Towards Sustainable Luxury Materials Selection: Measuring the Perceived Quality of Automotive Interior Materials

INNOVATION REPORT

Claudia Newton

The University of Warwick

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Abstract

Automotive companies are searching for new, innovative materials that attempt to redefine what is traditionally associated as a ‘luxury material’. Market research shows that future customers will demand tangible sustainability in vehicle interiors through the use of eco-friendly materials. However, research has also identified customer scepticism towards the quality of green products sold by luxury brands.

The perception of quality is typically determined by peripheral and sensorial product properties such as styling, shape and touch. The uncertainty of new materials compounded by the need to balance sustainability, sensory and emotional appeal mean it is no longer possible to rely on the designers’ intuition and experience to evaluate materials. Rigorous, robust methods which include both objective material assessments and the quantification of subjective, sensory and experiential attributes will maximize the chance of successful adoption by customers. They can also offer further insight, such as demonstrating that the Perceived Quality (PQ) of a cheaper material can be improved just by making the material softer using a foam backing, as was found in this research.

To address this, a new process has been developed to measure the perceived haptic quality of soft automotive interior materials. Studies were conducted in the UK and Hong Kong to generate user-defined metrics. Of these metrics, roughness and hardness had the largest impact on PQ, so mechanical testing was conducted to obtain objective measurements of both. The subjective and objective measurements were found to correlate strongly, implying that objective measurements alone could indicate a customer’s opinion of these materials.

The final stage of the process introduces a statistical model which uses the objective data to predict PQ scores. This is based around an Artificial Neural Network validated as accurate to within 4.5%. A graphical user interface was designed so practitioners can use the model to predict how customers may respond to a new material or a change in the surface characteristics of an existing material, without needing to conduct the initial customer research. The process has been integrated in part within the sponsor company and has influenced future research and business strategy in this area.

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Finally and most importantly, Tom, I couldn't have done this without you.

Declarations

I confirm that the work in this document is my own unless otherwise stated.

Claudia Newton, March 2017

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List of Abbreviations

ANN – Artificial Neural Network

ANOVA – Analysis of Variance

EngD – Engineering Doctorate

FMCG – Fast Moving Consumer Goods

GLM – Generalised Linear Model

GPA – Generalised Procrustes Analysis

HK – Hong Kong

JLR – Jaguar Land Rover

KE – Kansei Engineering

KES-F – Kawabata Evaluation System for Fabrics

MAPE – Mean Absolute Percentage Error

MDF – Medium Density Fibreboard

ME – Magnitude Estimation

NGO – Non-Governmental Organisation

NVH – Noise, Vibration and Harshness

OEM – Original Equipment Manufacturer

PCA – Principal Component Analysis

PU – Polyurethane

PVC – Polyvinyl Chloride

PQ - Perceived Quality

RGT – Repertory Grid Technique

RMS – Root Mean Squared

RO – Research Objectives

SD – Semantic Differential

TPO – Thermoplastic Olefin

WWF – World Wildlife Federation

"The way luxury companies choose to operate today will have a great impact on the world in the future. As the global population continues to grow, finite resources currently taken for granted will become increasingly constrained and luxury brands will have to innovate in order to create new materials"

(Positive Luxury, 2016)

1 Introduction

This research focused on material innovation for Class A components in the automotive industry (i.e. components by which drivers and passengers can see and touch). A methodological process for assessing and predicting the Perceived Quality (PQ) of materials was developed and integrated in part within the sponsor company. The wider intention of this research is to allow for a more systematic means of evaluating how a customer may react to the use of new, innovative and sustainable materials that may be used for automotive styling in the future.

Imagine that you are in the market for a new car. The exterior contour, colour, shape and branding of the vehicle will influence an initial perception of liking or disliking. The sound the door makes when opening and closing then contributes to this perception – a tinny, hollow sound may trigger a negative experience, yet a solid sound may instigate a positive one. A 'new car smell' often associated with the smell of leather may be pleasing or displeasing to you, depending on your preferences. The use of chrome may tempt you to touch that component. A cold sensation may evoke a perception of material authenticity and thereby delight and satisfaction, while a warm, plastic feeling may evoke a feeling of disappointment. Likewise, the use of seat stitching may be associated with handmade craftsmanship and the sensation of soft leather a feeling of luxuriousness.

There are many processes, tools and testing procedures available in materials science that can account for the technical specifications considered during material selection, such as permeability measures, check wear performance, colour fastness, friction, stretching, seam strength and flammability (Eason, 2011). However, what is lacking are tools and processes that can be used to evaluate the more experiential, sensory and emotional characteristics often evoked by materials, such as those described above. Despite now being considered essential in product design, these intangible aspects fail to be effectively supported when it comes to materials selection tools and processes (Karana et al., 2010, Wastiels and Wouters, 2012, Ashby and Johnson, 2013). These sensory aspects are typically evaluated by a Perceived Quality (PQ) department within an automotive original equipment manufacturer (OEM).

In the past, 'quality' in the automotive industry traditionally referred to objective, quantifiable measures such as the lack of build defects (i.e. fit-and-finish), reliability, durability and noise, vibration and harshness (NVH) control in a finished vehicle (Robinson, 2000, Tay, 2003). In recent decades, the notion of PQ has become an accepted aspect of quality which significantly impacts on a customer's overall impression of a product. PQ refers to how and what individuals perceive as quality - it therefore incorporates more '*experiential, subjective and emotional criteria'* within automotive quality (Tay, 2003). PQ is also sometimes used interchangeably with automotive craftsmanship (Turley et al., 2006, Ersal et al., 2011). However, a key issue identified in automotive design is that there are a lack of standardised and systematic processes, terminology and metrics that can be used to subjectively and objectively assess customer perception of quality (Stylidis et al., 2015).

Mary Barra, CEO and Chairperson of General Motors, states that the automotive industry is experiencing its 'fourth industrial revolution'. This is driven by the convergence of connectivity, electrification and changing customer needs. In turn, this means that automotive OEMs are striving to develop vehicles that are 'cleaner, safer, smarter and more energy efficient'. This is in contrast to the automotive industry in the past, that relied on mechanically controlled and petroleum fuelled vehicles. Instead, the future of the automotive industry will see cars that are interconnected, electronically controlled, safer and powered by a variety of energy sources (Barra, 2016). This is supported by Ingrassia (2015) who states that the global automotive industry is experiencing three technological transformations simultaneously:

1. The propulsion revolution: This will determine whether future vehicles replace the internal combustion engine with hybrid cars, battery-powered electric cars or hydrogen fuel cells.
2. The connectivity revolution: This will see more and more vehicles have internet services within their dashboards, from satellite navigation systems to advanced telecommunications.

3. The autonomy revolution: the driverless car.

These changes in the automotive industry also present PQ challenges. For example, electric vehicles are much quieter, which means that passengers may be more aware of aspects related to sound quality (e.g. squeaks and rattles); there will likely be much more emphasis on haptic feedback and usability for devices in connected vehicles and the advent of the driverless car will mean that passengers will be free to touch and feel different parts of the vehicle interior, which will change how materials are used.

At the same time, the luxury industry has experienced key changes and trends. One notable trend is the increase in pressure from non-governmental organisations (NGOs) and legislative bodies. These call for luxury companies to improve the social and environmental impacts of their operations, products and services and to be more transparent in their communications (Bendell and Kleanthous, 2007). Additionally, market research has indicated that millennials (defined as *"an individual experiencing young adulthood in the 21st century")* are much more environmentally aware than previous generations of customers, and are seeking brands that are committed to achieving social good and environmental responsibility (Positive Luxury, 2016).

New, more sustainable materials intended to redefine what is traditionally associated as a 'luxury material' are now more than ever being considered for use. For example, Rolls Royce claim to be looking for new materials that are currently not used in luxury automotive applications, rather than continuously using and searching for better leather (Robbins, 2013). Schweinsberg (2012) states that designers and engineers are searching for new materials, technology and design cues for luxury car interiors in order to maintain the exclusivity appeal desired by luxury customers. This search for new materials is leading practitioners into new areas of product development, e.g. by considering stone and minerals (such as onyx and amethyst) for trim materials, replacing the traditional wood and metal. Additionally, climate change has also put pressure on sourcing raw materials such as cotton, cashmere and silk, due to weather extremes causing droughts, floods and loss of agriculture (Brock, 2016). This highlights the need for luxury brands to strategically plan for long-term sourcing of these materials and could jeopardise sourcing of fibres that are used in the automotive industry, such as flax, hemp, kenaf and sisal (Faruk et al., 2014).

In an industry that has primarily used variations of the same type of trim material, these market changes suggest that OEMs will need to assess materials that have never been used for automotive applications before. With this, comes the need to ensure that these materials meet the high standards for quality set by the luxury industry, which is the focus of this research.

1.1 The Research Journey

The Design Council (2007) Double Diamond methodology was used as a high level structure for the research project. This provides a graphical representation (Figure 1) of the typical design process and emphasises the stages of convergent and divergent thinking often adopted during design research. It is separated into 4 stages (Table 1).

Table 1: The Design Council's four stages of design research

Discover **Insight into the problem**	*This marks the start of a project and begins with an initial idea or brief. This involved discussions with the project partners at JLR (the Corporate Sustainability and Compliance team) and conducting an initial literature review into luxury, sustainability and ethical consumption.*
Define **The area of focus**	*This stage involves interpreting and formulating the research problem and objectives based on the initial literature review. In this research, scoping of the industry problem was conducted via an interview study at Jaguar Land Rover. This was complemented by a secondary literature review to identify wider support for the interview findings.*

Develop **Potential solutions**	*The third stage reflects the development of solutions intended to meet the needs and objectives defined from the previous stage. This stage formed the main experimental data collection phase of the research.*
Deliver **Innovation in the application of knowledge**	*This last stage was adapted to reflect the requirements of an Engineering Doctorate (EngD): to deliver 'innovation in the application of knowledge'. In practice, this often refers to the delivery and launch of a final product, service or system. In this research, it is used to signify the contribution of this research to industrial practice within the engineering business.*

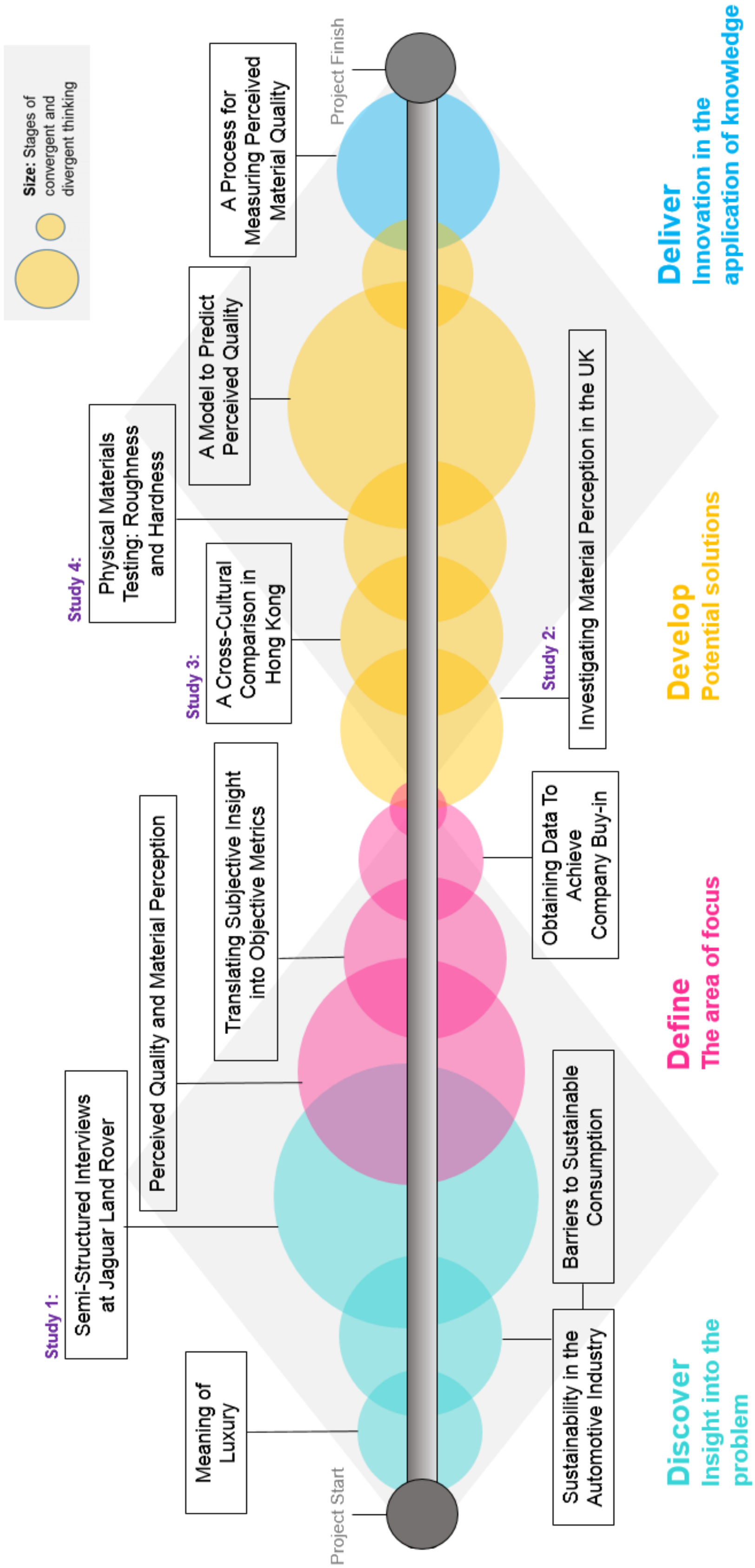

Figure 1: Illustrating the EngD research journey

1.2 Motivation and the Sponsor Company

Jaguar Land Rover (JLR) is a British manufacturing company specialising in luxury and premium car production. The company is made up of two iconic British brands: Jaguar, who specialise in manufacturing luxury sports saloons and Land Rover, who specialise in manufacturing premium all-wheel drive vehicles.

JLR's overall motivation for this research largely stems from their commitment to engage their stakeholders and consumers and to communicate sustainability effectively. A challenge was identified by the company, concerning how a luxury brand can respond to the demands of a sustainable future. Both brands must determine how to ensure that the products they produce meet the environmental legislation requirements, contain sustainable behaviours and achieve profitable growth for their shareholders.

A high level brief was initially provided, which included the following issues:

- Corporate values and behaviours towards sustainability.
- Preserving brand DNA while taking a sustainable approach.
- Factors which drive and deliver sustainable luxury i.e. technology and manufacture.
- Identifying consumer trends and global trend impacts.

These issues were narrowed down during the first phase of the research by conducting three literature reviews and an interview study at JLR. These are discussed in section 2.

1.3 Aim

The aim of this research was to develop a new process for measuring and predicting perceived material quality, in order to aid engineering decision making during materials selection and to ultimately improve and ensure customer satisfaction when exploring new, sustainable luxury materials in the future.

1.4 Portfolio Structure: A Guide

Figure 2 outlines the contents of the portfolio. There are six submissions in total, with submission 4 split into four separate reports.

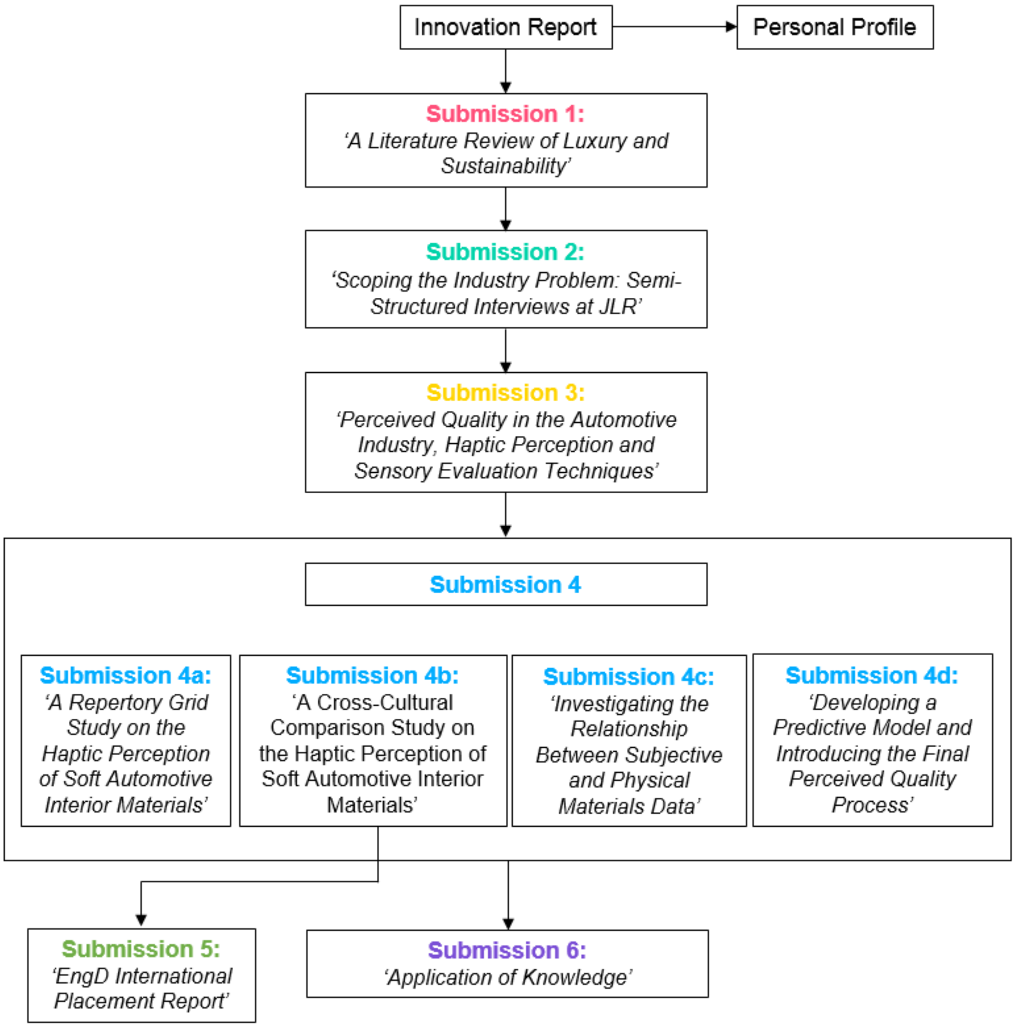

Figure 2: Portfolio submissions

Submission 1 discussed the definition of luxury, sustainability and the similarities and differences between each concept. It also reviewed advances in sustainability in the automotive industry; the need for customer research in Design for Sustainability and the associated issues with research methods exploring this. Lastly, the submission proposed the initial research questions and potential research direction.

Submission 2 reported the first study conducted, which was a series of semi-structured interviews and group discussions had with 20 JLR employees. These were conducted across the company with departments such as Marketing, Design, Materials Engineering and Perceived Quality. The aim of these interviews was to understand the current barriers and opportunities for implementing sustainable materials into future product development, corporate values and behaviours towards sustainability and to understand the materials selection process within the company. It was found that there was a huge desire to incorporate more sustainable and innovative materials within vehicle interiors. However, there were barriers which hindered the application of these materials, such as customer uncertainty and limitations within current processes responsible for evaluating the Perceived Quality (PQ) of new materials. These findings were further supported by a literature review exploring material innovation in the automotive industry. The scope of the project was then narrowed down to focus on developing a process for measuring PQ.

Submission 3 provided the background needed to understand PQ in the automotive industry. The research focused on measuring touch/feel quality, so a review of automotive interior trim and haptic perception was conducted. Lastly, a review of 13 research methods considered appropriate to address the research questions was completed. The outcome of this submission was a justification of the chosen research methods and an experimental plan for conducting sensory evaluation experiments exploring material perception, which could go towards developing the new PQ process.

Submission 4a reported the second study conducted, which was a sensory evaluation experiment conducted in the UK. This identified significant material attributes elicited directly from the user using the Repertory Grid Technique. Secondly, insights into Perceived Quality and preference for specific automotive interior trim materials were gained using free-modulus magnitude estimation. The outcomes of this submission were material metrics that can be used in the final PQ process developed (roughness and hardness) and material-specific insights (discussed in section 3 of this report).

Submission 4b is affiliated with Submission 5 as both are associated with the EngD International Placement. This submission reported the third study conducted at Hong Kong Polytechnic University, which was a replication of the study from Submission 4a. This submission provided validation for some of the findings from the UK study and an insight into cultural similarities and differences between the UK and Hong Kong.

Submission 4c outlined the fourth study conducted in collaboration with an undergraduate student as part of his final year project. The aim was to conduct physical surface roughness and compliance (stiffness) testing and to investigate the relationship between perceived roughness and hardness and their technical parameters. This provided technical cues and characteristics regarding surface roughness and stiffness that were found to have a positive effect on perception.

Submission 4d outlined the development of a statistical model that is able to take the data gathered from the UK study (Submission 4a) and the objective data from Submission 4c and use it to predict future PQ scores. This submission marked the end of the material perception and PQ experimental data collection and the last stage towards developing the process for measuring perceived material quality. This process was introduced as a whole at the end of the submission.

Submission 5 provided a reflection of the international placement conducted at Hong Kong Polytechnic University.

Lastly, Submission 6 discussed how the research has been integrated into Jaguar Land Rover. It includes a personal reflection of the EngD and ends with two testimonial letters and a statement from the project partners, which outlined the benefits that this research has delivered to the business.

2 Background

This section discusses the main findings from the literature reviews and an interview study within Submissions 1, 2 and 3 and discusses how wider research has progressed since the time of writing. It also provides a reflection of the research question and objectives formulated after the initial literature review and discusses how these were refined within the context of the research problem.

Three successive literature reviews and an interview study at Jaguar Land Rover were conducted to narrow the scope of the research. Firstly, a review of luxury and sustainability was conducted in Submission 1, which defined the two concepts and discussed their similarities, differences and preconceptions. It also reviewed state-of-the-art in 'Sustainable Luxury'. Secondly, a review of material innovation in the automotive industry is provided in Submission 2, highlighting some of the trends towards adopting new materials and potential barriers inhibiting the inclusion of these materials within product development – this is complimented by insights from a series of semi-structured interviews conducted across JLR to scope the industry problem. Lastly, the research was narrowed down to focus on Perceived Quality (PQ) so a review of PQ, haptic perception and automotive material perception was completed in Submission 3. A graphical summary of these literature reviews is illustrated in Figure 3.

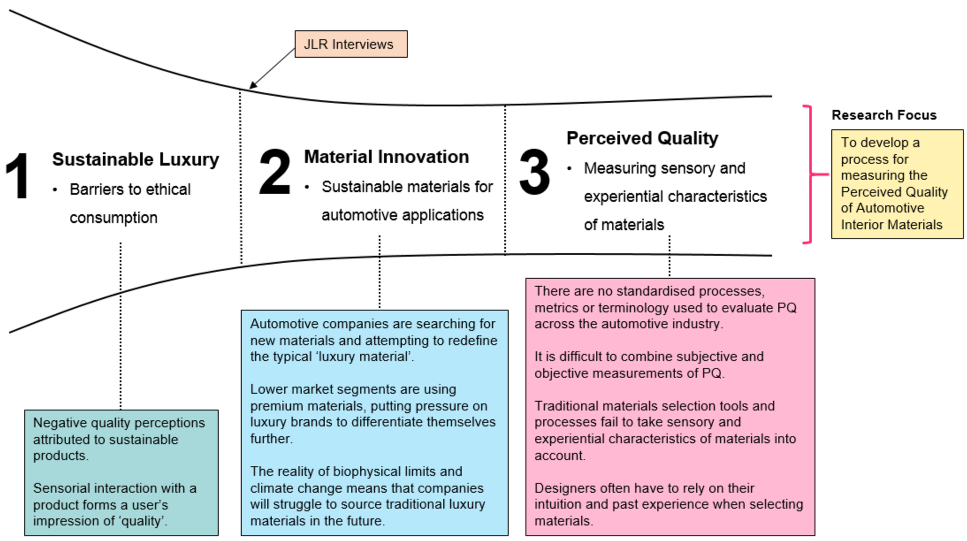

Figure 3: A graphical summary of the literature reviews conducted to scope the research

2.1 Sustainable Luxury

Past research has suggested that luxury and sustainability are paradoxical concepts. On the one hand, sustainability is associated with respect, responsibility and preservation for the environment and society. Conversely, luxury has been associated with feelings of wastefulness and carelessness (Cervellon and Shammas, 2013). However, a deeper understanding of both concepts uncovers similarities inherent in both, which are highlighted in Figure 4.

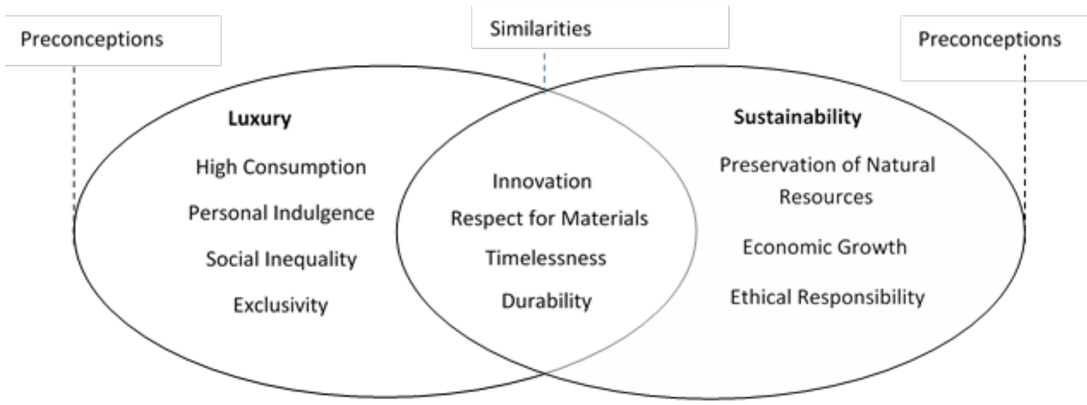

Figure 4: Similarities, differences and preconceptions between sustainability and luxury

Luxury is, by definition, durable (Kapferer, 2010). Luxury companies strive to carefully source their materials, ensuring that they can deliver the highest quality at a given price. There is a need for innovation in the luxury industry because of the association between luxury and scarcity. The illusion of scarcity (and exclusivity) of luxury products is typically controlled by the availability of raw materials or through constant innovation (Catry, 2003). This is particularly the case with brands dependent on technological processes, advancements and manufacture, such as those within the automotive and electronics industry. The need for innovation is often never-ending, as a product feature may become popular, then competitors will imitate these features and then these will trickle down from luxury, to premium to fast moving consumer goods (FMCG) brands. An example is the use of wood veneers and leather in the automotive industry, where it is not uncommon for lower-market brands to incorporate imitations of these in their vehicle specifications for a lower price.

The first and most prominent report on Sustainable Luxury was led by the World Wildlife Federation (WWF) in 2007, which was entitled the Deeper Luxury report.

