was transformed iteratively to match the target’s shape. In the ICP method, however, the template was now fixed, while the source targets were transformed, i.e., rotated and translated, to best match the reference. The estimate combination of the best rotations and translations was defined by a Mean Squared Error (MSE) cost function, which was minimized using a solution based on Singular Value
Decomposition (SVD) [154]. The cost function was solved with Apache Commons Mathematics Library (Apache Commons Math™) in Java programming.

The vertices lying on the boundary edge of the surface defining the proportion of the head that should be under helmet protection were used for the alignment. This region of the head was introduced in Section 4.3.3.4.2. This curve (Figure 5-13) position is crucial for the design of custom-fit helmets, as it ensures the same position of the main features of the head (i.e., ears, forehead, and occipital region) for all participants.

Figure 5-13: The curve used to define the vertices in correspondence for the rigid transformation.

**Least-Squares Fitting**

An algorithm based on the SVD was used to find the least-square solution of $R$ (Rotation) and $T$ (Translation) [154].

Given two 3D point sets with fixed correspondences $\{p_i\} = 1,2, \ldots, N$ (∈ the target) and $\{p'_i\} = 1,2, \ldots, N$ (∈ the template), we want to find $R$ and $T$ to minimize

$$\Sigma^2 = \sum_{i=1}^{N} \| q'_i - (Rq_i + T) \|^2$$  \hspace{1cm} (35)

As described in [154], one can rewrite $\Sigma^2$ by

$$\Sigma^2 = \sum_{i=1}^{N} \| q'_i - Rq_i \|^2$$  \hspace{1cm} (36)

with

$$q_i = p_i - p \quad \text{and} \quad q'_i = p'_i - p'$$  \hspace{1cm} (37)
\[ p = \frac{1}{N} \sum_{i=1}^{N} p_i \quad \text{and} \quad p' = \frac{1}{N} \sum_{i=1}^{N} p_i' \quad \text{(38)} \]

\[ \Sigma^2 \] can therefore be minimized directly using SVD to find \( R \), while \( T \) is found by

\[ T = p' - Rp \quad \text{(39)} \]

**Results**

The alignment examples in Figure 5-14 demonstrate the high benefit of the rigid body transformations. The head meshes are now well-centered together and allow accurate point-to-point comparison in the clustering algorithm.

### 5.3.9 Complete Algorithm

The following steps constitute the full transformation process that was applied to each head mesh in the database presented in Chapter 3:

**algorithm** Point-Set Registration 3D-HEAD-CLUSTERING is

**input:** Template Coarse mesh,  
Template Fine mesh,
Target Mesh,
Landmarks template coordinates,
Landmarks target coordinates,

**output**: Registered target mesh,

Read inputs;
Initialize kd trees;
while iteration $i \leq i_{\text{max}}$
  while transformation $X^i \neq X^{i-1}$
    Find preliminary correspondences between coarse template vertices and target vertices;
    Generate weights;
    Find $X^i$ for stiffness term $\alpha_i$ and landmark term $\beta_i$;
    Update coarse template mesh;
    Find preliminary correspondences between fine template and coarse template vertices;
    Update fine template mesh;
Perform rigid body transformations;
Write output;

$i_{\text{max}}$ is the total number of iterations of the outer loop that define the stiffness and landmark terms. The registration starts with a high stiffness value, allowing mostly rigid deformations. It is then slowly reduced to permit more localised displacements. For the present study, the process was iterated 10 times (Table 5-1) during which the stiffness term was changed the following way:

$$f or(0 < i \leq 10), \quad \alpha = k_0 e^{\lambda i}$$

where $i$ is the iteration number, $k_0 = 5000$, and

$$\lambda = \frac{\ln\left(\frac{k_{\infty}}{k_0}\right)}{i_{\text{max}}}$$

with $k_{\infty} = 15$. Additionally, $\beta = 0.25\alpha$. This optimization scheme (i.e., values for $i$, $k_0$, $\lambda$, $k_{\infty}$, $\alpha$, and $\beta$) was partly based on Hasler et al. [155], who also applied Amberg’s registration method to human body parts.

Table 5-1: Stiffness and Landmark terms values for the point set registration algorithm in the study.

<table>
<thead>
<tr>
<th>$i$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5000</td>
<td>1250</td>
</tr>
<tr>
<td>2</td>
<td>2622</td>
<td>656</td>
</tr>
<tr>
<td>3</td>
<td>1375</td>
<td>344</td>
</tr>
<tr>
<td>4</td>
<td>721</td>
<td>180</td>
</tr>
<tr>
<td>5</td>
<td>378</td>
<td>95</td>
</tr>
<tr>
<td>6</td>
<td>198</td>
<td>50</td>
</tr>
<tr>
<td>7</td>
<td>104</td>
<td>26</td>
</tr>
<tr>
<td>8</td>
<td>55</td>
<td>14</td>
</tr>
<tr>
<td>9</td>
<td>29</td>
<td>7</td>
</tr>
</tbody>
</table>
To assess if $X^j \neq X^{j-1}$, the Frobenius Norm of the difference was compared with an epsilon value $\varepsilon = 0.5$:

$$\| X^j - X^{j-1} \|_F < \varepsilon$$

(42)

### 5.3.10 Results and Verifications

An example of the point set registration process is shown in Figure 5-15 for one participant. As explained before, the template mesh is modified iteratively to fit the target mesh (i.e., the participant’s head scan). The transformation start with high stiffness value ($\alpha$) and then slowly decreases at each iteration to allow more non-rigid transformations.

Deviation analyses were performed between the target and the computed registered mesh to show the registration results for four participants in the database (Figure 5-16). The analyses compute the minimum Euclidean distance between two objects using the meshes’ vertices. From the colour bar on the left, it is noticed that most regions of the registered head scan were within $\pm1$mm of the original scanned data, except for the narrow band around the head where the HTO was applied before the transformation steps (see Section 3.4.6 for detail on the Hair Thickness Offset method). These dispersions values were considered appropriate for the remainder of the research study.
Figure 5-15: The point set registration process for one of the participants.
Figure 5-16: Deviation Analysis between the scanned data and the registered head mesh for four participants in our database.

This section presented a state of the art transformation process of the 3D head scans in our database. This process was necessary for future investigations on the data. For instance, the 3D-HEAD-CLUSTERING is introduced in the next section and is based on the transformed head scans.
5.4 The 3D-HEAD-CLUSTERING Algorithm

This segment presents the new clustering algorithm of the human head developed for the present study. A review of the standard clustering algorithms is first presented in Section 5.4.1. The review focuses specifically on common hierarchical clustering algorithms, which will serve as foundations for the development of the new method in Section 5.4.2.

5.4.1 Theoretical Background

Clustering algorithms are used to group objects that are “similar” to each other into relevant clusters. In the past, many researchers have proposed different clustering algorithms, which all have advantages and drawbacks. For example, connectivity models like hierarchical methods perform well for the generation of compact clusters, but can be slow when analysing large datasets \(O(N^3)\). They may also suffer from the so-called single-link effect, where apparent distant clusters end up connected due to a thin line of objects between them. Density models like DBSCAN [110] or OPTICS [111], and centroid models like \(k\)-means [112] and \(k\)-medoids [113], are faster to solve, but require input parameters that are usually difficult to define efficiently (e.g., \(minPts\) and \(\varepsilon\) for DBSCAN, \(k\) for \(k\)-means). For example, Niu et al. [101] clustered 3D head scans of Chinese soldiers using a \(k\)-means algorithm. They set the number of clusters \(k\) to seven but did not provide any detailed analysis that justified this selection.

Choosing the optimal number of helmet sizes to represent a population can be difficult. As was shown in Section 2.3, selecting too few can be problematic where a large ratio of users may end up with helmets that do not properly fit their heads. Similarly, selecting too many groups may also be bad, as this may increase the production cost of the helmet components like the shell by a significant margin. Therefore, it was decided to focus exclusively on hierarchical methods, as they do not require the number of clusters as input parameters. Moreover, the slow running time of the algorithm was not an issue in the present research as the size of our database was considerably smaller compared to other 3D anthropometric studies. Hierarchical clustering algorithms were used as a foundation for the development of the new clustering method.

The hierarchical clustering algorithm, also known as linkage clustering, is a method that groups objects together into clusters on the basis that close-by objects are more related to each other than objects that are further apart [156]. The common strategies are to use either a bottom-up (agglomerative) or a top-down (divisive) approach. In the agglomerative approach, the objects start in their own cluster and the pairs of clusters are merged together as one moves up the
hierarchy. In the divisive approach, however, objects start in one cluster and splits are performed recursively as one moves down the hierarchy.

Distances between these objects are computed using different distance metrics that can strongly influence the shape of the clusters. The most frequent metrics used to determine the distance between two objects $a$ and $b$ are:

- **Euclidean Distance**: $\|a - b\|_2 = \sqrt{\sum (a_i - b_i)^2}$

- **Squared Euclidean Distance**: $\|a - b\|_2^2 = \sum (a_i - b_i)^2$

- **Manhattan Distance**: $\|a - b\|_1 = \sum |a_i - b_i|$

- **Maximum Distance**: $\|a - b\|_\infty = \max_i |a_i - b_i|$

In addition, it is necessary to define a linkage criterion between the clusters, since there are multiple objects to compute the distance from when the clusters contain more than one element. The common linkage criteria are (where $d$ is the chosen metric, $A$ and $B$ are two sets of independent observations (clusters)), thus:

- **Complete linkage clustering**, where the distance between clusters equals the distance between the elements (one in each cluster) farthest away from each other.

  $\max \{d(a, b): a \in A, b \in B\}$

- **Single linkage clustering**, where the distance between clusters equals the distance between the elements (one in each cluster) closest to each other.

  $\min \{d(a, b): a \in A, b \in B\}$

- **Mean linkage clustering**, where the distance between clusters is equal to the average of all distances between pairs of objects in each cluster.

  $\frac{1}{|A||B|} \sum_{a \in A} \sum_{b \in B} d(a, b)$

- **Centroid linkage clustering**, where the distance between clusters is equal to the distance between their respective centroid positions.

The algorithm process is commonly presented in a Dendrogram (Figure 5-17), representing each step of the hierarchical clustering.

A threshold value can be set to stop the clustering algorithm before all elements are merged into one group or devised into clusters of single observations. The threshold value generally
falls into two types: (i) distance criterion: stop clustering when clusters are too far apart; and (ii) number criterion: stop after the required number of clusters has been reached. In the example in Figure 5-17, the algorithm was stopped when eight subjects were grouped into two clusters ({2,3,5} and {4,6,1,7,8}).

![Dendrogram of a traditional hierarchical clustering algorithm.](image)

**5.4.2 The New Algorithm Method**

**5.4.2.1 Definition**

Hierarchical clustering methods assume that “close-by objects” are more alike when distance measures between these objects are small. This assumption is particularly true when applied to the comparison of head shapes. Two persons with similar head shape will show small distance values for each pair of points defining their head geometry (i.e., Head Covering Point HCP).

The centroid linkage clustering algorithm was modified in our algorithm to sort optimally participants into clusters. Contrasted with a centroid linkage, we generated the clusters one after another iteratively in the computational process (instead of simultaneously). The idea was to extract, at each iteration, the most common head shape profile from the remaining 3D scans in the studied sample. This technique permitted the creation of several groups to choose from for each cluster, which was advantageous since the best-starting pair of participants (from the first step of the agglomerative approach) would not necessarily yield the most suitable cluster. The optimum group at each iteration was selected by evaluating the number of participants and the intra-cluster homogeneity (i.e., cluster internal quality criteria) within each computed group. Once a cluster was generated, participants from this cluster were removed from the sample, and the algorithm was repeatedly solved until the number of
participants classified in one of the clusters had reached a predefined threshold.

The 3D-HEAD-CLUSTERING algorithm introduced five key principles:

(1) The metric employed to determine the next participant to be included in the cluster was a squared Euclidean distance, which placed greater dissimilarities on objects that were farther apart. A linkage criterion based on the centroid distance was applied where the HCP coordinates of all participants in the cluster were merged after each step.

(2) The distance metric was only calculated between the current cluster and the remaining participants, as the goal was to create only one cluster per iteration. In the example below (Figure 5-18(a)), after subjects 4 and 6 had been grouped, only six pairwise comparisons (as opposed to 21 for a standard hierarchical clustering) were performed to reveal the next element in the group (4,6) vs 1, 2, 3, 5, 7, 8). Following the same rule, the group was built gradually until one of the stopping criteria was reached (Figure 5-18(a): the final group is 4,6,1,7,8).

(3) The stopping criterion was the maximum Euclidean distance between any two participants in the cluster at any of the HCP after extreme outliers were removed. We used this stopping criterion in two different implementations. In the first one, named InstaStop, we stopped the clustering process as soon as the next detected merge of objects had reached the predefined limit. In the second implementation, named LaterStop, we discarded such a merge and moved to the next possible candidate that passed the criterion. The clustering process was stopped once no more objects could be merged with the current cluster without trespassing the limit.

In addition, a minimum number of participants in each cluster was required.

(4) At each new iteration (i.e., new cluster selection), all the primary pairwise permutations were tested according to (2) and (3) unless the distance between the pair of participants at any HCP was above the threshold limit. This process allowed the creation of several groups to choose from each cluster. For instance, when the algorithm is executed on eight participants, a total of 28 single groups is generated \( \binom{8}{2} \) if they all pass the distance limit test. However, the odds of computing multiple times the exact same group of participants were high. In the example presented in Figure 5-18, the clustering process of the preliminary permutations of participants \( \{4,6\} \) and \( \{1,7\} \) merged at step number 4 (\( \{1,4,6,7\} \)) to reveal the same final group of participants (\( \{1,4,6,7,8\} \)) at step number 5.
Therefore, only independent groups were kept for the best group selection analysis.

At each iteration of the algorithm, an assessment of the number of participants and the intra-cluster homogeneity was conducted to select the optimum group for the current cluster number. A combination of criteria measures was used.

Figure 5-18: Dendrogram of the 3D-HEAD-CLUSTERING algorithm, in which the algorithm starts with permutation \{4,6\} (a) and \{1,7\} (b). Clusters merge at step number 4.

### 5.4.2.2 Best Group Evaluation Criteria Measures

At each iteration, a combination of four internal quality criteria, namely, \(a\), \(b\), \(c\), and \(d\), was used to select the group with, overall, most similar head shapes. The combination of these four parameters provided a broad understanding of the similarity and dissimilarity of the head shapes within each group. Figure 5-19 shows an example of the position dispersion of 30 participants at one of the HCP (orthographically projected for clarity).

For convention, \(N\) is the number of participants in one group, \(n\) is the number of HCP, \(p_{k-j}\) gives the point coordinates of participants \(j\) within one of the computed clusters at HCP \(k\), the red dot \(\overline{P_k}\) is the centroid point of all participants \(j\) in the group at HCP \(k\), and \(L_{k-j}\) is the distance between participant \(j\) and the group’s centroid coordinates \(\overline{P_k}\) at HCP \(k\).

The four parameters are defined as follows:

- \(a\) is the average mean deviation for each HCP in relation to the group’s centroid coordinates.

\[
\alpha = \frac{1}{Nn} \sum_{k=1}^{n} \sum_{j=1}^{N} L_{k-j} 
\]

- \(b\) is the standard deviation of \(a\).

- \(c\) is the maximal HCP mean deviation from the group’s centroid coordinates.

\[
c = \max_{k \in \{1, n\}} \frac{1}{N} \sum_{j=1}^{N} L_{k-j}
\]

- \(d\) is the maximal deviation of all \(L_{k-j}\) distances.
Each independent group was ranked according to the four parameters. In addition, a weighted rank average was calculated, giving more importance to parameters $a$ and $d$ for the final ranking. $d$ was given a weight factor of 4 to decrease the ranking of a group with extreme outliers HCP.

\[
Weighted \ Rank = \frac{2 \times rank(a) + rank(b) + rank(c) + 4 \times rank(d)}{8} \tag{53}
\]

The weighted rank was then adjusted to take the number of participants in each group into consideration, as the primary goal of the algorithm was to create large clusters while still maintaining decent clusters’ similarity measures. This adjustment was achieved with the definition of the Selection Criterion ($SC$). $SC$ was based on a negative exponential distribution function that considered the weighted rank and the number of participants in the group:

\[
SC = \frac{Weighted \ Rank}{\left( e^{-\frac{Nb \ of \ subjects \ in \ current \ group}{Max \ Nb \ of \ subjects \ in \ a \ group}} \right) - 1} \tag{54}
\]

The group with the lowest $SC$ was selected as the optimum group.
5.5 3D-HEAD-CLUSTERING algorithm applied to the population of Australia

5.5.1 Participants and Data Collection

The 2014 3D Anthropometric Database of Australian Cyclists (Section 3.4) was used to test the 3D-HEAD-CLUSTERING algorithm. A total of 200 participants was selected from the database. A detailed description of the data collection and the digitisation processes is presented in Section 3.4.4. The Hair Thickness Offset (HTO) and point set registration methods were applied, as described in Sections 3.4.6 and 5.3 (Figure 5-20).

![Typical 3D Head Scan from the 3D Anthropometric Database of Australian Cyclists.](image)

5.5.2 Results

The 3D-HEAD-CLUSTERING algorithm was solved using a distance stopping criterion of 20 mm. This value ensured the creation of compact clusters while still maintaining enough variability to allow large collections of participants within each cluster. Moreover, a cluster had to comprise at least 5% of participants from the sample to be considered a final cluster.

A total of four clusters, namely, clusters № 1, № 2, № 3, and № 4, were generated using the algorithm. This classified a total of 190 participants from the sample (95.0%). Table 5-2 summarises the results.

<table>
<thead>
<tr>
<th></th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
<th>Cluster 4</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting sample size</td>
<td>200</td>
<td>92</td>
<td>39</td>
<td>25</td>
<td>200</td>
</tr>
<tr>
<td>No. of Participants in the cluster</td>
<td>108</td>
<td>53</td>
<td>14</td>
<td>15</td>
<td>190</td>
</tr>
</tbody>
</table>
For cluster № 1, a total of 19900 pairs \( \left( \frac{N_s}{p} \right) = 19900 \) with \( N_s = 200 \) and \( p = 2 \) were tested twice (with InstaStop and LaterStop alternative) against the 20mm distance requirement; of these 16135 were under the threshold value. Amongst the 32270 groups computed \((2 \times 16135)\), 5091 were independents. Summary statistics of these independent groups for parameters \( a \) through \( d \) and group size (i.e., no. of participants) are presented in Table 5-3.

Table 5-3: Summary statistics of the best group selection criteria for cluster № 1.

<table>
<thead>
<tr>
<th>Parameter ( a ) (mm)</th>
<th>Mean ± SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter ( b ) (mm)</td>
<td>0.55 ± 0.12</td>
<td>0.28</td>
<td>1.61</td>
</tr>
<tr>
<td>Parameter ( c ) (mm)</td>
<td>5.25 ± 0.74</td>
<td>3.81</td>
<td>10.18</td>
</tr>
<tr>
<td>Parameter ( d ) (mm)</td>
<td>12.58 ± 0.92</td>
<td>10.67</td>
<td>17.98</td>
</tr>
<tr>
<td>Group size</td>
<td>66.5 ± 24.69</td>
<td>3</td>
<td>113</td>
</tr>
</tbody>
</table>

For cluster № 1, the best group selected was based on the 532nd initial best pairwise comparison. Parameter values \( a \) through \( d \) and their respective ranks, group size, and \( SC \) values for the best five groups are shown in Table 5-4. Table 5-5 shows the criteria parameter values for the four clusters.

