



UNIVERSITY OF
LIVERPOOL

**Virtual Synaesthesia: Crossmodal Correspondences and Synesthetic
Experiences**

Thesis submitted in accordance with the requirements of the University of Liverpool for the
degree of Doctor in Philosophy by

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March 2023

Abstract

As technology develops to allow for the integration of additional senses into interactive experiences, there is a need to bridge the divide between the real and the virtual in a manner that stimulates the five senses consistently and in harmony with the sensory expectations of the user. Applying the philosophy of a neurological condition known as synaesthesia and crossmodal correspondences, defined as the coupling of the senses, can provide numerous cognitive benefits and offers an insight into which senses are most likely to be 'bound' together.

This thesis aims to present a design paradigm called 'virtual synaesthesia' the goal of the paradigm is to make multisensory experiences more human-orientated by considering how the brain combines senses in both the general population (crossmodal correspondences) and within a select few individuals (natural synaesthesia). Towards this aim, a literature review is conducted covering the related areas of research umbrellaed by the concept of 'virtual synaesthesia'. Its research areas are natural synaesthesia, crossmodal correspondences, multisensory experiences, and sensory substitution/augmentation. This thesis examines augmenting interactive and multisensory experiences with strong (natural synaesthesia) and weak (crossmodal correspondences) synaesthesia. This thesis answers the following research questions: Is it possible to replicate the underlying cognitive benefits of odour-vision synaesthesia? Do people have consistent correspondences between olfaction and an aggregate of different sensory modalities? What is the nature and origin of these correspondences? And Is it possible to predict the crossmodal correspondences attributed to odours? The benefits of augmenting a human-machine interface using an artificial form of odour-vision synaesthesia are explored to answer these questions. This concept is exemplified by transforming odours transduced using a custom-made electronic nose and transforming an odour's 'chemical footprint' into a 2D abstract shape representing the current odour. Electronic noses can transform odours in the vapour phase generating a series of electrical signals that represent the current odour source. Weak synaesthesia (crossmodal correspondences) is then investigated to determine if people have consistent correspondences between odours and the angularity of shapes, the smoothness of texture, perceived pleasantness, pitch, musical, and emotional dimensions. Following on from this research, the nature and origin of these correspondences were explored using the underlying hedonic (values relating to pleasantness), semantic (knowledge of the identity of the odour) and physicochemical (the physical and chemical characteristics of the odour) dependencies. The final research chapter investigates the possibility of removing the bottleneck of conducting extensive human trials by determining what the crossmodal correspondences towards specific odours are by

developing machine learning models to predict the crossmodal perception of odours using their underlying physicochemical features.

The work presented in this thesis provides some insight and evidence of the benefits of incorporating the concept 'virtual synaesthesia' into human-machine interfaces and research into the methodology embodied by 'virtual synaesthesia', namely crossmodal correspondences. Overall, the work presented in this thesis shows potential for augmenting multisensory experiences with more refined capabilities leading to more enriched experiences, better designs, and a more intuitive way to convey information crossmodally.

Acknowledgments

I would like to thank the following people for helping with this research. First and foremost, I would like to thank my supervisors Prof. Alan Marshall and Prof. Sophie Wuerger for providing feedback and guidance.

Secondly, I would like to thank my wife Shammi Rahman and my family for their love, support and proofreading my publications before submission.

Thirdly, I would like to thank my collaborators Dr. Elias Griffith and Dr. Fred Jjunju for the help and support they provided throughout this project.

Finally, I would like to thank the Engineering and Physical Sciences Research Council (EPSRC) for providing the funding for the work in this thesis and Professor Alan Marshall for acquiring it.

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Preface

All the work presented was conducted in either the Immersive Reality Laboratory, part of the Advanced Networks Research Group (ANRG), Department of Electronic & Electrical Engineering or at the Department of Psychology, University of Liverpool, United Kingdom.

A version of Chapter 4 has been published in the journal IEEE Sensors as *Artificial Odour-Vision Synaesthesia via Olfactory Sensory Augmentation*. I was the lead investigator responsible for all major areas of concept formulation, creating and developing the experimental setup, analysis, conducting the human trials, and as manuscript composition. Professors Alan Marshall and Sophie Wuerger were the supervisory authors involved throughout this work in concept formulation and proofreading the manuscript. Dr. Fred Jjunju kindly recorded some of the prepared samples using the mass spectrometer and proofread the manuscript. Dr. Elias Griffith kindly printed some of the parts with his 3D printer used in the making of the first electronic nose and proofread the manuscript before submission.

A version of Chapter 5 and parts 1 – 8 of Chapter 6 has been published in the Journal of Perceptual Imaging as *Smelling Sensations: Olfactory Crossmodal Correspondences*. I was the lead investigator responsible for all major areas of concept formulation, creating and developing the experimental setup, analysis, conducting the human trials, and manuscript composition. Professors Alan Marshall and Sophie Wuerger were the supervisory authors involved throughout this work in concept formulation and proofreading the manuscript.