Within this, Bendell and Kleanthous (2007) analysed the environmental and social performance of ten luxury companies. It was found that there were no policies on social and environmental initiatives, no monitoring or reporting sustainability performance, and no engagement with stakeholders on this issue. In short, they were criticising the whole sector for lagging behind in terms of sustainability. Since then, many luxury companies now have a sustainability strategy and for the most part, they are reporting their performance. However, a more recent report titled *'2016 Predictions for the Luxury Industry: Sustainability and Innovation'* (Positive Luxury, 2016) has been published since, which highlights key pressures still faced by the luxury industry:

1) There is increasing legislation being put in place which will directly impact on luxury businesses. For example, the Modern Slavery Act in the UK requires companies to publish a public annual slavery and human trafficking statement. This will in turn, drive focus on transparency and the supply chain – it is thought that up to 71% of UK retailers and suppliers believe that there are slaves in their supply chain.
2) Social norms are changing, with high-profile celebrities encouraging sustainable lifestyles and influencing luxury companies into acting on their responsibilities. This also appears to be apparent in society as a whole, where Millennials in particular have different views on how companies must act.
3) The investment community is beginning to realise the worth of brands that manage their social and environmental practices. There are early indicators pointing towards an increase in market value of companies employing good sustainability practices. For example, managing and controlling the supply chain can reduce the risk of disruption and reputational damage, using less raw material and reducing energy and waste can lead to direct cost savings. Collectively, this could equate to lower risk and higher financial gains.
4) The reality of biophysical limits means that companies will struggle to source their products in the future. The process of extracting, growing and processing materials is becoming more difficult e.g. climate change is impacting on water availability and crop production worldwide, which is affecting the cotton-trade. There are also challenges concerning the energy

required to produce gems and minerals and the overall availability of them. Almost all the gold on the market is recycled, diamonds are scarce and exotic skins are under threat, making many of the raw materials intrinsic to the luxury industry vulnerable.

As noted by Beckham and Voyer (2014), academic literature on luxury consumer attitudes towards sustainability has presented contradictory results. For example, Steinhart et al. (2013) found that an environmental claim using an eco-label positively influenced consumer attitudes, providing justification for purchasing an indulgent product. In contrast, Achabou and Dekhili (2013) discovered that French luxury consumers negatively perceived the inclusion of recycled cotton in luxury clothing. Furthermore, consumers indicated that a brand's environmental commitment was the least important criteria during their purchase decisions, whilst quality, price and reputation were the most important criteria. This latter finding is supported by Davies et al. (2012) who concluded that ethics was not a priority to customers when buying luxury goods versus commodity goods. Additionally, Beckham and Voyer (2014) found that in their own study, participants perceived luxury products to be less desirable and luxurious when the product was labelled as 'sustainable'.

It has been argued that the ways in which sustainability attributes and objectives are incorporated into product development appears to be flawed and what is required is a shift in approach focusing on positive aspects of sustainability rather than compromise (Santamaria et al., 2016). It has generally been accepted that the luxury industry has an opportunity to achieve this, as luxury offerings are inherently desirable and the fundamental values of 'luxury' align with those of sustainability. The similarities between luxury and sustainability are discussed in further detail in Submission 1, however Ivan et al. (2016) provides a list of advantages for integrating sustainability into a luxury company's DNA, which expands on the key points discussed in Submission 1:

1) *It is part of the luxury business ethos:* aspects such as uniqueness, timelessness, heritage, rarity and beauty underpin sustainability principles.
2) *It is seen as an ethical business practice:* A company seen to be addressing social and environmental issues will benefit from added-value.

3) *It is a differentiator:* Advocating sustainability principles distances a company from issues such as 'fast fashion' and the 'throwaway society' and instead highlights the value of rarity, the use of noble materials and craftsmanship.
4) *It provides long-term return on investment:* Key characteristics fundamental to luxury and sustainability are timelessness and longevity. These align particularly well with the value of craftsmanship, which can be maintained throughout business generations.
5) *It is a duty for luxury companies to optimise sustainability:* The luxury industry by nature is an extremely profitable one and can therefore easily invest in social and environmental initiatives.
6) *Sustainability is an opportunity for innovation:* Increasingly, designers are searching for creative ways of using materials, designing and creating long-term impact for society.

However, despite these business advantages, there are still certain barriers that inhibit people from engaging in sustainable consumption.

2.1.1 Barriers to Sustainable Consumption

Although environmental awareness is widespread and increasing, the rate of reduction concerning consumption levels are well under the required targets (Santamaria et al., 2016). Submission 1 discussed the concept of the *'attitude-behaviour gap'* - where individuals say they are demanding ethical products but do not reflect this in their purchasing behaviour, suggesting that individuals struggle to translate their environmental concerns into their purchases (Sheeran, 2002, Papaoikonomou et al., 2011). Several barriers to sustainable consumption were highlighted, including:

- Price sensitivity - individuals feel that ethical derivatives of products are too expensive (Young et al., 2010, Öberseder et al., 2011, Richardson et al., 2005)
- Personal experience – individuals are more likely to consider changing their purchasing habits when a negative news story forces them to think about a certain ethical issue or when they were personally affected (Öberseder et al., 2011).

- Ethical obligation – In general, people would like to make a difference – especially when the price differential is small – but they also feel that it is ‘too difficult’ to engage in ethical consumption regularly (Young et al., 2010)
- Lack of information – people feel that they do not have enough information about ethical issues to inform their purchase decisions on this agenda (Young et al., 2010, Wheale and Hinton, 2007).
- Quality perception - the perceived quality of ethical goods was identified as being a clear influencing factor in consumers’ decision-making processes during consumption. It was clear that consumers were not willing to tolerate a loss in quality for ethical products. Some consumers also frequently believe that there is a trade-off decision to be made between sustainability and functional performance (Luchs et al., 2012).
- Inertia in purchasing behaviour - brand loyalty ultimately keeps individuals from straying from a brand in search for ethical derivatives. Additionally, consumers tend to be ‘locked-in’ to their current habits and over-estimate the inconveniences of sustainable consumption (Richardson et al., 2005).
- Cynicism - some individuals feel that sustainability marketing and communications are not genuine and that ethical claims are a strategy to take advantage of consumer goodwill and to charge higher prices. It is believed that the extra premium paid towards certain products do not reach the end beneficiary (Richardson et al., 2005).
- Guilt – some people retrospectively feel guilty when they decide not to purchase an ethical alternative of a product. Further supported by Young et al. (2010).

The barriers to sustainable consumption listed above are magnified in the luxury context (De Angelis et al., 2017), particularly when considering quality perception. Research indicates scepticism towards the quality of green products provided by luxury brands, with a belief that the quality of greener offerings must be less than that of conventional offerings provided by the same brand (Achabou and Dekhili, 2013, Griskevicius et al., 2010). When exploring the notion of ‘quality’ in a luxury context, a key insight emphasised by Steinhart et al. (2013) stood out:

> *"The perception of quality for a luxury product is determined during a customer's emotional rather than rational decision making process. This process is heavily influenced by the peripheral properties of a product (e.g. the design, styling, colour, shape, touch and expected pleasure)"*

This is further supported by Van Kesteren (2010), who note that the initial sensorial interactions with a product and its materials contribute significantly to the first judgment of quality by the user. During product interaction, users see the colour and form of the materials, they feel the texture, weight and temperature (Okamoto et al., 2013) and they hear the sounds materials make when moving the object (Fujisaki et al., 2015) – these all collectively influence the usability and experience associated with a given product (Fenko et al., 2010).

Thus, if an individual's quality perception is heavily influenced by these peripheral aspects, and customers experience a negative quality perception when considering sustainable products, a natural area of research to explore would be to investigate how this is measured and how to improve the quality perception of these peripheral product properties in response to the design of sustainable products.

From this initial literature review, two main aspects became apparent:

I. *A focus on customer perception:* Many of the articles on Sustainable Luxury highlighted the shift in customer perception towards social and environmental sustainability. However, as with sustainable offerings within the fast moving consumer goods (FMCG) sector, the issue surrounds the need to encourage consumers to act on their intentions. One of the most significant barriers that cause reluctance in purchasing sustainable luxury products is a perception of reduced quality e.g. Achabou and Dekhili (2013). The challenge then is to maintain the standards of quality and luxuriousness in products while optimising sustainability.

II. *A focus on material quality:* When reviewing definitions of luxury in Submission 1, there was an emphasis on the importance, craftsmanship and authenticity of the materials that make up a luxury product. As mentioned previously, the luxury industry will increasingly experience difficulties in sourcing traditional ‘luxury’ materials. Yet, the differentiation gap between what is ‘premium’ and what is ‘luxury’ is closing, especially in the automotive industry. Submission 2 explained that the automotive industry has seen leather turn into more of a commodity. This is because leather is no longer exclusive to luxury cars, as many cars in lower ranges have leather fitted in the interior, although the quality and grain of which varies. The quality of leatherette: ‘a synthetic leather-like material’, commonly made out of polyvinyl chloride (PVC) is also improving to the extent that many of these materials have a similar look, feel and durability to real leather. In turn, this means that luxury manufacturers will need to do more to differentiate themselves further from lower market segments to maintain the exclusivity appeal desired by luxury customers (Schweinsberg, 2012). This opens up the possibility of introducing new materials to the product development process that have never been used in an automotive context before.

These two aspects were combined to focus on the perception of materials used for Class A components (i.e. peripheral areas of a vehicle interior). This led to an interview study conducted at JLR and the second literature review in Submission 2, which explored material innovation in the automotive industry.

2.2 Semi-Structured Interviews at Jaguar Land Rover

A series of semi-structured interviews and group discussions were conducted with 20 JLR employees – these are reported fully in Submission 2. The aims of these interviews were to scope the industry problem by:

a) Understanding the materials selection process, the state of sustainable material innovation (including barriers and opportunities) and corporate values and behaviours towards sustainability.
b) Determining how customer research is conducted within the business.

2.2.1 Methodology

Semi-structured interviews were chosen as the most appropriate method for this study due to the exploratory nature of the technique. One of the main advantages of interviews is that they allow the researcher to discuss a certain topic in depth and face-to-face, but in a flexible manner. This means that interview data provides much more insight compared with using other data collection methods such as surveys or observation (Urquhart, 2012).

An interview guide (Figure 5) was developed which was taken to every interview. This lists the topics needing to be covered, along with potential questions. The topics were broken down into specific questions. Depending on the interviewee's answer (i.e. yes or no), additional questions were noted which were tailored to that answer.

This study obtained full ethical approval by the University of Warwick's Biomedical and Scientific Research Ethics Committee.

Thank you for agreeing to take part in this interview. I would just like to assure you that you will be kept entirely anonymous throughout this whole process and I will not be recording your name in any of the records resulting from this. ***Explain research project, why I am conducting interviews and with whom.***

Materials Selection Process

1) **Can I first ask you to describe your involvement with materials?**
   a) At what stage in the product development process does your work contribute towards? **(ask participant to map this on a printed product development process diagram)**
   b) What typical processes do you follow?
   c) Do you use any specific tools to do this?
   d) What department does your work feed on to?
   e) What type of materials do you typically work with?
   f) What decisions do your department make with regard to selecting materials for a given vehicle component?

Understanding of Sustainability

2) **How would you define 'sustainability'?**
   a) What do you know about sustainability in the automotive industry?
   b) Do you consider this important to your work?
   c) If **Yes**, what is your process for delivering environmental innovation? (e.g. do you have targets to work towards, and how do you measure it?)
   d) If **No**, do you have an interest in building up your knowledge of sustainability?
   e) What could help increase your knowledge of sustainability? (e.g. training, tools, databases?)

Sustainable Materials

3) **How involved is your department with sustainable materials?**
   a) If **Yes**, how do you measure environmental impact?
   b) If **No,** why not? Do you see this emerging in the future?

Customer Perceptions

4) **How do customer perceptions influence your day-to-day work?**
   a) If **Yes**, how? And how is it collected?
   b) What data sources do you use for this? Are they appropriate?
   c) If **No**, would you find it helpful if this data were available?
   d) How should this data be available?
   e) What would you like to know about customers that would benefit your work?

Cross-Departmental Collaboration

5) **How would you rate the state of cross-departmental collaboration at JLR?**
   a) If **Good**, which departments do you mainly work with?
   b) If **Bad**, do you think there is a need for this at JLR?
   c) How do you think collaboration could be improved upon?

Thank you for your time. Do you have any questions, or is there anything you would

Figure 5: Interview guide

2.2.2 Participants

Purposive sampling was used for the interviews as the information required was held by certain members of the organisation (Tongco, 2007). The interviewees were selected based on their organisational role and their designated department. 12 experts working on a specific vehicle programme were contacted via email. Of these, 3 replied and were willing to participate; 5 replied referring the researcher to other members of the organisation whom they believed would be of more help and 3 replied asking for a meeting with their whole team – the latter of which were treated as group discussions. In total, 20 JLR employees across Design, Marketing, Materials Engineering, Perceived Quality, Sustainability, Purchasing and Research participated in the interviews and group discussions.

2.2.3 Analysis and Results of Interviews

The interviews were transcribed verbatim and were subjected to thematic content analysis. The transcripts were coded using the software NVivo (Version 11 Pro) - a block and file approach was initially undertaken, which involved colour coding blocks of data within the context of the interview (Grbich, 2012). The coding process went through three iterations until all possible codes had been identified. This involved reading and re-reading the transcripts and reducing the data to ensure that all meaningful pieces of information were drawn out from the text. The entire coding framework along with example quotes can be referred to in Submission 2, however the final thematic map is illustrated in Figure 6 and further clarified in Figure 7.

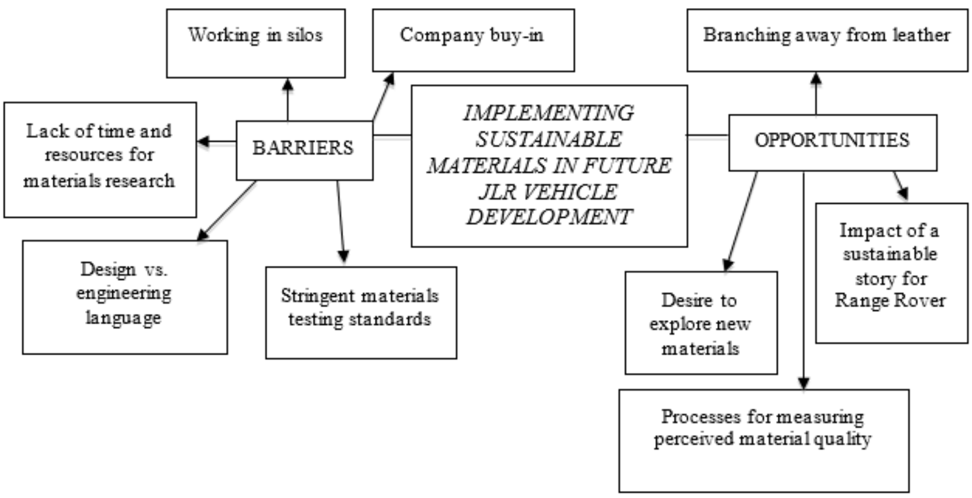

Figure 6: Code clustering, categorising and identifying themes

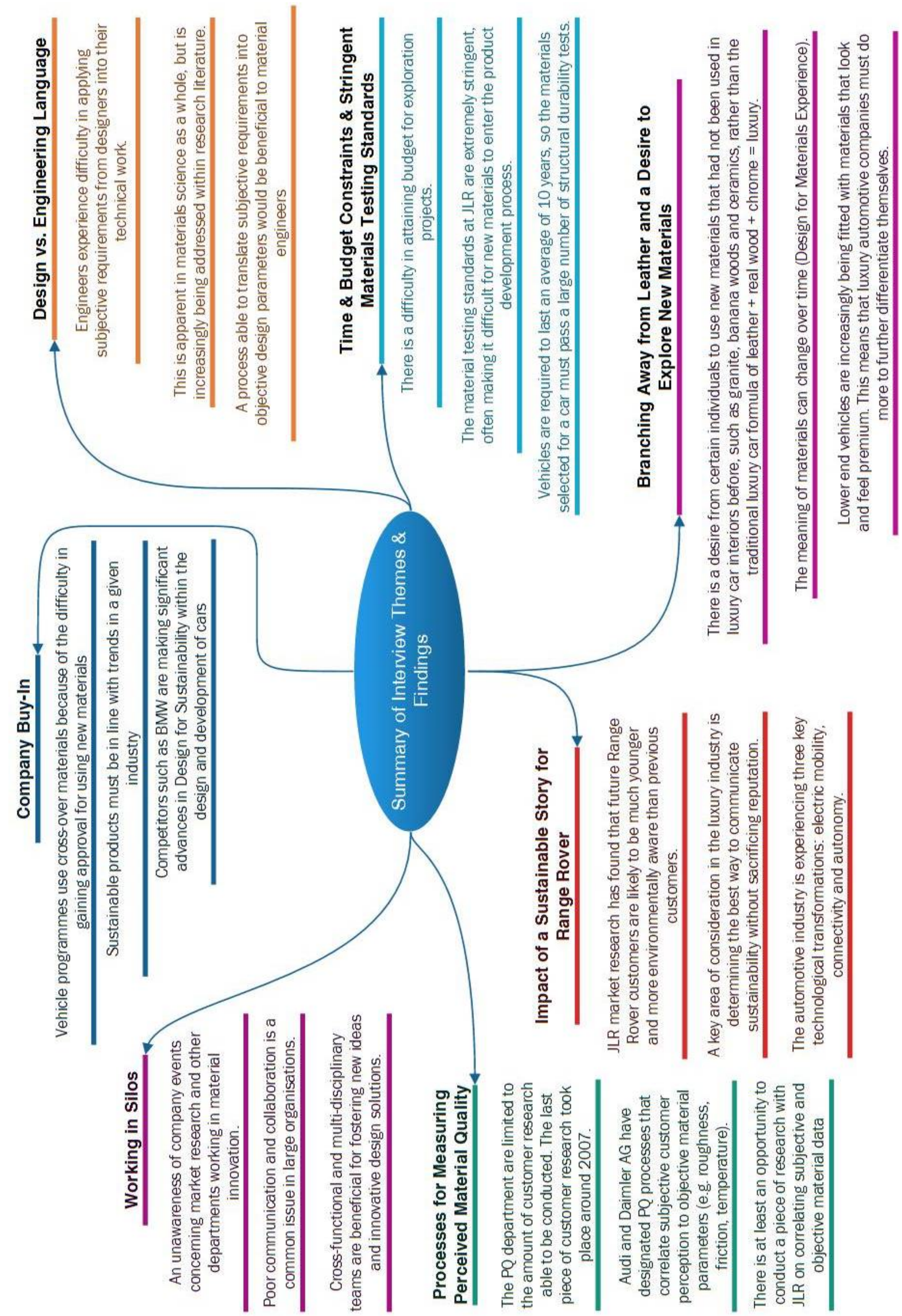

Figure 7: Summary of interview findings

One of the main aims of conducting these interviews was to understand the current state of sustainable material innovation at JLR, which these themes represent.

Although some themes are depicted as barriers, they can equally be considered as opportunities for improvement. For example, the 'lack of time and resources for materials research' became an ideal opportunity for this research project. Additionally, the 'design versus engineering language' created an opportunity to develop a process to improve this. 'Working in silos' was addressed by bridging the gap between Sustainability, PQ, Design and Materials Engineering while working towards a common goal and 'Company Buy-in' was achieved by developing a process which incorporates customer research into materials selection and obtaining quantitative data reflecting the insights from user research.

The key finding from these interviews which helped to narrow the scope of the research was the fact that there was a huge desire to incorporate sustainable, new and innovative materials into future vehicles, but there was a lack of customer research in this area. Additionally, a gap of knowledge was identified concerning the current process for measuring perceived material quality, which required user research and the quantification of subjective material attributes. These insights are further supported by a literature review in order to generalise the findings to wider industry needs. Since this literature review was conducted, further progress has been identified in industry with regard to sustainable luxury material innovation.

2.3 Sustainable Luxury Material Innovation: Ethics versus Aesthetics

Environmental sustainability of textiles is not yet the main focus for automotive OEMs, but is predicted to be in the future. Instead, sustainability in the automotive industry has thus far focused on fuel efficiency and vehicle light-weighting. Many OEMs use natural fibre reinforced thermosets and thermoplastics when developing more subtle components, such as door panels, package trays, seat backs and boot liners (Faruk et al., 2014). Most of these components are produced using natural composites based on polypropylene resin and fibres such as flax, hemp, kenaf and/or sisal. Using natural fibres such as these helps to lightweight a vehicle due to their lower density, as well as reducing the usage of costly materials such as glass, aramid and carbon fibres (Koronis et al., 2013), reducing CO_2, less reliance on foreign sources of oil, increased potential for recyclability (Holbery and Houston, 2006), biodegradability and reducing occupational health hazards (Du et al., 2014).

Typically, the use of natural fibre composites within the automotive industry is influenced by factors such as price, weight reduction, recycling and marketing incentives, as opposed to specific technical demands (Faruk et al., 2014).

Sinha et al. (2015) suggests that OEMs are hesitant to make improvements in environmental product declarations for peripheral areas of the car. This is presumably due to some of the preconceptions that some customers may have about the use of sustainable materials in car interiors. For example, Hetterich et al. (2012) explored customer attitudes and acceptance to the use of renewable and recycled materials in a car interior. Data were collected through the use of semi-structured interviews and a questionnaire to potential car buyers. The following reservations were found:

- Customers were afraid of a reduction in comfort and an unpleasant odour from natural fibres;
- Customers were afraid of safety issues;
- Quality defects effecting optics, haptics and wear;
- Durability of materials;
- Decomposition of materials;
- Flammability of materials;
- Effect of vermin;
- Disgust (e.g. swine or horse hair in seats);
- Poor colour-fastness;
- Allergic reactions;
- Origin of the materials;
- Degree of recyclability of renewable materials.

Despite these reservations, Hetterich et al. (2012) also found that car buyers favoured the social image associated with purchasing a car interior made with natural or renewable materials; they also perceived these materials to be innovative and it was found that the majority of participants would pay a price premium for an ecologically sustainable car interior if given the choice. However, these results indicate that there are preconceptions related to sustainable materials which were articulated by customers. Of particular interest to this research was the fact that many of these reservations relate to the Perceived

Quality (PQ) of the materials (e.g. comfort, colour-fastness and how the materials look, feel and smell). Ultimately, this highlighted the need for sustainable and natural materials to meet the expectations of customers in order to provide satisfaction for a given product (Ljungberg, 2007).

De Angelis et al. (2017) investigates the notion of 'design similarity' in the consumption of sustainable luxury products. It was hypothesised that luxury consumers may be more receptive to sustainable luxury products if the aesthetic design of such offerings were in line with previous products offered by a company. In contrast, if sustainable luxury offerings reflect the aesthetics of a typical "green product", and focus the design towards a different, potentially more innovative and more environmentally conscious design, then luxury consumers would be less willing to purchase and more susceptible to feelings of reduced quality. This brings to light the challenge faced by the luxury industry:

How do luxury companies balance sustainability with aesthetic, sensory and emotional appeal?

As such, De Angelis et al. (2017) stress that luxury brands such as Louis Vuitton, Prada, Armani, Rolex and Versace and others must incorporate materials that *"satisfy consumers' expectations for product sustainability without sacrificing the stylistic codes and aesthetic appeal that accompany their products".*

It was found that design similarity was most crucial when offering durable rather than ephemeral products. Ephemeral products are those that are short-term oriented and trend specific (e.g. clothing), whereas durable products are those that are more enduring (e.g. a watch or a luxury car). Customers indicated a reduced desire to purchase a durable luxury product if it was aesthetically similar to a typical "green product", due to durable products being more of a lasting investment rather than a trend piece. As such, De Angelis et al. (2017) recommend that luxury companies offering durable products should design their sustainable luxury products such that they match the company's existing 'stylistic identity and aesthetical codes'. This is supported by Davies et al. (2012) who found that aesthetics, quality and perceived value are the most critical factors influencing purchase decisions of luxury products and services. In contrast, consumers believed that ethics was not a priority when purchasing luxury products.

This belief underpinned the research: that first an understanding of what constitutes luxuriousness and high quality in materials should be established, of which this knowledge can be applied when searching for newer material offerings, including sustainable materials. This then helps to ensure that new materials meet the criteria of a “luxury material”.

With evidence suggesting that millennials care more about the environment than previous generations, it is logical to assume that sustainable innovation will transcend further into the design and styling of vehicles, rather than focusing on hidden components. A report commissioned by BMW predicts that by 2025, sustainable luxury in the automotive industry will be extremely prominent to customers (Dellion et al., 2015). ‘Self-indulgent’ luxury customers were found to be the most attractive segment to target. The purchase drivers for these customers include: design and interior, personalisation and smoothness of drive and connectivity. They value luxurious experiences, demand modern features and they are ready to pay a premium for a sustainable luxury car. However, what was most interesting for this research is that these customers were found to express a desire for tangible sustainability - they want the sustainability of the vehicle to be felt and seen through the application of durable and sustainable high quality materials. This highlights the need for conducting customer research in sustainable material perception, in order to pinpoint ways in which the usage of sustainable materials can be facilitated during product development in the luxury industry.

Some automotive OEMs have already begun the search for new materials. This was discussed briefly in section 1, which mentioned that companies such as Rolls Royce are searching for new materials that have never been used for automotive applications before. Some OEMs are challenging the use of handcrafted wood and leather as being synonymous with luxury. Bentley have spoken about their exploration into glass, textiles, silk and stone veneers (Moore, 2016). The company have conducted consumer research specifically focusing on the West coast of America and have found that the average high net worth individual is far more conscious about the environment. It has been identified that San Francisco is a place where *“no one wants leather anymore”.* This has led the company into investigating the use of protein leathers for future vehicles (Turner, 2016). Tesla have also announced a vegan leather alternative for their vehicle interiors (Zhang, 2016), which will likely prompt competing OEMs to try to provide the same.

Kering – a conglomerate that owns many luxury brands such as Gucci, Saint Laurent, Stella McCartney and Alexander McQueen – have launched their own materials innovation lab. This provides a library of sustainable materials and a team of technical experts working towards innovation in raw materials, fabric processing and manufacturing to ultimately create new, “greener” materials that can become available to the brands under Kering. As part of this work, the conglomerate has also strived to ensure that all collections are free from PVC (due to its environmental and health impacts).

Stella McCartney have implemented biodegradable and vegetable oil materials in their shoe collections. This contributes to their work of searching for non-leather materials for shoes and bags that do not rely on petroleum. The brands’ eyewear is additionally made from over 50% natural materials such as castor oil and citric acid. Gucci has also experimented with sustainable material innovation for their eyewear, where they launched biodegradable sunglasses made from “liquid wood” - comprised of sustainably sourced wood fibres, lignin and natural wax. However, with regard to phasing out PVC, it has been recognised that there are not enough options available in alternative plastics that meet the requirement of high quality and durability for luxury products (Kering, 2016).

These findings indicate the pressure faced by luxury companies to search for new materials that reduce social and environmental impacts associated across the lifecycle, whilst maintaining the standards set in the luxury industry. It also emphasises the role of materials in characterising and communicating a feeling of luxury.

The insights drawn from these literature reviews revealed three main issues:

1. There are market demands for new automotive materials, which will attempt to redefine what is traditionally considered a ‘luxury’ material.
2. The findings discussed in section 2.1 found that the reality of biophysical limits means that companies will struggle to source certain luxury materials in the future (Positive Luxury, 2016, Ersal et al., 2011).
3. Submission 2 found that lower end vehicles are increasingly being fitted with materials that look and feel premium, which means that luxury automotive companies must do more to further differentiate themselves.

2.4 Perceived Quality (PQ)

The third and final literature review which was conducted to narrow the scope of the research focussed on defining and discussing PQ in the automotive industry, haptic perception, customer satisfaction evaluation methods and sensory analysis techniques. PQ was also addressed in Submission 2 but was expanded on in Submission 3 as it became the focus of the research.