Table 5-4: Top 5 groups’ selection criteria values and ranks for cluster № 1. The best performing group is indicated in red font.

<table>
<thead>
<tr>
<th>Initial Permutation</th>
<th>( a ) (mm)</th>
<th>( b ) (mm)</th>
<th>( c ) (mm)</th>
<th>( d ) (mm)</th>
<th>( a ) rank</th>
<th>( b ) rank</th>
<th>( c ) rank</th>
<th>( d ) rank</th>
<th>Group size</th>
<th>( SC )</th>
</tr>
</thead>
<tbody>
<tr>
<td>532\textsuperscript{nd}</td>
<td>4.12</td>
<td>0.71</td>
<td>5.61</td>
<td>11.90</td>
<td>4243\textsuperscript{rd}</td>
<td>4683</td>
<td>3495\textsuperscript{th}</td>
<td>1340\textsuperscript{th}</td>
<td>108</td>
<td>23.34</td>
</tr>
<tr>
<td>481\textsuperscript{st}</td>
<td>4.12</td>
<td>0.72</td>
<td>5.61</td>
<td>11.90</td>
<td>4236\textsuperscript{th}</td>
<td>4805\textsuperscript{th}</td>
<td>3492\textsuperscript{nd}</td>
<td>1333\textsuperscript{rd}</td>
<td>108</td>
<td>23.42</td>
</tr>
<tr>
<td>541\textsuperscript{st}</td>
<td>4.05</td>
<td>0.72</td>
<td>5.58</td>
<td>11.62</td>
<td>4132\textsuperscript{rd}</td>
<td>4820\textsuperscript{th}</td>
<td>3463\textsuperscript{rd}</td>
<td>791\textsuperscript{st}</td>
<td>105</td>
<td>23.88</td>
</tr>
<tr>
<td>5038\textsuperscript{th}</td>
<td>4.07</td>
<td>0.70</td>
<td>5.54</td>
<td>11.82</td>
<td>4161\textsuperscript{st}</td>
<td>4566\textsuperscript{th}</td>
<td>3391\textsuperscript{st}</td>
<td>1175\textsuperscript{th}</td>
<td>106</td>
<td>24.31</td>
</tr>
<tr>
<td>159\textsuperscript{th}</td>
<td>4.07</td>
<td>0.68</td>
<td>5.52</td>
<td>11.87</td>
<td>4160\textsuperscript{th}</td>
<td>4373\textsuperscript{rd}</td>
<td>3350\textsuperscript{th}</td>
<td>1262\textsuperscript{nd}</td>
<td>106</td>
<td>24.44</td>
</tr>
</tbody>
</table>

Table 5-5: Clusters’ criteria values.

<table>
<thead>
<tr>
<th>Cluster</th>
<th>( a ) (mm)</th>
<th>( b ) (mm)</th>
<th>( c ) (mm)</th>
<th>( d ) (mm)</th>
<th>Group size</th>
<th>( SC )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.12</td>
<td>0.71</td>
<td>5.61</td>
<td>11.90</td>
<td>108</td>
<td>23.34</td>
</tr>
<tr>
<td>2</td>
<td>4.23</td>
<td>0.44</td>
<td>5.69</td>
<td>11.37</td>
<td>53</td>
<td>2.18</td>
</tr>
<tr>
<td>3</td>
<td>4.03</td>
<td>0.61</td>
<td>5.49</td>
<td>10.97</td>
<td>14</td>
<td>0.12</td>
</tr>
<tr>
<td>4</td>
<td>4.27</td>
<td>1.06</td>
<td>6.39</td>
<td>11.45</td>
<td>15</td>
<td>0.11</td>
</tr>
</tbody>
</table>
5.5.3 Algorithm Evaluation

The algorithm’s performance was evaluated by comparing the clustering results to four standards hierarchical methods, namely, the single-linkage, the complete-linkage, the mean linkage, and the centroid linkage algorithms. Similar to the 3D-HEAD-CLUSTERING, the distance metric was the squared Euclidean distance, and the stopping criterion was the maximum Euclidean distance between any two participants in the same cluster at any of the HCP. The threshold limit was also set to 20 mm. Likewise, we used this stopping criterion in the two different implementations (InstaStop and LaterStop, discussed in Section 5.4.2). Moreover, a cluster had to comprise at least 5% of participants from the sample to be considered a final cluster. The final number of clusters, the number of participants in a cluster, and the mean values of the four similarity measures are presented in Table 5-6.

Table 5-6: Clustering comparison of the 3D head dataset using standards hierarchical methods.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>No. of clusters</th>
<th>No. of participants inside a cluster. Ratio of the sample size</th>
<th>$\bar{a}$ (mm)</th>
<th>$\bar{b}$ (mm)</th>
<th>$\bar{c}$ (mm)</th>
<th>$\bar{d}$ (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D-HEAD-CLUSTERING</td>
<td>4</td>
<td>190 (95.0%)</td>
<td>4.16</td>
<td>0.71</td>
<td>5.80</td>
<td>11.42</td>
</tr>
<tr>
<td>Single-linkage InstaStop</td>
<td>4</td>
<td>74 (37.0%)</td>
<td>2.75</td>
<td>0.46</td>
<td>4.20</td>
<td>8.77</td>
</tr>
<tr>
<td>Single-linkage LaterStop</td>
<td>5</td>
<td>176 (88.0%)</td>
<td>3.88</td>
<td>0.61</td>
<td>5.38</td>
<td>11.42</td>
</tr>
<tr>
<td>Complete-linkage InstaStop</td>
<td>6</td>
<td>75 (37.5%)</td>
<td>2.60</td>
<td>0.39</td>
<td>3.90</td>
<td>9.01</td>
</tr>
<tr>
<td>Complete-linkage LaterStop</td>
<td>8</td>
<td>191 (95.5%)</td>
<td>3.54</td>
<td>0.54</td>
<td>4.87</td>
<td>10.89</td>
</tr>
<tr>
<td>Mean linkage InstaStop</td>
<td>6</td>
<td>99 (49.5%)</td>
<td>2.66</td>
<td>0.37</td>
<td>3.83</td>
<td>9.45</td>
</tr>
<tr>
<td>Mean linkage LaterStop</td>
<td>8</td>
<td>176 (88.0%)</td>
<td>3.34</td>
<td>0.44</td>
<td>4.59</td>
<td>10.56</td>
</tr>
<tr>
<td>Centroid linkage InstaStop</td>
<td>6</td>
<td>101 (50.5%)</td>
<td>2.82</td>
<td>0.42</td>
<td>3.95</td>
<td>8.98</td>
</tr>
<tr>
<td>Centroid linkage LaterStop</td>
<td>7</td>
<td>182 (91.0%)</td>
<td>3.43</td>
<td>0.52</td>
<td>4.79</td>
<td>11.02</td>
</tr>
</tbody>
</table>

5.5.4 Discussion

Table 5-6 demonstrates the superior performance of the 3D-HEAD-CLUSTERING algorithm over the standard hierarchical methods for the dataset considered. The proposed 3D-HEAD-CLUSTERING approach was able to classify a high proportion of the participants in the sample into one of the created clusters (95.0%), while still maintaining a low number of partition (four) and a relative fair degree of intra-cluster homogeneity (parameters $a$ through $d$) compared to the other methods. The hierarchical algorithms with LaterStop option were also able to classify a high proportion of subjects (up to 95.5% of the sample) but with more clusters (up to eight).

As the use of 3D anthropometric measurements for product design should not be associated with a large increase in manufacturing costs, keeping the number of available sizes for a specific product as low as possible should be of most importance when creating 3D sizing
systems. Clustering methods of 3D data for product design should, therefore, emphasise minimizing the number of groups for the population of interest while maximizing the shape resemblance of the participants in each group. This new clustering process would allow the designer to create close-fitted products that could address the current comfort and safety issues encountered in many applications.

The main drawback of hierarchical clustering is the cubic complexity $O(N^3)$ toward the sample size $N$, which makes it inadequate for large data sets of 3D scans. The overall order of growth of the new algorithm’s running time was even worse at $N^3 n$ for each cluster creation, with $n$ the number of HCP. However, the methods could still be competitive for a 3D database of a few hundred subjects. For example, the running time of the new algorithm on a standard desktop computer was only half a dozen hours for 200 3D head scans and 13000 HCP, making it roughly less than a day for 1000 subjects and 1000 HCP.

Despite the limitations of the proposed method, the study demonstrated that 3D anthropometric data of the head can be summarised and simplified into valuable information (i.e., headforms) for the products’ designers (see Case Study 3 in Section 5.6). Such processes should encourage ergonomists to increase the use of 3D data during the design of head and facial gear.
5.6 Case study 3: New Australian Headforms for Headgear Design

The aim of this case study is to demonstrate the practical use of the 3D-HEAD-CLUSTERING algorithm. One of the possible applications of such a method is to generate new headform models that better represent the head shape variability of the population studied. For example, new headforms are created in this segment for Australian cyclists based on the 3D database of head scans from Chapter 3 and the clustering results of Section 5.5. The models are compared to the current Australian headforms, where shape differences between the two designs are discussed.

5.6.1 Design

Four new headforms were constructed by combining the participants in a cluster using the Average tool of Geomagic Studio 12® software (Figure 5-21). The tool used one of the 3D head scans of a cluster as a reference object and changed its polygon mesh definition according to the average position of all participants. A local and global noise reduction process was also performed to remove sharp edges on the final mesh geometry. The reference head scan for the operation was selected by analysing the distance metric between all participants in the group and the average coordinates $\overline{P}_k$ of the HCP.

For cluster № 1, participant № 28 was the closest to the average position and was, therefore, selected as the reference object for the merging operation.

![Figure 5-21: The four headforms based on the computed clusters.](image_url)

5.6.2 Shape Evaluations

In this section, the shape characteristics of the newly generated headforms are assessed by, first, presenting summary dimensions of keys parameters of the head measurements. Then,
the models are compared successively and collectively through the use of deviation analyses and section evaluations at specific positions. Finally, the differences in terms of sizes and shapes are highlighted between the created models and the standard Australian headforms.

Table 5-7 shows the headforms’ dimensions in terms of the Head Circumference (HC), the Head Breath (HB), the Head Length (HL), the Sagittal Arc (SA), and the Bitragion Arc (BA). The head area (HA) and volume (HV) are also presented, based on the proportion of the head that should be under helmet protection. Graphic representations of these dimensions are displayed in Figure 5-22.

Table 5-7: Traditional 1D measurements of the computed headforms.

<table>
<thead>
<tr>
<th></th>
<th>HC (mm)</th>
<th>HB (mm)</th>
<th>HL (mm)</th>
<th>SA (mm)</th>
<th>BA (mm)</th>
<th>HA (mm²)</th>
<th>HV (mm³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Headform 1</td>
<td>570.8</td>
<td>156.1</td>
<td>201.5</td>
<td>384.2</td>
<td>351.3</td>
<td>69050</td>
<td>2.17×10⁶</td>
</tr>
<tr>
<td>Headform 2</td>
<td>568.2</td>
<td>154.7</td>
<td>200.4</td>
<td>365.8</td>
<td>344.7</td>
<td>65830</td>
<td>2.09×10⁶</td>
</tr>
<tr>
<td>Headform 3</td>
<td>589.6</td>
<td>163.0</td>
<td>207.1</td>
<td>411.2</td>
<td>373.9</td>
<td>76590</td>
<td>2.55×10⁶</td>
</tr>
<tr>
<td>Headform 4</td>
<td>533.9</td>
<td>146.5</td>
<td>187.9</td>
<td>353</td>
<td>302.7</td>
<td>59090</td>
<td>1.73×10⁶</td>
</tr>
</tbody>
</table>

Figure 5-22: Traditional 1D measurements of the head (shown on headform № 1). Red = HC, purple = HB, orange = HL, green = SA, blue = BA, yellow = proportion of the head that should be under helmet protection.

Cross-sections representations along the SA, HC and BA planes of the four headform models are displayed in Figure 5-23, while deviation analyses between the most common head shape in the sample (№ 1) and the three remaining models (around the helmeted head area) are presented in Figure 5-24.
Figure 5-23: Cross-sections projections of the created headforms. Green = № 1, blue = № 2, orange = № 3, purple = № 4. Left = SA plane, middle = HC, right = BA plane. Grid squares are 10x10mm.

Figure 5-24: Deviation analyses between the most common head shape (№ 1) and the other three headforms. Left = № 1 and № 2. Middle = № 1 and № 3, right = № 1 and № 4.

In Figure 5-25 through Figure 5-28, the four generated headforms are compared with the current Australia/New Zealand models defined in AS/NZS 2512.1:2009 [157]. The standard provides in-depth size information of 15 headforms for the testing and design of protective helmets. Code letters are used to designate the models (A to Q), which are specified according to the inside head circumference of the intended helmet design (ranging from 500mm to 640mm). The distance deviations of three of these standard headforms are investigated for each of the newly created models. The selection was based on the nearest head circumference values. Manual and global registration processes were applied for the alignment.
Figure 5-25: Deviation analyses between headform № 1 and the AS/NZS headforms G (left), J (middle), and K (right).

Figure 5-26: Deviation analyses between headform № 2 and the AS/NZS headforms G (left), J (middle), and K (right).
Figure 5-27: Deviation analyses between headform № 3 and the AS/NZS headforms K (left), L (middle), and M (right).

Figure 5-28: Deviation analyses between headform № 4 and the AS/NZS headforms C (left), D (middle), and E (right).
5.6.3 Discussion

Headform № 1 (Figure 5-21) revealed the most common head shape present in the sample, where more than 50% of the participants were combined. Its 570mm head circumference fits well inside most brands' Medium size in a three-size helmet system. Headforms № 3 and № 4 appeared to have merged the participants with relatively large and small head shapes, respectively. The two headforms seemed to be almost uniformly scaled up and down in relation to headform № 1, starting from an area around the hairline. We can, however, formulate two observations regarding these three “typical” sizes. First, the scale uniformity was not entirely true for № 3, where the regions at the back of the head (i.e., the occipital region and the end of the parietal region) were very similar to № 1 in terms of sizes and shapes, as seen in Figure 5-23 (left and middle) and Figure 5-24 (middle). Second, rather than showing a constant offset distance between the three models around the head area, it appears that the offset was more progressive, starting from a small value on the sides (temporal bones) and up to a maximum value at the top of the head (Figure 5-23 right and Figure 5-24 middle and right). These observations are critical for the design of properly fitted helmets. Nonetheless, the Australian/New Zealand Standard do not account for these differences at all, as seen in Figure 5-29 below for four of the headforms. A simple constant offset is used over the entire head shape.

Figure 5-29: Cross-sections projections of D, G, J and L AS/NZS headforms. Left = SA plane, right = BA plane. Grid squares are 10x10mm. A constant offset value is used.

One of the central outcomes from the head shape clustering of Australian cyclists was the formation of headform № 2 and its large differences in terms of shape with the other models. Accounting for more than a quarter of the population studied, the average head circumference, head breadth, and head length were very similar to № 1. However, the sagittal arc and the head area and volume were significantly smaller. The main shape differences with
№ 1 were located at the top of the head (Figure 5-23 and Figure 5-24 (left)), where participants in this cluster seem to have a more elongated head in the Z-axis direction (Figure 5-20) than the ones in № 2. For decades, the industry sizing standard for headgear purchase was centred on the head circumference value. Considering the above remarks, using head circumference as the sole fit parameter for the selection of helmets is certainly not ideal. This shortcoming was already highlighted by Robinette and al. in 1994 [75].

Two main findings emerge from the comparison of head shapes between the proposed new headforms and the Australian/New Zealand Standards. First, we notice that none of the standards fit the new models accurately, with large positive and negative deviations for the supposedly nearest three headforms. Second, the regions on the sides of the frontal and parietal bones are consistently overestimated by the Standards, as seen in the yellow and orange colours in Figure 5-25 to Figure 5-28. To a lesser extent, the forehead, the tip of the parietal bone, and the occipital bone are typically underestimated (blue colours). These discrepancies between the head shapes of Australian cyclists and the current Standards headforms could lead to the design of headgear that has large gaps on the front sides of the head, and is too tight on the front and back. Although, the compression point around the tight areas might not always be true, as helmet designers tend to add large offset values between the headforms and the liner to fit the maximum number of cyclists within the minimum number of sizes. However, the fit characteristic of the helmet is often reduced in that type of design practice, whereas helmet fit has been shown to play an important role in cyclist safety during a crash [18, 158, 159].

In conclusion, this case study demonstrated the potential benefits of using 3D anthropometric data and clustering algorithms, like the 3D-HEAD-CLUSTERING, to design better-fitted helmets. Indeed, using the proposed clustering algorithm and the newly generated headform could potentially change the way engineers design standard helmets. They could now design better-fitted helmet by using the headforms’ shape as the new inside surface of the helmet liner (offset by a certain amount to account for air circulation and the addition of thin comfort padding). Moreover, only a slight increase in the number of sizes available (from three to four in this example) would increase significantly the ratio of customers who can find helmets that properly fit their head shape.
5.7 Summary of Research Outcomes

The chapter presented a new algorithm, named 3D-HEAD-CLUSTERING, which was based on a modified hierarchical method (i.e., centroid linkage) for the clustering of head shapes. In this method, multiple pairwise comparisons inside each loop of the hierarchical clustering algorithm were performed, which allowed the creation of several groups to choose from at each iteration. The selection was based on four parameters (i.e., $a$, $b$, $c$, and $d$) and the number of participants contained in each group. These measures gave a broad understanding of the head shape similarity within each group.

The proposed algorithm successfully classifies subjects into clusters by analysing the full head shape variation of the sample. Compared to other clustering methods, 3D-HEAD-CLUSTERING was able to categorize participants into fewer groups and provided a fair degree of intra-cluster homogeneity, while still classifying a high ratio of the sample (95.0%).

Four groups were created using this algorithm and the 3D anthropometric database of head shape introduced in Chapter 3. These groups are used in the mass customisation process presented in Chapter 6 to ensure that only small and controlled shape variations are implemented during the design process of the custom-fit helmet models.
6. A DESIGN FRAMEWORK FOR THE MASS CUSTOMISATION OF CUSTOM-FIT BICYCLE HELMET MODELS

6.1 Chapter Summary

This chapter presents the final design steps of the mass customisation of bicycle helmets introduced in the present research. The results presented in Chapters 3, 4 and 5 provide the basis for the development of a design framework for the mass customization of custom-fit bicycle helmets.