A version of Chapter 6 has been published in i-Perception as *Visual-odour correspondences are partly explained by physicochemical features* as part of the proceedings of the AVA Virtual Spring Meeting 2021. A version of Chapter 6 at the time of writing is under review in Nature Scientific Reports as *Physicochemical features partially explain olfactory crossmodal correspondences*. I was the lead investigator responsible for all major areas of concept formulation, creating and developing the experimental setup, analysis, conducting the human trials, abstract, and poster composition. Professors Alan Marshall and Sophie Wuerger were the supervisory authors involved throughout this work in the concept formulation and proofreading of the abstract and the poster.

A version of Chapter 7 has been published in the journal Heliyon as Predicting the crossmodal correspondences of odours using an electronic nose and has been published in the workshop SensoryX'21 as Predicting the colour associated with odours using an electronic nose. I was the lead investigator responsible for all major areas of concept formulation, creating and developing the experimental setup, analysis, conducting the human trials, and manuscript composition. Professors

Alan Marshall and Sophie Wuerger were the supervisory authors involved throughout this work in concept formulation and proofreading the manuscript.

All of the analyses and the bulk of the figures presented in this thesis were made in MATLAB R2018b by MathWorks™.

Glossary

Synesthetes	A person who has synaesthesia.
Synaesthesia	A neurological condition in which the stimulation of a sensory modality triggers a concurrent perception in another modality.
Sensory Modality	One aspect of a stimulus that invokes perception which may (i.e., temperature and pressure) or may not (i.e., light and sound) be in the same sense .
Perception	The ability to become aware of something through one of the five senses.
nm	Nanometres.
Hz	Hertz.
Synesthetic	Experiencing or relating to synaesthesia.
Cognition	The process of knowing, including remembering, reasoning, and attending.
kHz	Kilohertz.
ppm	Parts per million.
DAPCI	Surface desorption atmospheric pressure chemical ionisation.
PCA	Principal Component Analysis.
Discrimination	The understanding and recognition of a fundamental difference between one thing and another.
MS	Mass spectrometry.
Deafferentation	A loss of input from a sensory modality.
Hedonics	Characterised by or relating to pleasure.
RGB	Red, Green, and Blue.
QoE	Quality of experience.
kV	Kilovolt
N ₂	Dinitrogen
Df	Degrees of freedom
p-value	Probability value
H ₀	Null hypothesis
H _a	Alternate hypothesis
α	Alpha
Somatosensory	Relating to or denoting a sensation in pain, pouch, temperature or body position.
Physicochemical	Relating to physical chemistry.
Spatio-temporal	Having the properties of both space and time.

Perceptual gestalt	Perceptual gestalt is the different ways humans group stimuli together in endeavour to make sense out of it. The five principles are proximity, similarity, continuity, connectedness, and closure.
Assimilation	The process of taking in and understanding information or ideas.
E-nose	Electronic nose
MSE	Mean Squared Error

Chapter 1

1.1 Introduction

The need to convey information has been and always will be crucial for the advancement of civilisation; humans can string sounds together in an infinite number of ways to create meaningful messages. The memory for stimulus is one factor that separates humans from other animals. Information can be conveyed to all of our senses (vision, audition, touch, olfaction, and gustation). With the advent of modern technology, information can be conveyed in a more sophisticated manner; such systems could allow a blind person to navigate via sound and/or touch. This information is usually conveyed crossmodally as a 'substitute' or 'replacement' for a sensory modality.

The coupling of senses happens naturally in a neurological condition known as synaesthesia [1]. Whereby the stimulation of a sensory pathway triggers a concurrent perception in another pathway [1]. For example, a person with synaesthesia could hear a sound which could involuntarily evoke an experience of shape, colour, and movement that represents the sound they have just heard; this form of synaesthesia is called Chromesthesia. This concurrent perception can also occur same sense (i.e., people may see graphemes with a perceptually coloured overlay). People with any form of synaesthesia are known as synesthetes. Synesthetes can have the ability to feel sounds, hear colours, and even taste pain. The most common and studied form of synaesthesia is grapheme-colour, where an individual's perception of graphemes (letters, numbers, and symbols) produces a simultaneous perception of colour. Synaesthesia affects approximately 1 in 2000 people [1] An example of this phenomenon is shown in Figure 1.

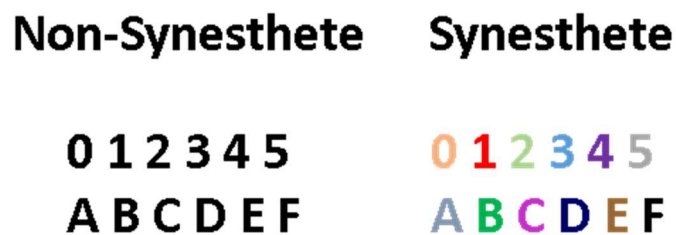


Figure 1. Example of what a non-synesthete sees compared to what a colour-grapheme synesthete might see.