PQ is sometimes used interchangeably with ‘craftsmanship’ in the automotive industry and is defined as:

‘The perception of quality experienced by a customer, based on sensory interaction and emotional impact’ (Turley et al., 2006)

Stylidis et al. (2015) separates PQ into two groups:

a) Technical Perceived Quality - This signifies a more engineering approach to PQ. It is divided into 4 components which coincide with some of the most dominant sensory modalities: *visual quality, feel quality, sound quality and smell quality.* This is supported by Bhise (2011) and Robinson (2000), where it is generally accepted that PQ is largely determined by sensorial interaction with a product. Examples of each are provided in Figure 8.
b) Value Based Perceived Quality– This represents the overall customer experience, including customer behaviours, values and branding.

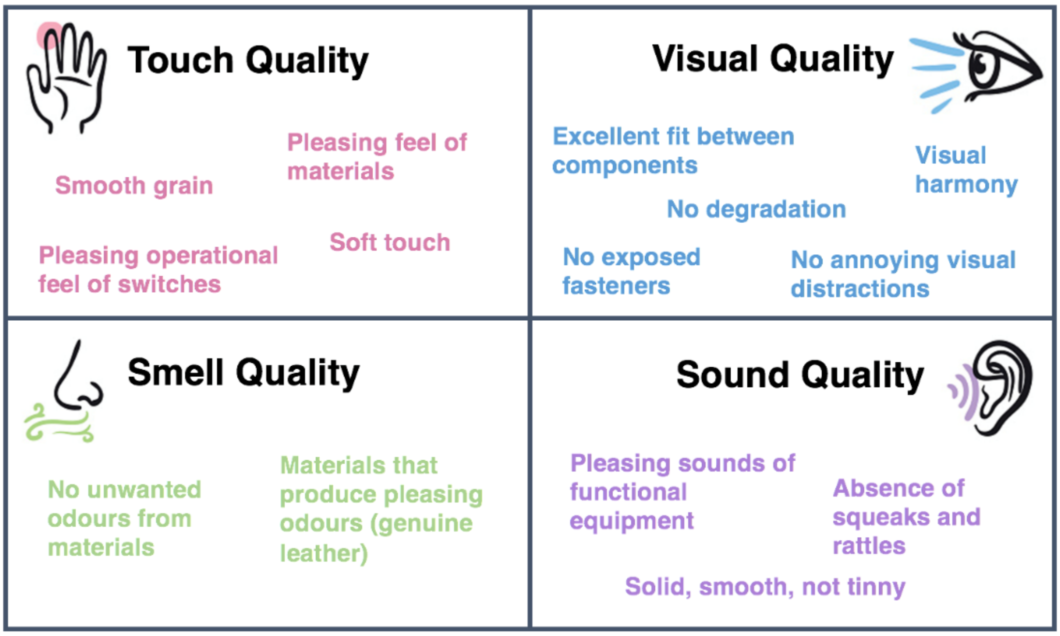

Figure 8: Automotive PQ characteristics

It should be noted that in industry, there are sometimes dedicated departments that consider some of the characteristics illustrated. For example, a human factors team may consider haptic feedback, usability and operational feel of switches and materials engineering may consider degradation. Ultimately, these all influence a customer's perception of quality.

Two distinct industry problems were highlighted by Stylidis et al. (2015), which refer to the ways in which PQ in the automotive industry is measured:

1. There appears to be a deficiency of a common terminology explaining and defining the many aspects of PQ.
2. Implementation of PQ measurement methods and tools is difficult in practice – particularly ones incorporating objective, engineering material assessments and the quantification of subjective, sensorial attributes.

The second problem was found to also be evident in the wider practice of materials science. Experiential and sensorial material characteristics within automotive styling can play an enormous role in customer purchase decisions. For instance, Audi have stated that up to 60% of a customer's purchase decision is based on styling and design rather than technical performance (Kreuzbauer and Malter, 2005, Ranscombe et al., 2012). However, the ways in which experiential and sensory characteristics of materials can be objectively measured is a particularly difficult task. Generally, designers are supplied with a target feeling (e.g. luxuriousness), which is derived from market analysis. Designers tend to therefore rely on past experience and intuition regarding these aspects, which may not always be reliable, particularly when dealing with newer materials (Wastiels et al., 2012).

As mentioned in section 1, these intangible aspects fail to be effectively supported when it comes to traditional materials selection tools and processes, although a growing body of research is being conducted to address this (Karana et al., 2010, Wastiels and Wouters, 2012, Ashby and Johnson, 2013). The issue is that materials selection has been a technical-led domain, with the intangible perspective of materials receiving relatively little attention until recently (Pedgley, 2010). Researchers have therefore advocated the need for designers to be aware of the engineering as well as experiential perspective of materials, in order to be more informed about how material properties can influence the overall product experience (Pedgley et al., 2016). Additionally, it is often difficult for designers to communicate material requirements to engineers and materials scientists, and vice versa. As such, researchers such as Ashby and Johnson (2013) and Wilkes et al. (2015) highlight the need for ways in which subjective perception can be identified and translated into data that can readably be used by those within both design and engineering.

2.4.1 Measuring PQ in the Automotive Industry

In general, many automotive manufacturers will have formed designated teams who are responsible for assessing, measuring and improving the perception of quality of the final vehicle. According to Stylidis et al. (2015), the two most important aspects of PQ practice are:

1. Identifying the influences on the customer during product evaluation.
2. Measuring and assessing the importance of the product attributes that have an impact on purchase decision.

Bhise (2011) explains that research investigating PQ is based on:

- **Customer perception** of the product once the customer experiences it (i.e. sees and uses the product).
- **How well the product is executed** to possess visual, sound, touch, feel and smell quality, as well as usability and aspects of surprise and delight.
- **How the product affects its perception of quality** – i.e. image and brand.

These can be measured using the following methods:

1. **Checklists.**
2. **Objective measurements** (e.g. gloss levels, compressibility, roughness and friction).
3. **Subjective evaluations** using perceptual rating scales or comparisons using acceptable reference samples.
4. **Customer clinics** or studies to understand customer preferences and the ability to perceive discriminate and categorise PQ characteristics.

<u>Haptic Perception</u>

This research focused on haptic perception, as the intention was to focus on one sensory modality entirely rather than all four at once. Haptic perception was selected over visual, sound or smell perception because sound and smell quality are typically addressed in other departments at JLR, rather than under the PQ remit. It was determined that there was more scope under haptic quality - as visual quality measurements were much more developed in the company - so this became the research focus. However, the final process would be developed such that any sensory modality could theoretically be evaluated.

Okamoto et al. (2013) defines haptic perception as being "*the perception of the qualities and properties of material surfaces by touch".* It is comprised of two layers: psychophysical and affective. The former refers to the perception of physical properties (e.g. surface roughness or smoothness). The latter refers to more experiential and emotional perceptions such as 'richness, cleanliness and kindness'.

There are many areas of haptic research in the automotive industry, but in general it tends to focus on mechanical controls (e.g. handles, flaps, lids), electric controls (e.g. switches, rotary actuators, operating levels) and surface materials (e.g. leather, lacquered surfaces, decors and trim) (Enigk et al., 2008).

Audi have a team comprised of members from their technical divisions responsible for the design and engineering of surface contours and materials in the vehicle. Additionally, they include members of the company with no direct link to the technical applications in vehicle development in order to gain a wider perspective. Together with customer surveys, the team have formed objective and subjective assessment methods that reflect how vehicle haptics are perceived by users. The results of which are used to develop the vehicle interior. Audi have developed a scoring system, which characterises haptic impression of materials in four ways (Grunwald, 2008):

1. *Softness feel* (initial stiffness and progression, using a downward movement)
2. *Resilience perception* (recovery characteristics after a material has been pushed down – a slow recovery leaves a fingertip impression on the surface after unloading)
3. T*ouch/stroke feel* (roughness and static friction of a material coinciding with a lateral movement)
4. *Temperature perception* (heat dissipation from a surface e.g. coldness of chrome, warmth of leather).

Daimler AG has also recognised that customers are not only seeking functional vehicles but they also want their vehicles to be 'works of art'. This is achieved in part by attractive design and high quality materials. In particular, Enigk et al. (2008) pose questions such as:

- What materials do customers regard as top-quality?
- What is the distinguishing feature of real leather?
- What do plastic surfaces have to look like if they are not to be perceived as inferior or distracting?

Contrary to Audi, Daimler's haptics laboratory is situated at their Customer Research Centre. The team there is comprised mainly of psychologists specialising in perception. However, they do ensure close collaboration with the development, design and marketing teams. Daimler has developed a five-point methodology for optimising the haptics of driver control and surface materials (Grunwald, 2008):

1. *Conceptual analysis of the problem*
    - Analysis of the problem, target definition.
    - Research (e.g. perception thresholds, strengths and weaknesses of existing components).
    - Analysis of physical functional principles (technical measurement of models e.g. force-travel characteristics, surface texture.
    - Project planning.
2. *Definition of customer requirements and customer relevant criteria*
    - Exploratory qualitative customer study.
    - Identification of customer relevant requirements and criteria.
3. *Design of new controls or modification*
    - Optimisation of models with regard to customer relevant criteria.
    - Creation of new model components with various parameter graduations.
4. *Identification of optimum haptics parameters in the lab and/or field trial*
    - Experimental customer trial in the laboratory/field for determining the optimum haptics parameters by means of systematic variation of model variants and parameter graduations (e.g. by regression, variance, cluster analyses and factor analyses).
5. *Definition of requirements specifications*
    - The insights gained from the research then feed into the development of technical specifications which can be communicated to suppliers and stakeholders.

Enigk et al. (2008) suggest that field trials do not necessarily need to be conducted for exploring material covering areas of a vehicle. Instead, they suggest that physical analyses of surface materials (e.g. softness, texture) are enough to make assumptions about material properties and their impact on customer perceived quality. The Research Engineer (RE) argues that both subjective and objective analyses of surface materials are required in combination in order for a baseline comparison to be determined. A qualitative study on the perception of surface materials can reveal the metrics associated with PQ specific to the user, rather than basing it on expert opinion.

Moreover, it is argued that a baseline of customer perception is needed to determine the level of perception amongst the target population – for example, younger versus older customers or customers from differing cultures. After this is established, physical analyses may be used to predict or determine the subjective impression of materials and to also ascertain the optimum physical parameter at which a 'high quality' material comes under – this information can then be communicated to suppliers.

In the case of analysing automotive seat comfort, the typical approach is to benchmark a competitor seat, which becomes a target to work towards. A subjective evaluation is performed using a structured survey. This directs occupants to assign perceptions of comfort/discomfort to specific regions of the seat. This is then fed back into the development process, where prototypes are built and retested for subjective quality in iterations until the perceived seat comfort exceeds that of the target competitor seat (Kolich et al., 2004). This occurs when assessing material quality, where interior materials in competitor cars are subjectively rated and benchmarked by experts, offering a target feeling that acts as a baseline.

An issue with these typical processes is that the teams responsible for assessing subjective quality struggle with the fact that the output of these processes lack experimental rigour, despite offering face validity. This then leads to prototypes being developed that are unable to produce the expected results in future subjective evaluations or only offer marginal improvements in quality at best. Additionally, the processes are extremely time-consuming and expensive. However, it is argued that these drawbacks would be justified if the process could guarantee a positive rating for comfort (in this case, through the use of statistical modelling). The authors also argue that more attention should be paid when developing subjective evaluation processes, particularly with regard to '*survey wording, the type and number of rating scale categories, the verbal tags associated with the categories and the method of quantification'* (Kolich et al., 2004).

Ultimately, these findings call for a more systematic means of understanding customer perception and quantifying these into actionable insights when measuring PQ and comfort in the automotive industry. Submission 3 found that this has largely been addressed through Kansei Engineering, which is a methodology aimed at translating subjective insight into engineering parameters (this is explained in more detail in section 3).

The interviews in Submission 2 found that the JLR PQ department would benefit from a way of including mechanical material measurements in their process. The focus of the research was finally narrowed down to the development of a new, more systematic process for measuring the perceived quality of automotive interior materials. Specifically, one which is able to incorporate real user research and translate these into engineering criteria.

Combining subjective and objective materials data can be especially useful when exploring sustainable materials. Section 2.1.1 listed some of the preconceptions that automotive customers have when considering the use of sustainable materials for automotive interiors. Many of these were PQ issues, including a perceived reduction in optics, haptics, smell and comfort (Hetterich et al., 2012). This is where sensory evaluation and the correlation of subjective and technical data can come in useful. An understanding of the material characteristics that constitute a perception of high quality or luxuriousness for certain materials can be gathered using sensory analysis techniques and perceptual scaling. These can then be related back to technical design parameters responsible for these characteristics so that this information can be referred back to when selecting materials.

Figure 9 illustrates the key needs identified from conducting the three literature reviews and the interview study at JLR, which are based in the context of materials selection. It can be seen that these needs are interrelated, which demonstrates that the issues faced are evident not just in JLR, but the automotive industry and the wider practice of materials science.

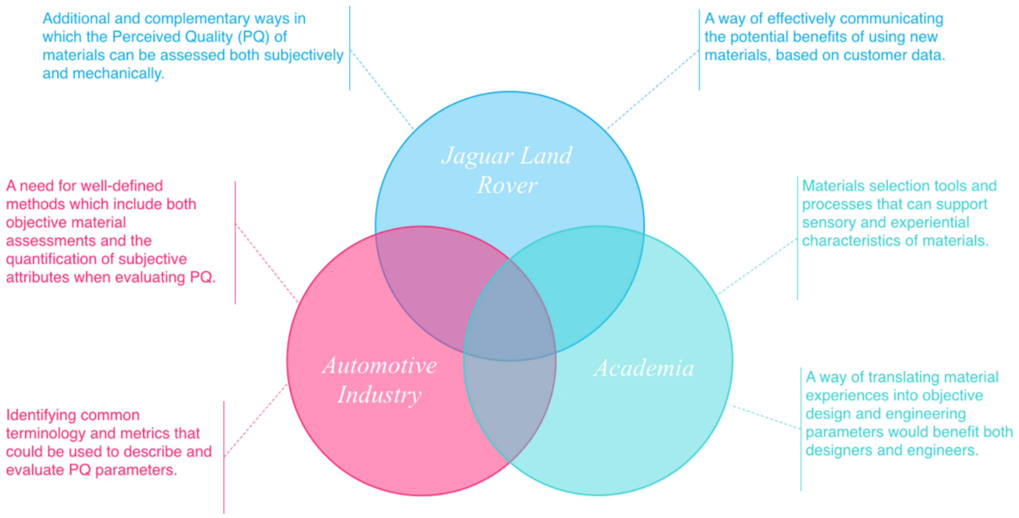

Figure 9: Key industry needs identified from literature and a JLR interview study

2.5 Formulation and Refinement of Research Questions

The three literature reviews and interview study helped to refine the research questions. Firstly, the following question and objectives were defined at the end of Submission 1:

Research Question and Objectives (Iteration 1)

How can luxury brands improve the sustainability of their products without negatively affecting customer satisfaction?

The preliminary research objectives aimed to address this question are:

- RO1: To develop an understanding of the meaning of luxury and sustainability to consumers and prioritised attributes of a luxury vehicle.
- RO2: To understand current methods used when conducting customer clinics at JLR.
- RO3: To develop a methodology that can be used during these clinics.
- RO4: To develop a decision making model for materials selection for automotive interior trim.
- RO5: To test and apply this to an industry context.

These research objectives were focussed on customer perception (especially quality perception) and materials, so these findings informed the semi-structured interviews conducted at JLR. From these, the following questions and objectives were refined with particular emphasis on developing a process for materials selection and understanding how customer research regarding material perception is currently conducted within the automotive industry and specific to JLR.

Research Question and Objectives (Iteration 2)

1. ***What are the haptic characteristics that constitute a feeling of luxuriousness in materials?***
2. ***Does the customer's knowledge of sustainability affect their perception of quality in a product?***
3. ***How can the subjective and aesthetic characteristics of materials be translated into their objective engineering requirements?***
    - RO1: To test, refine and validate sensory analysis techniques for evaluating the perceived quality of materials.
    - RO2: To conduct customer workshops to identify perceived quality ratings of materials.
    - RO3: To understand which material characteristics constitute a feeling of luxuriousness.
    - RO4: To translate subjective material characteristics into objective, engineering metrics by conducting the relevant technical testing.
    - RO5: To understand customer receptivity to the use of sustainable materials in luxury automotive interiors.
    - RO6: To determine the types of sustainability communication strategies which resonate well with customers.

The first question intended to address the issue of defining 'luxury' as it could mean something different from person to person. If luxury companies are to maintain the standards set in the industry with regard to searching for and creating new materials, it would be useful to identify the characteristics that constitute that feeling of luxuriousness from a customer standpoint. These insights can then be used as a baseline when searching for and selecting new materials. This research question therefore aimed to pinpoint the haptic characteristics associated with luxury materials used for automotive trim and as such define metrics and criteria that could be used when evaluating new materials.

The second question refers to whether sustainability should or should not be communicated in the luxury industry at all. Specifically, it aimed to explore the influence on perception when information regarding sustainability (e.g. sourcing, environmental impacts, manufacturing process) was given to participants. After discussing this with the project partners, it was agreed that exploring this question could significantly reduce the pool of participants, as two groups would ideally have needed to be investigated (one with and without the sustainability information). As such, it was decided to focus on the first question, as a baseline understanding of what constitutes a 'quality material' was paramount to developing the overall PQ process.

Lastly, the third question aimed to translate the subjective material insights collected from the first question into technical design parameters. Blumenthal and Herbeth (2014) note that analysis techniques within sensory science are typically used in the automotive industry to:

- Better understand customer perceptions;
- Develop new products which meet customer expectations;
- Help communicate on sensations within the organisation;
- Improve the training of driving experts;
- Establish links between subjective perceptions and their technical measures, which can then be communicated to suppliers as part of their proposal and specifications requests.

The first four points are addressed using the first research question. The latter is addressed using the third research question. This is particularly useful in the automotive industry, where quantitative data provides more impact when communicating results across the company. Additionally, translating subjective insight into technical parameters allows designers and engineers to identify how a material sensation can be improved. As discussed in section 2.4, this issue of combining experiential and engineering material understanding is evident in PQ in the automotive industry and the wider practice of materials science.

The final research questions and objectives are presented below. These included an additional objective (RO5), which aimed to explore whether an overall PQ score can be predicted. Collectively, these contributed to the development of a new, more systematic process for measuring perceived material quality.

Final Research Questions and Objectives

1. ***What are the haptic characteristics that constitute a feeling of luxuriousness in materials?***
2. ***How can the subjective and aesthetic characteristics of materials be translated into their objective engineering requirements?***
    - RO1: To test, refine and validate sensory analysis techniques for evaluating the Perceived Quality of materials.
    - RO2: To conduct customer workshops to identify Perceived Quality scores for soft interior materials.
    - RO3: To understand which material characteristics constitute a feeling of luxuriousness.
    - RO4: To translate subjective material characteristics into objective, engineering metrics by conducting the relevant mechanical testing.
    - RO5: To investigate whether Perceived Quality scores can be predicted using statistical modelling.

2.6 Section Summary

This section outlined the research background and steps taken to narrow the scope of the project. It was found that past literature exploring barriers to sustainable consumption in society identified an overall negative perception of quality when considering sustainable derivatives of products. This is magnified in the luxury context, where research has indicated consumer scepticism towards the quality of green products provided by luxury brands.

The perception of quality was found to be typically determined by peripheral and sensorial product properties (such as design, styling, shape and touch). Sensory perception (especially visual and haptic) tends to be measured by a ‘Perceived Quality’ (PQ) department in an automotive OEM. A key issue in automotive design is a lack of standardised processes for measuring PQ and there is a need for well-defined methods which include both objective material assessments and the quantification of subjective attributes when evaluating PQ – however this is often difficult to do in practice.

Automotive design trends have indicated that OEMs are searching for new materials which are able to redefine what is traditionally perceived as a ‘luxury’ material. This is driven by various forces, including:

- The need for competitive differentiation as premium and mass market brands are increasingly using materials with a similar look and feel to luxury materials (such as leather and wood).
- The reality of biophysical limits has meant that luxury brands will need to be more strategic in the long-term when sourcing their raw materials.
- Increased customer demand for automotive sustainable luxury in the future, particularly ‘tangible sustainability’ through the use of high quality sustainable materials which can be felt and seen by the customer.

These findings all suggest that new materials are being considered that have never been used in the automotive industry before. In order to ensure that these materials achieve a high perception of quality, the processes responsible for assessing the sensory and experiential characteristics of materials need to be up-to-date and effective. It was found that the JLR PQ team would benefit from being able to translate subjective perception into technical, engineering criteria for materials. Therefore, the aim of the research was to develop a new process for measuring PQ which relies less on less on intuition and more on real user research, mechanical measurements and predictive modelling.

3 *Developing the Process for Measuring Perceived Material Quality*

This section outlines the process for measuring and predicting perceived material quality. This can be implemented into an automotive Perceived Quality (PQ) department and can then be streamlined to allow for rapid customer research. The reports under Submission 4 can be considered as the building blocks to this process. This chapter brings all of these constituent parts together. Guidelines and recommendations for applying this process are provided in Appendix 1.

3.1 *The Research Approach*

The approach taken to develop this process is illustrated in Figure 10.

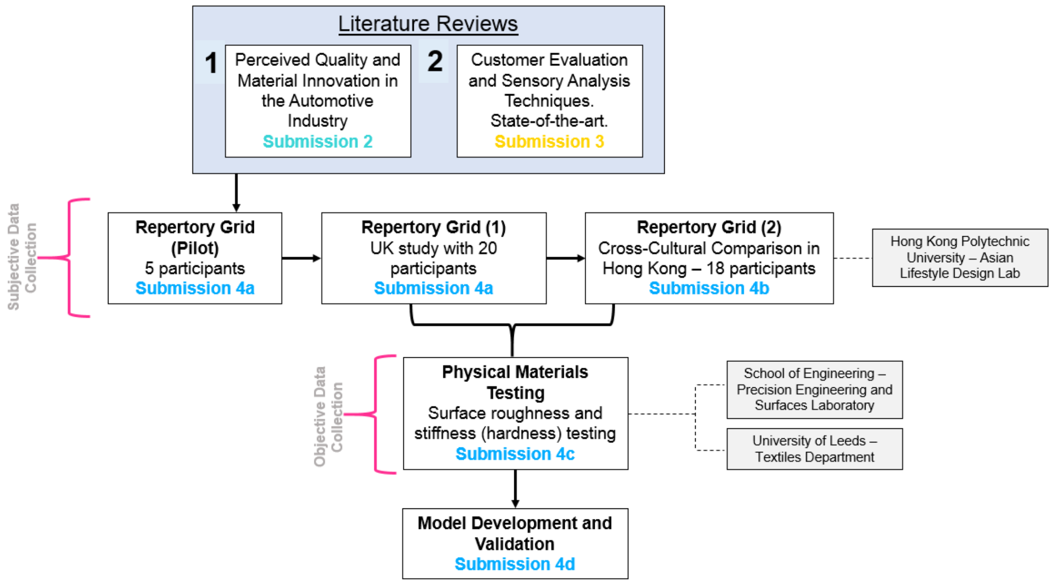

Figure 10: Summary of approach for developing the overall PQ process

Firstly, a literature review was undertaken on PQ and material innovation in the automotive industry – these insights were a development of the findings from the interviews conducted at JLR. Another literature review was conducted, which reviewed the potential methods that could be used to address the research questions and objectives presented in section 2.5. 13 methods were reviewed in total, covering customer satisfaction evaluation methods (e.g. Kansei Engineering, Quality Function Deployment, Conjoint Analysis) and sensory analysis techniques (e.g. Perceptual scaling, Free Verbalisation, Free-Sorting). The Repertory Grid Technique (RGT) and Magnitude Estimation were ultimately selected. This decision was based on assessing strengths and limitations of the techniques as well as previous literature and state-of-the-art in material perception research.

Two RGT studies were conducted, after an initial pilot test using 5 participants. Then, the physical materials testing was conducted and the subjective and objective data were correlated. Lastly, a series of predictive models were developed using generalised linear modelling, non-linear regression and artificial neural networks. The aim of these models was to take the data obtained from the previous studies (RGT and the mechanical test-work) and predict future PQ values without needing to conduct the initial consumer interview.

A summary of this experimental work is reported further in this section, while providing an explanation of the process as a whole. However, for more detailed explanations, refer to Submissions 4a, 4b, 4c and 4d.

3.2 Kansei Engineering

The philosophy underpinning the work was based on Kansei Engineering, which originated in Japan. It was developed by Mitsuo Nagamachi as an '*ergonomic consumer-oriented technology for new product development'*. The term 'Kansei' refers to a customer's subjective impression of 'products, situations or surroundings' (Lokman, 2010) particularly when faced with a purchase decision. An example of a customer's kansei when purchasing a new car may be features such as "speedy, easy to control and stylish" (Nagamachi, 1999). Kansei Engineering (KE) is able to take these 'kansei' and translate them into physical design specifications or elements (Nagamachi, 1995).

The general process of KE largely follows these 4 steps:

1. <u>Grasping the consumer's feeling (i.e. kansei):</u> This refers to the process by which the ergonomic and psychological aspects important to a customer are captured and understood. These are represented in the form of adjective words (or sometimes verbs) (Schütte, 2005). They are typically

gathered using secondary sources such as product reviews and/or industrial magazines.

2. Identify the design characteristics from the consumer's kansei: This stage involves identifying relevant design elements or parameters that specifically relate to each kansei word from the previous stage (Nagamachi, 1999). A survey or an ergonomic experiment can be conducted to establish this relationship. However, Schütte (2005) argues that unlike the previous step there is no theory or consistency in identifying product properties and ensuring that those selected are relevant to the user. Instead, the author suggests that potential properties can be collated using relevant sources (e.g. material databases). These are then reduced to the most important properties which can then be further evaluated. A physical property must be found to match each kansei word.

3. Synthesis: The previous two steps are combined in the synthesis stage i.e. for every Kansei word there are a number of product properties. For example, Bahn et al. (2009) found that the perception of luxuriousness with respect to surface materials used for automotive dashboards was mainly affected by the coefficient of static friction. Identifying the material characteristics that can positively influence perception then makes it possible to communicate these to suppliers in order to ensure the optimum composition of surface materials.

   The next step would be to analyse the interactions between the Kansei words and the associated design attributes. This is most commonly carried out through the use of semantic differential scales. A semantic differential (SD) scale is anchored by two semantically opposite terms. For example, in the context of materials, the two anchor points for an SD scale could be rough-smooth: these are two extremes of the same dimension. Generally, the pair of adjectives are represented as one positive term and the other negative. Once the results have been obtained, a factor analysis is generally applied to the dataset in order to uncover the underlying covariance in the data. The goal of which is to identify the minimum number of dimensions that can meaningfully explain the data – this type of factor analysis is part of principal component analysis (Cunningham and Wallraven, 2011).

This technique has been used widely in the automotive industry. It has been used when measuring customer perception of interior components such as push switches (Wellings et al. (2010), and wood grain and metallic appliqués (Bhise et al. (2005). Sarma et al. (2010) used SD scales to explore the effect of material characteristics on customer perception of automotive interior materials in order to explore the correlation between subjective and physical material characteristics. Similarly, Karana and Nijkamp (2014) used SD scales to investigate perceptions of natural materials. Lastly, Jindo and Hirasago (1997) at Nissan applied Kansei Engineering to the design and specification of automotive speedometers and steering wheels, using semantic differential scales to collect subjective perceptions of a number of designs. The results of which were used to determine the most desired specification for each component.