This chapter is guided by the following key research steps. First, the clustering results from Chapter 5 are further processed in Section 6.3 to compute the minimum and maximum head shapes within each group. These shapes are created using numerous Boolean operations on the available 3D head scans. They are then used in Section 6.4 where a new method called 3D-HEAD-CLASSIFIER is developed. The method classifies new customers’ head shapes into one of the four existing groups of individuals from Chapter 5. The minimum and maximum head shapes are also used in Section 6.6 for the design of 3D generic helmet models for each of the four group sizes considered.

During the customisation process, the inside surfaces of these generic models are then modified to fit the head shape of an individual. In order to use the head shape as an input element during the design process, the 3D scan (i.e., polygon mesh) needs to be first transformed to a surface model. The transformation is achieved via an automated process using B-spline functions and curves and surfaces fitting algorithms (Section 6.5).

Using Finite Element Analysis methods, Section 6.7 explains how the generated helmet models comply automatically with the relevant safety standard if and only if certain conditions are met. Finally, Section 6.8 provides a comparison of helmet fit accuracy between the customised helmets created and the three commercially available models from Section 3.2.1. The HELMET-FIT-INdex method from Chapter 4 is used for this evaluation.

This chapter answers the following key research questions related to the present study (Section 1.3):

Q1. How can bicycle helmet customisation address fit problems currently reported in the
literature?

Q4. How to assign new individuals into predefined groups of similar users according to his/her head shape?

Q5. How to use parametric design models to automatically modify the generic 3D model of a bicycle helmet in view of customisation?

Q6. In the custom-fit process, how to ensure that all the newly created helmet models comply automatically with the relevant safety standards?
6.2 Introduction

Mass customisation (MC) aims at providing customised products or services to consumers in large volumes and at costs reasonably low compared to conventional customisation processes [114-116]. More specifically, MC systems seek to reach customers as in the mass produce market, but try to consider them individually as in the one-on-one production method.

In this research, a MC framework for the design of custom-fit bicycle helmets is presented. Custom-fit means that the product is personalised in respect of shape and size. It is the transparent level in the Gilmore and Pine level of customisation [122] (see Section 2.6), where products are almost fully altered to match the needs of each individual (i.e., the need for well-fitted helmets). However, a modular approach in the design process is retained and only the inside foam liner of a generic helmet model is altered to fit the customer’s head shape and size.

As discussed before, safety standards and certification may be one of the main reasons for the lack of MC systems of helmets. According to international and national standards, helmets are to be tested on a range of standard mannequin heads called headforms. They aim to represent the full range of head dimensions, geometries, and shapes within a specific population. Physical helmets of the intended design are tested in a set of experiments specified in standards. Certifying every customised design using multiple physical helmets (e.g., 10 specimens are required in [60]) would certainly not be cost- and time-effective. An innovative approach is introduced in this chapter for the automatic ‘certification’ of custom-fit bicycle helmet models where the best and worst case helmet of each group size is validated using Finite Element Analysis. Using this procedure, we can assume that all the customised helmets generated are safe to use if their head shapes fall between these limits.

The fit accuracy of the generated customized helmets was verified using the HELMET-FIT-INDEX developed in Chapter 4.
6.3 Minimum and Maximum Head Shape Representation

The aim of the present chapter was to create custom-fit helmet models that comply with the relevant safety standards. To achieve this goal, only small and controlled variations of the liner thickness were permitted during the customisation process. This was to ensure that the shock absorption capabilities of the helmets were not dramatically altered after the design of a customised model. These small variations were implemented within each computed group size (Chapter 5), since individuals in each group had very similar head shapes.

Considering the customisation method described above, the Maximum Head Shape surface (MaH) that can be accommodated in a group was created. During the customisation process, this surface (MaH) could never be violated on the external side. It was the worst-case scenario (i.e., the smallest liner thickness at all locations around the helmet) of a specific helmet model size. Similarly, the Minimum Head Shape surface (MiH) was defined. It was the best-case scenario (i.e., the largest liner thickness at all locations around the helmet) of the same helmet model size. This surface could never be violated on the internal side and was created to limit the maximum weight for each helmet size.

MaH and MiH were constructed using Boolean operations within Geomagic Studio 12®, and the same point set registration process was used on each participant’s head scan (Section 5.3).

The Union and Intersect tools were used to compute the MaH and MiH, respectively, as shown in the example in Figure 6-1 and Figure 6-2 for two participants in cluster № 3 (presented in Chapter 5). Figure 6-3 shows the raw head shapes of cluster № 3 after the same union and intersection Boolean operations have been applied to all the individuals in the cluster. The outer and inner surfaces of the combined head shapes were then repaired, smoothed out and cleaned before the point set registration process was applied (Figure 6-4).

![Figure 6-1: Union Boolean operation between the first two participants in cluster № 3. The maximum shape is kept. The MaH is created by combining every individual in a cluster in a similar way.](image_url)
Figure 6-2: Intersect Boolean operation between the first two participants in cluster № 3. The minimum shape is kept. The MiH is created by combining every individual in a cluster in a similar way.

Figure 6-3: MaH and Mih for cluster № 3 after the Boolean operations.

Figure 6-4: Final MaH (top row) and MiH (Bottom row) for clusters № 1 to № 4 (from left to right).
6.4 3D-HEAD-CLASSIFIER

In machine learning, clustering techniques are considered as *unsupervised procedures* where objects are grouped into categories based on some measure of intrinsic similarity, whereas *supervised learning* is an algorithm of classifying new observations into one of the available categories. Such algorithms that categorize objects in concrete implementations are known as *classifiers*.

In this project, we developed a novel classifier, called 3D-HEAD-CLASSIFIER that categorizes participants into one of the four computed groups. Because a participant’s head shape could belong to more than one cluster, a series of criteria was used to select the best performing group for each individual. Moreover, participants could also belong to no cluster.

The 3D-HEAD-CLASSIFIER was developed as follows:

1. **Point Set Registration:** The new participant’s head shape is registered according to the procedure highlighted in Section 5.3.
2. **Initialization:** The Head Covering Points (HCP) positions (Figure 6-5) are recorded for the new participant and the minimum and maximum head shapes (MaH and MiH) of the four computed clusters (Figure 6-4).
3. **Space Partitioning:** \( K \)-d trees are constructed for each MaH and MiH shapes.
4. **Nearest Neighbour Search:** A point search algorithm is run to find the closest correspondences between the HCP of the participant’s head and the MaH and MiH shapes.
5. **Classification:** Distance metrics are computed for these correspondences to assess whether or not the tested head shape is inside the minimum and maximum limits of each cluster’s space.
6. **Optimized Cluster Selection:** If a participant belongs to more than one group, a set of parameters was used to assess which of the clusters would produce the thinnest (and hence lightest) customised helmet for the head shape considered.
6.4.1 Nearest Neighbour Search for Head Covering Points Correspondences

Euclidean distance metrics were used to assess if the tested head shapes were within the boundary limits of one of the four computed clusters. However, instead of computing these distances between the labelled HCP, it was first decided to update the preliminary vertices correspondences using $K$-d trees and the Closest Point Search Algorithm. Even though the point set registration process ensured that similar deformations apply within triangles located in the same region of the head (the stiffness term of the cost function in Section 5.3.3), it was not guaranteed that the smallest distance from one vertex $i$ of a registered mesh to another would be located at this specific point $i$ (Figure 6-6).

Figure 6-6: Example of distance metrics ($d_i$) between two registered meshes at seven Head Covering Points. The smallest distances are not necessarily between the same labelled points (e.g., $d_3'$ and $d_6'$).
Instead, preliminary correspondences between every vertex of the tested head mesh and the vertices of both the MaH and MiH were found using Nearest Neighbour Search (NNS) (e.g., Figure 6-7).

The NNS problem is stated as follows: given a set of points \( u \in U \) (i.e., the MaH or MiH meshes), and a set of query points \( v \in V \) (i.e., the tested head mesh), find for all \( v \) the closest point to \( U \). The simplest solution is to compute the distance for each query point to all the points in the MaH and MiH meshes and keep track of the closest point. However, for each NNS, this linear search has a running time of \( O(3n) \) where \( n \) is the number of vertices.

A space-partitioning method called \( K \)-d tree (\( K \)-dimensional tree) was used to solve the runtime problem of NNS. The \( K \)-d tree method has a \( O(\log n) \) average complexity in the case of randomly distributed points [160]. \( K \)-d tree is a binary tree where each node has at most two children. It is a generalization of the binary space partitioning method that subdivides recursively a space into sets using hyperplanes. Every node in the tree is associated with one of the \( K \)-dimensions (\( x, y, z \) for 3D), where the hyperplanes are perpendicular to that dimension.

The tree construction consists of splitting the set of data by selecting the median of the vertices in the subtree with respect to the splitting plane. The splitting plane is changed recursively between the \( K \)-dimensions as one moves down the tree. The points equal to the median can appear on either side of the splitting plane. In the present study, these points were consistently assigned to the left of the subtree. The process is repeated until each point is independently defined in a node. Such a node is called a leaf. An example of a \( K \)-d tree decomposition of 20 data points is shown in Figure 6-8. The resultant \( K \)-d tree is shown in...
Figure 6-9. The data are split along the axes’ median in sequence until each point is defined in a leaf. Figure 6-10 shows an example of the start of the tree decomposition of a polygon mesh. Only the left subtree is considered in the subsequent steps in this representation.

Figure 6-8: Example of a $K$-d tree decomposition of 20 data points. $q$ is the query point.

Figure 6-9: The resulting $K$-d tree. The node in green is called the root, the nodes in red are called the leaves. The $x$ and $y$ values shown are the axes’ median for the subtree considered.
Figure 6-10: Example of a $K$-d tree decomposition of a polygon mesh. For clarity, only the left child at each node splitting plane is shown.

Once the trees have been built for the boundary shapes, each vertex of the tested head shape follows the steps below in order to identify its correspondence amongst the vertices (an example is presented based on the $K$-d tree decomposition of 20 points defined in Figure 6-8. The query point used is $q = (5.3, -0.7)$):

a) Starting from the root node, the routine moves down the tree up to a leaf by either moving left or right at each node depending on whether the point axis value is smaller or larger than the splitting plane (i.e., the median). The leaf is saved as the ‘Current Best’ (CB).
b) The algorithm then ‘undoes’ the routine and moves the tree up to the root. At each node, it checks whether there could be any points on the other side closer to the CB. A hypersphere around the query point is used for this task. Its radius is equal to the current nearest distance.
Figure 6-13: \( r = 2.7 > (5.3 - 4.5) \) → left side is tested. [15] is tested but is not closer than CB.

Figure 6-14: \( r = 2.7 > (-0.7 + 1) \) → left side is tested. [14] is the new CB.

Figure 6-15: \( r = 1.6 > (-0.7 + 1.9) \) → left side is tested. [12] is the new CB. \( r = 1.0 < (-0.7 + 1.9) \) → left side is not tested. \( r = 1.0 < (5.3 - 1.1) \) → left side of the root node is not tested. [12] is the FB.

In this example, the right side of the node [16,20] is not tested because the region is
not inside the hypersphere 1. Then the left side of node [15,16,17,18,20] is tested, but only its left children of its left children [15] is tried (the only region inside the hypersphere 1). Next, the node [10,11,12,13,14,15,16,17,18,20] is tested similar to a) and a new Current Best is found ([14]). Hypersphere 2 is used. Similarly, point [12] is found and is the Final Best (FB) point. In this example, the entire left subtree of the root is not tested.

6.4.2 Classification Procedure

This section describes the classification procedure used in the 3D-HEAD-CLASSIFIER to assign a customer’s head shape to one of the four computed groups. The classification followed this five-step procedure:

1. The Euclidean distance metrics between the HCPs of the tested head shape and the vertex correspondences in the MaH and MiH shapes are first computed (grey lines in Figure 6-16 and Figure 6-17). The vertex correspondences are obtained using NNS.

2. The distances between these correspondences (MaH and MiH) at each HCP of the tested head shape are then recorded (green lines in Figure 6-16 and Figure 6-17).

3. For each HCP of the tested shape, a point is considered outside the boundary limit of a cluster if any of the two calculated distances in (1) was superior to the distance computed in (2) above.

4. If more than 99% of the HCPs are located inside the boundary limits, the shape is considered to belong to the tested cluster.

5. If a head shape belonged to more than one cluster, the selection is made based on the sum of distances between the HCPs of the head and the MaH. The cluster with the smallest sum of distances is then selected.
Figure 6.16: An example of a tested head shape located inside the boundary limit of one of the computed clusters. Grey and green lines are Euclidean distance metrics.

Figure 6.17: An example of a tested head shape that is considered outside the boundary limit of one of the computed clusters. Grey and green lines are Euclidean distance metrics.

### 6.4.3 Classification Results

Fifteen participants from the 3D Anthropometric database of Australian cyclists (Section 3.3) were chosen to test the 3D-HEAD-CLASSIFIER. The selected 15 participants were not part of the headform study defined by the 3D-HEAD-CLUSTERING algorithm (Section 5.4).

Table 6.1: Group classification for the 15 participants. An “X” means that the head shape belongs to the cluster. The red “X” is the final selection.

<table>
<thead>
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<th>Participants</th>
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<th>Cluster No 2</th>
<th>Cluster No 3</th>
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Table 6-1 presents the results. Out of the 15 participants, 14 were classified inside one of the four clusters (93.3%). Four of them were classified into two clusters. Figure 6-18 shows the cross-sectional graphic representation of a participant’s head mesh between the two limits of cluster № 3.

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Figure 6-18: Cross-Section view of a participant (blue) sandwiched in between MaH and MiH shapes (orange) of cluster № 3.
6.5 Participant’s Head Shape Basic Curve and Surface Extraction

Section 6.4 above classifies participants into one of the four computed groups in view of customisation. However, the classified head shapes are still not ready for 3D design and need to be transformed from polygon meshes to surface models.

Although many CAD systems could compute the surface directly from the polygon mesh for each participant, manual human operations are still required. Using computation to generate the surface automatically will minimise human involvement during the mass-customisation process.

The aim of this section was, therefore, to create an automated process that transforms the mesh of a 3D head scan into a surface model.

The surface required, named HPP, is built on the Head Protection Proportion area defined in section 4.3.3.4.2 during the HELMET-FIT-INDEX study (Chapter 4). The HPP was built using two geometric elements: the Head Covering Curve (HCC) and the Head Covering Surface (HCS). Both elements and the HPP are shown in Figure 6-19 for the template mesh model used during the point set registration process in section 5.3.

Figure 6-19: yellow = HCS, blue = HCC, brown = template mesh, green = HPP. On the left, the computed HCS (defined as a B-Spline surface) extends below the HCC (defined as a B-Spline curve) and covers the provided data points from the HPP area. The right image shows the final HPP surface that serves as an input element during the customisation process.
6.5.1 Curves and Surfaces Essentials

In this subsection, we introduce key elements of the curve and surface extraction problem relevant to the present objective, that is, converting a human head mesh model into a surface representation through an automated process.

6.5.1.1 Implicit and Parametric Forms Representation

The representation of curves and surfaces in geometric modeling is primarily based on two methods: the implicit and parametric equations. Implicit equations define implicit associations between the coordinates $x$ and $y$ points lying on a curve, or coordinates $x, y$ and $z$ points lying on a surface. The equations follow the forms $f(x, y) = 0$ for curves, and $f(x, y, z) = 0$ for surfaces. For example, $f(x, y) = x^2 + y^2 - 1 = 0$ for a circle of unit radius centered at the origin, and $f(x, y, z) = x^2 + y^2 + z^2 - 1 = 0$ for a sphere of unit radius centered at the origin.

Parametric equations, however, define the curves $C(u)$ and surfaces $S(u, v)$ as a function of parameters (one parameter $u$ for curves and two $u, v$ for surfaces). Parametric functions have the form of:

$$C(u) = (x(u), y(u))$$

$$S(u, v) = (x(u, v), y(u, v), z(u, v))$$

The parametric representation of a curve is not unique. For example, one possible definition of the circle of unit radius is given as:

$$x(u) = \cos(u)$$

$$y(u) = \sin(u) \quad 0 \leq u \leq 2\pi$$

One way to understand these functions is to think of the parameter $u$ as a representation of time, where the function $C(u)$ gives $x, y$ coordinates of a point lying of the curve at time $u$.

Similarly, a parametric representation of a sphere is given as:

$$x(u, v) = \sin(u) \cos(v)$$

$$y(u, v) = \sin(u) \sin(v)$$

$$z(u, v) = \cos(u) \quad 0 \leq u \leq \pi, 0 \leq v \leq 2\pi$$

While it is difficult to argue which method is more appropriate for geometric modeling (modern CAD systems use both methods concurrently), one major drawback of the implicit form is the fact that one can only define curves in two-dimension space (i.e., $xy, xz$ or $yz$ planes). Conversely, parametric functions can easily be extended to three-dimension space.
(i.e., \( C(u) = (x(u), y(u), z(u)) \)).

Since the HCC and HCS are described in three-dimensional spaces, the present study focused the review exclusively on parametric forms. (See [161, 162] for more detail on the use of implicit forms in computational geometric systems.)

### 6.5.1.2 Power Basis and Bézier Curves

Power Basis and Bézier are two common parametric methods for defining curves using polynomial expressions. Polynomials are popular in computer systems thanks to their simple and mathematically well-interpreted representation. They are also efficient and accurate when processed in a computer.

An \( n \)th-degree power basis curve is defined by:

\[
C(u) = (x(u), y(u), z(u)) = \sum_{i=0}^{n} u^i a_i \quad 0 \leq u \leq 1 \tag{59}
\]

where the \( n + 1 \) functions \( \{u^i\} \) are the basis functions, and the \( \{a_i\} \) are the coefficients of the power basis representation. The points on the curve are best computed using Horner’s method [163]. Power Basis can represent a wide array of shapes but are generally not used extensively in computer-aided design systems, as the coefficients \( \{a_i\} \) provide little information about the shape of the curve itself.

The Bézier curves are mathematically equivalent but provide more freedom for shape definitions and modifications thanks to the geometric coefficients \( \{P_i\} \), called control points, embedded in the parametric form:

\[
C(u) = (x(u), y(u), z(u)) = \sum_{i=0}^{n} B_{i,n}(u)P_i \quad 0 \leq u \leq 1 \tag{60}
\]

where the basis functions \( \{B_{i,p}(u)\} \) are defined by the Bernstein polynomials [164] as:

\[
B_{i,n}(u) = \frac{n!}{i!(n-i)!} u^i (1-u)^{n-i} \tag{61}
\]

Figure 6-20 shows an example of a third-degree Bézier curve (\( n = 3 \)), with \( C(u) = (1-u)^3P_0 + 3u(1-u)^2P_1 + 3u^2(1-u)P_2 + u^3P_3 \). The connected lines formed by \( \{P_0, P_1, P_2, P_3\} \) (red in the Figure) are called the control polygons. Bézier curves are more adapted for interactive design approaches. The shape of the curve is modifiable easily by altering the position of the Control Points in the three-dimensional space.
The choice of the basis functions determines the geometric characteristics of the curve. For Bézier curves, these functions are solely defined by the degree $n$.

Even though polynomials provide many advantages for the representation of curves and surfaces, weaknesses in their definition remain. For example, they are unable to represent conics such as circles, ellipses, and hyperbolas precisely. Since conics can be represented using rational functions (the ratio of two polynomials), rational Bézier curves can overcome this issue. Their parametric form is given as:

$$
C(u) = \sum_{i=0}^{n} B_{i,n}(u)w_i P_i / \sum_{i=0}^{n} B_{i,n}(u)w_i \quad 0 \leq u \leq 1
$$

where the $w_i$ are scalars, called the weights.

Rational curves can define conics, but also provide more control over the shape of other curves. Increasing the weight of an individual control point has the desirable outcome of dragging the curve toward that point. Figure 6-21 shows the effect of altering the weight factors $w_i$ on a five-degree rational Bézier curve.

However, the main drawback of Bézier curves (polynomial or rational) is that a high degree $p$ is required in order to satisfy a large number of constraints and/or to describe complex free-form shapes. For example, $(n - 1)$-degree is required to fit a polynomial Bézier curve through $n$ data points. High degree curves also suffer from numerical instability [165].
6.5.1.3 B-Spline Curves

B-spline basis functions can overcome this shortcoming by defining curves and surfaces that are piecewise polynomial or piecewise rational. A curve \( C(u) \) is broken into \( m \) \( n \)-th-degree segments and defined over \( u \in [a, b] \). The parameters values \( u_0 = a \leq u_1 \leq \cdots \leq u_m = b \) are called knots, and \( U = \{u_i\}, 0 \leq i \leq m \) the knot vector.

In the following sections, only piecewise polynomial functions (B-spline) are introduced, as B-spline curves and surfaces are the preferred method in the present study for the fitting of the HCC and HCS (Sections 6.5.2 and 6.5.3). We encourage the reader to seek more information about piecewise rational (i.e., NURBS) in [165].

A \( p \)-th-degree B-spline curve is defined by:

\[
C(u) = \sum_{i=0}^{n} N_{i,p}(u)P_i \quad a \leq u \leq b
\]  

(63)

where \( \{N_{i,p}(u)\} \) are the \( p \)-th-degree B-spline basis functions defined on the non-uniform knot vector \( U = \{a, \ldots, a, u_{p+1}, \ldots, u_{m-p-1}, b, \ldots, b\} \). \( a \) and \( b \) are repeated \( p + 1 \) times at the start and end of the vector in order to make the end points of the curve coincide with the first and last control points. Commonly, the knot vector is normalised by setting \( a = 0 \) and \( b = 1 \). The degree \( p \), number of control points \( n + 1 \), and number of knots \( m + 1 \), are related by \( m = n + p + 1 \).

Note that the B-spline representation, with a knot vector \( U = \{0, \ldots, 0, 1, \ldots, 1\} \) with 0 and 1 repeated \( p + 1 \) times \((n = p)\), is a generalization of the Bézier representation.

B-spline basis functions can be evaluated by a number of different ways, i.e., truncated power functions [160], blossoming [166], and recurrence formula [167, 168]. The recurrence formula
is generally preferred for computer applications. The ith B-spline basis function is evaluated by the recursive formula as:

\[ N_{i,0}(u) = \begin{cases} 1 & \text{if } u_i \leq u < u_{i+1} \\ 0 & \text{otherwise} \end{cases} \]

\[ N_{i,p}(u) = \frac{u - u_i}{u_{i+p} - u_i} N_{i,p-1}(u) + \frac{u_{i+p+1} - u}{u_{i+p+1} - u_{i+1}} N_{i+1,p-1}(u) \] (64)

From this equation, we note one of the main advantages of B-spline Basis functions over Bézier's. Since \( N_{i,p}(u) = 0 \) if \( u \) is outside \([u_i, u_{i+p+1})\), only \( p + 1 \) knots affect the shape of the curve at any given points, addressing the need of local support in curve design and modification.

### 6.5.1.4 B-Spline Surfaces

B-Spline surfaces are an extension of B-Spline curves where a bidirectional net of control points is used. Basis functions are defined in two directions with distinct knot vectors \( U \) and \( V \). The surface is defined by:

\[ S(u, v) = \sum_{i=0}^{n} \sum_{j=0}^{m} N_{i,p}(u) N_{j,q}(v) P_{i,j} \] (65)

where \( p \) and \( q \) are the degrees of the B-spline curves in \( u \) and \( v \) directions, respectively. Furthermore:

\[ U = \{0, \ldots, 0, u_{p+1}, \ldots, u_{r-p-1}, 1, \ldots, 1\} \]

\[ V = \{0, \ldots, 0, v_{q+1}, \ldots, v_{s-q-1}, 1, \ldots, 1\} \] (66)

\( U \) has \( r + 1 \) knots, and \( V \) has \( s + 1 \) (\( r = n + p + 1 \) and \( s = m + q + 1 \)).

A B-spline surface is shown in Figure 6-22 where \( n = 8, \ m = 5, \) and \( p = q = 5 \).

To evaluate a point on a B-spline surface (i.e., \((u, v)\) provided), one must first find the knot span in which \( u \) lies and compute the non-zero basis functions \( N_{i-p,p}(u), \ldots, N_{i,p}(u) \). Then, in a similar approach, the knot span in which \( v \) lies is established and the non-zero basis functions \( N_{j-q,q}(v), \ldots, N_{j,q}(v) \) are computed. Finally, the non-zero basis functions are multiplied with the corresponding control points (i.e., \( S(u, v) = [N_{k,p}(u)]^T [P_{k,l}] [N_{l,q}(v)] \) \( i - p \leq k \leq i, j - q \leq l \leq j \)).
6.5.2 Curves Fitting

This section describes the extraction of the Head Covering Curve (HCC) of each participant’s head mesh using B-Spline functions through computation.

Based on the template mesh described in Section 5.3, 50 points that should belong to the HCC of each participant were extracted. Since all the participants shared the same mesh parameterisation (point set registration algorithm), one could easily extrapolate the location of these points for each participant, as shown in Figure 6-23 and Figure 6-24.
Curve fitting can be subdivided into two categories: interpolation and approximation. In interpolation, the constructed curve satisfies the input data by passing through the given points precisely, whereas, in approximation, the computed curves only approximate the data provided in order to reduce the possible measurement errors or noise that may be encoded in the data. A maximum deviation error is often specified between the calculated curve and the given data in approximation.

Because the selected points may not be aligned properly for each participant’s head mesh, it was decided to select an approximation method for the HCC fitting process. However, since both methods are strongly related to each other, a quick introduction of the interpolation method is first provided. The approximation process is then presented subsequently. Furthermore, a description of the End Point Derivatives method (EPD) is provided to demonstrate how the HCC was closed with the required degree of curvature continuity.

During the fitting process, geometric data such as point location (measured data) are required as input. Additionally, the degree $p$ of the B-spline curve must be specified. If $C^r$ continuity is needed, then $p$ should at least be equal to $r + 1$ [165]. Like most free-form design applications, a $C^2$ continuity was selected (i.e., curvature continuous) for the HCC design ($p = 3$).

### 6.5.2.1 Interpolation

We define $\{Q_k\}, k = 0, ..., n$ as the measured points provided for the curve fitting process.
Furthermore, we have the \( U = \{u_0, \ldots, u_m\} \). A \( \{\bar{u}_k\} \) value, called the location parameter, which is assigned to each \( Q_k \), giving rise to a system of linear equations \((n + 1) \times (n + 1)\) in the form of:

\[
Q_k = C(\bar{u}_k) = \sum_{i=0}^{n} N_{i,p}(\bar{u}_k) P_i
\]

(67)

where the control points \( P_i \) are the \( n + 1 \) unknowns.

Before solving the system of equations, one must define the parameters \( \{\bar{u}_k\} \) and \( U \). Common methods to define the \( \{\bar{u}_k\} \) are: equally spaced (not recommended), chord length, and centripetal length [165]. The commonly used method is the chord length, as it usually gives an adequate parameterisation to the curve for a vast array of applications. We applied this method in this work.

**Chord length method:** let us define the total chord length \( d = \sum_{k=1}^{n} |Q_k - Q_{k-1}| \), \( \bar{u}_0 = 0 \) and \( \bar{u}_n = 1 \), then,

\[
\bar{u}_k = \bar{u}_{k-1} + \frac{|Q_k - Q_{k-1}|}{d} \quad k = 1, \ldots, n - 1
\]

(68)

Similarly, multiple methods exist for the parameterisation of the knot vector. The averaging method is often recommended for interpolation [165].

**Averaging method:** let us set \( u_0 = \cdots = u_p = 0 \) and \( u_{m-p} = \cdots = u_m = 1 \), then

\[
u_{j+p} = \frac{1}{p} \sum_{i=j}^{j+p-1} \bar{u}_i \quad j = 1, \ldots, n - p
\]

(69)

The system of linear equations (eq. 67) is solved by Gaussian elimination without pivoting using LU Decomposition [169] and Forward-Backward substitution. We solve the linear system using the Apache Commons Mathematics Library (Apache Commons Math™) in Java programming.

Figure 6-25 shows the interpolating curve of one participant. Although the curve fitted the given data perfectly, a porcupine curvature analysis shows (Figure 6-26) that the curve is not particularly smooth, with an excessive number of inflection points and large curvature magnitude.
6.5.2.2 Approximation

In interpolation, the number of control points \( n + 1 \) is automatically determined by the degree \( p \) and the number of measured points \( m + 1 \). Conversely, approximation requires more advanced analysis to calculate the number of control points, and is usually calculated by the mean of a curve error bound \( E \) during an iterative fitting process (i.e., \( E \) is compared to the desired accuracy at each iteration).
One possible approach for the iterative process is to first start with a minimum number of control points, then fit an approximate curve, and, finally, check the deviation of the curve from the data. If the deviation satisfies $E$, then the process stopped; otherwise the number of control points increased and the loop restarted.

In this section, we first present a method of fitting an approximate B-spline curve using the least squares problem \[165\]. The method selected enables the use of a linear problem that can be solved easily and directly using LU Decomposition and Forward-Backward substitution.

Assuming that $p \geq 1$, $n \geq p$, and \( \{Q_k\} \ k = 0, ..., m \) with $m > n$ (measured points) are given. Accept that $Q_0$ and $Q_m$ are equal to $P_0$ and $P_m$, respectively. The remaining $Q_k$ are approximated in the least squares sense by:

$$ f = \sum_{k=1}^{m-1} |Q_k - C(\bar{u}_k)|^2 = \sum_{k=1}^{m-1} \left| R_k - \sum_{i=1}^{n-1} N_{i,p}(\bar{u}_k)P_i \right|^2 $$

with

$$ R_k = Q_k - N_{0,p}(\bar{u}_k)Q_0 - N_{n,p}(\bar{u}_k)P_m \quad k = 1, ..., m - 1 $$

$f$ can be minimised by setting its derivatives equal to zero, giving rise to the system of $n - 1$ equations in $n - 1$ unknowns as:

$$ (N^TN)P = R $$

where $N$ is the $(m - 1) \times (n - 1)$ matrix of scalars

$$ N = \begin{bmatrix} N_{1,p}(\bar{u}_1) & \cdots & N_{n-1,p}(\bar{u}_1) \\ \vdots & \ddots & \vdots \\ N_{1,p}(\bar{u}_{m-1}) & \cdots & N_{n-1,p}(\bar{u}_{m-1}) \end{bmatrix}, $$

$R$ is the vector of $n - 1$ points

$$ R = \begin{bmatrix} N_{1,p}(\bar{u}_1)R_1 + \cdots + N_{1,p}(\bar{u}_{m-1})R_{m-1} \\ \vdots \\ N_{n-1,p}(\bar{u}_1)R_1 + \cdots + N_{n-1,p}(\bar{u}_{m-1})R_{m-1} \end{bmatrix} $$

and

$$ P = \begin{bmatrix} P_1 \\ \vdots \\ P_{n-1} \end{bmatrix} $$

The $\{\bar{u}_k\}$ are computed using chord length method, while the knot vector $U$ is generated using Piegl’s approximation knot method \[165\]:

$$ i = \text{int}(jd) \quad d = \frac{m + 1}{n - p + 1} $$
\[ \alpha = jd - i \]
\[ u_{p+j} = (1 - \alpha)\bar{u}_{i-1} + \alpha\bar{u}_i \quad j = 1, \ldots, n - p \]

Since the number of measured points provided is always the same for all participants (i.e., 50), we did not envisage that the optimised number of control points calculated through an iterative process would radically change between the different head shapes tested. The fitting accuracy of the HCC for the given data was not of significant importance in this application. However, we focused on the “quality” of the final curve in terms of smoothness properties (i.e., a low number of inflection points and no quick changes in curvature direction and amplitude). For these reasons, the iterative processes were disregarded and the number of control points for the HCC was fixed at 20 for all participants.

Although the HCC created by the least-squares approximation method shows a smoother result (Figure 6-27) compared to the interpolation, one main issue remains. As shown in Figure 6-27, there is a curvature discontinuity at the closure point. This is because approximating closed curves requires the estimation of derivatives.

Figure 6-27: Approximation of the HCC. The black circle shows the curvature discontinuity at the closure point.

The computation of closed piecewise polynomial and rational splines has been the subject of many studies [165, 170-173]. Peigl’s [173] method was adopted for the present study as it is very similar in terms of computation procedures to the linear least squares problem presented above.
6.5.2.3 Closed Curve using End Derivatives

A three-step process is used to generate a closed curve with curvature continuity.

- First, a local curve is fitted to the provided data but with the closure points on the opposite side of the head mesh. For example, if the final HCC has its closure point at the front of the head (Figure 6-27), we first compute a local curve with the closure point at the back of the head. The approximation method presented in section 6.5.2.2 is used to compute this intermediary curve.

- Second, we estimate the derivatives at the “final” (e.g., front of the head in the example above) closing point using the derivatives of B-spline basis functions using the following formula [165]:

\[
N_{i,p}^{(k)}(u) = p \left( \frac{N_{i,p-1}^{(k-1)}}{u_{i+p} - u_i} - \frac{N_{i+1,p-1}^{(k-1)}}{u_{i+p+1} - u_{i+1}} \right)
\]

\(N_{i,p}^{(k)}(u)\) denotes the kth derivative of \(N_{i,p}(u)\), with \(k < p\).

- Finally, we approximate the given data using the closing point derivatives based on Piegl’s algorithm [173].

The end control points are computed using the end derivatives \(D\). For \(p = 3\) and \(k = 2\), we have:

\[P_0 = Q_0\]
\[P_1 = \frac{1}{N_{1,p}^{(3)}(0)} \left[ D^{(1)} - N_{0,p}^{(1)}(0) P_0 \right]\]
\[P_2 = \frac{1}{N_{2,p}^{(2)}(0)} \left[ D^{(2)} - N_{0,p}^{(2)}(0) P_0 - N_{1,p}^{(2)}(0) P_1 \right]\]
\[P_n = Q_m = P_0\]
\[P_{n-1} = \frac{1}{N_{n-1,p}^{(1)}(1)} \left[ D^{(1)} - N_{n,p}^{(1)}(1) P_n \right]\]
\[P_{n-2} = \frac{1}{N_{n-2,p}^{(2)}(1)} \left[ D^{(2)} - N_{n,p}^{(2)}(1) P_n - N_{n-1,p}^{(2)}(1) P_{n-1} \right]\]

The remaining of the control points \(P_3, \ldots, P_{n-3}\) are computed by least squares minimisation in the form of:

\[(N^T N)P = R\]

where \(N\) is the \((m - 1) \times (n - 5)\) matrix of scalars.
\[ N = \begin{bmatrix} N_{3,p}(\bar{u}_1) & \cdots & N_{n-3,p}(\bar{u}_1) \\ \vdots & \ddots & \vdots \\ N_{3,p}(\bar{u}_{m-1}) & \cdots & N_{n-3,p}(\bar{u}_{m-1}) \end{bmatrix}, \]  

(80)

\[ R \text{ is the vector of } n - 5 \text{ points} \]

\[ R = \begin{bmatrix} N_{3,p}(\bar{u}_1)R_1 + \cdots + N_{3,p}(\bar{u}_{m-1})R_{m-1} \\ \vdots \\ N_{n-3,p}(\bar{u}_1)R_1 + \cdots + N_{n-3,p}(\bar{u}_{m-1})R_{m-1} \end{bmatrix} \]

(81)

with

\[ R_k = Q_k - \sum_{i=0}^{2} N_{i,p}(\bar{u}_k)Q_i - \sum_{j=0}^{2} N_{n-j,p}(\bar{u}_k)Q_{n-j} \quad k = 1, \ldots, m - 1 \]  

(82)

The HCC approximation result using least-square and end derivatives of one participant is presented in Figure 6-28. The B-spline curve is curvature continuous with an acceptable smoothness level for the intended application.

Figure 6-28: The HCC of one participant using the approximation method and end derivatives at the closure points. The entire curve is curvature continuous.

6.5.2.4 HCC fitting algorithm

In this section, we summarise the procedures developed to compute the HCC. The proposed assembled algorithm produces an accurate solution to the fitting problem without manual interaction. However, we acknowledge that the curve could also be generated through many different methods, especially using rational B-spline (NURBS).
**algorithm** HCC-FITTING is

**input:** Template Fine mesh,
Registered participant mesh,
Measured points extracted from the template mesh,
Number of control points,

**output:** CAD file of the HCC

*Read inputs;*
*Extrapolate measured point’s location on the registered participant mesh;*
*Find derivatives at closure point;*
*Create location parameters based on the chord length method;*
*Create knot vector based on Piegl’s method;*
*Compute end control points based on the derivatives;*
*Compute remaining of the control points using least squares minimisation;*
*Write output of the HCC in .igs format;*

### 6.5.3 Surfaces Fitting

The task of fitting a surface to given data points is much more complex than for curves. It is a common problem in the field of reverse engineering. Over the past two decades, a great amount of research has been published on surface reconstruction.

The problem can be expressed in the following way: given a set of data point \( \{Q_t\}, t = 0, \ldots, T \), we look for a surface \( S \), which approximates each point within a tolerance \( \varepsilon \):

\[
\|S(\bar{u}_t, \bar{v}_t) - Q_t\| < \varepsilon
\]  \hspace{1cm} (83)

where \( S(\bar{u}_t, \bar{v}_t) \) is a point on the surface associated with the data point \( Q_t \). Assuming a B-Spline surface is used for the reconstruction, a simple least-squares problem can be formulated as:

\[
f = \sum_{t=0}^{T} \|S(\bar{u}_t, \bar{v}_t) - Q_t\|^2
\]  \hspace{1cm} (84)

and could be solved for the control points if the knot vectors and parameter values are defined. However, the solution does not guarantee that the surface meets the tolerance value and that the surface is “reasonably” shaped (i.e., the surface must curve when necessary but nowhere else).

Commonly, three main problems can arise from automatic surface fitting processes. First, B-Spline surfaces can only represent rectangular regions but must fit data points from \( n \)-sided sections. Second, measured data points are often noisy and unevenly distributed, which caused the surface to unnecessary curve around the poorly scanned regions during the fitting procedure. Third, parameters that affect the shape greatly (i.e., location parameters and knot
vectors) need to be estimated beforehand, which can compromise the accuracy of the surface result.