4. Test of Validity and Model Building: A mathematical or non-mathematical predictive model is built to use for future predictions for products. Typically, some form of factor analysis is conducted (e.g. Principal Components Analysis) or Multi-Dimensional Scaling. This provides information regarding the correlation between the Kansei words and which of the words are of highest importance within the semantic space (Schütte and Eklund, 2005). Linear regression modelling can then be applied to the results (e.g. Quantification Theory Type I or Generalised Linear Modelling).

KE is more of a methodology rather than a singular method or technique. Instead, it is considered more of a collection of techniques that follows the general process described above (Wellings et al., 2008). It is most prominent in the automotive industry, with companies such as Mazda, Nissan, Ford, Saab and Volvo all utilising this methodology. The most famous example of a Kansei Engineering application in industry is the Mazda Miata (also known as MX-5), although it has also been used in the textile, food, electronics and cosmetics industries (Levy, 2013). KE has also been used to explore visual and haptic impressions of materials used in automotive interiors (You et al., 2006, Bahn et al., 2009). Kansei Engineering therefore seems to be a tried and tested methodology for investigating material perception in an automotive context.

The Repertory Grid Technique (RGT) was chosen to address a potential issue in Kansei Engineering, where there is a reliance on using secondary data sources in the first stage of the methodology to construct rating scales. This has been demonstrated by Steinberg et al. (2015), who emphasises that the use of marketing reports, product reviews and/or product specifications to collect kansei words is potentially risky as these data sources may be incomplete. Direct interaction with the customer is also a missing key component, meaning that their sensory input is not captured using the traditional means of collecting kansei words. This direct interaction with the customer is also useful for clarifying insights with participants in order to ensure that the data collected accurately reflects an individual's perceptions. Using secondary sources does not allow for this, and if the data sources do not have sufficient references of the kansei words, it then becomes difficult for engineers to apply these insights into product development accurately without using an element of guesswork (Steinberg et al., 2015). RGT is described in further detail in section 3.4.1.

3.3 The Research Process

Figure 11 illustrates the entire research process undertaken. This consisted of 5 stages, which were influenced by the general stages in a KE methodology described in section 3.2:

1. Generation of a user-defined sensory lexicon.
2. Scoring of materials.
3. Qualitative and quantitative data analysis.
4. Physical materials testing.
5. Model development.

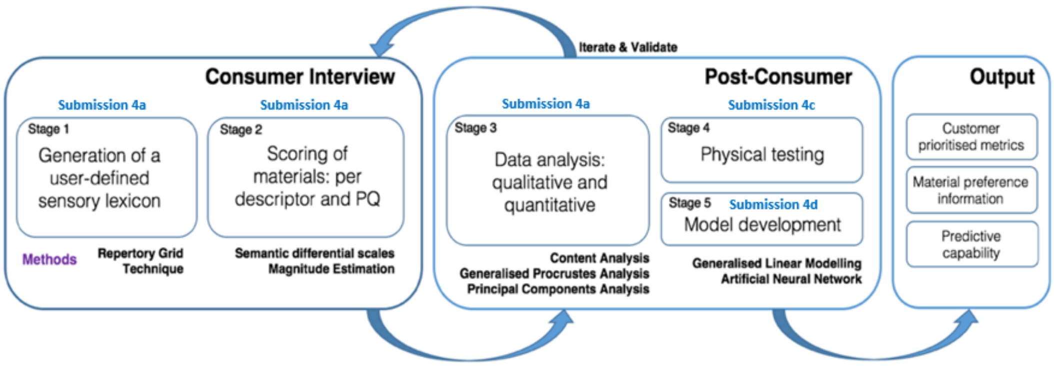

Figure 11: A process for measuring perceived material quality

Each stage is described in more detail in the following sections.

3.4 Stage 1: Generation of a User-Defined Sensory Lexicon

A new process was being developed, so it was necessary to identify the relevant metrics needed to evaluate haptic quality. A challenge in materials selection is determining the appropriate criteria to measure haptic perception and identifying the desired values for each criteria (Larson, 2015). Verbal elicitation methods were found to be an effective way of generating user-defined material attributes corresponding to the sensory modality being investigated (e.g. visual, touch, smell, sound characteristics). An attribute can be defined as '*properties, qualities or characteristics of the phenomena that are measurable to a certain degree'* (Paul et al., 2008).

When verbal elicitation methods are used, metrics can be determined based on customer perception. This produces a sensory lexicon, which can then be used to compare expert and customer perceptions and to ensure that experts are using the same vocabularies and intensities of stimuli experienced by their customers (Blumenthal and Herbeth, 2014). This research used the Repertory Grid Technique (RGT) to generate material attributes directly from the user, which is explained in the next section.

At present there are no standardised metrics for measuring PQ in the automotive industry. Additionally, Stylidis et al. (2015) found that an issue in PQ in industry as a whole is the lack of a standard terminology that can be used to explain the many aspects of PQ (e.g. sound, smell, touch and visual quality components). Verbal elicitation methods such as RGT are therefore useful when addressing this issue.

3.4.1 The Repertory Grid Technique (RGT)

RGT stems from Personal Construct Psychology, which is based on the premise that individuals arrange their interactions and experiences with the world around them into conceptual ‘constructs’. The theory suggests that individuals have a set of constructs that are unique to them. For example, when looking to purchase a car, one person may organise their choices based on mileage, whereas another person may prioritise fuel economy, colour or brand.

As a research technique, it is used to extract data from participants in a structured and non-biased way. It typically takes the form of a one-to-one interview between the researcher and participant. Researcher/interviewer bias is lessened because the method allows the participant to disclose constructs that are important to them, consumer needs are therefore directly derived from participants during an RGT interview (Van Kleef et al., 2005). In traditional surveys or interviews, the researcher asks the participant a set of pre-structured questions, which may or may not be important to the participant (Goffin and Lemke, 2010).

Figure 12 illustrates the process used in this research to conduct two Repertory Grid experiments.

Figure 12: The Repertory Grid process undertaken in this research

1. *Selection:*

   To begin, a domain or topic of interest has to be chosen and defined. Then, the researcher has to select 6-12 different examples or ‘elements’ in the chosen domain with which participants can then interact with during the course of the interview. The examples should reflect a wide variety of potential constructs.

   In this research, the elements used were nine material samples (Table 2 and Figure 14) used for luxury automotive interiors. All of these materials are either leather, fabric, polyurethane (PU) or PVC, meaning that they were all soft, wrap-able materials as opposed to hard materials such as veneers, plastic or chrome. Including a range of soft materials, rather than focussing on just fabrics for example, meant that a representative coverage of the topic area was investigated (Easterby-Smith, 1980).

The impact of a foam interlayer on perception was also investigated in this research. A foam interlayer refers to a layer of foam beneath a trim material, as illustrated in Figure 13.

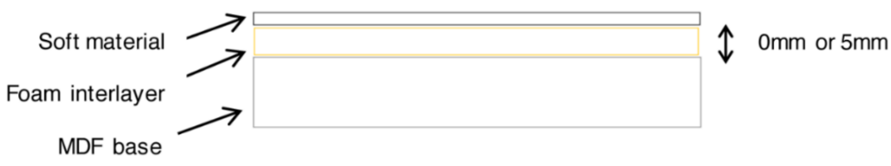

Figure 13: Composition of material samples with a 5mm foam interlayer

This was a particular area of interest for the project partners at JLR. The premium automotive sector generally uses a foam interlayer when wrapping a material around a component (e.g. the armrest) to increase comfort. However, when considering aspects such as cost and light-weighting, the foam interlayer can sometimes be considered at risk of reduction or removal.

An opportunity was recognised to explore the extent to which the presence of absence of foam between the soft material and its base had an impact on participants' perception of quality and/or preference. To avoid using just the material samples alone (i.e. as swatches), the materials were wrapped around 200x100mm blocks of medium density fibreboard (MDF).

Table 2: Material samples used for the Repertory Grid triading process

Triad	Material Code	Type	Name/Grain	Interlayer
1	191	Fabric	Steel Cut 30% Wool	0mm
	841	Fabric	Microfibre/suede cloth	0mm
	995	PVC	Taurus	5mm
2	384	TPO	-	0mm
	134	PU	-	5mm
	441	Fabric	Wool Blend	0mm
3	195	PVC	Cuir Grain	5mm
	426	Leather	Windsor	5mm
	135	PVC	Technical Grain	5mm

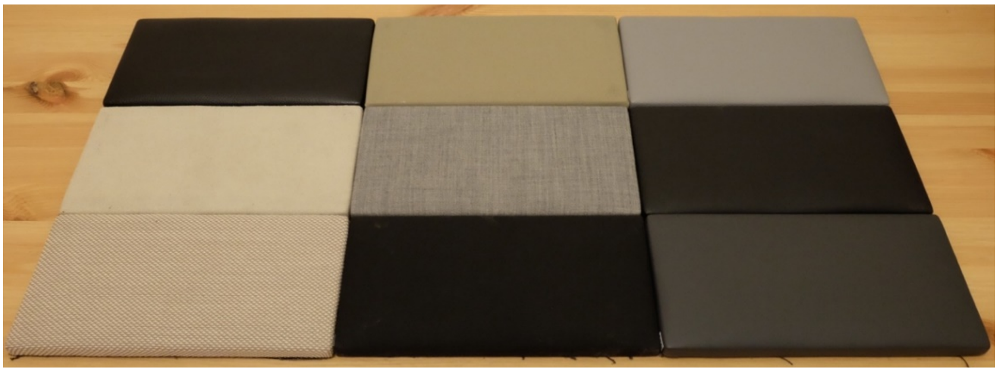

Figure 14: The nine materials used for the triading process

2. *Triading:*

   This involves the random selection of three samples which are then presented to the interviewee. The participant is asked to group together two similar examples and describe why these are different to the third example.

   To give the interviews more context, participants were told that the materials were all currently used for car interiors. Specifically, participants were asked to imagine themselves in a scenario where they were reviewing and selecting different materials for their car. This was important, as their perception and requirements for a car interior could be very different to buying furniture, for example, so this was used to set expectations.

   By going through this triading process, a bi-polar construct is formed and can be used to create a rating scale. This process continues until as many constructs are identified as possible. An example of a typical dialogue between the interviewer and participant is illustrated in Figure 15, which shows the elicitation of the construct "rough" as opposed to "smooth".

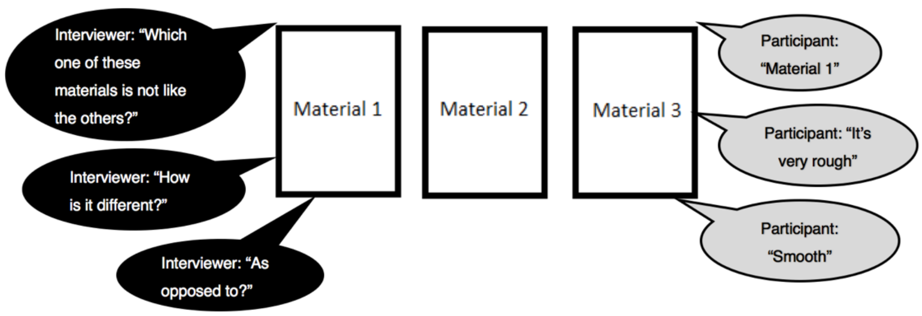

Figure 15: Triading example between interviewer and participant

3. *Rating:*

Once all possible constructs were elicited, participants were asked to rate all 9 materials in the triads using 5-point rating scales, of which their own adjectives were used as the anchor points. For example, in Table 3 the first construct elicited was 'Smooth' as opposed to 'Rough'. Therefore "1" would be assigned to a material if the participant perceived it to be smooth, or "5" if they perceived it to be rough. Participants rated each of the nine materials using their own constructed bipolar scales.

During this stage of the process, it was not necessary to ask participants to construct their scales from positive to negative in terms of their preference, as stage 2: 'Scoring Materials' would pick up on this insight and record preference data.

This process removes ambiguity in the research process, as participants form the constructs and scales and rate the materials themselves. Once the rating process is complete, a matrix is formed which makes up the repertory grid. Table 3 provides an example of a repertory grid from the UK study.

Table 3: Individual repertory grid from UK study

EMERGENT CONSTRUCTS (MATERIAL ATTRIBUTES) 1	Material 191	Material 841	Material 995	Material 384	Material 134	Material 441	Material 195	Material 426	Material 135	**IMPLICIT CONSTRUCT POLES 5**
Smooth	5	2	3	2	2	4	2	1	4	Rough
Cold	3	3	2	2	4	3	2	2	2	Warm
Spongy	2	2	2	5	1	3	4	4	4	Hard
Textured	4	3	4	5	2	2	3	4	2	Untextured
Comfortable	3	3	3	4	3	3	2	3	3	Uncomfortable

In this research, two Repertory Grid experiments were conducted: one in the UK with staff and students at the University of Warwick and one in Hong Kong (HK) with participants from HK Polytechnic University. Overall, 38 interviews were conducted across both experiments, all of which lasted for approximately 45 minutes to an hour per participant.

3.5 *Stage 2: Scoring Materials*

In combination with the ratings obtained from the last stage of the RGT interviews, this research also used the method of Magnitude Estimation (ME) to understand how participants rated their perception of quality and preference. Magnitude estimation is commonly used in sensory profiling and assumes that individuals are able to make numerical estimations regarding the perceived intensity of a stimulus (Skedung et al., 2011).

A review of 13 appropriate methods was conducted in Submission 3 before deciding on the final research methods used. In the past, typical studies concerning perceived comfort and other psychological dimensions tended to use category scales. These are scales that are anchored using verbal and/or numerical labels (e.g. comfortable – slightly comfortable – uncomfortable – very uncomfortable) – similar to the scales formed during the RGT interviews.

Category scales remain to be extremely popular to use because of their simplicity, ease of use, reliability and adaptability. However, as emphasised by Cardello et al. (2003) a key problem with using category scales is that it cannot be assumed that the points on the scale represent equal intervals (i.e. the difference between 'comfortable' and 'slightly comfortable' is not equivalent to the difference between 'slightly comfortable' and 'uncomfortable'). Because of this issue, the scale is an ordinal rather than interval scale. This diminishes the potential for parametric statistical testing and model development, which was necessary for Stage 5 of the process (section 3.8). A summary of the different types of measurement scales is provided in Table 4.

Table 4: The four levels of measurement. Source: Kposowa et al. (2012)

Nominal	The numbers on a nominal scale represent labels or names to identify items, classes or categories. A nominal variable only has two distinctive categories (e.g. true/false, yes/no, agree/disagree).
Ordinal	Ordinal scales can be used to determine the rank order of the concept being measured (e.g. a scale anchored by 'strongly agree' – 'agree' – 'neutral' – 'disagree' – 'strongly

	disagree'). An order of magnitude is apparent, unlike in nominal scales. However, the distance between numbers are not necessarily equal, so we do not know if the difference between 'strongly agree' and 'agree' is equivalent to the distance between 'disagree' and 'strongly disagree'.
Interval	Interval scales possess the features of the scales above (distinctiveness and order of magnitude). In contrast, interval scales have equal intervals or distances between the numbers on a scale (e.g. age is on an interval scale – where the distance/interval between the ages 20 and 21 is equal to the distance between the ages 38 and 39).
Ratio	Ratio scales have the characteristics of distinctiveness, order of magnitude and equal intervals. Additionally, ratio scales have an absolute or natural zero, reflecting the complete absence of the concept being measured. For example, on a scale measuring level of income, a zero rating implies a complete absence of money.

Magnitude Estimation was chosen because instead of providing ordinal data, it provides ratio level data. This means that subjective sensory responses using this technique can be accurately quantified (Cardello et al., 2003). In this research, participants were asked to indicate their perception of quality and preference for the 9 materials used in the RGT interviews (Table 2 and Figure 14), as well as a further 14 similar materials (Table 5 and Figure 16). This was on a 100-point free-modulus magnitude estimation scale (1 indicating low quality/disliking and 100 indicating high quality/liking). Previous studies have used 100-point scales to measure the perception of material luxuriousness (Bahn et al., 2009) and perceived haptic comfort in textiles (Sztandera, 2008).

Table 5: 14 soft automotive interior materials used during the interviews

Material Type	Material Code	Name/Grain	Interlayer
Fabric	531	Aunde 30% Wool	0mm
	291	Treves Orbi 100% Poly	0mm
	461	Technical Grain	0mm
	391	Flax material	0mm
	731	100% Polyester (X761)	0mm
PVC	465	Technical Grain	0mm
	495	Neoprene	0mm
	835	Neoprene	5mm
	305	Taurus	0mm
	665	Cuir Grain	0mm
Leather	529	Windsor	0mm
	927	Taurus	5mm
	326	Taurus	0mm
PU	714	Ultra Tech	0mm

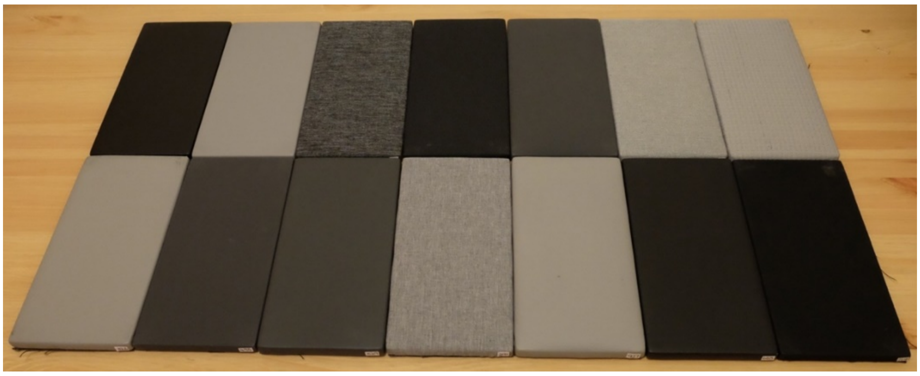

Figure 16: 14 materials used during the interviews

The relationship between 'quality' and 'preference' was explored to objectively determine the relationship between the two concepts. It was hypothesised that there could be some instances where participants may perceive a material to be high quality but they may not necessarily like them and vice versa. This was proven in the Hong Kong study, where it was found that on average, participants rated the flax fabric as being 54% for PQ, which was relatively low. Conversely, the same fabric was rated the most preferred fabric at 66% in the same study. This finding indicated that although participants believed the fabric to be relatively average for quality, they still liked the material. Ultimately, exploring the relationship between

PQ and preference helped to determine whether future sensory material evaluations require investigators to ask participants to indicate both quality and preference for materials or only one over the other.

After checking for outliers and cleaning the data, the average PQ and preference ratings were plotted against each other (Figure 17 shows the results for the UK study). An R^2 of 0.71 was achieved, which indicates a strong positive linear correlation between PQ and preference.

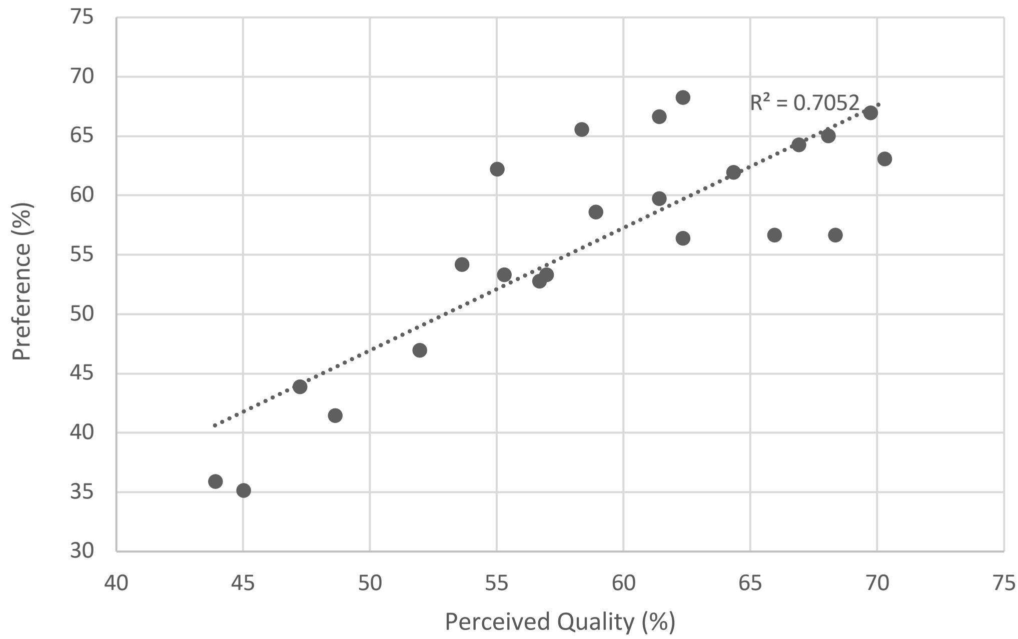

Figure 17: Average PQ and preference relationship for the UK study

This relationship was also investigated in the Hong Kong study (Figure 18). This resulted in an R^2 of 0.75. These strong correlations suggest that participants tend to perceive both terms as being interchangeable. It also suggests that practitioners only need to ask participants to rate their perception of quality, while simultaneously gaining insights about preference and vice versa. The Hong Kong results were therefore able to verify the UK findings.

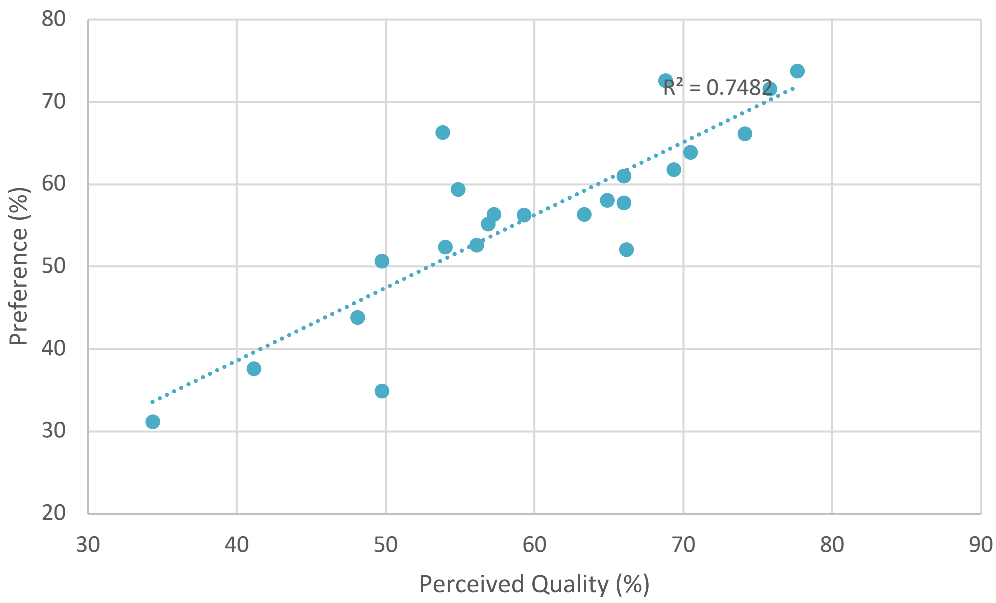

Figure 18: Average PQ and preference relationship for the Hong Kong study

This stage provides material-specific insights to practitioners (e.g. it is able to determine the most popular grain or colour for PVC or leather, or which fabrics score higher than others). These findings provide actionable insights that can be used to explore these materials further, as well as suggesting possible material modifications that could increase PQ (e.g. making a material softer, smoother or more resilient).

3.5.1 The Impact of a Foam Interlayer

As mentioned in section 3.4.1, the materials were wrapped around 200x100mm blocks of MDF. There were 7 pairs of materials within the sample – these were used across the repertory grid interviews and the magnitude estimation scoring and can be referred to in Table 2 and Table 5. Within each pair, there was one material with no foam interlayer and one with a 5mm interlayer.

The comparison of participants' average PQ ratings are shown in Figure 19 for the UK study and Figure 20 for the Hong Kong study. It can be seen that the majority of materials were rated higher for PQ when there was 5mm of foam under the material, excluding PU Ultra Tech in the UK study. Interestingly, PVC neoprene was rated equally in both studies, suggesting that this material is perceived positively regardless. This is presumed to be because the material was very smooth and very soft.

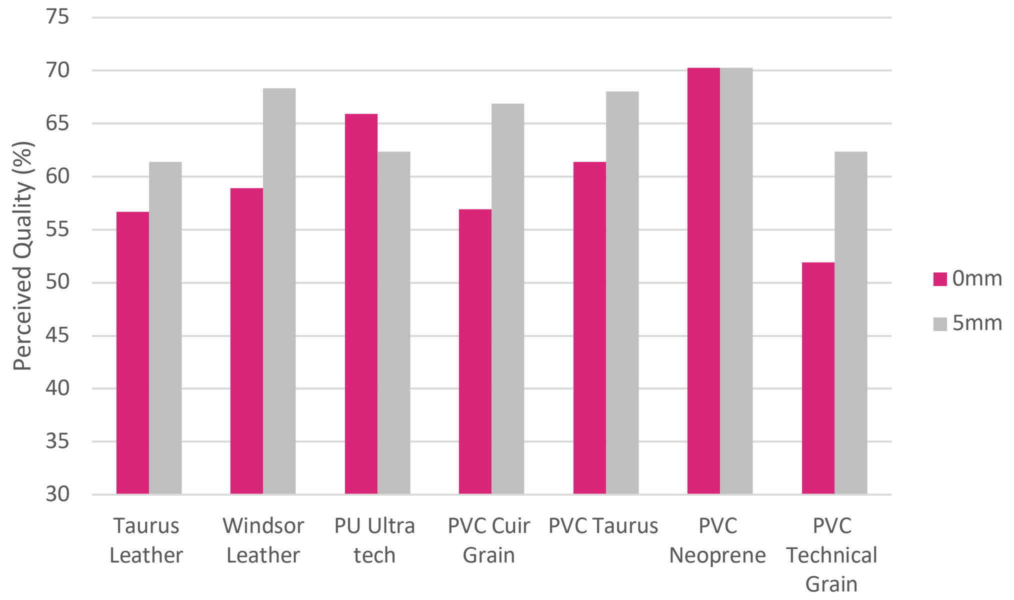

Figure 19: Interlayer comparison for the UK study

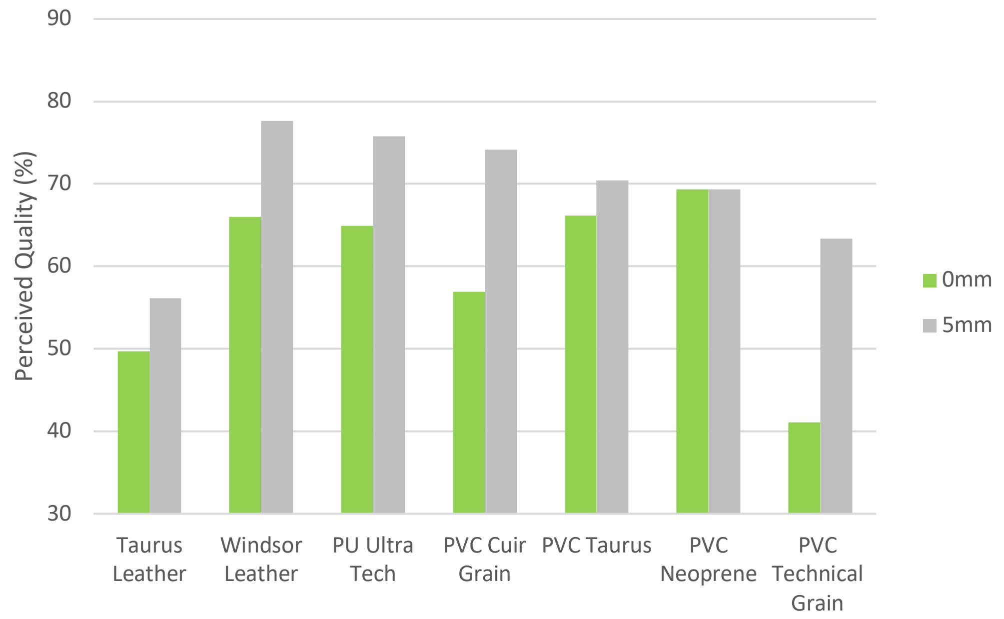

Figure 20: Interlayer comparison for the Hong Kong study

The results were subjected to a two-way ANOVA with replication in Microsoft Excel to determine whether the presence of an interlayer has a statistically significant impact on perception. During an analysis of variance (ANOVA), the p-value is compared with the designated significance level (denoted as α or alpha). Here, the significance level of 0.05 was used, which specifies a 5% chance that an impact on PQ exists when there is no actual difference.