An adequate summary of the surface fitting problem is given by Weiss et al. [174]:

The surface must approximate each point within tolerance and must be aesthetically pleasing and predictable. We also expect the surface to extend in a reasonable way beyond the boundaries of the point cloud and over regions where no data is available. Finally, we would like to obtain a non-redundant surface representation automatically, which has a reasonable number of control points only.

When the control points, the knot vectors, and the location parameters are unknown, the surface fitting problem becomes a highly non-linear problem, which can be solved through a sequential search. One strategy is to fix some unknowns while the others are optimised, and then fix another part before the best solution is computed. For example, in the curve approximation problem, the knot vector and location parameters are first estimated and then the control points are computed using least-squares problem. For surfaces, one approach consists in approximating the point cloud by a continuous surface and then gradually smoothing it using iterative procedures. (See [174-178] for some papers on different strategies for automatic surface fitting.)

One of the most important characteristics of the fitting procedure is to assign suitable parameter values to the measured data points. While numerous papers have been published on the selection of such parameters, most of them have focused on the cumulative chord length and centripetal methods, which assume that the points are arranged in a special pattern (i.e., grid points). However, most of the point clouds generated by 3D scanning technologies are randomly distributed, as shown in Figure 6-29.
One option for the initial parameterisation of irregularly spaced and randomly distributed data points is to fit a base surface on the data points. The base surface must roughly reflect the shape of the point cloud considered [176, 179].

In the present study, a method introduced by Gálvez et al. in [180] was adapted. The authors addressed the surface reconstruction problem in this paper using an iterative genetic algorithm approach. Both the location parameters and knot vectors are evaluated at each step of the iteration process using a genetic algorithm before calculating the control points by least-squares methods. To complement Gálvez et al.’s method, we used the HCS of the template mesh (yellow in Figure 6-19 left) as the base surface approximation for the initial iteration for every participant (human heads are similarly shaped), which speeds up the optimization problem.

In the subsequent sections, we first introduce general characteristics of genetic algorithms and then explain in more detail how the surface reconstruction problem was solved for the HCS of participants.

6.5.3.1 Introduction to Genetic Algorithm

Cost function minimization problems can be solved using many different approaches, including exhaustive search, analytical optimization (gradient, Lagrange multipliers), downhill simplex
method and line minimization (Newton and quasi-Newton methods). However, these algorithms tend to converge on local minimum instead of the global minimum.

In the past three decades, the development of new algorithms in evolutionary computation (EC) brought new ideas to the field of optimisation to overcome this issue. Some of these methods include the genetic algorithm [181, 182], particle swarm optimization [183], ant colony optimization [184], and evolutionary algorithms [185]. These methods convey new solutions to the search space at each iteration (evolution) to avoid being trapped in local minima. They commonly represent optimisation processes present in natural phenomena.

More specifically, the genetic algorithm (GA) is an optimization method based on the characteristics of genetics and natural selection. To minimize the cost function, a GA lets evolution modify the individual genes of an initial population under special selection rules.

### 6.5.3.1.1 Variables and cost function

Cost functions generate output from a set of input variables called a chromosome. We aim at optimizing the output of the cost function through an iteration process by discovering better values for the chromosome. The chromosome is defined by an array of input variables $p_i$ as:

$$ chromosome = [p_1, p_2, ..., p_{Nvar}], $$

while the cost function may be a mathematical function or an experiment based on these input variables. Moreover, constraints or bound limits can be applied to the input variables to avoid unreasonable values.

Independent and dependent variables can be defined in a chromosome. However, additional care must be applied during evolution (i.e., crossover and mutation) when working with dependent variables in order to guarantee correct interactions. Variable interaction is called epistasis. A GA is best suited when epistasis is medium to high.

### 6.5.3.1.2 Initial population

The GA starts with an initial group of chromosomes $N_{pop}$ called the population. Often, variables are normalized to have values spanning between 0 and 1, if defined on a continuous scale. Chromosomes are generally initialised with random values unless epistasis is present.

The first steps of the iteration process consist of solving the cost function for the population and rank the chromosomes by their respective values.
6.5.3.1.3 Natural Selection

Since we want to minimize the cost function, we then discard the chromosomes with the highest cost. The ratio of chromosomes kept for the next step in the GA process is called the selection rate and is denoted $X_{rate}$. Fifty percent of the chromosomes are often kept in the natural selection process. This rate allows a good compromise between too few (not enough dissimilar genes for the offspring) and too many (bad performers can have descendants) survivors [186].

6.5.3.1.4 Pairing

Next, the discarded chromosomes from the previous step are replaced by new offspring. The process consists of selecting continuously two chromosomes (the parents) to generate two offspring until the next population is full again.

Multiple approaches exist to pair the two required chromosomes, i.e., pairing from top to bottom, random paring, weighted random pairing, and tournament selection. Weighted random pairing and tournament selection are preferred, since they typically model natural phenomena in an adequate manner.

In a weighted random pairing, mating probabilities are assigned to each chromosome according to their cost function value. Essentially, the lower the cost function, the higher the chance to be selected for mating. Rank weighting can also be used (i.e., fitness ranking of the chromosome in the population).

One can use tournament selection in order to avoid sorting chromosomes by their cost function at each iteration of the GA (this can be time-consuming for large populations). The method consists of selecting a subgroup of chromosomes (two or three), and then select the chromosome with the lowest cost as the parent. The process is then repeated for the second parent.

6.5.3.1.5 Mating

The genes of the offspring should be a mix of both parents. Different mating techniques exist, depending on the nature of the input variables. For example, when binary coding is used, one can define a randomly selected crossover point in the genes. Parent #1 then passes its genes to the left of the crossover point to offspring #1 and its genes to the right of the crossover point to offspring #2, and inversely for parent #2.

For continuous variables, one simple method, called uniform crossover, consists of picking
multiple points in the chromosomes and then swapping the variables between the parents at these points. The problem is that no new information is introduced to the offspring.

The blending methods solve this problem by combining variable values from the two parents into new variable values in the offspring [187].

\[ p_{\text{offspring}#1,n} = \beta p_{\text{mother},n} + (1 - \beta) p_{\text{father},n} \]
\[ p_{\text{offspring}#2,n} = (1 - \beta) p_{\text{mother},n} + \beta p_{\text{father},n} \]

where \( \beta \in [0,1] \). The transformation above can either be applied to all variables, to just a few randomly selected points, or on the right side or left side of a randomly selected crossover point.

6.5.3.1.6 Mutation

To avoid rapid convergence, and hence the possibility of being trapped in a local minimum, the GA introduces new solutions in the search space through the use of mutations. A mutation rate \( X_{\text{mut}} \) is defined. The total number of mutations to be processed in the population is

\[ \# \text{mutation} = X_{\text{mut}} \times N_{\text{var}} \times N_{\text{pop}} \]

Mutation can appear in any variable of any chromosome belonging to the current population, except the “current” best chromosome. A mutation rate of 20% is often selected [186].

6.5.3.1.7 Convergence

The iterative process can be stopped when an acceptable solution has been reached, or when a set number of iterations has been exceeded.

Evaluating if the solution is acceptable can be done through the use of population statistics (mean and minimum cost). Another option is to keep track of the cost function value of the worst chromosome before mating and mutation to assess if the algorithm has converged.

6.5.3.2 Solving the surface reconstruction problem for digitized head shapes using Genetic Algorithm

We first define the measured points \( \{Q_t\}, t = 0, ..., T \) for the template mesh in the study (i.e., first extracted semi-manually using Geomagic Studio 12®, and then exported in a formatted text file). The \( Q_t \) are then extrapolated to each participant’s mesh based on the point set registration algorithm applied earlier in the present research workflow (Figure 6-30). No manual operations are required to generate the point cloud of each participant. A total of 13000 points was considered for the present study.
To solve the least-square problem, we must associate location parameters \((\bar{u}_t, \bar{v}_t)\) to each of the \(Q_t\). Therefore, the fitting problem can be express by:

\[
E_{lsq} = \sum_{t=0}^{T} (Q_t - S(\bar{u}_t, \bar{v}_t))^2 = \sum_{t=0}^{T} \left( Q_t - \sum_{i=0}^{n} \sum_{j=0}^{m} P_{i,j} N_{i,p}(\bar{u}_k) N_{j,q}(\bar{v}_k) \right)^2
\]

(88)

with \(n + 1\) and \(m + 1\) the number of control points in the \(u\) and \(v\) directions, respectively.

6.5.3.2.1 The base surface

As explained earlier, we define the HCS of the template mesh as the base surface during the fitting process (Figure 6-31). The surface was created using Geomagic Studio 12®.

The surface is defined by 19 control points and a degree of 3 in both directions \((n = m = 18, p = q = 3)\). The knot vectors \(U\) and \(V\) are normalised and non-periodic.
6.5.3.2.2 Step 1: Data points parameterization

We obtain a parameterization of the measured points \( Q_t \) by using a GA. The least squares problem defined above is the cost function where we use the initial knot vectors \( U \) and \( V \) and the control points \( P_{i,j} \) of the base surface. The population size is set to 100. The chromosomes are defined by the location parameters values \((\bar{u}_t, \bar{v}_t)\) arranged in a two rows matrix.

\[
\text{chromosome}_i = \begin{bmatrix}
\bar{u}_0 \\
\bar{v}_0 \\
\bar{u}_1 \\
\bar{v}_1 \\
\vdots \\
\bar{u}_T \\
\bar{v}_T
\end{bmatrix}
\] (89)

Each parameter is assigned a random real-coded value between the interval [0,1].

The selection rate is set to 50%, while a ranked weighted random pairing method is applied to select the parents. We implement the mating using a blending method for all the parameters \((\bar{u}_t, \bar{v}_t)\), using the same parameter \(\beta\) for the offspring. A mutation rate of 20% is used. The algorithm is stopped when the cost function of the best chromosome does not change after 10 consecutive iterations.

6.5.3.2.3 Step 2: Knot vectors parameterization

Similarly, we compute the knot vectors \( U \) and \( V \) with a GA. The cost function, population size,
selection rate, selection method, and mutation rate are identical to the GA described in step 1. The chromosomes are defined by the $U$ and $V$ arranged in a two rows matrix. The first and last $p + 1$ and $q + 1$ knots values are 0 and 1, respectively. Since $p = q = 3$,

$$chromosome_i = \begin{bmatrix} 0 & 0 & 0 & 0 & u_0 & u_1 & \ldots & u_{n-3-p} & u_{n-2-p} & u_{n-1} & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & v_0 & v_1 & \ldots & v_{m-3-q} & v_{m-2-q} & v_{m-1} & 1 & 1 & 1 \end{bmatrix}$$ (90)

In contrast to the location parameters that are independent variables in randomly distributed data points, the knots values cannot spread randomly in the interval $[0,1]$. A uniform, non-periodic knot vector must be defined by non-decreasing values. Therefore, for the initial population, we assign a bound limit to each knot from which their value can be randomly selected. The lower bound limit of knot $u_i$ is equal to the upper limit of knot $u_{i-1}$. Likewise, the upper bound limit of knot $u_i$ is equal to the lower limit of knot $u_{i+1}$. The length of the bound limit is $1/(n - p)$ (or $1/(m - q)$).

For the mating process, we first randomly select a crossover point that can be located in either knot vectors ($U$ or $V$). If the crossover falls inside $U$, then offspring #1 inherits the knot vector $V$ from the mother, and offspring #2 inherits the knot vector $V$ from the father. Then we use a single crossover swap for the vector $U$ of the two offspring. For example, offspring #1 inherits the knots $u$ on the left side of the crossover point from the mother, and the knots $u$ on the right side of the crossover point from the father. Finally, $U$ is sorted by increasing values to avoid the creation of incorrect non-periodic knot vectors. The method is used in a similar way if the crossover point falls inside $V$.

A knot $u_i$ selected for mutation is replaced by a randomly selected value that can be located inside the $[u_{i-1}, u_{i+1}]$ interval.

6.5.3.2.4 Step 3: Control points calculation

After defining the location parameters and knot vectors through the GA, we update the control points’ coordinates of the B-spline surface through least-squares minimization method. The fitting problem can be defined as follows: for all measured points $\{Q_t\}, t = 0, \ldots, T$, we want to fit a B-spline surface $S$ defined as:

$$Q_t = \sum_{i=0}^{n} \sum_{j=0}^{m} P_{i,j} N_{i,p}(\bar{u}_k) N_{j,q}(\bar{v}_k)$$ (91)

The expression can be rewritten in the matrix form as:

$$Q = N(\bar{u}_t) \cdot P \cdot N(\bar{v}_t)$$ (92)

190
which leads to the general expression as:

$$M^T \cdot Q = M^T \cdot M \cdot \text{vec}(P)$$ \hspace{1cm} (93)

where $Q$ is a column vector of length $(T + 1)$, vec$(P)$ is the vectorization of matrix $P$ (i.e., linear transformation which converts a matrix into a column vector by stacking its columns on top of one another) with length $(m + 1) \times (n + 1)$, and $M$ is a matrix of outer products (denote as $\otimes$) of the basis functions $N(u)$ and $N(v)$.

$$M = \begin{bmatrix}
N_{0,p} \otimes N(\tilde{v}_0) & N_{1,p} \otimes N(\tilde{v}_0) & \cdots & N_{n,p} \otimes N(\tilde{v}_0) \\
N_{0,p} \otimes N(\tilde{v}_1) & N_{1,p} \otimes N(\tilde{v}_1) & \cdots & N_{n,p} \otimes N(\tilde{v}_1) \\
\vdots & \ddots & \ddots & \vdots \\
N_{0,p} \otimes N(\tilde{v}_T) & N_{1,p} \otimes N(\tilde{v}_T) & \cdots & N_{n,p} \otimes N(\tilde{v}_T)
\end{bmatrix}$$ \hspace{1cm} (94)

The above linear system was solved using Singular Value Decomposition approach [154] (see Section 5.3.8 for more detail about the method) which is available in Apache Commons Mathematics Library (Apache Commons Math™) in Java programming.

### 6.5.3.2.5 Step 4: Data points reconstruction for error calculation

After each iteration, the data points are reconstructed using the B-spline surface parameters (parametric values, knot vectors and control points). The computed values denoted $\hat{Q}_t$ are then compared to the original data points $Q_t$ using the mean error value:

$$ME = \sum_{t=0}^{T} |Q_t - \hat{Q}_t|$$ \hspace{1cm} (95)

The process described above of using GAs and least squares to update the control points positions is repeated until $ME$ converges.

### 6.5.3.3 HCS fitting algorithm

The section summarises the procedures developed to compute the HCS. The proposed assembled algorithm produces an accurate solution to the fitting problem without manual interaction. However, we acknowledge that the curve could also be generated through many different methods, especially using rational B-spline surfaces (NURBS).

**algorithm** HCS-FITTING is

**input:** Template Fine mesh, 
Registered participant mesh, 
Measured points extracted from the template mesh, 
Base surface parameters (knot vectors, degrees, control points) 
Parameters values (population size, Xrate, Xmut)

**output:** CAD file of the HCS
Read inputs;
Extrapolate measured point’s location on the registered participant mesh;
While ME has not converged:
   Run GA on location parameters;
   Run GA on knot vectors;
   Compute control points positions using least-squares method;
Write output of the HCS in .igs format.

6.5.4 Evaluation

The accuracy of the fitting algorithm was evaluated by generating deviation analyses between the computed HCSs and the head meshes of five selected participants from the sample. The selected participants represent a wide variety of head shapes; this included small, large, narrow, wide, round, and elongated shapes. As displayed in Figure 6-32 below, the surface accurately captured the head shape of the tested participants (i.e., positive and negative mean deviations are low, extremum values are almost non-existent) and, therefore, it can be used during the automatic design process of the customised bicycle helmet models.
Positive Mean Deviation: 0.120mm
Negative Mean deviation: -0.113mm

Positive Mean Deviation: 0.112mm
Negative Mean deviation: -0.103mm

Positive Mean Deviation: 0.093mm
Negative Mean deviation: -0.099mm
Figure 6-32: The HCC (blue) and HCS (yellow) of five participants from the Australian cyclist database. The right picture is the deviation analysis between the HCS and the participant’s registered head mesh.
6.6 Customised Helmet Design using Parametric Modelling

6.6.1 Generic Model

The next step in the mass customisation (MC) system was to design the helmets using Computer Aided Design and parametric modelling techniques. The MC process involved designing generic helmet models, which were then modified on the inside (i.e., the shape and thickness of the foam liner) to fit the head shape of a specific individual. The design process was split into two phases: the standardisation design and the customisation design. The process is demonstrated below for group № 1 that was developed during the clustering study in Chapter 5.

The MC process begins with the standardisation phase by creating a generic helmet model. The first step in standardisation phase was to design the rigid surfaces, which should be common to all customised helmet models within the group. All the Figures below show the design process of a bicycle helmet design developed by the author.

In this example, the outside was created using two free-form surfaces with G2 curvature continuity (Figure 6-33). The surfaces were primary defined around the MaH shape (red dash in Figure 6-33) with an offset distance between 22 and 40 mm. The bottom boundary limit (green in Figure 6-33) was created using the HCC of MaH (red in Figure 6-33), MiH (blue in Figure 6-33), and the 108 individuals classified in cluster № 1 from Chapter 5 (white in Figure 6-33). The MaH and MiH shapes were introduced in Section 6.3, and the HCC in Section 6.5.

Figure 6-33: Initial outside surface of the generic customised helmet model for cluster № 1. The side view on the right shows the outline profiles of the MaH (red dash) and the MiH (dash blue) surfaces, and the HCC of the MaH (red), the MiH (blue) and the 108 individuals in the cluster (white). The green line is the bottom boundary limit of the generic model.

The next step involved creating the inside surface of the generic helmet using the MiH surface.
as an input element (Figure 6-34). This is the maximum liner thickness a custom-fit helmet can inherit after the customisation process.

Figure 6-34: The inside design of the generic helmet based on the MiH surface (blue). Right is a section view along the mid-plane.

The last step of the standardisation design phase involved the creation of ventilation holes. A five-row system of large openings was used at the top of the helmet (Figure 6-35). Four apertures were also added at the back with rounded and elongated shapes. The reinforcement features (yellow surfaces in Figure 6-36) were positioned in such a way to avoid interference with the customer’s head shape during the customisation process. This was achieved by keeping the geometric elements of all the reinforcement features above the MaH surface (red in Figure 6-36).

Figure 6-35: The generic bicycle helmet model for group № 1.
Figure 6-36: The design of the reinforcement features of the generic bicycle helmet model. P1, P2, and P3 are three planes passing through the main aeration planes of the helmet. The three section views along these planes are represented. The green surfaces are the helmet liner sections intersecting the associated plane. These surfaces can be trimmed down during the customisation process. The yellow surfaces are the opening reinforcements. They are fixed and cannot be changed. The pink contours are the reinforcement sections at the specific cutting plane. Similarly, the red dash lines represent the intersection of the planes with the MaH surface. As shown in the graphics, minimum distance values were kept between the red and pink elements to allow a slight gap between the top features of the customised helmet and the head of every customer in the group.