The results from the UK study are shown in Table 6. Since the p-value (material) is 0.016, which is lower than 0.05, we can conclude with 95% confidence that there are significant differences between the material types. Additionally, since the p-value (interlayer) is 0.007, which is lower than 0.05, we can conclude that the presence of an interlayer does have a statistically significant impact on Perceived Quality. Lastly, the p-value (interactions) is 0.339 which exceeds 0.05, meaning that there was no interaction effect. This is a positive finding, which shows that the presence of an interlayer did not make all materials feel a similar level of quality – there were variances in perception depending on the material type (as can be seen in Figure 19 and Figure 20). Therefore, the materials are always distinguishable regardless of whether an interlayer was used or not. Similarly, participants were able to tell which of the two samples had an interlayer and which did not for every material type.

Table 6: Two-way ANOVA output for the UK study interlayer results

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Material	3776.87	6.00	629.48	2.65	**0.02**	2.14
Interlayer	1760.14	1.00	1760.14	7.42	**0.01**	3.88
Interaction	1624.86	6.00	270.81	1.14	0.34	2.14
Within	56493.11	238.00	237.37			
Total	63654.98	251.00				

The two-way ANOVA results for the Hong Kong study also found that the presence of an interlayer had a statistically significant impact on perception. The p-value was effectively zero (3.57E-10), which demonstrates an even stronger finding as to the impact of a foam interlayer. Similar results were found for the preference ratings, which can be referred to in Submission 4a (the UK study) and 4b (the cross-cultural comparison).

Overall, the results suggest that the perception of a lower quality material could potentially be improved just by adjusting the amount of foam beneath a trim material, which could provide beneficial cost-saving implications as cheaper materials could be used. It also identifies the materials by which a foam interlayer has the most effect on. For example, average PQ significantly increased for the PVC technical grain sample with a 5mm interlayer, which was most evident in the Hong Kong study. In contrast, the foam appeared to have relatively little effect in comparison when used in combination with the Taurus leather in both studies.

This finding was useful to JLR and has influenced further work in the company surrounding the impact of a foam interlayer. An internal customer clinic was conducted by the JLR Surface Materials Integration team since this research, which correlated softness and preference ratings within vehicles to reference samples. These reference samples were mounted on boards, which can be referred to when benchmarking vehicles. Using reference samples such as these helps to ensure consistency in ratings recorded by different engineers. The results also provided the team with evidence and data to demonstrate how much of a significant effect on perception can be achieved by making a material feel softer when pushing down on a component.

3.6 *Stage 3: Qualitative and Quantitative Data Analysis*

The analysis process for an RGT study typically involves stage 1 and 3 illustrated in Figure 21. When it is necessary to aggregate data from an RGT study (e.g. when several participants are asked to rate the same stimuli), Generalised Procrustes Analysis is generally applied, which generates a consensus view of all of the data.

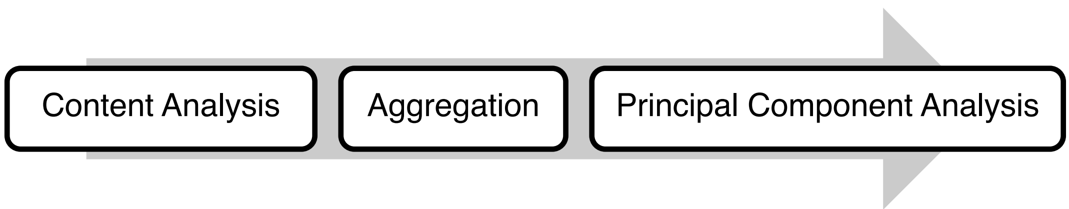

Figure 21: Repertory Grid data analysis stages

3.6.1 *Qualitative Content analysis*

The first stage of data analysis involves pooling all of the constructs and then categorising and grouping them according to their meanings (Jankowicz, 2005).

For example, Table 7 shows that the attribute 'hard' was elicited 21 times, however some other descriptors were also used by participants to describe material hardness/softness, including *'spongy, padded and springy'.* A miscellaneous category is created when there are unclassifiable descriptors, or descriptors that had only been elicited once during the interviews, which are therefore not enough to be classified into their own category (Jankowicz, 2005). The process of content analysis involves:

1. Identifying the categories (material attributes).
2. Allocating the constructs to the categories. During this, each construct was coded based on which interviewee provided the construct and the order in which it was elicited. For example, in Table 7, the construct '1.1' corresponds to the first interviewee and their first construct verbalised; '3.1' corresponds to the third interviewee and their first construct verbalised).
3. The end results are tabulated (Table 7).
4. The frequency under each category was calculated: i.e. which categories have more constructs and which have fewer?

Table 7: Finalised list of material descriptors (constructs) after RGT content analysis

Category	Descriptors	Interviewee Construct No.	Sum	Proportion (%)
		Sensory		
Hard-Soft	A solid feeling when pushing downwards on the material. *Spongy, padded, springy*	1.2, 2.5, 4.1, 5.1, 6.3, 7.4, 8.6, 9.3, 10.1, 11.3, 12.3, 13.2, 14.2, 15.2, 16.2, 17.8, 18.3, 19.3, 20.4, 17.7, 20.6	21	19.44
Rough-Smooth	The perception of unevenness of the material surface when using a lateral movement. *Bumpy, coarse, less smooth*	1.1, 2.3, 3.1, 4.3, 5.2, 6.1, 7.1, 8.2, 9.1, 10.3, 11,2, 13.4, 14.1, 15.3, 16.1, 18.1, 19.1, 20.1	18	16.67

Textured-Untextured	Used similarly to 'rough'	2.1, 4.4, 6.4, 9.4, 10.2, 12.1, 14.3, 17.9, 18.5, 19.6, 20.3	11	10.19
Cold-Warm	The sensation of coldness to the touch when using a static movement.	3.5, 4.5, 5.3, 7.2, 9.2, 14.4, 18.2, 19.2	8	7.41
Leathery-Textile	The feeling of leather-like materials as opposed to fabric, cloth-like materials.	2.2, 7.5, 10.5, 11.4, 12.2, 14.5, 15.1, 16.4	8	7.41
Frictional-Slippery	The resistance felt when touching the material using a lateral movement.	1.4, 8.4, 16.7	3	2.78
Rigid-Flexible	The feeling that the material is not flexible. *Sturdy, stationary*	3.3, 5.4, 17.2	3	2.78
Absorbent-Repellent	The perception that the material could easily soak up liquid. *Porous*	16.5, 17.1	2	1.85
Experiential				
Comfortable-Uncomfortable	The perception of comfort specifically when sitting on the material.	1.5, 2.4, 4.2, 8.3, 9.5, 13.3, 15.5, 18.4, 19.5	9	8.33
Pleasant-to-Touch-Unpleasant	A positive feeling when touching the material.	1.3, 3.4, 15.4	3	2.78
Hard-Wearing-Delicate	The perceived durability of the material.	8.5, 17.4, 19.4	3	2.78
Natural-Artificial	The perception of being an 'environmentally friendly' material.	3.2, 7.6, 20.4	3	2.78
Expensive-Cheap	The perception of being a 'luxurious' material.	6.2, 8.1, 13.1	3	2.78

	Well made			
Miscellaneous				
Plastic – Un-uniform Visible weave – No visible weave 2 dimensional surface – 3 dimensional surface Shiny – Matte Hairy – Not hairy Utilitarian – Decorative Rubbery/silky - leathery Sticky – Non-sticky Easy to clean – Hard to clean		8.7, 17.5, 17.3, 17.10, 7.3, 20.5, 15.6, 2.6, 10.4, 11.1, 16.6, 17.6, 16.3	13	12.04
Total			**108**	100

It is generally best practice to conduct a reliability check on the content analysis. To do this, an independent collaborator repeats the categorisation process, where the elicited constructs are categorised into their own groups, after which the results between the two are compared (Jankowicz, 2005). In this research, a reliability check was conducted which resulted in a good consensus, however this process was repeated until 100% agreement between the research engineer (RE) and collaborator was achieved – the results can be referred to in Submission 4a and 4b.

3.6.2 Aggregation and Principal Component Analysis

The next stage of analysis involves aggregating the data to analyse all grids collectively. It should be noted that aggregation of Repertory Grids should be performed with care as the technique was initially developed for individual use. The software Idiogrid (Grice, 2002) was used in this research. All 20 grids were inputted into the software in order to perform a Generalised Procrustes Analysis (GPA).

GPA is a multivariate technique often used to analyse multiple grids. It is particularly suited for analysing multiple Repertory Grids because it is able to plot individual level data (Rowe et al., 2005), providing that either the elements or constructs are constant among all participants. In this case, the elements (materials) were the same for all interviews. The same analysis approach has been demonstrated by Mak et al. (2013), who conducted an RGT study on evaluating food consumption amongst tourists in Hong Kong, and used GPA to analyse 29 grids. GPA is also recommended when analysing results from descriptive sensory analysis experiments (Gacula Jr, 2008).

Figure 22 illustrates the steps typically taken to perform a GPA on RGT results. The aim of GPA is to take the 20 individual grids from the interviews to generate a 'consensus view' of all of the data. This involves a process of rotating and scaling the data until a position of maximal agreement across all grids is achieved. The results are then averaged and one grid is created from the 20 individual grids – this is called the 'consensus grid'.

The next step is to reduce the dimensionality of the GPA consensus grid. The goal of dimensionality reduction is to reduce the number of random variables under consideration while still maintaining as much information (variance) as possible. In turn, this is able to help with classification, visualisation and compression of high-dimensionality data (van der Maaten et al., 2009).

A Principal Component Analysis (PCA) was used for dimensionality reduction. This is a multivariate statistical procedure used to extract weighted composites of variables that account for the maximum amount of variance underlying a dataset (Fransella et al., 2004). Running a PCA reduces the data into fewer dimensions (known as '*principal components*'). It is also possible to identify how much information is lost when reducing the data. In RGT, a PCA is able to take the material attributes identified during the interviews and rank them according to their influence on overall perception. This then narrows down the attributes while still retaining the most important variance.

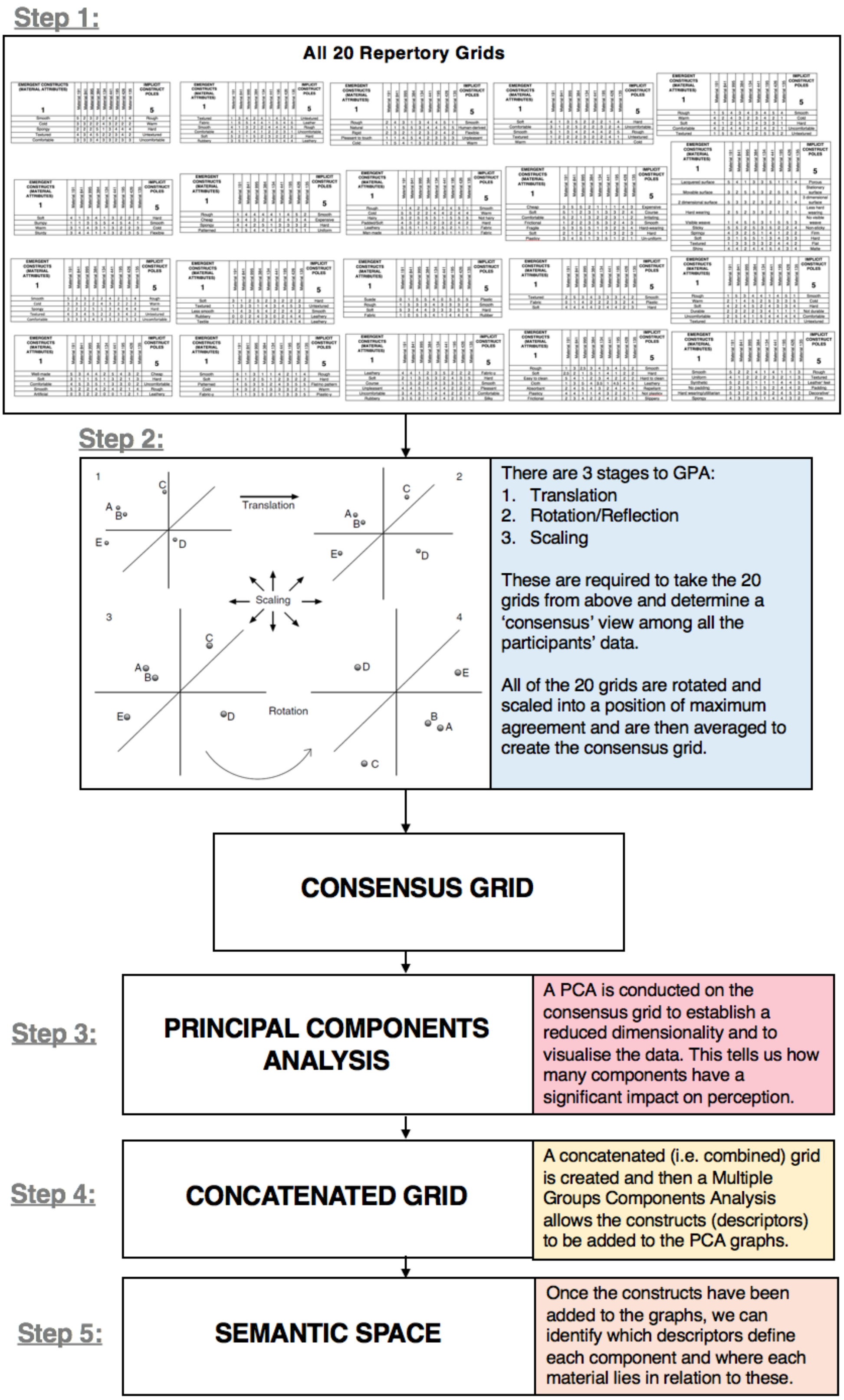

Figure 22: GPA steps. Image source in step 2: Lawless (2013)

A PCA can be conducted on the consensus grid using Idiogrid, which generates the output presented in Table 8. The eigenvalues show that 4 components are able to explain 90% of overall perception. This is determined by assessing which of the values are the largest before experiencing a sharp drop in numbers. For example, in the table below, component 4 has an eigenvalue of 1.15, while component 5 has an eigenvalue of 0.43. This is the first sharp drop in values, which means that component 5 represents a relatively insignificant component. A rule of thumb that helps to determine the number of components to retain is '*Kaiser's Criterion*', which suggests retaining components with eigenvalues above 1 (Yong and Pearce, 2013).

Table 8: Idiogrid PCA output

Component	Eigenvalue	% Variance	Cumulative %	Scree
1	2.24	27.98	27.98	*******
2	2.04	25.53	53.51	******
3	1.8	22.53	76.04	******
4	1.15	14.36	90.4	****
5	0.43	5.34	95.74	**

The rotating and scaling of the data means that the components lose their physical meaning. So, after identifying that 4 components are significant, the next step is to define what each of these components mean (i.e. which of the material attributes identified during the interviews belong to each of the 4 components?). This is achieved by creating a concatenated (i.e. combined) grid, which can be referred to in the Appendix of Submission 4a. The PCA results for the UK study for the first two components are shown in Figure 23. It can be seen that Component 1 which explained 27.98% of the variance was defined by the constructs 'smooth' as opposed to 'rough'. Component 2 explained 25.53% of the variance and was defined by the constructs 'hard' as opposed to 'soft'. Collectively, the graph shows that these attributes contribute to 53.51% (just over half) of overall perception.

The PCA semantic space positions each material relative to their ratings for the two components. It can be seen in Figure 23 that the Windsor leather was perceived as being the smoothest material, while the steel cut 30% wool was the roughest. The thermoplastic olefin (TPO) sample was perceived as the hardest material and the PU sample the softest.

This process of overlaying the material attributes onto the PCA semantic space was repeated until all 4 principal components were defined. This revealed that component 3 was defined by the attribute "warm" as opposed to "cold", which contributed to 22.53% of overall perception. Lastly, component 4 was defined by the attribute "natural" as opposed to "synthetic", which explained 14.36% of overall perception.

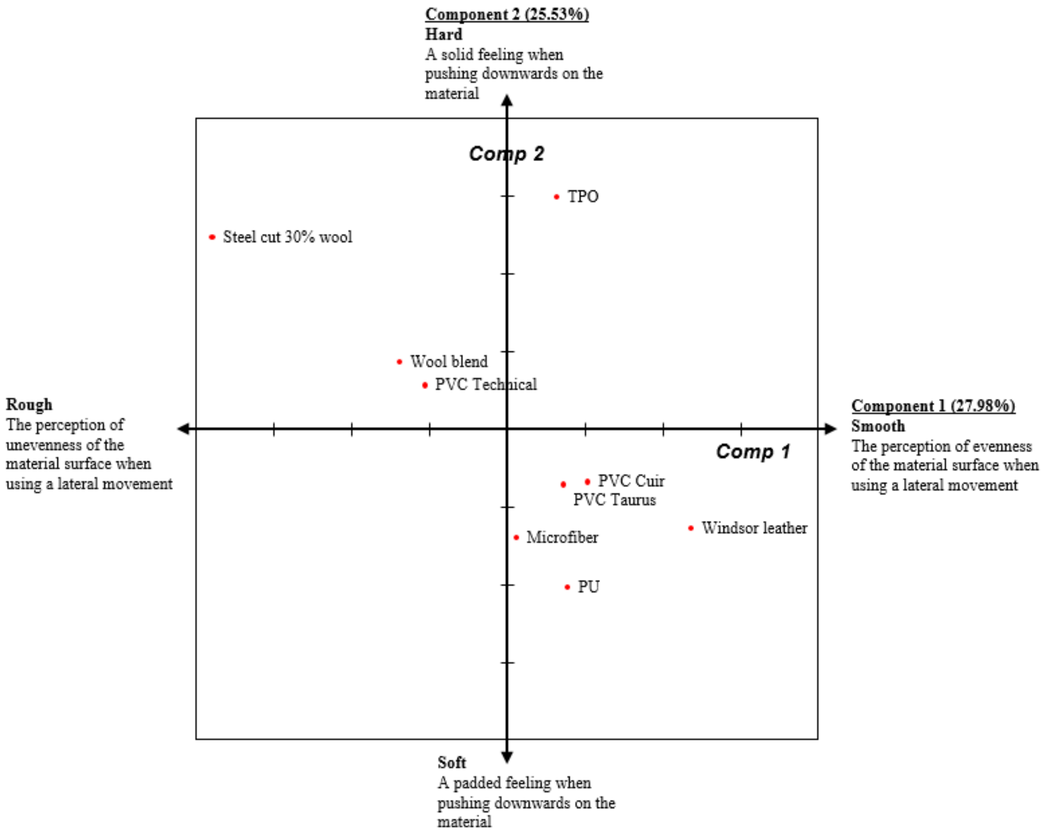

Figure 23: PCA semantic space for components 1 and 2 from the UK study

Plotting 2D PCA semantic spaces is useful for defining each component. However, as it is not possible to visualise more than 3 components on one semantic space, the results can also be plotted onto a radar diagram. This allows us to visualise all of the components in combination. A diagram such as this could be used to assess how materials compare based on these 4 significant attributes.

Figure 24 illustrates the radar diagrams from both the UK and Hong Kong studies. It was easier to interpret the diagrams when the materials were split into two groups: fabrics in one group and leather, PVC, PU and TPO in the other.

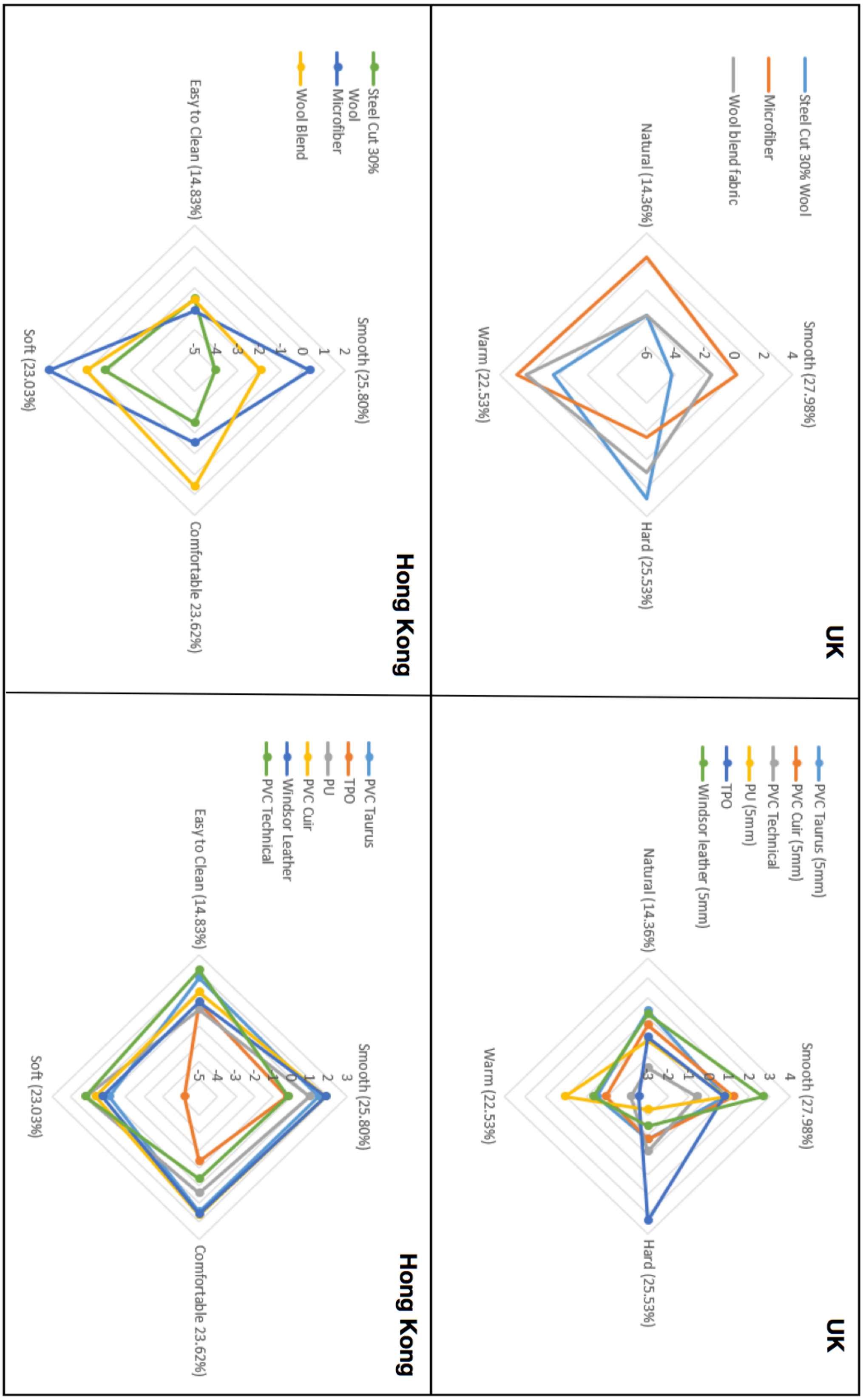

Figure 24: PCA radar diagrams for the UK and Hong Kong studies

The radar diagram for the fabric samples in the UK study (top left of Figure 24) show that the steel cut 30% wool and the microfiber appear to be extreme opposites of each other. These results can be assessed in conjunction with the PQ ratings to identify which of these materials were perceived as the highest/lowest quality. As explained in section 3.5, participants were also asked to indicate their perception of quality and liking on 100-point scales (0 indicating very low quality/disliking and 100 indicating very high quality/liking). The results are presented and summarised in section 3.6.3. However, to demonstrate how the PQ ratings can be used in conjunction with the radar diagram, the average PQ results for the 9 materials explored during the Repertory Grid interviews are presented in Table 9.

Table 9: Average PQ ratings for the nine materials used in the RGT interviews

Material	Average PQ rating
Steel cut 30% wool	48.61
Microfiber	58.33
Wool blend	47.22
PVC Taurus (5mm)	68.06
PVC Cuir (5mm)	66.88
PVC Technical (5mm)	62.35
PU (5mm)	62.35
TPO	43.89
Windsor leather (5mm)	68.33

The results show that participants tended to favour materials that were perceptually smoother, warmer, softer and more natural. For example, the fabric that was perceived the highest quality was the microfiber and out of the PVC and leather samples, the Windsor leather came out as highest quality. The radar diagram can be used to visually assess how materials rated positively or negatively sit in relation to each of the 4 significant attributes.

The radar diagram on the top right of Figure 24 plots the PVC, leather, PU and TPO samples in relation to the 4 significant attributes. Interestingly, the materials rated the highest and lowest quality (Windsor leather and TPO) appear to be extreme opposites. This reaffirms the assumption that materials that are perceptually smoother, softer, warmer and more natural are perceived more positively. The diagrams from the Hong Kong study are also included for reference.

3.6.3 Magnitude Estimation (ME) Analysis

The ME ratings were percentage scores attributed to each material from all participants (for example, a participant may have rated the PVC neoprene as being 70% on a scale of 0-100% - the higher the score, the higher quality the participant perceived the material to be). The results were collated for all participants and the descriptive statistics were assessed and used to summarise the data.

As well as the mean, which was used to understand the ranking of the materials explored in this research, the other key pieces of information taken from the descriptive statistics were the standard error of the mean (SE mean) and the standard deviation (StDev). Standard deviation values are able to provide an insight about how all participants collectively rated the materials (i.e. whether they were in agreement or not). Standard error of the mean tells us how much certainty there is that the calculated mean from these responses is similar compared to if a larger population was asked.

Table 10 presents the descriptive statistics for the PQ ratings of all materials investigated in the UK study. The material that yielded the lowest SE mean was the PU Ultra Tech (0mm), which also received the lowest standard deviation value. The smaller the SE mean value, the more precise an estimation this is of the population mean. For standard deviation, the lower the value, the smaller the spread in the data. This means that participants rated this material most similarly than any other material sample.

Conversely, Fabric X761 (100% Poly) received the highest standard deviation and SE mean values, meaning that participants were less in agreement in their ratings for this material. TPO received the lowest mean rating and PVC Neoprene (0mm) received the highest. This last finding was somewhat expected. It was unsurprising that the TPO obtained the lowest mean rating, as it was a very hard, rigid and plastic material. PVC neoprene had a very similar feel to the Windsor leather (which was technically the highest quality material of all the samples). However, what is most surprising is that a material with no interlayer achieved the highest mean score for PQ. Although this score is almost identical to PVC neoprene with a 5mm interlayer (70.31% compared to 69.71%), it does suggest that perhaps this material does not necessarily need the interlayer to improve perception. This contributes to more of an informed decision as to when and where interlayer could be used for a vehicle interior.

Table 10: Descriptive statistics for PQ ratings of all materials in the UK study

Material	N	Mean	SE Mean	StDev	Min	Q1	Median	Q3
Steel cut 30% wool fabric	18	49	5.7	24.2	10	20	60	70
Microfiber/suede cloth	18	58	4.9	20.9	15	40	70	71
Treves Orbi Wool Blend	18	47	4.3	18.1	10	30	50	60
Fabric X761	18	45	6.0	25.3	5	20	50	66
Flax fabric	18	64	3.4	13.4	40	53	63	74
Technical Grain Fabric	18	55	5.3	22.6	10	39	60	70
Treves Orbi 100% Poly	18	55	4.6	19.4	20	40	60	71
Aunde 30% Wool Fabric	18	54	5.1	21.5	10	40	58	71
PVC Taurus (0mm)	18	61	4.4	18.9	30	44	68	80
PVC Taurus (5mm)	18	68	3.3	14.2	40	60	70	80
PU Ultra tech (0mm)	18	66	2.2	8.8	50	60	63	70
PU Ultra tech (5mm)	18	62	2.8	11.3	40	50	60	70
PVC Cuir Grain (0mm)	18	57	3.6	15.3	30	48	60	70
PVC Cuir Grain (5mm)	18	67	2.8	11.1	40	60	70	75
Windsor Leather (0mm)	18	59	3.8	16.1	30	50	60	70
Windsor Leather (5mm)	18	68	2.9	12.3	50	58	70	80
PVC Technical Grain (0mm)	18	52	5.5	23.4	10	28	60	70
PVC Technical Grain (5mm)	18	62	3.5	14.5	40	50	60	73

PVC Neoprene (0mm)	18	70	3.1	12.5	50	60	73	80
PVC Neoprene (5mm)	18	70	3.3	13.5	45	60	70	83
Taurus Leather (0mm)	18	57	4.3	18.2	20	40	60	70
Taurus Leather (5mm)	18	61	5.0	21.1	20	48	68	80
Thermoplastic olefin (0mm)	18	44	4.4	18.8	5	29	50	60

The average PQ results can be visualised in the form of a bar graph (Figure 25 and Figure 26), which makes it easier to see how each material ranks compared to others.

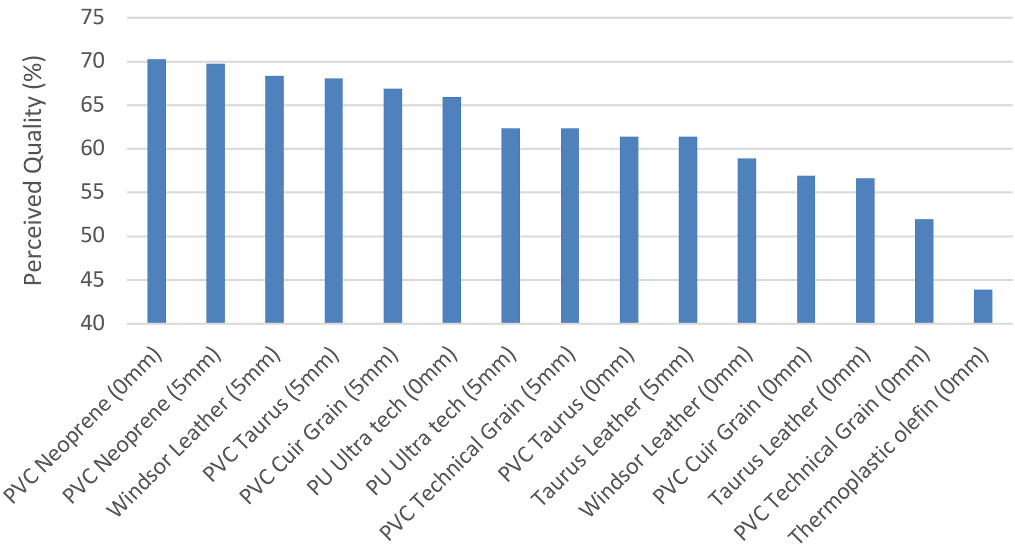

Figure 25: Average PQ ratings for PVC, leather, PU and TPO (UK study)

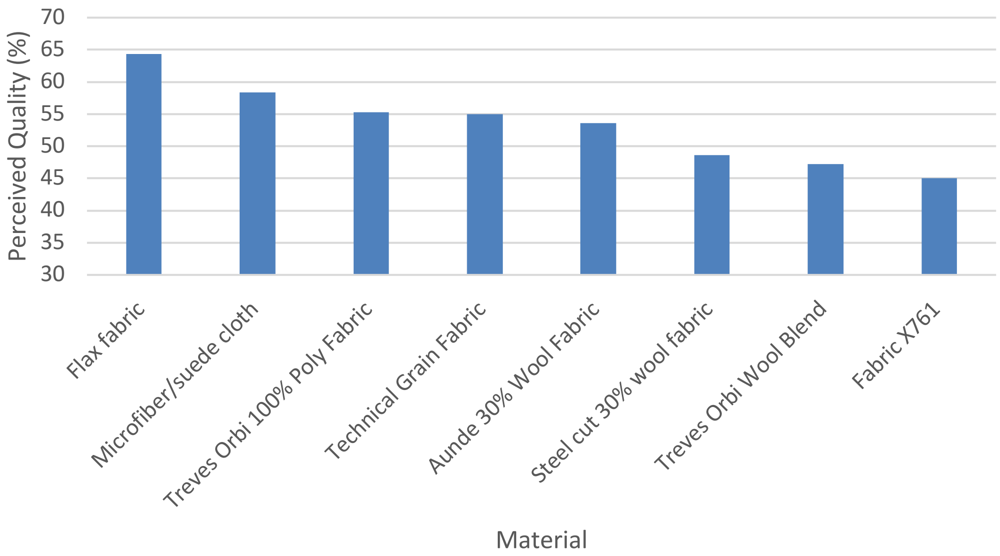

Figure 26: Average PQ ratings for fabrics (UK study)

A one-way ANOVA was conducted to determine whether the differences between the means for each material were statistically significant. This is determined by assessing the p-value against the designated significance level of 0.05.

As the p-value equals 0.000, we can conclude that there are statistically significant differences between these materials.

Table 11: One-way ANOVA output for PVC, leather, PU and TPO

Source	*DF*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*
Material Name	14	13257	946.9	3.87	0.000
Error	255	62471	245.0		
Total	269	75728			

A one-way ANOVA cannot identify exactly which materials are different, so a post hoc test is typically conducted to confirm where the differences occurred. A post-hoc Tukey test was conducted - the results of which are shown in Table 12. This test runs a comparison between every possible pair of materials. It can be seen that the PVC neoprene 0mm and 5mm samples, as well as the TPO are all statistically different from one another. The remaining samples all share a grouping letter, which means that we cannot confidently conclude that there are statistical differences between each of the materials. This means that the percentage differences between the materials that share a letter are not enough to categorically say that one has performed differently than the other.

Table 12: Grouping information using the Tukey method with 95% confidence

Material	***N***	***Mean***	***Grouping***		
PVC Neoprene (0mm)	18	70.28	A		
PVC Neoprene (5mm)	18	69.72	A		
Windsor Leather (5mm)	18	68.33	A	B	
PVC Taurus (5mm)	18	68.06	A	B	
PVC Cuir Grain (5mm)	18	66.89	A	B	
PU Ultra tech (0mm)	18	65.94	A	B	
PVC Technical Grain (5mm)	18	62.33	A	B	
PU Ultra tech (5mm)	18	62.33	A	B	
Taurus Leather (5mm)	18	61.39	A	B	C
PVC Taurus (0mm)	18	61.39	A	B	C
Windsor Leather (0mm)	18	58.89	A	B	C
PVC Cuir Grain (0mm	18	56.94	A	B	C
Taurus Leather (0mm)	18	56.67	A	B	C
PVC Technical Grain (0mm)	18	51.94		B	C
Thermoplastic olefin (0mm)	18	43.89			C

A one-way ANOVA was also conducted for the fabric samples, of which no differences were found between the materials. This suggests that none of the fabrics came out as being very high or low quality, presumably because of the similarity in samples and the low number of fabrics explored in this research.

3.7 Stage 4: Physical Materials Testing

Typically, during a sensory evaluation task, it is not uncommon for users to elicit attributes that are able to be physically or mechanically measured. Previous studies have found a correlation between sensory perception and objective material measurements. For example, Wongsriruksa et al. (2012) found a strong positive correlation between perceptual ratings of roughness, hardness and coldness with their measured values for surface roughness, elastic modulus and thermal effusivity. The materials explored were woods, polymers and metals. Similarly, Skedung et al. (2011) found a correlation between roughness and finger friction to perceived coarseness of different types of printing paper. Ramalho et al. (2013) also found a correlation between the perception of smoothness and slipperiness to friction measurements of five different fabrics.

In the automotive industry, it is valuable to establish links between subjective perceptions and their technical measures, as these can then be communicated to suppliers as part of their proposal and specifications requests (Blumenthal and Herbeth, 2014). In this research, surface roughness and material stiffness (hardness) measurements were conducted. These attributes were taken forward because they were found to be the two consistent material attributes which had a statistically significant impact on perception across both studies in the UK and Hong Kong.

3.7.1 Roughness Testing

An undergraduate university project was set up with a student from the School of Engineering at the University of Warwick, as part of his third year project. This project involved conducting the physical roughness and hardness (stiffness) testing - the results of which are summarised in this section but for further detail, refer to Submission 4c.

Roughness was initially measured using an optical profiler (e.g. in Figure 27). This is a non-contact method that uses vertical scanning interferometry, which reflects a light off a surface to measure the height profile of a surface up to 10mm (Thompson, 2016).

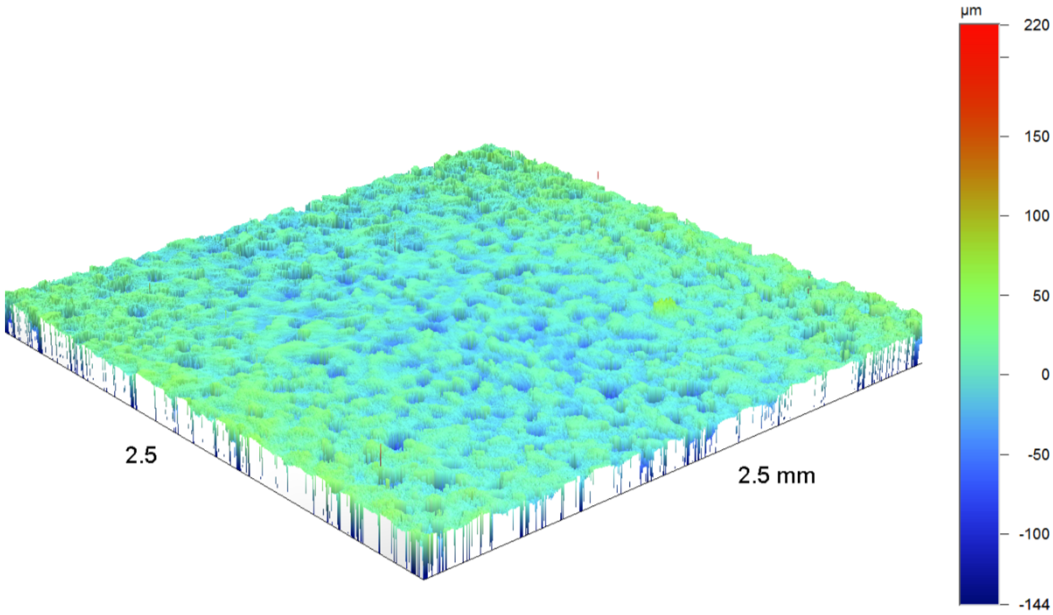

Figure 27: 3D image of PVC neoprene sample

Optical profilers work well for smooth, reflective surfaces. However, many of the materials used in this research were fabrics, which are inherently non-reflective and had too steep angles for light to reflect off of. All of the materials were therefore arranged to be re-tested at the University of Leeds in their textiles department.

Materials were tested using the Kawabata Evaluation System for Fabrics (KES-F). This was developed in Japan by the Hand Evaluation and Standardisation Committee. The KES-F system is comprised of 4 instruments (KES-FB1-4) and is able to objectively measure fabric extension, shear, bending, compression, surface friction and roughness. For the purposes of this research, only surface roughness was recorded and correlated with the subjective perceptual ratings for roughness previously collected.

The testing results are shown in Table 13, where 'warp' refers to testing to samples lengthways and 'weft' refers to testing the materials sideways.

Table 13: Surface roughness results from the KES-FB4 system

Material	WARP			WEFT			Average		
	MIU	MMD	SMD	MIU	MMD	SMD	MIU	MMD	SMD
Windsor Leather	0.16	0.01	2.00	0.16	0.01	1.80	0.16	0.01	1.90
Taurus Leather	0.20	0.01	3.26	0.20	0.01	3.44	0.20	0.01	3.35

PU Ultra Tech	0.24	0.01	5.18	0.24	0.01	2.88	0.24	0.01	4.03
PVC Cuir	0.27	0.01	3.68	0.32	0.01	4.42	0.29	0.01	4.05
PVC Technical	0.26	0.02	5.32	0.27	0.02	8.47	0.27	0.02	6.89
PVC Taurus	0.27	0.01	3.20	0.28	0.01	6.89	0.27	0.01	5.04
Treves Orbi 100% Poly	0.34	0.04	3.70	0.29	0.09	10.06	0.32	0.07	6.88
Treves Orbi Wool Blend	0.22	0.07	3.26	0.24	0.06	3.30	0.23	0.06	3.28
Technical Fabric	0.24	0.06	8.20	0.32	0.06	5.81	0.28	0.06	7.01
Aunde 30% Wool	0.32	0.03	3.51	0.27	0.05	3.76	0.30	0.04	3.63
Steel Cut 30% Wool	0.17	0.02	11.64	0.29	0.04	20.00	0.23	0.03	15.82
Flax	0.30	0.03	3.45	0.24	0.01	2.15	0.27	0.02	2.80
X761 - 100% Poly	0.23	0.07	10.38	0.29	0.07	15.86	0.26	0.07	13.12
Microfibre	0.43	0.01	2.14	0.45	0.01	8.11	0.44	0.01	5.12

Average mean deviation of surface roughness (μm) was plotted against the average perceptual roughness ratings (Figure 28). It can be seen that an R^2 of 0.86 was achieved, indicating a strong correlation between the perceptual and objective data. This means that participants were able to discern the differences in roughness for the materials explored.

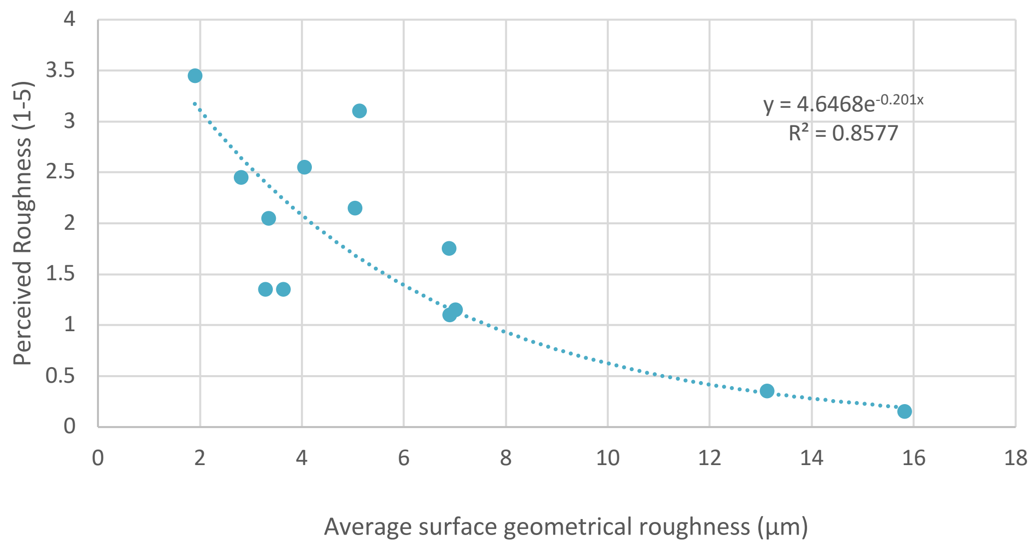

Figure 28: Comparing the relationship between subjective and objective roughness measurements

The smoothest material of all the samples was the Windsor leather (which was also technically the highest quality material rated by JLR). This was perceived as being the third highest quality material at 68% (reported in Submission 4a). The roughest material was the Steel Cut 30% Wool, which in the UK perceptual study yielded an average PQ rating of 41% - the second lowest quality material as perceived by participants.

Overall, when compared with the PQ estimation results from stage 2 (section 3.5), the results suggest that in general, the smoother the material, the higher the PQ. The results can also be used to identify optimum roughness ranges for each material type (i.e. PVC, leather and fabric). For the fabrics included in this research, the results indicate a more positive perception for materials with a roughness value of around 2.798 μm (i.e. the flax fabric), while fabrics with a roughness value of over 13.120 μm (X761 – 100% Poly) to 15.818 μm (Steel cut 30% wool) receive a very negative perception of quality and preference.

For PVC and leather, the results indicate a positive perception for materials with a roughness value of around 1.900 μm (Windsor leather), while materials with a roughness value of over 6.890 μm (PVC Technical grain) receive more of a negative perception. This demonstrates how physical material properties can be used as useful indicators for PQ, as these can be referred back to along with the PQ scores. If a PQ department is unable to conduct another customer clinic due to time or resource constraints, the physical measurements can be conducted in-house which can then be used to estimate how customers may respond to a particular material.

3.7.2 Stiffness (hardness) Testing

Material hardness was also measured and correlated to subjective hardness. The stiffness of a material is the dominant factor for softer materials (Wongsriruksa et al., 2012), as opposed to the Young's Modulus for hard materials (Tiest and Kappers, 2009). Stiffness (*k)* is defined as the ratio between an applied force (F) and displacement (i.e. the force needed for a certain deformation of the material) (Tiest and Kappers, 2006):

$$k = \frac{\Delta F}{\Delta\, l}$$

Force-displacement measurements were tested using a Hounsfield H1Ks Benchtop Test Machine (Figure 29). The equipment configuration was comprised of a flattened bolt with a contact area of approximately 100mm^2. This was used as the contact probe and was attached directly into the load cell, which had a rated capacity of 5N. This load cell was selected since it was the most accurate reflection of the range of force typically exerted by a human finger, which previous literature has identified this as being between 0.2 and 4N (Tiest and Kappers, 2006, Thompson, 2016).

Figure 29: PVC Cuir grain (5mm) sample under a compressive load using the Hounsfield H1kS Benchtop Test Machine configuration. Source: Thompson (2016)

Three tests were performed on each sample (run 1, 2 and 3), which were conducted within the range of 0.1-5N with an accuracy of ±0.5%. The 5N load cell has a force measuring resolution of 0.02μN, while the displacement measurement equipment had a resolution of 1μm and an accuracy of ±0.05% of full scale.

A single displacement value was needed to compare the objective data with the subjective data. When considering the way in which an individual interacts with a material to determine its hardness (for example, in the perceptual studies reported in Submissions 4a and 4b), a decision was typically made between pushing down on a material and before reaching the base of the sample. As such, the values at 50% displacement were chosen to be compared with the subjective data to reflect participants' confirmed judgement of hardness or softness. This is because participants would likely have come to a decision as to how hard or soft the material was at this point.

The gradient was obtained using a central difference scheme:

$$k_i = \frac{F_{i+1} - F_{i-1}}{l_{i+1} - l_{i-1}}$$

It was then smoothed using a moving average to determine a single displacement value:

$$\overline{k_i} = \frac{1}{n}\sum_{i-\frac{n}{2}}^{i+\frac{n}{2}} k_i$$

Table 14 presents the single values at 50% displacement which can then be used to assess the correlation between perceived and physical hardness. The average PQ ratings are also presented in the table to ascertain whether the harder or softer materials yielded the highest or lowest estimated PQ.

Table 14: Stiffness results at 50% displacement

Material	***k* 50% Displacement**	**PQ (%)**
Aunde 30% Wool	1.35	54
Fabric X761	1.59	45
Flax	1.12	64
Microfibre	0.87	58
PU 0mm	5.77	62
PU 5mm	0.95	66
PVC Cuir Grain 0mm	7.27	57
PVC Cuir Grain 5mm	1.29	67
PVC Neoprene 0mm	7.19	70
PVC Neoprene 5mm	1.08	70
PVC Taurus 0mm	6.14	61
PVC Taurus 5mm	1.02	68
PVC Technical Grain 0mm	7.13	52
PVC Technical Grain 5mm	1.21	62
Steel Cut 30% Wool	1.10	49
Taurus Leather 0mm	8.03	57
Taurus Leather 5mm	1.43	61
Technical Grain Fabric	1.34	55
TPO	0.97	44
Treves Orbi 100% Poly	1.18	55
Treves Orbi Wool Blend	1.18	47

Windsor Leather 0mm	6.91	59
Windsor Leather 5mm	1.44	68

The results were plotted on a graph with the subjective data. Figure 30 below plots all of the material samples. An R^2 of 0.81 was obtained, indicating a relatively strong correlation. The green points on the graph indicate materials that had a 5mm foam interlayer and the red points indicate materials with no interlayer. The purple points indicate the fabric samples – these are grouped near the 5mm samples, presumably because these felt more padded than the 0mm samples, as the fabric swatches were already backed with a thin layer of foam. It is therefore clear that there are two groupings either side of the trend line, which can be attributed to the amount of interlayer used for the samples.

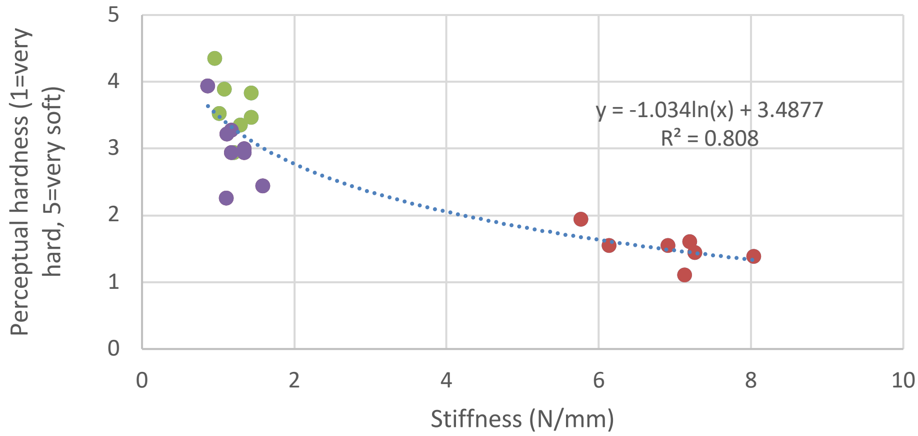

Figure 30: Correlation between subjective and physical hardness (green points indicate materials with a 5mm interlayer, purple dots indicate fabrics with 3mm interlayer and red dots indicate materials with no interlayer).

Overall, when referring back to the average PQ estimations from stage 2 of the process (section 3.5 and Submission 4a) the results show that softer materials (i.e. those with a 5mm foam interlayer) were perceived much more positively than those with no interlayer. However, there were two groupings of the materials either end of the trend line in Figure 30, which indicates that participants were only able to distinguish whether there was or was not an interlayer present, rather than differences in hardness and softness for each specific material. These findings indicate that it may be more effective to focus resources on other areas of improvement (e.g. making a material smoother), as it is known that participants are able to distinguish between these features more. Instead, interlayer can be used to make a material feel softer.

3.8 Stage 5: Model Development - Predicting Perceived Quality

The final stage of the proposed PQ process involved developing a statistical model that is able to predict future PQ values without always needing to conduct the initial consumer interview (as per stage 1). The capability of predicting PQ is valuable in the automotive industry, where time and resource constraints may limit the opportunity to conduct sufficient customer clinics exclusive to PQ. This has led industrial practice to shift towards the use of more rapid techniques, which are able to gather results faster with less resource.

A statistical model can be referred to as a theoretical representation of the real world. They are often used to understand and/or evaluate the performance of an observation or a relationship between a number of known variables (Frees, 1996). The purpose of a model is to use some predictors (known as X variables: X_1, X_2, …, X_k) and estimate a response (known as the Y variable). This association between the X and Y variables mean that a change in the response variable will occur because of a change in the predictor variable(s). At the same time, a model of this association will make it possible to predict a Y variable value if the X variable value is known (Pardoe, 2012).

In this research, the aim of the model was to predict a PQ score based on surface roughness and hardness data, which were the two attributes found to have the largest impact on PQ. Additionally, materials were categorised into 3 groups: fabric, leather and poly (PVC and PU). Therefore, the response variable was the PQ values attributed to each material during stage 2 (scoring materials), where participants were asked to indicate their perception of quality and preference on a 100-point scale (0 indicating very low quality and 100 indicating very high quality).

The research obtained both subjective and technical roughness and hardness data – both of which could act as predictors in the model. Submission 4d therefore investigated which type of predictor should be used (Figure 31) and also which type of model worked best.

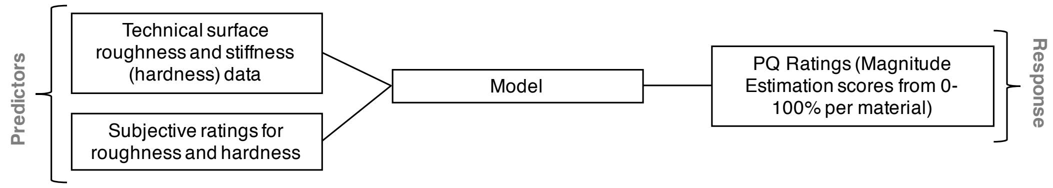

Figure 31: Modelling process

Regression modelling was found to be a common way of predicting textile comfort. For example, Sztandera (2008) used regression analysis to predict tactile fabric comfort using mechanical properties as the independent variable and perceptual comfort scores (ranging from –100 to 100) as the dependent variable. They also asked participants to subjectively rate their perception of 17 properties, including material thickness, grittiness and fuzziness. Models were developed using both mechanical data and subjective data. Despite achieving moderately accurate models, the authors suggest using an Artificial Neural Network (ANN) instead, due to its ability to capture more complex relationships.

The comparison between regression models and ANNs was found to be relatively popular. Kumar and Dhinakaran (2015) note that ANNs are a widely used and effective way of predicting how individuals perceive the sensory comfort of clothing. It was emphasised that when compared with alternative statistical modelling techniques (e.g. regression modelling), neural networking offers a faster and more flexible predictive approach for textile comfort perception. This explains why the performance of linear regression models are often compared with artificial neural networks (e.g. Ansari and Riasi (2016), Kolich et al. (2004)), as it is not uncommon for the estimation errors to be lower for ANN's than linear regression models. Therefore, ANNs are often regarded as a more effective approach to predicting customer perception and/or behaviour compared with regression modelling (Ansari and Riasi, 2016).