The second phase of the customization process involves the customisation of the custom-fit design, where the head shape of an individual (i.e., HPP surface) was used as an input element for the modification of the generic helmet model (presented in the standardization phase). The procedure consisted of combining the HPP and HCC shapes to create a new inner surface of the helmet liner. A simple split operation was implemented. Figure 6-37 shows an example of the process where the head shape of an individual (orange) was used to generate the customised helmet. Dress-up features such as fillets, chamfers and drafts were then added to finalise the model.
The helmet shell was also defined as a standard component (Figure 6-38). It was designed using most of the outer surfaces of the helmet liner. The bottom boundary of the side surface was defined using the maximum HCC in the group. The maximum HCC represented the highest helmet boundary position for any individual in the group.

The helmet model was designed using CATIA V6 CAD software (Dassault Systèmes®, Vélizy-Villacoublay, France) and the Knowledgeware workbenches used in the parametric system.
This approach permitted the development of a fully parametric, integrated system where the helmets were automatically customised based on the customer’s head shape.

6.6.2 Customised Models

Using the MC procedures highlighted above, custom-fit helmet models were created for the 116 individuals classified in group № 1 (108 from the 3D-HEAD-CLUSTERING algorithm in Chapter 5, and 8 from the 3D-HEAD-CLASSIFIER in Section 6.4). Figure 6-39 shows an example of custom-fit helmet models created for five of these individuals. A cross-sectional view of the five helmet liners is presented in Figure 6-40, where the different liner thicknesses resulting from the customisation process can be evaluated.

Figure 6-39: Examples of customised helmet designs for five individuals included in group № 1.
Figure 6.40: A cross-sectional view of the five customised helmet models. Each colour represents the cross-section of each participant.

Table 6.2 presents the helmet liners statistics in terms of volumes and thicknesses for the 116 custom-fit designs tested. The data are compared to the best-case (maximum thickness) and worst-case (minimum thickness) helmets generated from the MaH and MiH surfaces. Results demonstrate that the custom-fit models lie in between these limits, with values spreading inside the available ranges. Although the proportion of individuals classified in group № 1 is large, the generated customised helmets seem to be fairly similar in terms of volume. Using a standard foam density of 65 kg/m³, the difference in the liners’ weight, between the two extreme cases, is only 23 grams. However, the liner thicknesses varied up to 14 mm between different helmet models. This might cause annoyance to some customers who would end up with bulky helmets on their heads (in terms of thickness). A simple solution would be to implement more standard sizes to the MC framework by modifying the stopping parameter of the 3D-HEAD-CLUSTERING in Chapter 5. However, a high increase in production cost could be anticipated.

Table 6.2: Customised helmet liner statistics. Sample size = 116

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Mean ± SD</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Best Case</th>
<th>Worst Case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Helmet liner volume (cm³)</td>
<td>1798 ± 52</td>
<td>1640</td>
<td>1988</td>
<td>2116</td>
<td>1484</td>
</tr>
<tr>
<td>Mean liner thickness (mm)</td>
<td>36.6 ± 1.8</td>
<td>31.4</td>
<td>39.7</td>
<td>44.3</td>
<td>29.4</td>
</tr>
<tr>
<td>Minimum liner thickness (mm)</td>
<td>30.3 ± 2.3</td>
<td>25.1</td>
<td>38.8</td>
<td>38.8</td>
<td>25.1</td>
</tr>
<tr>
<td>Maximum liner thickness (mm)</td>
<td>53.2 ± 3.6</td>
<td>46.7</td>
<td>61</td>
<td>61</td>
<td>46.7</td>
</tr>
</tbody>
</table>
6.7 Verification using Finite Element Analysis (FEA)

A novel verification method was developed for the generated custom-fit helmet models. The procedure rests upon the idea that every single customised helmet created within a group should be safe to use, when the worst- and best-case helmets (i.e., helmets based on the MaH and MiH surfaces) comply with the relevant safety standards. Consequently, the physical tests required for certification should only be performed for the two extreme models of each group. This assumption was verified by using a validated drop impact test simulation model that complied with the Australian standards [63]. The simulation was performed in Abaqus 6.14 (Dassault Systèmes®, Vélizy-Villacoublay, France).

Only a simplified description of the process is provided in this section. (For more information, please refer to the Ph.D. thesis of H. Mustafa in [39].)

6.7.1 FEA Method Description

Geometric data of the helmet liners, the shell, headforms and the flat anvil were imported to the software. The helmet shell was meshed using triangular S3R linear shell elements, and the liners were meshed with C3D10M modified quadratic tetrahedral elements. Distortion control was also applied to all elements of the liners to avoid excessive distortion. C3D10M tetrahedral elements were used to mesh the Australian standard J-headform [38], and C3D8R, an 8-node linear brick element, was chosen for the flat anvil. The headform selection was based on deviation analyses between the computed mean shape of cluster № 1 and the standard Australian headforms. The most resembling headform, i.e., J-headform, was then selected for the simulation (see Figure 5-24 through Figure 5-28 in Section 5.6 for more detail about the selection) as part of the requirements set by Australian standards [63].

The helmet liners were modelled using an isotropic crushable foam material with a density of 65 kg/m³. Volumetric hardening parameters, such as the ratios of the initial yield pressures in hydrostatic tension and compression and the uniaxial compressive data of expanded polystyrene (EPS), were taken from literature [188]. Other material properties of helmet components such as the shell and J-headform were extensively described in [11, 189]. Penalty contact property with a friction coefficient of 0.4 was adopted for interactions between all surface contacts in the simulation. Tie constraint was applied between the inner surfaces of the shell and the outer surfaces of the liner to simulate in-mould bonding, which is common for bicycle helmets [188]. A homogenous shell section with a corresponding thickness of 0.40-
0.45 mm was assigned to the helmet shell. The anvil and headform were defined as rigid bodies, and the bottom face of the anvil was fixed in every degree of freedom.

The customized helmets were tested on three impact locations, crown, front and sides (as shown in Figure 6-41), replicating similar positions to those in the experimental impact tests. The impact velocity of the helmet and headform were set to 5.44 ms⁻¹, which was obtained from experimental drop impact tests [189].

![Image of helmet testing](image)

Figure 6-41: Impact locations of the customized helmet: side, front, and top.

### 6.7.2 FEA Results

The validated simulation model described above was used to conduct virtual drop impact tests for five custom-fit helmet models created for group № 1 (Figure 6-38). The worst-case and best-case scenarios were also tested.

According to the AS/NZS standard for bicycle helmets, a bicycle helmet should obtain peak linear acceleration below 250 g to be considered a safe helmet [63]. In the drop test simulation, the peak linear accelerations (PLA) of the seven helmets were plotted against time at three main impact locations, i.e., top, front and side (Figure 6-42). It is clear from the graphs that all custom-fit helmets tested (grey) recorded PLAs below the safety limit value of 250 g. For the three impact locations, the worst-case helmets (red) recorded the highest PLAs, while the lowest PLAs were obtained by the best-case helmets (green).
Figure 6-42: Peak linear acceleration of five custom-fit helmets (grey), the best-case helmet (green), and the worst-case helmet (red). The simulations were performed at three locations, namely, the front (top graph), the top (middle graph), and the side (bottom graph).

This is consistent with the known fact that PLA is highly dependent on the helmet thickness. As shown in Table 6-2, the worst-case helmet has the thinnest liner, and the best-case helmet has the thickest liner. The PLAs for the five helmet models were in between the best-case and the worst-case helmets at the three locations. Again, this result is also consistent, because the thicknesses of these custom-fit helmet models were in between the worst-case and the best-case helmets.

In conclusion, all the customised helmets created through the MC framework manage to achieve PLA below 250 g as long as the liner thicknesses are between the worst- and best-case helmets. This statement is true when the worst case scenario pass the impact tests requirements described in [63]. Although the best-case model is not essential to verify the method, it was added to the simulation to ensure that all the custom-fit models generated for
a group hold similar impact characteristics. For example, it is now established that a drop test at the front location in any of the customised helmets in group № 1 would have a PLA between 108.4 g and 174.3 g.

Considering the above, we conclude that all the customised helmet models generated with the proposed design framework will comply with the relevant safety regulations in Australia and, therefore, could be sold in the Australian marketplace.
6.8 Fit Evaluation via the HELMET-FIT-INDEX Method

The accuracy of fit for the customised helmets created was assessed using an objective evaluation method called the HELMET-FIT-INDEX (HFI). The method was introduced in Chapter 4. Based on 3D anthropometry, reverse engineering techniques, and computational analysis methods, the index provides a fit score, between a helmet and an individual’s head shape, on a scale ranging from 0 (excessively poor fit) to 100 (perfect fit).

The three essential parameters used in the HFI formula are the Standoff Distance SOD (the average distance between the head and the helmet’s liner), the Gap Uniformity GU (the measure of SOD dispersion), and the Head Protection Proportion HPP (the measure of the head surface area percentage under helmet protection).

\[
HFI = \begin{cases} 
100 \times \exp \left( 0.13 - \frac{|SOD - 6| - 0.12GU}{HPP} \right) & \text{for } 4 > SOD > 8 \\
100 \times \exp \left( -\frac{0.12GU}{HPP} \right) & \text{for } 4 \leq SOD \leq 8
\end{cases}
\] (96)

The suitability of the index to assess the helmet fit was validated using the cyclist’s subjective assessments of three commercially available helmets (Section 4.3.4).

Most of the participants included in the HFI study in Chapter 4 were also involved in the grouping analysis in Chapter 5 and the custom-fit design study of bicycle helmets presented in this chapter. This configuration permitted the comparison of helmet fit between the three commercially available models (Sections 3.2.1 and 3.3) and the new customised helmets created in this Chapter.

Sixty-one of the 116 individuals in group № 1 with a customised helmet model had also taken part in the fit study from Chapter 4. Therefore, the fit accuracy of the custom-fit models was assessed using a sample size of 61. The first row of Table 6-3 presents the HFI statistics of the custom-fit helmet models generated for these specific individuals. The raw head meshes data generated by the 3D scanner were used for the analyses (Figure 6-43) to produce results as accurate as possible (i.e., using the registered head meshes or the HPP surfaces would have produced much higher HFI values). The next three rows of Table 6-3 show the same HFI statistics for the three commercially available helmets.
Table 6-3: Custom-fit helmets assessment study - Summary Statistics – Data are mean (95% CI) – Sample size is 61

<table>
<thead>
<tr>
<th></th>
<th>SOD (mm)</th>
<th>GU (mm)</th>
<th>HPP</th>
<th>HFI (/100)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Custom fit Helmet group № 1</td>
<td>2.5 (2.3, 2.7)</td>
<td>0.9 (0.8, 1.0)</td>
<td>0.96 (0.96, 0.96)</td>
<td>80.1 (79.3, 80.8)</td>
</tr>
<tr>
<td>Helmet A</td>
<td>9.0 (8.8, 9.4)</td>
<td>4.0 (3.8, 4.1)</td>
<td>0.83 (0.82, 0.84)</td>
<td>52.8 (50.9, 54.6)</td>
</tr>
<tr>
<td>Helmet B</td>
<td>8.3 (7.9, 8.7)</td>
<td>3.7 (3.5, 3.9)</td>
<td>0.85 (0.84, 0.86)</td>
<td>55.7 (53.6, 57.7)</td>
</tr>
<tr>
<td>Helmet C</td>
<td>9.9 (9.6, 10.4)</td>
<td>4.2 (4.1, 4.4)</td>
<td>0.83 (0.82, 0.83)</td>
<td>48.2 (46.0, 50.4)</td>
</tr>
</tbody>
</table>

Figure 6-43: Deviation analysis of a participant’s customised helmet. SOD is 1.99mm, GU is 0.87mm, HPP is 0.95 (HFI = 78.1).

The HFI difference between the customised and commercial helmets was assessed using three paired-samples t-test (Appendix L). The differences were statistically significant, with \( p < 0.0005 \). The interpretation of the Cohen’s \( d \) values showed a strong practical difference (\( d > 0.8 \)) for the three tests. As expected, that custom-fit design of helmets improves the fit accuracy significantly.
6.9  Summary of the Research Outcomes

The major objective of this thesis was to develop and to verify a novel approach for the design of bicycle helmets. A custom-fit digital helmet model was generated using an automated process. In order to achieve this objective, multiple innovative procedures were presented:

1. The customisation framework was developed based on the clustering results (from Chapter 5) where four groups of individuals with similar head shape were presented. This categorization enabled the creation of four new standard helmet sizes for the implementation of the customisation platform. The idea was to perform the customisation at the group level and follow a modular approach by only personalising the inside surfaces of the helmet foam liner. In order to do so, generic helmet models were created for each group based on the minimum and maximum head shapes embedded in a group.

2. The customisation process was then implemented. It involved four steps: (i) digitization of the customer’s head shape (detailed in Section 3.4), (ii) categorization into one of the four predefined groups, (iii) transformation of the polygon mesh (i.e., 3D head scans) to standard mathematical surface models, and (iv) modification of the inside shape of the generic helmet model based on these customers’ head surfaces. Step (ii) was achieved using supervised learning techniques. A new method named 3D-HEAD-CLASSIFIER was developed. To the author’s best knowledge, this is the first time that 3D head scans are objectively classified into predefined groups of individuals based on their similar head shapes. For step (iii), complex curves and surfaces fitting techniques were applied to automate the transformation process. B-spline curves and surfaces were used. Step (iv) was accomplished through standard 3D modelling techniques, where a simple split operation was performed between the created generic helmet model and the transformed data of the digitized head.

3. The verification of customised-fit helmets. It was also shown in this chapter that the customised helmets created comply with the relevant drop impact test standards if their liner thicknesses were within specific boundary limits. The limits were set by the best and worst case helmets for each group. This finding should significantly help with the potential commercialisation of the created custom-fit helmet models where only the worst-case helmet model of each group needs to be physically tested.

4. The evaluation of fit accuracy. Finally, section 6.8 presented the evaluation of fit accuracy, via the HELMET-FIT-INDEX (Chapter 4) method. The customised models were
compared to three commercially available helmets and the results showed that the HFI was significantly higher for the customized helmet.

The mass customisation framework presented in this chapter could now be seen as an alternative design approach for bicycle helmet models. This design technique may lead to better-fitted helmets for a wider range of customers compared to traditional methods.
7. CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

This thesis provided a detailed characterisation of a new mass customisation design framework for bicycle helmet models. Such a characterisation was needed to solve the recurring issues and limitations of conventional methods still in use today to design, test, and manufacture protective headgear.

These problems have been identified in the introduction in Section 1.1 and the literature review in Chapter 2. Of the issues outlined, solving the helmet fit problem has been the main goal for the present research. Poor helmet fit has been linked to a reduction of the protective characteristics of the headgear during impacts, as well as to an increase of the perceived discomfort by the wearer. The logic behind the present work was that a properly fitted helmet could prevent roll-off after the first impact, which has been responsible for many injuries and deaths amongst cyclists. In addition, a better-fitted helmet would also enhance comfort and could, therefore, encourage more cyclists to wear one during cycling, which is one of the major recreational activities in the country.

One of the major causes of poor helmet fit is attributed to inappropriate designs, which are related to the intrinsic characteristics of today’s helmet manufacturing methods. As shown in Section 2.3, a wide range of consumers may experience inappropriate helmet fit with the current one, two, or three helmet sizing systems proposed by most brands. Helmet fit issues become more serious for individuals with irregular or uncommon head shapes, such as round and elongated forms, who frequently end up buying a helmet that does not fit because of the limited choice offered by manufacturers.

One obvious solution to the fit problem is to adopt a personalisation approach, where the helmets are customised directly using the shape and size of the user’s head. This approach, often called custom-fit design, has been widely used for other user-centred products, but has yet to be applied to helmets. Therefore, the present research aimed to fill this gap in the literature by developing an automated process to produce a complete, custom-fit 3D model of a bicycle helmet for an individual. In addition, the created custom-fit helmet had to comply with the relevant safety standards without being subjected to physical tests. This was
important because conducting physical tests on all the generated customised models would be impractical.

The proposed customisation framework involved the implementation of a series of advanced computational processes, parametric design techniques, and simulation analyses. Some of these methods were directly applied from existing work in the literature or slightly modified to match the specific requirements of the present research study. However, new methods were also introduced to deal with the modern type of data sources adopted in this work. For example, highly accurate 3D anthropometric data were recorded using state of the art technologies for each individual involved in the study (Chapter 3). Accordingly, the 3D-HEAD-CLUSTERING (Section 5.4) and the 3D-HEAD-CLASSIFIER (Section 6.4) methods were developed to work efficiently with these data. They were used to categorise and classify individuals based on head shape similarity.

The present work has shown that using a customisation approach to design bicycle helmets led to better-fitted models for a large range of consumers. This demonstration was made possible through the utilisation of a new objective assessment method of helmet fit, called the HELMET-FIT-INDEX (HFI), introduced in Chapter 4. When applied to 61 individuals on both the generated customised helmets and three commercially available models in Section 6.8, strong statistical and practical differences were observed in favour of the new designs. The mean HFI was $80.1/100$ for the customised helmets and $52.8/100$, $55.7/100$, and $48.2/100$ for the three existing models.

As described in Sections 1.2 and 1.3, eight research activities and six research questions were formulated based on this mass customisation scheme. In this chapter, the main findings of the results from previous chapters will be discussed.

In addition, the conclusions for the eight research activities are presented below. The presentation order has been changed to match the chapters’ and sections’ order of this thesis.

### 7.1.1 3D Anthropometry Database

**Activity #5.** Build a database of 3D head scans of Australian cyclists. This was discussed in Chapter 3. Note that Activity #1 was a sub-task of Activity #5.

The main objective of this activity was to develop a 3D head scan database for the Australian population. A total of 222 Australian residents volunteered for the survey in 2014, covering a wide range of the population, aged from 18 to 80+, of both genders. An advanced handheld 3D
scanner was used to digitize the participants’ heads. The resulting scans were then post-processed and aligned to a common axis system defined, using three planes spanning the Sagittal Arc, the Head Circumference and the Bitragion Coronal Arc. The Hair Thickness Offset (HTO) was developed and applied to the polygon meshes of each participant within the region of the hairline. Unlike previous similar studies of the human head, the HTO method ensured that the final head scans in this survey represented more accurately the head shape of each participant.

7.1.2 Helmet Fit Index (HFI)

**Activity #7.** Develop a quantitative index to evaluate the fit accuracy of bicycle helmets in relation to a person’s head shape and size.

The method was introduced in Chapter 4 and applied to the generated customised helmet models in Section 6.8.

The objective assessment of fit can provide in-depth understanding of how a wearable product performs for the target population. This is especially true for helmets, where fit plays a significant role in both, the cyclist’s safety during crashes and his/her perceived feelings about comfort. However, only sparse methods have been introduced in the literature for the objective evaluation of helmet fit accuracy. This research activity was formulated to fill this gap.

A novel computational method was developed to compute the HELMET-FIT-INDEX (HFI) for a specific person and a specific helmet (Section 4.3). The approach combined 3D scanning techniques and analysis of the gap distribution between the head and the inside surfaces of the helmet to determine the three fundamental parameters used in the HFI formula, namely, the Standoff Distance SOD (the average distance between the head and the helmet), the Gap Uniformity GU (the measure of SOD dispersion), and the Head Protection Proportion HPP (the measure of the head surface area percentage under helmet protection). The HFI was defined by an exponential distribution and it provided a fit score on a scale from 0 (excessively poor fit) to 100 (perfect fit). The HFI formula was then adapted for the evaluation of local regions of the head, namely, the front, top, right, left, and back.

A correlation study between quantitative (HFIs) and qualitative (subjective assessment) data was implemented for 117 Australian cyclists. Three commercially available helmets were selected and evaluated numerically by both techniques. Regression analyses and within-subjects studies were computed (Section 4.3.4). Results showed that the index was a useful
and suitable indicator of bicycle helmet fit, especially when comparing multiple helmets together.

### 7.1.3 3D data post-processing framework

**Activity #2.** Build a post-processing framework where the 3D head scans are transformed for future use.

The basic post-processing steps were presented in Section 3.4 and covered by the requirements of Activity #5. The steps included the removal of hair bumps and fabric folds on the recorded 3D head scans, as well as the use of some flattening tools to minimise angles between individual polygons, and a rewrapping tool to generate a more uniform spacing and resolution between each point. In addition, non-manifold triangles were discarded, small components were deleted, self-intersection triangles were repaired, and spikes were removed from the polygon meshes.

Further to these steps, a more advanced processing method called point set registration was applied to the data. This was discussed in detail in Section 5.3. More specifically, the Optimal Step Nonrigid Iterative Closest Point (ICP) algorithm (N-ICP-A) was applied. The method consisted of transforming a high-resolution mesh iteratively named the *template*, to match a person’s mesh named the *target*. The targets were all the 3D head scans recorded in the database. This transformation enabled the comparison of the 3D scans on a point-by-point basis and was used for the development of the new clustering algorithm of human head shapes. The resulting optimization was a classic linear least squares problem, which was solved using Cholesky and QR Factorizations. Other computational methods were used during the process to enable the transformation of the template mesh, including Nearest Neighbour Search and Ray Tracing algorithms.

Finally, a third transformation process was described in Section 6.5 to extract, through a computation approach, the head surface model of an individual’s polygon mesh. This surface was directly used as an input element in the mass customisation design system. The surface, named HPP, was built on the Head Protection Proportion area defined in the HELMET-FIT-INDEX study. The HPP was built using two geometric elements, i.e., the Head Covering Curve HCC and the Head Covering Surface HCS. Both were constructed using B-Spline functions. The HCC was constructed via an approximation method and the End Points Derivatives algorithm. Fitting a surface to given data points was a much more complex problem than for curves and direct solving methods required some specific configurations to be applied. These were not
met in this fitting problem. Therefore, an iterative method was implemented through a genetic algorithm to construct the HCS. Although many CAD systems could compute the head surface directly from the polygon mesh for each participant, substantial manual human operations are still required. The use of computation methods like the ones presented in this work ensured that the proposed mass customisation framework was completely automated.

7.1.4 Clustering algorithm

**Activity #6.** Create groups of individuals with high head shape similarity.

To achieve this objective, a new clustering method was introduced. It has been named the 3D-HEAD-CLUSTERING algorithm and was presented in Chapter 5. The method was built on top of a standard hierarchical clustering algorithm called centroid linkage. However, as opposed to centroid linkage, the 3D-HEAD-CLUSTERING performed multiple pairwise comparisons inside each loop of the hierarchical clustering algorithm, which allowed the creation of several groups from which to choose at each iteration. The best group selection was then based on four parameters (i.e., $a$, $b$, $c$, and $d$) and the number of participants contained in each group. These measures gave a broad understanding of the head shape similarity within each group. Four groups were created when applied to the 3D anthropometric database of head shapes from Chapter 3. A total of 95% of the population was classified within one of these groups. Compared to other clustering methods, the algorithm was able to categorize participants into fewer groups and provided a fair degree of intra-cluster homogeneity, while still classifying a high proportion of the studied population. Keeping the number of groups small was necessary to limit the costs associated with the fabrication of the standard components in the mass customisation framework.

7.1.5 3D Head Classifier

**Activity #3.** Implement classification procedures where the user’s head shape is categorized into a predefined group of individuals with similar head shapes.

A new classifier, called the 3D-HEAD-CLASSIFER, was developed stemming from the classification results of the new clustering algorithm. It was presented in Section 6.4. The goal was to categorize new customers into one of the four computed clusters using head shape similarity. The process first involved creating two headform models for each group-size, using the head shape of all the individuals classified in these groups. These models were constructed using Boolean operations (Section 6.3) to represent the minimum and maximum head shapes within a group. They were named the MaH (Maximum Head) and MiH (Minimum Head)
shapes. Then the classifier was built to assess if the new head shapes fall within these two forms. The Nearest Neighbour Search algorithm and $K$-d trees space partitioning methods were used for this assessment. A series of criteria parameters was also used to select the best performing group if an individual belonged to more than one cluster. Fourteen participants of the 15 tested were classified as within one of the four clusters.

To the author’s best knowledge, this is the first time that a classifier has been developed to categorise individuals into previously-generated group-sizes based on the complete shape of their head. Until today, only the head circumference of the individual has been used to select one of the helmet sizes provided by a manufacturer.

7.1.6 Custom-fit Helmet design

**Activity #4.** Automate a 3D design parametric technique, which uses digitized head scans of users to create custom-fit bicycle helmet models.

The whole idea behind the proposed custom-fit design process was to perform the customisation at the group level, where only the inside surfaces of the helmet foam liner were modified to fit the customer’s head shape. To do so, generic helmet models were created for each of the four-computed group-sizes based on the minimum and maximum head shapes embedded in a group (MaH and MiH). The customisation was, therefore, performed on these generic models after the classification algorithm had been run on the new customer head shape. This design procedure was described in Section 6.6. For the present study, a new helmet design was implemented to verify the method. The full design process was only shown for group № 1, the most popular cluster, within which 54% of the participants in the sample had been classified. The outside of the helmet was created using two free-form surfaces with G2 curvature continuity. For the vents, a five-row system of large openings was used at the top of the helmet, as well as four apertures at the back with more rounded and elongated shapes. Customisation steps were implemented on the 108 individuals classified in group № 1. Results showed that only 23 grams separated the lightest and heaviest helmets in this group.

This is the first time that a modular approach has been used to customise helmets. Using this method will ensure relatively low production costs compared to a full personalisation process where even the outside components of the helmet (e.g., the shell) would be unique.

7.1.7 Finite element verification

**Activity #8.** Develop a validated FEA method to test shock absorption characteristics of
customised bicycle helmets. The method should follow the requirements of the Australian standard.

Finally, a numerical technique was developed to verify the safety characteristics of the customised helmets. This method was presented in Section 6.7 in a simplified and concise format. (For detailed information, readers are advised to refer to a parallel study developed by fellow Ph.D. colleague Helmy Mustafa at RMIT University [8, 9, 39].) The procedure relied on the concept that every single customised helmet created within a group was safe to use if the worst-case helmet (i.e., helmets based on the MaH and MiH surfaces) complied with the relevant safety standards. Consequently, the physical tests required for verification should only be performed for the worst-case model of each group. This assumption was demonstrated by using a validated drop impact test simulation model that complied with the Australian standard. The tests were conducted on the worst- and best-case helmets and five customised helmets from group № 1 at three locations around the head: the front, the top, and the side. The recorded peak linear accelerations (PLA) of the customised helmets were all located within the PLA values of the worst- and best-case helmets. In addition, the PLA of the worst-case helmet was well below the 250 g limit at the three impact locations. Therefore, it was concluded that all the customised helmets created complied with the requirements of the current safety standards by using the design protocol of the proposed mass customisation design framework.
7.2 Summary of Original Contributions

The key original components of this thesis are summarised as follows.

1. A novel mass customisation design framework for bicycle helmets was developed where the inside surfaces of the headgear were modified to fit customers’ head shapes. This is the first time that such a system has been published for this kind of user-centred product [4].

2. A 3D anthropometric database of Australian cyclists was compiled to achieve this objective. The database consisted of 222 volunteers. The head shapes were recorded via a state of the art white light 3D scanner, enabling high accuracy and precision of the data. This is, to date, the largest known 3D anthropometric database of the head in Australia [6].

3. An innovative index was also introduced to assess the fit accuracy of helmets for individuals quantitatively. The method, named the HELMET-FIT-INDEX, was validated using subjective assessments of helmet fit and was used to confirm the fit benefits of the customisation approach presented. This method marked a significant improvement in the objective assessment of fit for user-centred products and could be reused in a multitude of applications and research studies [2, 5].

4. A set of post-processing methods was implemented to transform the raw 3D head scans into practical data. More specifically, the polygon meshes were converted, through computation, to surface models that could be used directly in the custom-fit design process. Such methods included mesh regularization through a Point Set Registration algorithm with linear least squares problems, and curves and surfaces fitting approximation using B-Spline functions via the end point derivatives procedure and a recent genetic algorithm [4].

5. The mass customisation system called for the creation of user groups with high head shape similarity. To achieve this goal, an ingenious clustering algorithm named 3D-HEAD-CLUSTERING was developed. The algorithm was designed to deal with the specific shape characteristics of the human head. Four groups were created based on the database of Australian head shapes. As shown in this thesis, the clustering results of the new method were superior to standard hierarchical clustering algorithms [3, 4].

6. Further to the grouping of individuals, the system demanded the development of another machine learning method in the customisation process. The 3D-HEAD-CLASSIFIER was introduced and it was able to categorize new customers into one of
the four computed groups. The classification was based on the minimum and maximum head shapes included in each group and the procedures of the Nearest Neighbour Search algorithm. To the author’s knowledge, this is the first time that such a method has been initiated in the literature [4].

7. A novel validation technique for certification of customised helmet models was also presented. Using the finite element analysis method, it was shown that the generated models complied automatically with the relevant safety standard if and only if the worst-case helmet in each group passed the requirements of the drop impact test specified in the standard [4, 8, 9]. This advance is critical for the success of the mass customisation framework introduced in this research. Indeed, certification usually requires testing physically ten or more samples for each model. Doing so on all customised models would be impractical.
7.3 Limitations and Recommendations for Future Work

The implementation of advanced manufacturing technologies is essential for successful development of mass customisation systems. However, this was not described in this study where the focus was primarily on the design constraints. Therefore, the full mass customisation framework should be characterised to recognize this new helmet production method as a viable alternative to standard processes. Future work must focus on these limitations.

Promising fabrication techniques such as additive manufacturing (AM) (e.g., 3D printing) could be considered for this implementation. However, 3D printing the helmets directly is not a practical option at the moment. This is because the mechanical properties of the available materials differ significantly from the well-known foam materials, like expanded polystyrene (EPS), that have been used extensively in this industry in the past four decades. One option that the author intends to present in the future is the combination of AM with common moulding techniques. In this proposal, interchangeable inserts would be incorporated inside a generic helmet mould. The inserts would be designed based on the customised helmet models and manufactured using AM. This technique would, therefore, combine the benefits of AM for mass-customisation and the standard manufacturing techniques and materials used in the industry today.

Obviously, the mass customisation framework presented in this thesis for bicycle helmet models could also be applied to other types of helmets, such as motorcycle, baseball, jockey, American football, cricket, mountaineering sports, and construction helmets. The method would need to be adapted to the specific requirements of the headgear in each instance, including design and safety factors. It is envisaged that the system could also be accommodated to other types of user-centred products such as gloves, glasses, and running shoes.
APPENDICES
A. Questionnaire–Fit Assessment Study

Bicycle Helmet Fit and Comfort Study Questionnaire

1. Participant details:
   a. Date of Birth (DD/MM/YY):
   b. Gender: □ Male □ Female
   c. Ethnic/Ancestral background:
      - Australasian: □ Australian / New Zealander □ New Guinean and Pacific Islands
      - European: □ Northern European (UK, Finland, etc.) □ Western European (France, Germany, etc.)
      - Asian: □ Southeast Asia (Indonesia, Malaysia, etc.) □ East Asian (Japan, Korea, China, etc.)
      - American: □ North American □ South American
      - South African:
   d. Cycling Activity: □ Recreation / Utility / Touring □ Competition / Training
   g. Cyclist mass (kg):
   b. Height (cm):

2. Helmet use:
   a. When cycling, how often do you wear a helmet?
      □ always □ half the time □ never □ most of the time □ rarely
   b. Main reason for not wearing a helmet (if applicable):
      □ inconvenience □ discomfort □ vision □ other:

4. Helmet fit requirement:
   Helmet fit user ideal. In a scale from 1 to 10, please rate your ideal degree of pressure on your head when wearing a bicycle helmet. If it was a very loose feeling and 10 very tight, what value would best describe your fit requirement?
   1 2 3 4 5 6 7 8 9 10

   Helmet fit user importance. In a scale from 1 to 10, please rate the importance to achieve your ideal fit in a bicycle helmet model. When purchasing a new helmet, is it essential that it match your ideal degree of pressure on your head (10) or you can buy one which doesn’t (1) but satisfied others parameters?
   1 2 3 4 5 6 7 8 9 10

5. Helmet fit assessment:
   In a scale from 1 to 10, please rate how fit and comfort are achieved in the provided helmets. 1 being very bad comfort and fit feeling, and 10 being excellent fit and comfort. Please rate for the overall helmet model and for the 3 described regions. Pick the best size for you first.

<table>
<thead>
<tr>
<th>Helmet A</th>
<th>Helmet B</th>
<th>Helmet C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Met Koos</td>
<td>Met Crossover</td>
<td>Ned Lightning</td>
</tr>
<tr>
<td>Size: M or L</td>
<td>Size: UN or XL</td>
<td>Size: SM or ML</td>
</tr>
<tr>
<td>Overall Fit Assessment value</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Top region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Front region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Back region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Right region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
<tr>
<td>Left region fit</td>
<td>/10</td>
<td>/10</td>
</tr>
</tbody>
</table>

Thierry Perret-Ellena (PhD Student, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University, thierry.perret-ellena@rmit.edu.au, 9925 6169)
B. Questionnaire–Grouping Study

Bicycle Helmet Fit and Comfort Study Questionnaire

1. Participant details:

<table>
<thead>
<tr>
<th>a. Date of Birth (DD/MM/YYYY):</th>
<th>b. Gender:</th>
<th>☐ Male ☐ Female</th>
</tr>
</thead>
</table>

c. Ethnic/Ancestral background:

- Australian:
  - Australian / New Zealander
  - New guinea and Pacific Islands
- European:
  - Northern European (UK, Finland, etc.)
  - Western European (France, Germany, etc.)
  - Eastern European (Russia, Ukraine, etc.)
  - Southern European (Spain, Italy, etc.)
- Asian:
  - Southeast Asian (Indonesia, Malaysia, etc.)
  - East Asian (Japan, Korea, China, etc.)
  - South and Central Asian (Indian, the subcontinent)
  - North Asian (Asian portion of Russia)
- American:
  - North American
  - South American
- African & Middle Eastern:
  - Western, Central and Eastern African
  - North African & Middle Eastern
  - South African

d. Cycling Activity:

- ☐ Recreation / Utility / Touring
- ☐ Competition / training

g. Cyclist mass (kg):

b. Height (cm):
C. Consent Form

Invitation to participate in a research project

Project Title: Digital design of head fitting customized sport helmets using 3D Morphing algorithms

Investigators:
- Thierry Perret-Ellena (PhD Student, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University).
- Helmy Mustafa El Bakri (PhD Student, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University).
- Dr. Toh Yen Fang (Senior Lecturer, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University).
- Prof. Dr. Aleksandar Subic (Dean of Engineering, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University).

Dear …………………………………………………………………………,

You are invited to participate in a research project conducted by RMIT University.

Who is involved in this research project? Why is it being conducted?
The research study on head fitting customized sport helmet is primarily lead by two PhD students, namely Thierry Perret-Ellena and Helmy Mustafa. Their first supervisor is Prof. Dr. Aleksandar Subic and their second supervisor is Dr. Toh Yen Fang. All of the people mentioned are from the School of Aerospace, Mechanical and Manufacturing Engineering, Royal Melbourne Institute of Technology (RMIT), Australia. The research is being conducted to look at the possibilities of sports helmet customization according to the shape and dimension of the user's head.

Why have you been approached?
As a person who is involved in cycling (as commuting or recreational activities), you are invited to take part in a research study on user centred customization of bicycle helmet.

What is the project about? What are the questions being addressed?
The research will look deeply into user-centred mass customization of bicycle helmet. Fit is one of the general concern of professional cyclist and recreational cycling enthusiast. As investigators, we hope to learn the qualitative public responses to the fit of current bicycle helmet.

If I agree to participate, what will I be required to do?
If you agree to participate, you will need to answer a number of questions on your cycling experience and your helmet use in the questionnaire form. Subsequently, you will have to sit on a provided chair while a 3D scanner takes anthropometric measurement of your head. You will be asked to wear a wig/swim cap while the 3D scanner project different light patterns onto your skin and record 3D point coordinates on your head. It is expected to take no more than 10 minutes to fill the questionnaire and 20 seconds to record the 3D data of your head. The session will take place at our RMIT facilities in Bundoora East campus, Melbourne, Victoria.

What are the risks or disadvantages associated with participation?
There will be no discomfort or risk involved in your participation in this study. The 3D scanner equipment we possess is safe to use with humans as it only projects white light in the area to be scanned.

What are the benefits associated with participation?
While we intend that this research may improve helmet performance in the future, we cannot and do not guarantee or promise that you will receive any personal direct benefits from this study. However, as a thank-you gift for taking part in our survey, we will create a small figure of your face and print it in 3D using rapid prototyping machine. The object is expected to be about 50mm in height and made of ABS plastic.

What will happen to the information I provide?
In order to make arrangements with you for a brief interview and to conduct the study, personal information will be collected initially, including name and contact details. Information that will be collected from you will be de-identified with code number and may include gender, age, weight, height, head shape and dimension, and cycling experience. Only the code numbers that have been de-identified will be used for analysis and presented in publications. The information that is obtained in connection with this study and that can be identified with you will remain strictly confidential and will be disclosed only with your permission or except as required by law. If you give us your permission by signing this document, we plan to publish results in relevant scientific conferences and journals. Results from the study and personal data collected (3D scan) will be available to you on request. In any publication, information will be provided in such a way that you cannot be identified. Data of this project will be stored in a locked office, in locked filing cabinets and will be retained for a minimum of 5 years. Paper materials will be disposed of through secure waste systems at RMIT. Electronic data will be erased utilizing the recommended protocols at that time.

What are my rights as a participant?
Your decision whether or not to participate will not prejudice your future relations with RMIT University. If you decide to participate, you are free to withdraw your consent and to discontinue participation at any time without prejudice.

Whom should I contact if I have any questions?
If you have any questions, please feel free to ask us. If you have any additional questions later, the investigators will be happy to answer them.
What other issues should I be aware of before deciding whether to participate?
Your involvement to participate is wholly voluntary, and your comfort and wellbeing takes precedence over the research. Physical body measurements will only be taken if you are willing. We anticipate that there will be no risks or discomfort related to the participation in this study.