3.8.1 Modelling Process

The work within Submission 4d was conducted in collaboration with a data scientist, who has extensive experience in model development and scientific programming environments. The RE lead this collaboration by providing the specifications for the model development, such as the type of models, the inputs needed and the methods used for evaluating model performance.

Three modelling techniques were used to determine the most appropriate model for predicting PQ: Generalised Linear Modelling (GLM), Nonlinear Regression Modelling and Artificial Neural Networks (ANNs). Two models were developed using each approach: one using just the subjective roughness and hardness data from stage 2 (Submission 4a) and one using the technical, objective data from stage 4 (Submission 4c).

These three techniques were selected and developed in that order because it is generally regarded as good practice to try linear regression first, as linear models are easier to use, develop and interpret. If it is not possible to achieve a good fit with linear regression, then a nonlinear model may be more effective (Kposowa et al., 2012). In reality, the relationship between the materials and PQ was nonlinear, so the linear model would have oversimplified the relationship between the predictors and the response. For example, if a material is rough, making it twice as smooth may cause a large increase in PQ. However, if a material is already very smooth, making it even smoother may have little effect on PQ. A linear model would not capture this: a given change in roughness will always result in the same change in PQ estimate, regardless of how rough it is.

A nonlinear regression model was therefore developed as a comparison - this technique is much more complex as there are effectively an infinite number of possibilities as to what the model function could be. A 19-parameter nonlinear model was presented in Submission 4d, which obtained improved results (discussed in section 3.8.4 of this report) when compared to the GLM. However, it was determined that this model was too complicated to offer any additional benefit compared to a neural network.

Lastly, an ANN was developed. This is a nonlinear regression technique formed using an arrangement of mathematical ‘neurons’ inspired by natural neurons in the human brain. Typically, neurons receive signals through synapses - once the signals are strong enough (i.e. when they surpass a given threshold), the neuron is activated and emits a signal through the axon (Gershenson, 2003). ANNs are designed to work in a similar way, which can then be used for problem solving and knowledge engineering (Lolas and Olatunbosun, 2008).

The main benefit of using an ANN is that it finds the function and model parameters itself. It is also more reliable in the long term, as it cannot be guaranteed that a nonlinear model will continue to be as accurate as new data comes in (e.g. when new materials or material properties are explored). An ANN in contrast, is able to adapt its function to fit new data effectively.

3.8.2 Training and Validating the Models

A process of cross-validation was used during model development. This involved categorising the material data into two sets: training and validation with a 70/30% proportion. It is generally regarded as good practice to use two samples when building a statistical model (Finlay, 2014, Peck et al., 2013) and the 70/30% proportion is common when partitioning the data into these datasets (Pardoe, 2012). The data for the training materials were used to parameterise the model and the predictors from the validation materials dataset were inputted into the model to obtain the PQ estimates.

Partitioning the data in this way made it possible to estimate (and therefore create) the models using the training data and then make an unbiased assessment of which model performs best by investigating the fit of the models with the validation data.

For the neural network, 10% of the training data was set aside for the training algorithm to perform some internal tests to avoid issues such as overfitting the model. This process of partitioning the data for cross-validation is also evident for building artificial neural networks (e.g. Hui et al. (2004), Lolas and Olatunbosun (2008)).

3.8.3 Evaluating Model Performance

The methods used to evaluate the model performance were:

- **R^2 value** (also known as the coefficient of determination).This value indicates the extent to which the independent variables help to predict the dependent variables (Kposowa et al., 2012) and they can be used to interpret the proportion of the information within the data that is explained by the model. An R^2 value is always between 0-100%. The closer the value is to 100%, the better the model fits the data. For example, an R^2 of 0.75

indicates that the model is able to explain three-quarters of the variation (Kuhn and Johnson, 2013).

- **Mean absolute percentage error (MAPE).** This is defined as:

$$MAPE = \frac{100}{\mathrm{N}} \sum_{n=1}^{N} \left| \frac{y - \hat{y}}{y} \right| \tag{1}$$

A MAPE value is also normalised to a percentage. However, the smaller the number, the better the performance of the model (Asiltürk and Çunkaş, 2011).

- **Error assessment.** This is defined as the difference between measured and estimated response as shown in (2). Two main attributes are considered: root-mean-squared (RMS) error defined in (3), which indicates the average error across all materials, and the maximum absolute error defined in (4), which indicates the peak error. When summarising and plotting the results, the mean material data (or mode, for ordinal data) is used as an input to the model. This provides a PQ estimate which can be compared against the mean measured PQ for each material.

$$\delta_{err} = y - \hat{y} \tag{2}$$

$$\delta_{mean} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \delta_i^2} \tag{3}$$

$$\delta_{peak} = \max\left(|y - \hat{y}|\right) \tag{4}$$

The smaller the RMS and maximum absolute error values, the more effective the model is (Pardoe, 2012).

3.8.4 Model Performance Results

Table 15 presents a summary of the model performance for each type of model. It can be seen that all models performed well, achieving average RMS error rates between 1-6%. It was found that all models performed similarly or better with technical rather than subjective data. This suggests that it may not be necessary to conduct frequent subjective consumer evaluations of perceived material quality providing there is in-house test equipment responsible for measuring surface roughness and material stiffness. This has beneficial cost and time-saving implications, as running consumer research trials can be time-consuming and expensive.

Table 15: Summary of model performance results

Model Performance - Statistical Error Values					
		R^2	MAPE	RMS Error (%)	Peak Error (%)
GLM Technical	Training	0.71236	8.4633	4.44	9.42
	Validation	0.77189	6.9551	6	13.11
GLM-Interactions Technical	Training	0.90443	4.6543	3.16	7.2
	Validation	0.65623	7.4652	5.74	10.01
GLM Subjective	Training	0.72895	7.6138	5.79	11.73
	Validation	0.69247	7.6111	5.29	7.7
Nonlinear Regression Technical	Training	N.A	4.906	3.34	6.53
	Validation	N.A	4.5381	3.09	5.26
ANN Technical	Training	0.97591	2.2423	1.61	4.26
	Validation	0.83195	4.449	3.31	4.48
ANN Subjective	Training	0.77629	7.1885	4.9	8.98
	Validation	0.71693	7.9121	5.7	8.9

The GLM was moderately effective with R^2 values of 0.71 (training) and 0.77 (validation). However, the peak error was approximately 13% for the validation dataset, which means that the model may not be as accurate with new data moving forward. In regression modelling, it is sometimes possible to reduce the error by adding interaction terms. Various interaction terms were applied and it was found that adding a multiplicative term between roughness and material category could reduce the peak error to approximately 10% which was an improvement, however the R^2 for the validation dataset fell to 0.66 compared to 0.77 previously.

The nonlinear regression model was able to predict PQ within 5-6% accuracy. However, its complexity meant that the proposed advantage over ANNs – interpretability of parameters – was not realised. The GLM was the least accurate of the three and so was discounted, but may be viable in the future when there is a larger dataset of measurements and material types.

For now, the ANN with technical data provided the best predictive power of all of the models. This achieved R^2 values of 0.98 (training) and 0.83 (validation). The RMS error rates were 1.7% (training) and 3.3% (validation) and the peak error rates were 4.26% (training) and 4.48% (validation).

The peak error results are most relevant when assessing whether a model is sufficiently validated and therefore works as accurately as possible with new data. As can be seen in Table 15, the peak error for the ANN Technical was less than 5%, which is extremely effective. Overall, these results mean that the end user can be confident that the ANN is able to predict PQ scores for new soft materials reliably and accurately. The fit results are shown graphically in Figure 32.

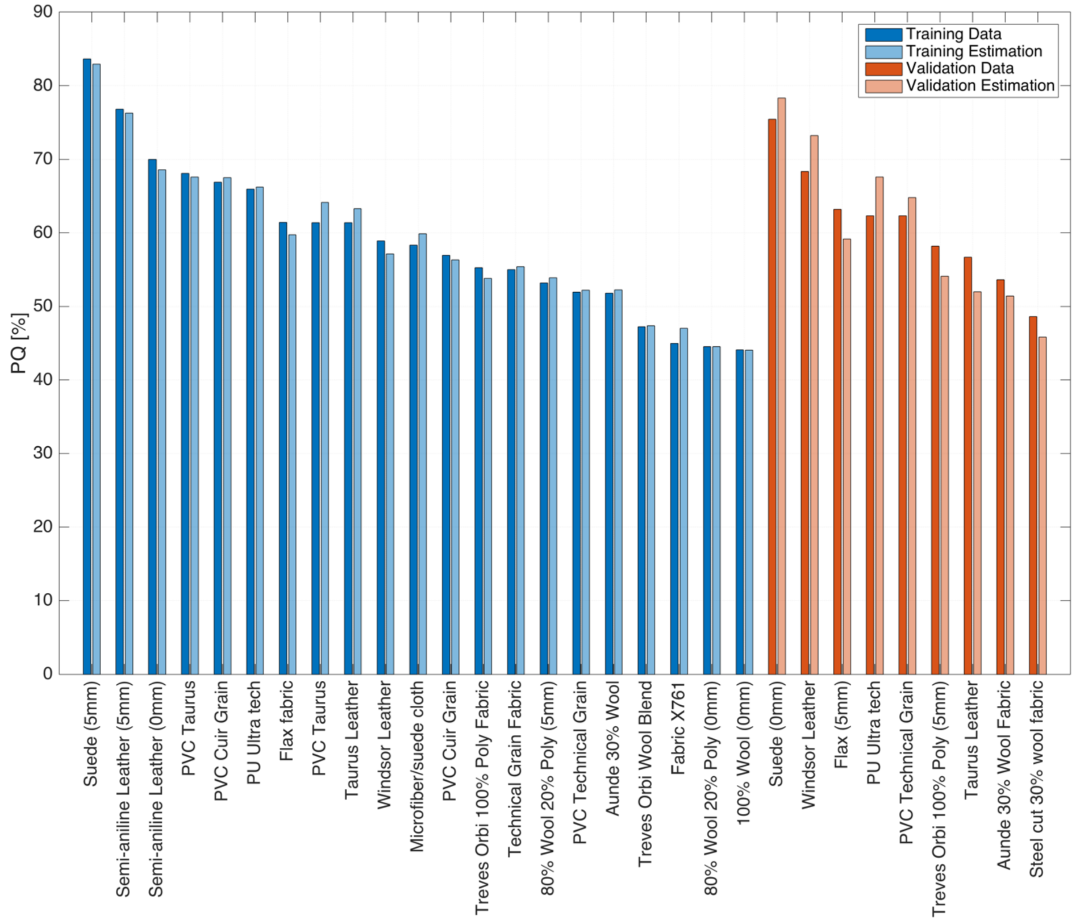

Figure 32: Estimation results for ANN fitted with a single hidden layer of 5 neurons

A schematic of the ANN is shown in Figure 33. It was found that a single hidden layer of 5 neurons gave a good fit for the subjective and objective models, with more neurons or layers not improving the fit significantly. Therefore, a single-layer feed-forward artificial neural network was developed.

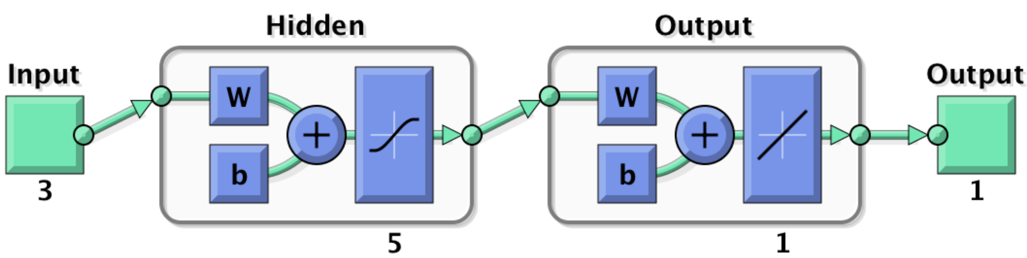

Figure 33: Schematic of an ANN with 3 inputs, one hidden layer with 5 neurons and one output

3.9 Development of a Graphical User Interface (GUI)

After determining that using an ANN with the technical data resulted in the best model for predicting the PQ of new materials, a GUI was also created using MATLAB. This allows an end user to use the model without having to interact with the underlying code directly, as it is likely that the user will not be familiar with machine learning or programming.

The GUI is shown in Figure 34. In its present form, the interface is able to perform two key tasks. First, it uses the existing model to estimate the PQ for a new material. The user can input the required predictors (in this case, material type, roughness measurement and stiffness measurement) and click a button (‘Predict PQ’) to get the predicted response.

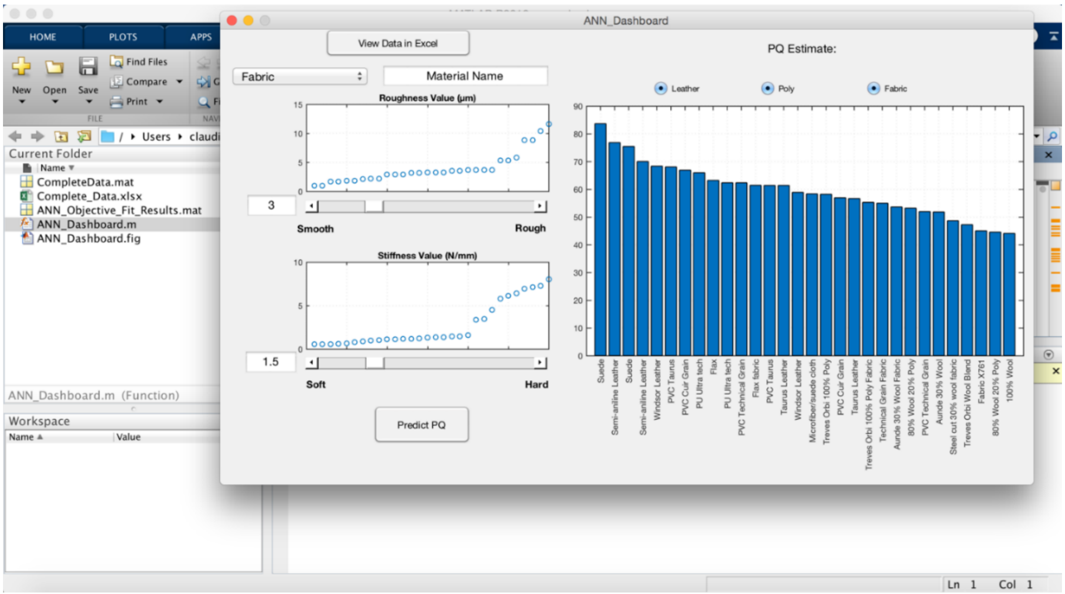

Figure 34: MATLAB user interface used to predict the PQ of new materials

To select the material type, a dropdown menu was created. This gives the user an option to select ‘fabric’, ‘leather’ or ‘poly’ – the latter option is used for polyurethane (PU) and polyvinyl chloride (PVC) combined, due to the research only exploring one type of PU sample. These three options are available based on the materials used for this research, but further material types can be made available during subsequent development. After the material type is selected, the user can then manually input the name of the material. The roughness and stiffness values can either be inputted by manually typing the value or by using the slider below each graph.

The ‘Predict PQ’ button can then be selected and a numerical PQ estimate will appear above the right hand graph. As well as providing the numerical PQ estimate, the interface could also use graphical tools to provide some context, for example showing where that material fits in amongst others of its type (as illustrated in Figure 35). Data on the graph can also be limited to material type, rather than displaying all materials on one group (e.g. just the fabrics or leather).

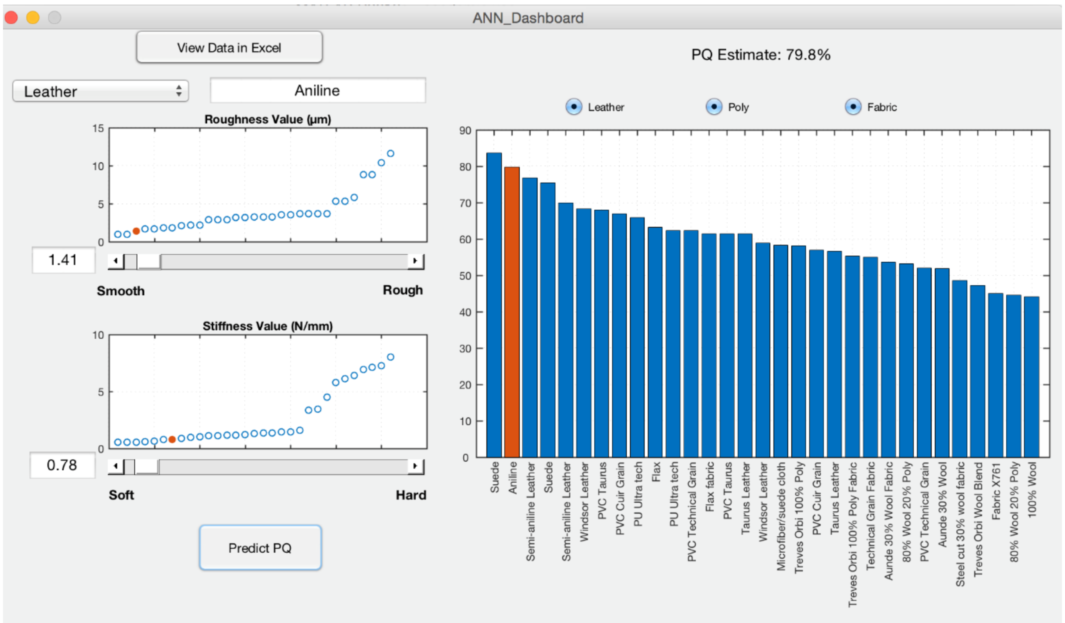

Figure 35: MATLAB user interface showing a new material being compared with the materials within the model

Secondly, the interface allows the user to update the model if new data are available. This would be most appropriate for when more materials have been evaluated at customer clinics, and could also be if new material data are available (a new property such as thermal conductivity, or a new type such as splitting “poly” into PU and PVC). In this case, the user could add this information to the spreadsheet of material data, and then, through the interface, import the data and re-run the ANN training. The ‘View Data in Excel’ button opens the main spreadsheet containing the material data to allow for this. This process of adding information as and when new research is conducted would ultimately improve and build on the model through iterations.

When the model was first introduced to JLR, it was recommended that it should be used cautiously. For example, it could be used as a first pass to quickly choose a few materials from a larger sample. The selected materials could then be evaluated in customer clinics to obtain PQ measurements. Additionally, the model could be used to explore how a change in material characteristics would impact on its estimated PQ score (e.g. would making a material fractionally smoother or softer with added foam interlayer make the estimated PQ score higher or lower?).

Once the model proves to be sufficiently accurate through added use, this second step could largely be removed, although period re-training of the model may be necessary if new types of material are chosen. Additionally, it is recommended that another customer clinic with representative luxury customers is conducted, in order to ensure that the predictions are representative of the target population.

3.10 Streamlining the Process for Industry Use

Figure 36 illustrates the streamlined version of the original process (initially presented in Figure 11).

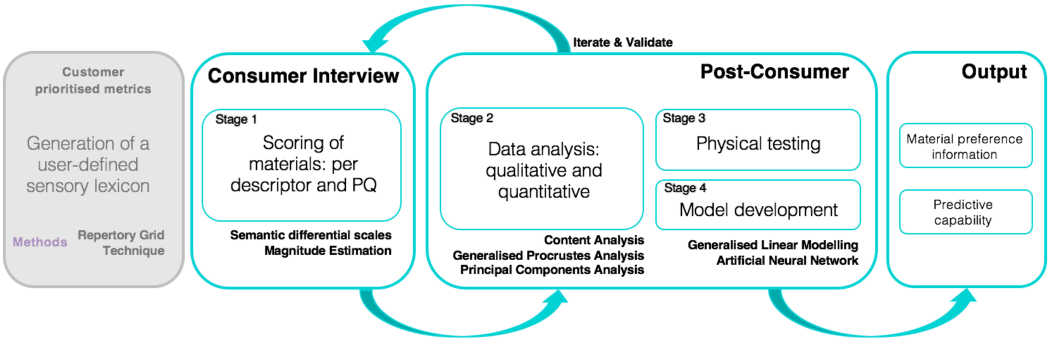

Figure 36: Streamlined process for measuring perceived material quality

The main difference between the processes is the lack of the 'generation of a user-defined sensory lexicon' stage of the consumer interview. In this research, the Repertory Grid Technique (RGT) was used, but in general, alternative verbal elicitation techniques could be explored. The aim of that initial stage was to determine customer prioritised metrics using the consumers' language, in order to eliminate any bias caused by relying on expert assumption and intuition. If a sufficient customer clinic is conducted using RGT with real, representative customers (8-15 participants per market as recommended in literature (Grill et al., 2011)), a series of metrics (and therefore rating scales) would already be established e.g. a scale for roughness, hardness, warmth. These would depend on whether the participants elicited these and whether the statistical analyses identified these as being significant on perception. Nevertheless, at this point, a set of metrics would be established that could then be used in subsequent customer clinics.

Omitting the RGT stage significantly reduces the duration of a consumer interview, as each individual RGT interview lasts approximately 45 minutes to an hour. This is valuable in industry because, as mentioned previously, the automotive industry is particularly fast paced and so requires rapid techniques. The streamlined consumer interview would therefore only take approximately 10-15 minutes, depending on the number of materials explored.

The latter stages of the process would remain unchanged. The only difference between the process diagrams is the lack of 'customer prioritised metrics' in the output box. This is because these will already be established in the initial customer clinic adopting the full process.

4 Conclusions

The purpose of this research was to develop a new, more systematic process for measuring perceived material quality based on real user research, mechanical material assessments and predictive modelling. By doing so, an understanding of the characteristics that constitute luxuriousness and high quality in automotive interior materials could be achieved. These insights could then be applied when assessing newer, innovative and sustainable materials that appear to be rising in popularity across not only the luxury automotive industry, but the luxury industry as a whole.

The ways in which the research was disseminated and integrated within the sponsor company is outlined in detail in Submission 6 - this is complimented by a statement and two testimonial letters in support of the impact of the research from the project partners and senior managers at Jaguar Land Rover.

The main contribution of this research was a new, repeatable process for measuring perceived material quality. The process can be used in various ways (e.g. streamlined and used in rapid customer clinic scenarios and/or as a scoring system when benchmarking materials within a Perceived Quality (PQ) department). It can also in theory be applied to any sensory modality (e.g. visual, haptic, sound or smell quality), as RGT has been successfully used within sound evaluation (Grill et al., 2011). However, this should be explored further in an automotive context in order to pick up on specific nuances that should be accounted for for different senses.

The research led to new practice being implemented in the sponsor company's current PQ scoring system. Specifically, this research allowed the JLR PQ Surface Materials Integration team to implement a new "Touch & Feel" section to their material quality scoring process, which evaluates JLR vehicles against competitor vehicles just on haptic perception.

This business process improvement was influenced by a number of findings from this research. For example, it was found that material roughness and hardness had the most significant impact on PQ – this finding was also validated by conducting the second study in Hong Kong. The Repertory Grid interviews identified user-defined metrics with associated reference materials that can be used as a scoring system when evaluating new materials. These help to eliminate guesswork and can act as a guideline for practitioners when rating new materials on the same scale. An example of a reference scale with its associated materials is shown in Figure 37.

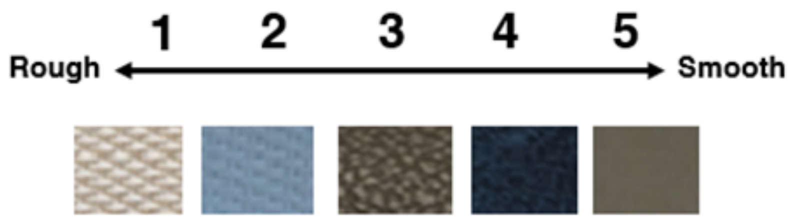

Figure 37: Rating scale for perceived roughness with corresponding reference materials

The process of scoring materials, obtaining a single PQ score on a scale of 0-100 and conducting the relevant physical materials testing identified material-specific insights that can be used to pinpoint optimum surface finishes and characteristics that can be used as a baseline for improvement and a means of comparison when searching for new materials. For example, it was found that in general, the rougher the material, the lower the perception of quality and preference – this also provided evidence for the JLR PQ team to assign a lower score to materials with increased surface roughness.

These results could especially be useful in the future when new materials are being developed. Understanding the technical parameters of a 'luxury material' opens up the possibility of engineering new materials with specific parameters in mind, which would help to ensure customer satisfaction. This is supported by the fact that the subjective and objective material measurements for roughness and hardness were found to correlate strongly, implying that objective measurements alone could indicate a customer's opinion of these materials.

It was also found that materials with a 5mm foam backing (known as an 'interlayer' in the automotive industry) received significantly higher PQ scores than materials that had no interlayer. It also identified which types of material that interlayer works best on and the materials where it has only a minor effect on. This provides a cost-effective and informed way of improving the perceived quality of materials by adjusting the foam interlayer used beneath the trim material and the base of the component. This finding has influenced additional research and strategy in JLR, which further investigates the impact of a foam interlayer.

Lastly, it was found that PQ scores can be reliably predicted using an Artificial Neural Network (ANN) using the technical material roughness and hardness data as predictors. This model provided the best predictive power of all of the models developed in this research, including a Generalised Linear Model and a nonlinear regression model. The final model was validated as accurate to within 4.5% and was used to build a graphical user interface that can be used as a rapid way of predicting how customers may respond to a new material or a change in an existing material (with regard to its roughness and hardness characteristics). It can also be used as a communication tool when discussing company buy-in for considering new materials, as quantitative customer data is often seen as more valuable in the automotive industry. A member of the JLR PQ team was trained to use and develop the model using MATLAB.

Finally, contributions were also made to academic teaching on an undergraduate Design for Safety and Comfort module and a technical accreditation scheme Perceived Quality module exclusive to JLR. Additionally, a peer-reviewed conference paper and invited workshop talks were delivered focusing on Sustainable Luxury.

4.1 Research Limitations

Sample Representativeness

The main limitation of the research was that the participants involved were generally not luxury customers. Ideally, owners of luxury cars would have been recruited. It is logical to assume that the scores for quality and preference may have been different if luxury customers were able to be recruited. This is because they are likely to be surrounded by more products, services and experiences of a higher quality (e.g. they may be used to real leather in their cars already, luxury hotels, business or first-class travel), so luxury customers may be more able to pick up differences between material textures and they may have a higher standard of quality and preference to begin with.

After it was determined that it would not be possible to contribute to an existing customer clinic arranged by JLR, the focus of the project shifted to developing and validating a process that could be used in future customer clinics and for JLR's internal scoring system. Therefore, staff and students from the university were recruited. This is not uncommon within academic research. There are also studies that use experts and company employees as 'customers' e.g. Bhise et al. (2005) which arguably introduces bias to the experiment. For example, Yun et al. (2004) recruited 15 ergonomics experts at a university and 15 trim designers from Hyundai-Kia Motors to take part in a study evaluating vehicle interior craftsmanship. For this EngD, the decision was made to use car owners that were not experts in vehicle design, materials engineering and were not JLR employees. The decision to not use experts in vehicle design was made to mitigate the risk of recruiting participants who had frequent exposure to vehicle interior materials.