Yours sincerely,

Thierry Perret-Ellena
PhD Student,  
School of Aerospace, Mechanical and Manufacturing Engineering,  
Royal Melbourne Institute of Technology (RMIT), Australia

Helmy Mustafa El Bakri  
PhD Student,  
School of Aerospace, Mechanical and Manufacturing Engineering,  
Royal Melbourne Institute of Technology (RMIT), Australia

Prof. Dr. Aleksandar Subic  
Dean of Engineering,  
School of Aerospace, Mechanical and Manufacturing Engineering,  
Royal Melbourne Institute of Technology (RMIT), Australia

Dr. Toh Yen Pang  
Senior Lecturer,  
School of Aerospace, Mechanical and Manufacturing Engineering,  
Royal Melbourne Institute of Technology (RMIT), Australia

You will be given a copy of this form to keep.

Any complaints about your participation in this project may be directed to the Executive Officer, RMIT Human Research Ethics Committee, Research & Innovation, RMIT, GPO Box 243, Melbourne, 3001. The telephonic number is (03) 9925 2221. Details of the complaint procedure are available from the above address.

PARTICIPANT CONSENT FORM

Portfolio: Science, Engineering & Technology
School of: Aerospace, Mechanical & Manufacturing Engineering (SAMME)

Name of participant: ..............................................................

Project Title: User-centred customization of bicycle helmet study

Name(s) of investigators: 1. Thierry Perret-Ellena
2. Helmy Mustafa
3. Dr. Toh Yen Pang
4. Prof. Dr. Aleksandar Subic

1. I have received a statement explaining the interview/questionnaire involved in this project.
2. I consent to participate in the above project, the particulars of which - including details of the interviews or questionnaires - have been explained to me.

3. I authorise the investigator or his or her assistant to interview me or administer a questionnaire.

4. I acknowledge that

   (a) Having read Plain Language Statement, I agree to the general purpose, methods and demands of the study.
   (b) I have been informed that I am free to withdraw from the project at any time and to withdraw any unprocessed data previously supplied.
   (c) The project is for the purpose of research and/or teaching. It may not be of direct benefit to me.
   (d) The privacy of the personal information I provide will be safeguarded and only disclosed where I have consented to the disclosure or as required by law.
   (e) The security of the research data is assured during and after completion of the study. The data collected during the study may be published, and a report of the project outcomes will be provided to Albion Sports. Any information which will identify me will not be used.

Participant’s Consent

Participant: ___________________________ Date: _________________

(Signature)  

Witness: ______________________________ Date: _________________

(Signature)  

Participants should be given a photocopy of this consent form after it has been signed.

Any complaints about your participation in the project may be directed to the Executive Officer, RMIT Human Research Ethics Committee, Research & Innovation, RMIT (PO Box 247), Melbourne, 3001. The telephone number is (03) 9925 2531. Details of the complaints procedure are available from the above address.

Contact details of investigators:

- Thiem-Piret Elena (PhD Student, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University,
- Helmy Mustafa El Bakri (PhD Student, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University,
- Prof. Dr. Aleksandar Subic (Dean of Engineering, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT

Version 1.0/October 7, 2013
Dr. Toh Yen Pang (Senior Lecturer, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University)
D. Consent Form for Recording of Personal Images

Consent Form for Recording of Personal Images of Participants (Photos and Videos)

<table>
<thead>
<tr>
<th>College/Portfolio</th>
<th>Science, Engineering &amp; Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td>School of</td>
<td>Aerospace, Mechanical &amp; Manufacturing Engineering</td>
</tr>
<tr>
<td>Name of participant:</td>
<td></td>
</tr>
<tr>
<td>Project Title:</td>
<td>User-centred customization of bicycle helmet</td>
</tr>
<tr>
<td>Name(s) of investigators:</td>
<td>(1) Thierry Perrot-Ellena Phone: 03 9925 6109</td>
</tr>
<tr>
<td></td>
<td>(2) Helmy Mustafa Phone: -</td>
</tr>
</tbody>
</table>

1. I have received a statement explaining the recording of my image for the above project.
2. I consent to participate in the above project, the particulars of which—including details of the recording of images—have been explained to me verbally and in the written project description.
3. I authorise the investigator or his or her assistant to record images of me.
4. I understand that:
   (a) I am giving consent to have my image taken for the purpose of analysing heat distribution
   (b) That not all taken images will be used in this project
   (c) That I am giving permission to have my image taken
      □ But any identifying features must be disguised
      ... or ...
      □ My personal image will be published or presented without any attempt made to disguise my identity
      (d) That my image will be taken
      □ But my personal image may be altered when published
      ... or ...
      □ My personal image may not be altered or used out-of-context without my approval
   (e) These images will be published in a report/thesis/project to RMIT University.
   (f) Any used or unused personal images from this project will be destroyed upon completion of the project including electronic images, which shall be deleted.
   (g) I am free to withdraw from the project at any time and to withdraw images of me that have been previously supplied prior to any publication of the report.
   (h) The project is for the purpose of research. It may not be of direct benefit to me.
   (i) Unless otherwise agreed, copyright for a resultant image will remain with the main investigator in this project.

Participant’s Consent

Participant: ___________________________ (Signature) Date: ___________________________

Witness: ___________________________ (Signature) Date: ___________________________

Participants should be given a photocopy of this consent form after it has been signed.

Version 1.0 January 12, 2011

Page 1 of 2
Contact details of investigators:

- Thirery-Perret, Elena (PhD Student, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University)
- Helmy Mustafa El Bakri (PhD Student, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University)
- Dr. Toh Yan Pang (Senior Lecturer, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University)
- Prof. Dr. Aleksandar Subic (Dean of Engineering, School of Aerospace, Mechanical & Manufacturing Engineering, RMIT University)
E. Ordinal Logistic Regression

Ordinal logistic regression is used to predict an ordinal dependent variable, given one or more independent variables [190].

The following are required in order to run an ordinal logistic regression:

- One dependent variable that is measured at the ordinal level.
- One or more independent variables, which are continuous, ordinal or categorical. However, ordinal variables have to be treated as being continuous or categorical [190].

Ordinal dependent variables can be analysed using different types of ordinal logistic regression models. To understand these different types, we need to consider the definition of an ordinal variable as a categorical variable with ordered categories. Three main methods have been considered to capture the ordered nature of these categories: adjacent, cumulative and continuation categories [191-194]. In this study, we applied the most common type of ordinal logistic regression, which uses cumulative categories [195].

Cumulative logits and the binomial logistic regression

The odds of an event occurring is the probability of it occurring divided by the probability of it not occurring. For a dichotomous question with “yes” or “no” value, for example, the odds of answering “yes” are:

\[
\text{odds} = \frac{\text{Prob}(\text{yes})}{\text{Prob}(\text{no})}
\]  

(97)

If the “yes” and “no” values are coded “1” and “0”, respectively, the odds of answering “yes” become:

\[
\text{odds} = \frac{\text{Prob}(\text{cat.}=1)}{\text{Prob}(\text{cat.}=0)} = \frac{\text{Prob}(\text{cat.}=1)}{1 - \text{Prob}(\text{cat.}=1)}
\]

(98)

A logit is the natural log of the odds of an event occurring:

\[
\text{odds} = \ln \left( \frac{\text{Prob}(\text{cat.}=1)}{\text{Prob}(\text{cat.}=0)} \right) = \ln \left( \frac{\text{Prob}(\text{success})}{\text{Prob}(\text{failure})} \right)
\]

(99)

The log odds of an event occurring (a success) can be modelled as a linear expression of a set of independent variables \( (IV_i) \), which is what occurs in binominal logistic regression:
$$\logit(\text{success}) = \ln \left( \frac{\text{Prob}(\text{success})}{\text{Prob}(\text{failure})} \right) = \alpha + \sum_{i=1}^{n} \beta_i * IV_i$$

Odds ratio and probabilities can then be calculated with the computation of intercept and slope coefficients.

When an ordinal dependent variable is considered as one or more cumulative categories, one can use a series of binomial logistic regressions run simultaneously on cumulative logits. In essence, cumulative logits split an ordinal variable in two. One side, considered the success, includes the lower categories of the variable, and the other side, considered the failure, includes the remaining (higher) categories of the variable. For instance, if we reflect the above on an ordinal variable containing four levels, i.e., "Strongly Disagree", "Disagree", "Agree" and "Strongly Agree", the three corresponding cumulative categories would be:

- (1) Target category: "Strongly Disagree". Other categories: "Disagree", "Agree" and "Strongly Agree".
- (2) Target category: "Strongly Disagree" and "Disagree". Other categories: "Agree" and "Strongly Agree".
- (3) Target category: "Strongly Disagree", "Disagree" and “Agree”. Other categories: "Strongly Agree".

The first cumulative logit (1) would have the following natural log:

$$\logit(\text{success}) = \ln \left( \frac{\text{Prob}(\text{success})}{\text{Prob}(\text{failure})} \right) = \ln \left( \frac{\text{Prob}(\text{cat.} \leq \text{"Strongly Disagree"})}{\text{Prob}(\text{cat.} > \text{"Strongly Disagree"})} \right) = \alpha_1 + \sum_{i=1}^{n} \beta_{1i} * IV_{1i}$$

Following this approach, the probability of being classified into the ‘lower’ categories as opposed to the ‘higher’ categories for each dichotomisation of the ordinal dependent variable based on cumulative categories can be predicted using multiple binomial logistic regression. However, the effect of the independent variables can be different for each cumulative logit, making an overall statement about the effect of an independent variable on the ordinal dependent variable not possible. The way around the problem is to assume that each cumulative logit gets the same effect from each independent variable (i.e., the slope
coefficients are identical but the intercepts can differ): \[
\ln \left( \frac{\text{Prob(cat.} \leq j)}{\text{Prob(cat.} > j)} \right) = \alpha_j - \sum_{i=1}^{n} \beta_i \ast IV_i \quad (102)
\]

Assumptions

Two assumptions need to be tested for the ordinal regression to provide practical results:

(1) There is no multicollinearity, i.e., no high correlation between two or more independent variables. In order to validate this assumption, dummy variables need to be created for ordinal independent variables [196]. Dummy variables are defined as a series of dichotomous variables coded either “0” or “1” in such a way that all the information of the original variable is represented. The number of dummy variables to be created for a categorical variable is the number of its categories minus one. For example, with the ordinal variable above, containing four levels, three dummy variables are generated (i.e., Strongly Disagree, Disagree, and Agree). A participant is coded as “1” if it is a member of that category and “0” if it is not. A participant with “0” in all three categories would mean that its response was “Strongly Agree”.

Multicollinearity diagnostics are then computed between the dependent variable and the independent variables (i.e., continuous or dummy variables). The statistics VIF (Variance Inflation Factor) [197] indicates if a collinearity problem exists.

(2) The regression problem has proportional odds, i.e., each independent variable has an identical effect at each cumulative split of the ordinal dependent variable (see the previous section). Proportional odds can be tested by two different approaches:

- First, by using the Brant-Test of Parallel Lines [195] that compares the model fit between the proposed proportional odds model and a cumulative odds model that does not include the proportional odds assumption.
- Second, by running separate binomial logistic regressions for the cumulative categories of the ordinal dependent variable. The estimated slope coefficients (and by extension, the odds ratios) should be the same for each binomial logistic regression run on each dichotomised cumulative category.
F. Friedman Test

This test [198], used to detect if there are any statistically significant differences between three or more related groups, is the non-parametric alternative to the repeated measures ANOVA. The related groups’ assumption is important here, since the same participants were assessing the fit scores for the three studied helmets. Each group represents a repeated measurement on the same dependent variable. A non-parametric test was selected for this analysis because the fit scores $F_x$ (dependent variable) were measures on an ordinal scale.

The independent variable was the helmet model. This is a categorical variable with three related groups, i.e., helmet A, helmet B, and helmet C.

The method consists of ranking the helmet fit scores for each participant together, and then considering the values of ranks for each helmets. The test statistic is given by the $Q$ value that can be approximated by that of a chi-squared distribution if the number of observations is large (> 15).

Null and Alternative Hypothesis

The null and alternative hypotheses for the Friedman test were:

- $H_0$: The distribution of the fit assessment scores $F_x$ for each of the three helmets is the same.
- $H_A$: At least two of the group’s distributions (i.e., population median) differ.

Post Hoc Tests

Like most within-subjects studies, the Friedman test does not provide information of which of the groups differ from each other. It only determines if there is a significant overall effect of the independent variable over the dependent variable. In order to identify these differences, one can run post hoc tests between all the possible variations of group comparisons.

These comparisons are run through Wilcoxon signed-rank tests that have a significance level adjusted using a Bonferroni correction [111]. The Wilcoxon signed-rank test [112] is the non-parametric alternative of the paired-samples $t$-test for ordinal dependent variables.
G. One-Way Repeated Measures ANOVA

The test is an extension of the paired-samples t-test for three or more related groups.

The following is required in order to run the test:

- One dependent variable that is measured at the continuous level (HFI scores, which are measured on a scale from 0 to 100).
- One independent variable that consists of three or more categorical levels (helmet studied, which has three models).

Null and Alternative Hypothesis

The null and alternative hypotheses for the one-way repeated ANOVA test were:

- $H_0$: Population HFI means for the three helmets are equal.
- $H_A$: At least one population HFI mean is different.

Post Hoc Tests

Similar to the Friedman’s test, post hoc tests were computed to determine where the differences between the levels were located (if any differences existed). Post hoc tests were selected as the best method for these analyses (over planned contrasts, as we had no specific hypotheses about the differences between the levels of the independent variable. The Bonferroni post hoc test was used).

Effect Size

The sample effect size based on within-subjects factor variability, called partial eta squared or $\eta^2$, was calculated to provide information on the magnitude of the differences, if such differences existed.

Assumptions

Three assumptions need to be tested in order to provide usable results:

1. There should be no significant outliers in any level of the within-subjects factor (independent variable). Specific comments on how we dealt with outliers throughout the analyses are provided in the subsequent section.

2. The dependent variable (HFI scores) should be approximately normally distributed for each level of the within-subjects factor.

3. There should be sphericity in the data. That is, the variances of the differences between all
combinations of levels of the within-subjects factor must be equal. Mauchly’s test of sphericity [113] is used in this study. If this assumption is violated, the repeated measure ANOVA may return biased results. A correction, called epsilon or $\varepsilon$, can be made to adjust the degree of freedom used in calculating the p-value. The Greenhouse-Geisser [154] method is used in this test to estimate this adjustment.
H. Hypothesis Test for a Proportion

**Null and Alternative Hypothesis**

The null and alternative hypotheses for the test were:

- $H_0: p_{HFI} = p_0$.
- $H_A: p_{HFI} \neq p_0$.

Where $p_0$ the overall probability of selecting the best helmet and $p_{HFI}$ is the proportion of correct guesses achieved by the HFI.

**Assumption**

In order to apply the normal distribution framework in the context of a hypothesis test for a proportion, the success-failure condition must be verified. That is, at least 10 successes and 10 failures are expected to be observed in the sample.
I. Independent samples t-test

Independent samples t-tests were computed to determine whether differences existed between the means HFI scores of males and females, both at the global and local levels, and for the three helmets.

The following are required in order to run the test:

- One dependent variable that is measured at the continuous level (HFI scores, which are measured on a scale from 0 to 100).
- One independent variable that consists of two categorical levels (gender).

**Null and Alternative Hypothesis**

The null and alternative hypotheses for the independent samples t-tests were:

- $H_0$: The population HFI means for males and females are equal.
- $H_A$: The population HFI means of the two groups are not equal.

**Effect Size**

Cohen’s $d$ [146] value was used to determine the effect size of the independent samples t-tests. It provides a measure of the practical significance of the results. To calculate it, the mean difference between the groups is divided by the pooled standard deviation.

**Assumptions**

Three assumptions need to be tested in order to provide usable results:

1. There should be **no significant outliers**.
2. The dependent variable (HFI scores) should be **approximately normally distributed**. A Shapiro-Wilks test is used [148].
3. There should be **homogeneity of variances** in the data. A Levene’s test is used [102].
J. One-Way ANOVA test with Custom Contrasts

The test One-way ANOVA is an extension of the independent samples t-test for three or more groups.

The following are required in order to run the test:

- One dependent variable that is measured at the continuous level (HFI scores, which are measured on a scale from 0 to 100).
- One independent variable that consists of three or more categorical levels (ethnic groups, which has four levels).

*Null and Alternative Hypothesis*

The null and alternative hypotheses for the one-way ANOVA test were:

- $H_0$: Population HFI means for the four ethnic groups are equal.
- $H_A$: At least one population HFI mean is different.

*Simple and Complex Contrasts*

The decision was made to use contrasts [105] to determine where the differences was located between the groups, if such differences existed. As opposed to post hoc analysis that tests all pairwise comparisons of the independent variable, contrasts only tests specific comparisons, which are either simple (i.e., differences between two groups) or complex (i.e., differences between a combination of two groups or more).

As the objective of the study was to highlight the differences between Caucasians and Asians, only two simple and one complex contrasts were used. The differences were computed between both European and Australasian people (assessed individually and combined), and Asian people.

*Assumptions*

Similarly to the independent sample t-tests, there were three assumptions to assess in order to provide practical results. That is, no significant outliers, approximately normally distributions for each level of the independent variable, and homogeneity of variances in the data.
K. Kruskal-Wallis test

The Kruskal-Wallis test [104] is the non-parametric equivalent of the one-way ANOVA. It is used to determine if there are statistically significant differences between two or more groups of an independent variable that can be either continuous or ordinal. It is referred to when the data fail the assumptions of the one-way ANOVA, and/or when the dependent variable is ordinal.

Assumption

There is one important assumption for the test. It is necessary to determine whether the distribution of scores (HFIs) for each group of the independent variable (ethnic background) have the same or different shape. If the distributions have a similar shape, the test is used to determine if there are differences in the distributions of the groups. If the distributions have a dissimilar shape, the test is used to determine if there are differences in the medians of the groups. Shape of the distributions can be assessed with histograms or boxplots.

Post Hoc Test

In this study, Dunn’s procedure with a Bonferroni adjustment [111] was used to illustrate which group of the independent variable (ethnic background) differ from another group.
L. Paired-samples t-test

The following are required in order to run the test:

- One dependent variable that is measured at the continuous level (HFI scores, which are measured on a scale from 0 to 100).
- One independent variable that consists of two categorical levels (helmet model).

Null and Alternative Hypothesis

The null and alternative hypotheses for the paired-samples t-tests were:

- \( H_0: \) The population HFI means difference between the two helmets studied is equal to zero (\( \mu_{diff} = 0 \)).
- \( H_a: \mu_{diff} \neq 0 \)

Effect Size

Cohen’s \( d \) [146] value was used to determine the effect size of the paired-samples t-tests. It provides a measure of the practical significance of the results. To calculate it, the mean difference between the groups is divided by the pooled standard deviation.

Assumptions

Two assumptions need to be tested in order to provide usable results:

(1) There should be no significant outliers in the HFI differences between the two helmets.

(2) The dependent variable (HFI scores) should be approximately normally distributed. A Shapiro-Wilks test is used [148].
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