Material Samples

Visual characteristics (e.g. colour, grain) may have had an impact on material ratings. Despite ensuring that the samples were neutral in colour, some participants stated that at times the colour of materials affected their judgement of quality – particularly the lighter, grey materials seemed to be associated as being poorer quality than the black materials. This could have been avoided either by ensuring that the materials were exactly the same colour, by blindfolding participants or enclosing the materials in boxes, thereby isolating the sense of touch or through the use of coloured lights (either red, green and/or blue) at low intensity (Meilgaard et al., 2006).

The materials were also somewhat devoid of context. This was desired to an extent so that we could understand intuitive and general perception of a wide range of materials, some of which are not currently used in vehicles. There is a chance that these perceptions could change once the materials are in vehicles, as the presence of surrounding features and components may have an impact on perception.

Technical Parameters

Two technical parameters were explored in this research: surface roughness and material stiffness (hardness). These two were chosen to take forward because they were elicited by all participants and they were the two parameters that were both found to have a highly statistically significant impact on PQ. Two additional parameters were found to be significant in the UK study: warmth/coldness and natural/artificial. In the Hong Kong study, the attributes comfortable/uncomfortable and easy to clean/hard to clean were significant too. It is logical to assume that had at least heat transfer been physically measured and incorporated into the predictive model, the accuracy would have been improved even more so. As such, guidelines have been provided to the sponsor company if they do wish to incorporate further material attributes into the model.

The Use of the Repertory Grid Technique (RGT)

A limitation concerning RGT is that it focuses on verbal labels and therefore poses constraints on an individuals' ability to articulate their opinions of materials. Some may struggle with this, as coming up with certain adjectives may be difficult. People may therefore only focus on easily accessible constructs (Fransella et al., 2004), although using a laddering interviewing technique can help participants to explain what they mean. Fortunately, the attributes identified during the RGT interview are consistent with previous research in this area.

There is also literature that suggests that alternative verbal elicitation methods are better for identifying subjective dimensions for a given domain. A study comparing six qualitative methods found that methods requiring participants to sort products according to their perceptions (e.g. a sorting task and RGT) generated fewer subjective dimensions compared to techniques such as word association and sentence completion (Masson et al., 2016). These findings suggest that RGT and free sorting methods seem to drive the elicitation of more "objective" dimensions of a sensory type – this is favourable for this research as RGT was used to define objective metrics for the overall PQ process - but suggests that a different method may be more appropriate if investigating more emotional criteria.

4.2 Future Research Opportunities

The research has provided insights into how to systematically measure and predict perceived material quality using customer assessments, which had not previously been conducted at JLR. The findings resulting from the research have already influenced additional areas of investigation and provided a solid foundation for future research opportunities. Specifically, five opportunities were identified:

1. *Determining the optimal depth of interlayer specific to vehicle components*

The research findings showed that the presence of an interlayer has a significant effect on PQ and preference. However, what this does not show is the optimum depth of interlayer for specific materials. To investigate this, the study would have had to have used duplicates of materials using a range of foam depths (e.g. 3mm, 5mm, 7mm), which would have increased the material sample size considerably. Additionally, the study did not explore the presence of a foam interlayer for fabric samples. Future studies could explore this further. A future study could be conducted whereby the lowest perceived quality materials are trimmed using a thicker interlayer – the results of which could be compared with the initial dataset. Context could also be explored, which would investigate the priority areas of a vehicle interior that would or would not require an interlayer based on the areas and components of the vehicle that drivers are drawn to.

2. *Measuring heat transfer*

In the UK study, the warmth or coldness of a material was found to be the third significant attribute that influences perception. Future research could explore the correlation between perceived warmth/coldness and technical heat transfer measurements. These results could also be built into the predictive model which may improve accuracy even further.

3. *Investigating the Perceived Quality of hard materials*

This research only explored the perception of soft, wrap-able materials including fabrics, leather, PU and PVC. It would be interesting to explore the perception of hard materials typically used for automotive interiors such as wood veneers, plastics and chrome. As discussed in section 2.3, automotive OEMs are also looking to incorporate new materials that have never been used in vehicles before (e.g. replacing wood veneers with stone and minerals). A customer research clinic could be conducted using these new materials to understand and anticipate customer reaction to this change.

4. *Expanding the process to the other sensory modalities (e.g. sight, smell, sound)*

This research investigated how the touch/feel quality of materials impacts on Perceived Quality. In general, the process could also be applied to other sensory inputs, such as sight, smell and sound. For example, future research could investigate how a certain colour or grain impacts on perception by undertaking a similar study to the Repertory Grid experiments. Participants could be asked to describe the visual characteristics of the materials and then rate them. Similarly, if exploring interior sound quality, participants could be asked to listen to and describe various recordings.

5. *Further cross-cultural research*

Although the cross-cultural comparison in this research did not discover any major cultural differences in material perception, it would still be interesting to conduct more research exploring different regions. For example, an upcoming trend in the automotive industry at the moment is exploring alternative materials to leather. Bentley have conducted research in the West coast of America and have identified a large market looking for vegan leather alternatives.

4.3 Final Reflection

Overall, the research has provided some much needed insight as to how the Perceived Quality (PQ) of automotive interior materials can be both subjectively and objectively measured. The research has led to new practice being implemented in the sponsor company's current PQ scoring system. The wider intention is that the research can contribute to the development of standardised processes and terminology for measuring PQ across the automotive industry. The initial theme of the research was 'Sustainable Luxury', however instead of focusing the research on searching for alternative sustainable materials that could be used for luxury automotive interiors, it was felt that it would be more beneficial and long-lasting to develop a means of assessing the quality of materials already perceived to be luxurious, and then apply this knowledge when searching for, selecting or even engineering new sustainable luxury materials.

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Appendices

Appendix 1: Guidelines and Recommendations for Applying the Process

Figure 38 illustrates the steps that typically need to be taken to apply the process.

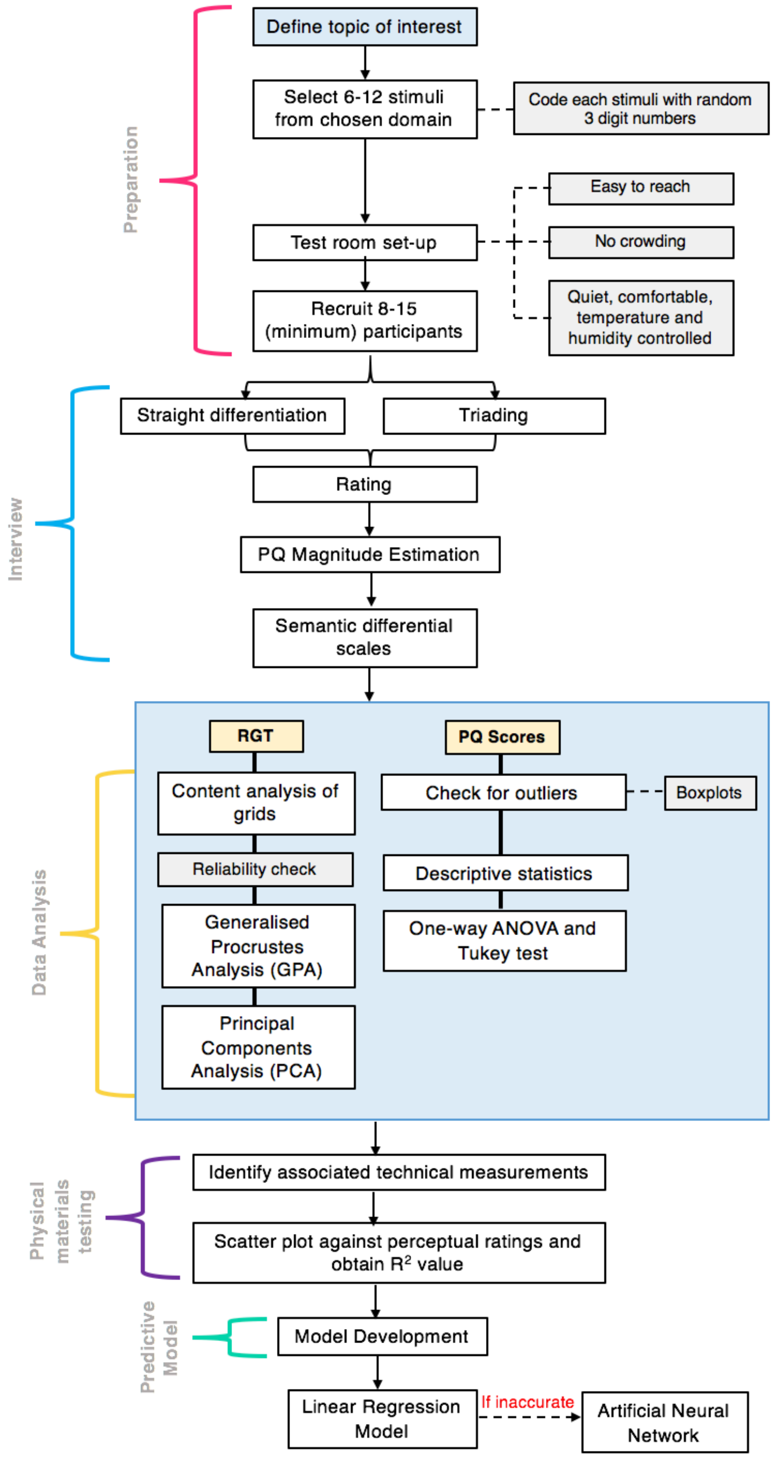

Figure 38: Steps taken to apply the process

Preparation

Define Topic

Firstly, the topic of interest needs to be defined e.g. visual, sound, smell and/or touch quality.

Select Stimuli

Appropriate stimuli must then be selected (e.g. hard/soft materials, whole vehicle components). A rule of thumb is to select between 6-12 stimuli.

> *Use a wide range of stimuli, including extremes (e.g. very rough and very smooth materials) – this will help participants with the verbal elicitation task during the interview.*

Code Samples

In sensory evaluation experiments, samples must be coded randomly in order to prevent participants from being subconsciously drawn to a particular numbered sample.

> *Avoid single or double letters and digits, including letters or numbers that are used for companies, area codes or test numbers.*
>
> - *Instead, use combinations of three-digit random numbers.*
> - *Subtly arrange codes based on a sample characteristic e.g. the materials used in this research followed a system whereby fabric codes always ended in a 1, PVC ended in a 5, the middle number for all leather codes was a 2 and TPO and PU ended in a 4 - this allowed the RE to distinguish between the different types of materials without needing to look at the material label.*
> - *Discreetly place the code on the sample to avoid distraction e.g. Figure 39 (Meilgaard et al., 2006).*

Figure 39: A coded material sample

Test room set-up

The room setup for sensory evaluation studies must be sufficiently controlled to ensure that the effects of biases are minimised, participants' sensitivity to the stimuli are maximised and any extraneous variables are eliminated.

- *Ensure that test areas are 'centrally located, easy to reach, free of crowding and confusion and comfortable, quiet and temperature controlled'.*
- *If exploring haptic perception, ensure a range of 50-65 +/- 2% relative humidity in the test environment.*
- *If a one-to-one interview is due to be conducted, with no prior training needed, a well ventilated room or quiet area equipped with a table and chairs is sufficient (as depicted in Figure 40).*
- *Try to avoid presenting stimuli which is devoid of context (e.g. by just using material swatches). In this research, materials were wrapped around blocks of MDF with a foam interlayer beneath. Some studies have also used whole vehicle components (e.g. a dashboard, switch pack) and some have required participants to rate materials physically inside a vehicle.*
- *If one sensory modality is chosen as the topic of interest, it is recommended that it is explored in isolation of other modalities e.g. to isolate the sense of touch, participants could be blindfolded, materials could be hidden or red, green and/or blue lights could be used at low*

Figure 40: The test-room interview set-up for the UK Repertory Grid study

Interview

Figure 41 illustrates the four steps taken to conduct a typical Repertory Grid interview.

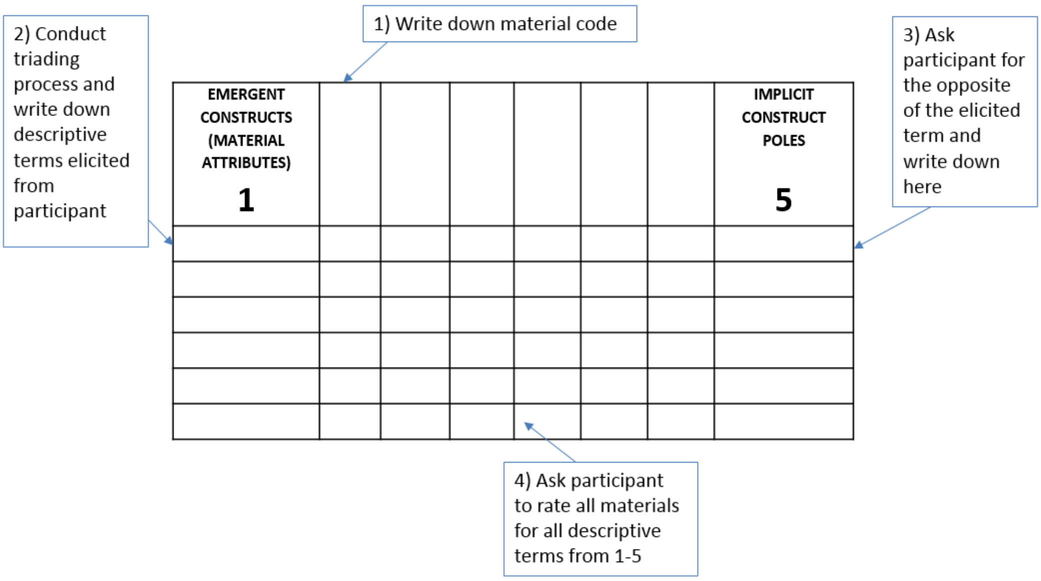

Figure 41: Steps needed to take during an RGT interview

Use a laddering interviewing technique to ensure that each construct is fully understood.

- *Ask questions such as 'how?' and 'in what way?' to allow participants to fully explain their reasoning (Jankowicz, 2005).*

Grid Layout

During the pilot interviews, it was found that participants had difficulty completing the task when a typical grid design such as Figure 41 was used - it was not intuitive to them that each column and row was supposed to represent a scale.

Instead, consider Figure 42 where the first column displays the elicited constructs and the polar opposite in one place, helping participants to understand that this forms a scale from 1-5.

- *Use pre-made scales so participants can just tick their desired rating.*

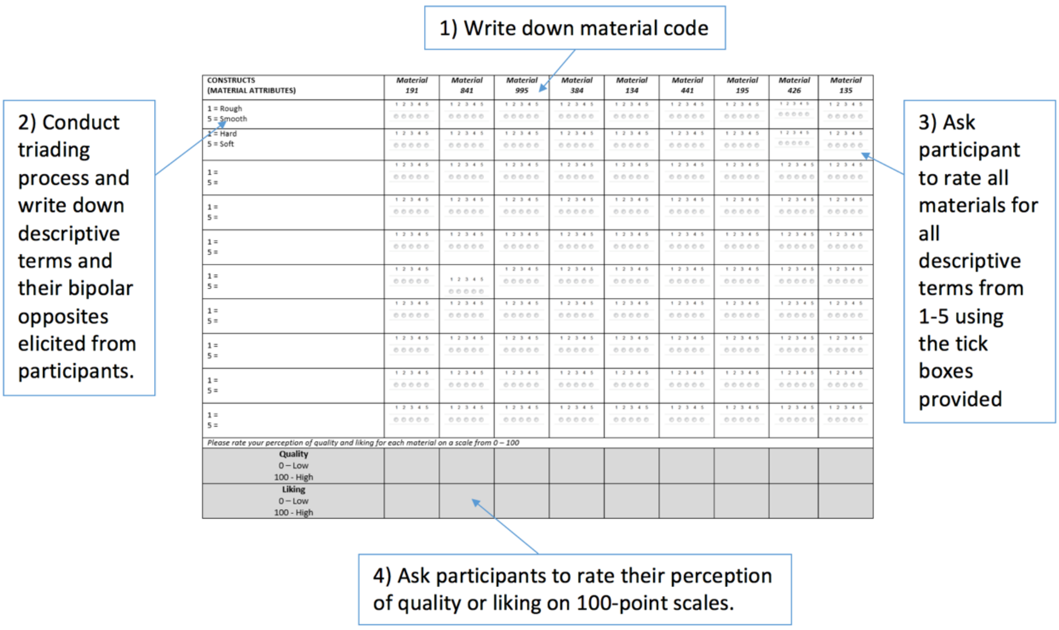

Figure 42: Modified grid with process steps

Data Analysis

The software Idiogrid (Grice, 2002) was used to perform the Generalised Procrustes Analysis and Principal Component Analysis. The program is freely available to download and is specifically designed for assessing RGT results, which offers a straightforward and informed means of analysing the data.

It is recommended to clean the data and search for any outliers prior to plotting the magnitude estimation results.

> *Assess boxplots for each individual variable. Boxplots are based on the interquartile range (IQR), which refer to the distance between the lower and upper quartiles. In this research, Minitab 17 was used to plot the data. If there are a high number of outliers, it may be useful to determine the source of them.*

In this research, a high number of outliers were found to originate from 2 participants in the UK study, which warranted further exploration. Histograms were plotted for both participants against the average of all remaining participants. Figure 43 and Figure 44 show the histograms plotted for Participant 14 in the UK RGT study overlaid against the average results across all remaining participants. It can be seen that P14's results are significantly different from the average results of the 19 participants for both preference and PQ. For preference, the results skew dramatically to the left (the lower extreme of the 100-point scale). No ratings exceeded 51% and a score of 0% was given to 9 of the material samples – the most frequent rating was 2%. In contrast, the most frequent average preference ratings for the 19 participants was 60%, with no values falling below 35%. For PQ, the most frequent rating was 30% for P14, while the most frequent average rating for all participants was 62%. The process was repeated with P18's results.

These two participants stood out to the RE while conducting the interviews. The participants both went through and rated the materials extremely quickly, often without taking the time to properly interact with the sample and carefully consider their answers.

As well as listening to what interviewees are saying, also observe their behaviour as subconscious behaviours can also give some insight.

As these ratings from P14 and P18 were particularly extreme, it was decided to remove these values from the dataset.

Outlier removal should be performed with care as scientifically interesting information could simply be discarded. In this case, the PQ results were used for subsequent model development for predicting PQ (in Submission 4d). Keeping these outliers in the dataset could then adversely lead to model misspecification, biased parameter estimation and incorrect results. It is therefore important to identify them prior to modeling and analysis (Ben-Gal, 2005)

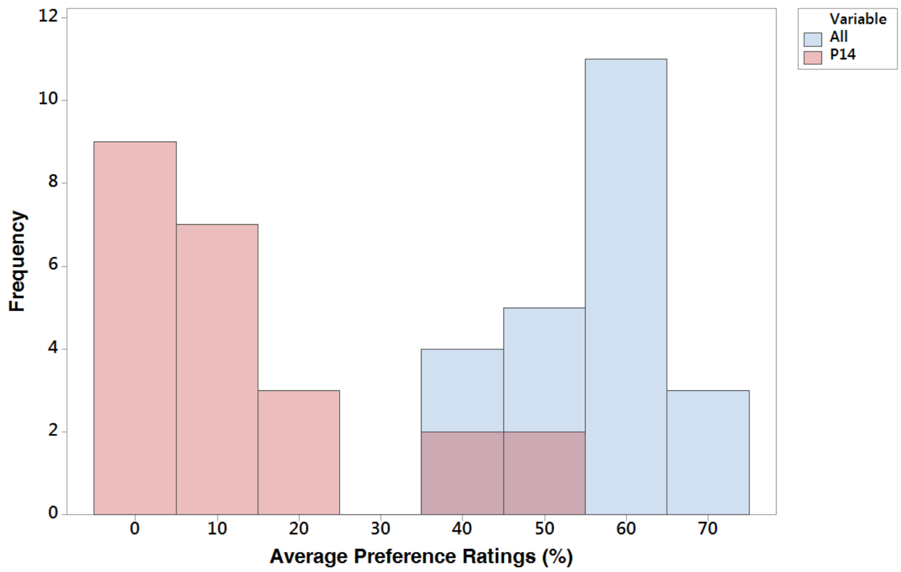

Figure 43: Histogram comparing Participant 14's results against the rest of the data (Preference)

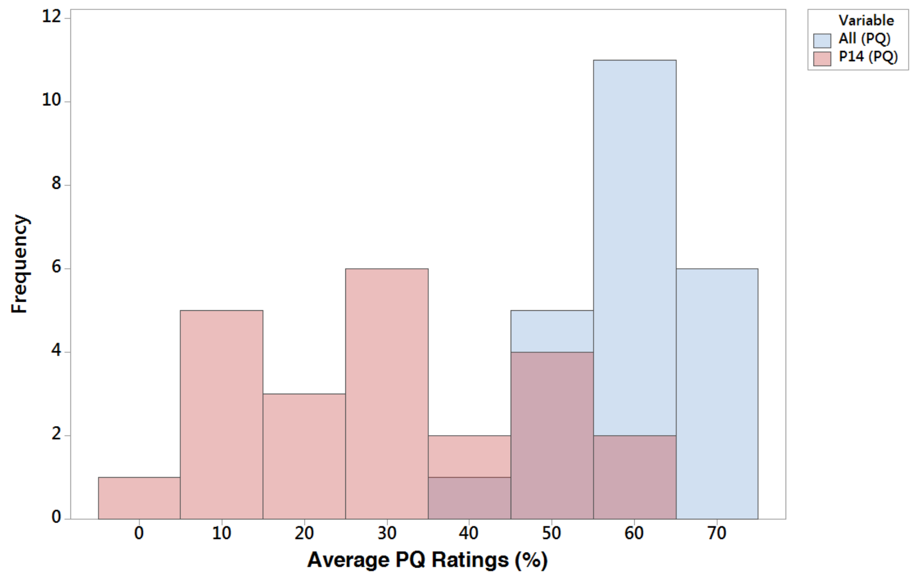

Figure 44: Histogram comparing Participant 14's results against the rest of the data (PQ)

Physical Materials Testing

Consideration should be taken when selecting the type of test equipment used to measure physical material characteristics.

In Submission 4c, it was found that an optical profiler was not effective when measuring the surface roughness of fabrics but it did work with reflective materials, such as leather and PVC.

In general, there are two ways to measure surface roughness: using contact type or non-contact type instruments. The former involves a stylus which directly contacts the material surface. This traces along the sample, which is recorded and measures surface roughness. The latter involves a light being emitted from the instrument, which is reflected off the material and recorded.

Non-contact type instruments – such as optical profilers – are unlikely to damage materials. They are therefore more accurate for measuring soft or viscous materials. However, the issue found in this research was that the fabric samples were too rough or had too steep angles for light to reflect off of, so the equipment was not able to pick up an accurate representation of the surface profile.

Instead, the samples were arranged to be re-tested at the University of Leeds textiles department, using a contact instrument called the Kawabata Evaluation System for Fabrics (KES-F). The system is able to measure fabric extension, shear, bending, compression, surface friction and roughness (Kayseri et al., 2012).

Secondly, there are different ways in which material 'hardness' is defined, which governs the type of measurement procedure appropriate for a given material. The main property associated with hardness is the Young's modulus, defined as the ratio between stress and strain (Tiest and Kappers, 2009). This is particularly applicable for harder materials (e.g. metals, woods, polymers). Conversely, the stiffness of a material is the dominant factor for softer materials (Wongsriruksa et al., 2012). Stiffness is defined as the ratio between an applied force and displacement (i.e. the force needed for a certain deformation of the material) (Tiest and Kappers, 2006). Care should therefore be taken when defining the attribute which needs to be measured.

Predictive Model

Pardoe (2012) offers a set of general guidelines that can be used when developing regression models. These were arranged into a diagram shown in Figure 45.

It is good practice to perform regression modelling first. If the results prove to be inaccurate and the error cannot be reduced after applying stepwise regression and by including interaction terms (Frees, 1996), then nonlinear regression modelling (such as neural networks) is recommended (Kposowa et al., 2012).

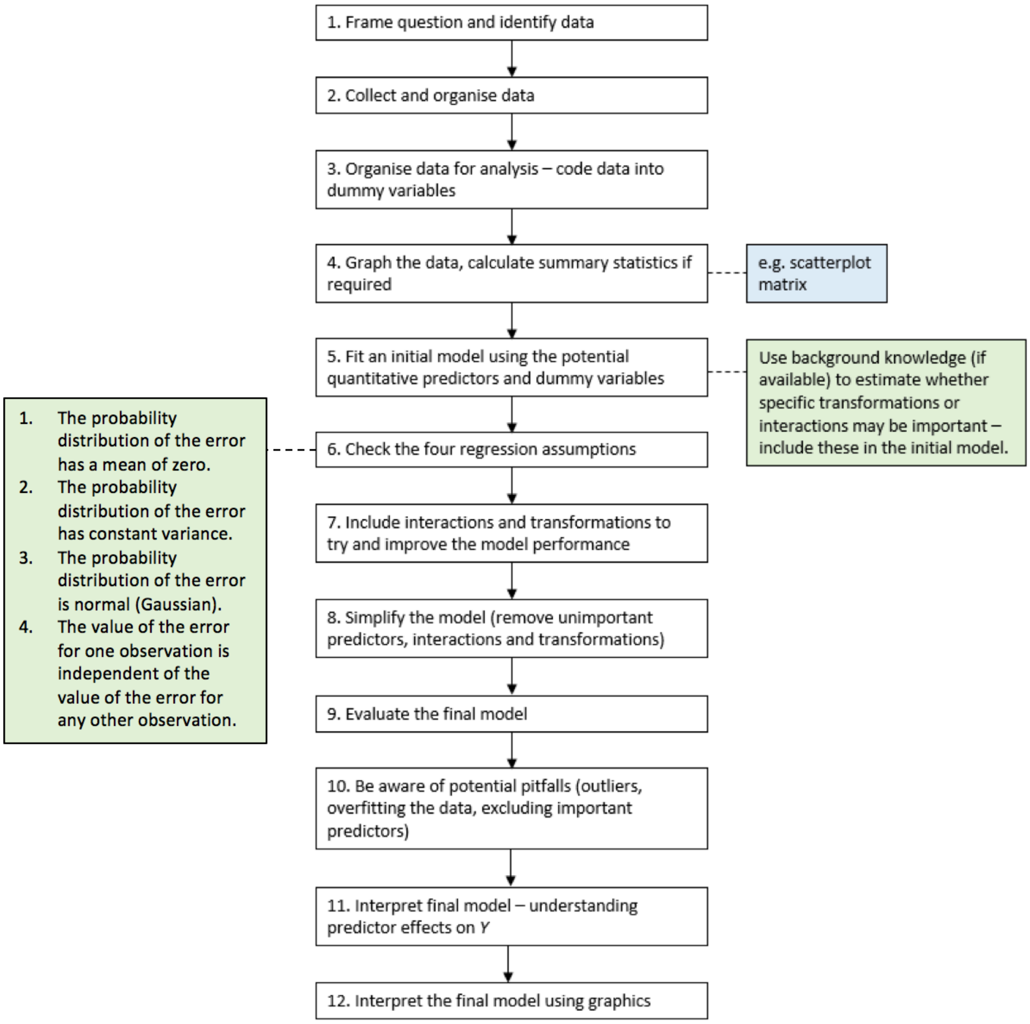

Figure 45: Regression model building guidelines. Source: Pardoe (2012)