People with synaesthesia typically exhibit cognitive benefits relating to their form of synaesthesia. In the case of grapheme-colour synaesthesia, people typically have enhanced perceptual processing and creativity [2], improved grapheme-related recall [3], and enhanced autobiographical memory [4]. These benefits are not limited to grapheme-colour synaesthesia, although

it is essential to note there can be disadvantages to synaesthesia typically related to incongruency. Notable people who have synaesthesia include Billy Joel, Vincent Van Gogh, Billie Eilish, Kanye West, and Lorde [5]. Billie Eilish uses her form of synaesthesia as inspiration for creating her music videos [5]. Kanye West has a form of chromesthesia (seeing sounds) and stated on the talk show Ellen “Everything I sonically make is a painting. I see it. I see the importance and the value of everyone being able to experience a more beautiful life.” Finally, Lorde stated she uses her form of chromesthesia as a driving force behind all of her work. “If a song’s colors are too oppressive or ugly, sometimes I won’t want to work on it. When we first started ‘Tennis Court’ we just had that pad playing the chords, and it was the worst textured tan color, like really dated, and it made me feel sick, and then we figured out that pre-chorus and I started the lyric, and the song changed to all these incredible greens overnight!” [5]. It may be possible to virtually re-create synaesthesia using modern technology (i.e., augmented reality) to create ‘virtual synaesthesia’, but the question remains on to what extent is this possible (e.g., does virtual synaesthesia replicate the same or some of cognitive benefits behind natural synaesthesia?).

Taking inspiration from nature, the sensory experience perceived by humans is somewhat limited in that we only perceive a small portion of it; for example, humans can typically see wavelengths approximately between 380 to 700 nanometres, which constitutes a small fraction of the electromagnetic spectrum. These non-visible wavelengths to humans are not inherently unseeable either. Snakes, for instance, can, in part, perceive a portion of the infrared spectrum, and bees are thought to see the ultraviolet. This reduced perception of the world around us is not limited to the visual domain; dogs, for instance, can hear between 67 to 45,000 Hz, while humans can only perceive between 20 to 20,000 Hz. From an evolutionary point of view, the human experience of reality is constrained by our biological receptors. However, the bottleneck of our biological receptors need not apply with the advent of modern technology, thermal cameras, for instance, let us visualise temperature, and hearing aids allow a deaf person to hear.

Crossmodal correspondences are the consistent associations between stimulus features in different sensory modalities and are shared among most of the population [6]. For instance, people may associate the smell of lemon with an angular shape [7] or the scent of musk with a brass instrument [8]. These correspondences are considered a weak form of synaesthesia [9]. Martino and Marks define the difference between crossmodal correspondences and synaesthesia as “crossmodal correspondences in weak synaesthesia are systematic and contextual, those in strong synaesthesia are systematic and absolute (display a one-to-one mapping)”. In other words, crossmodal correspondences require context, whereas synaesthesia does not. Crossmodal correspondences can

be considered a form of sensory expectations. Incongruency with the expected and actual expectations of an experience can lead to experiences being perceived as less pleasant [10]; congruency can enhance the perceived quality of experience in human-machine interfaces [11], [12] and products [13]. As crossmodal correspondences and synaesthesia provide some insight into which sensory modalities may be bound together, either in the general population or the synesthetic population, and both deliver benefits that may be exploited in terms of human-computer interaction, both will be considered in this thesis. Crossmodal correspondences are well explored in the literature. However, the reason why these correspondences occur has diverse characterisation with a focus on only the psychological dimensions, such as knowledge of the source (i.e., [6], [14], [15]) and the perceived pleasantness of the stimuli (i.e., [6], [8], [16]). To effectively utilise crossmodal correspondences it is crucial to understand their nature and origin so that they can be better exploited.

Olfaction is the sense of smell. When volatile molecules enter our nasal cavity, our olfactory receptors detect these molecules this olfactory information is then projected via the olfactory bulb to other cortical areas where olfactory perception occurs [17]. A physical, perceptual, and semantic representation of the odour is formed via a neural signal transmitted in the olfactory pathway [18], [19]. Our nasal cavity contains thousands of olfactory receptors [20] believed to recognize specific chemical features [21]. The specificity and limit of detection of the human nose rely on the cross-reactivity of the olfactory receptors to produce the final perception of an odour. Olfaction is often considered a vestigial sense in humans that has been downgraded throughout evolution to make way for the dominant sense of vision [22]. However, there is increasing knowledge that olfaction is more acute than previously thought [22]. The research in this thesis primarily focuses on the use of olfaction in various areas, mainly because compared to the other senses (vision, touch, and hearing), the chemical senses (smell and taste) are relatively unexplored.

Perception in the real world is multisensory and often includes a combined input from visual, auditory, tactile, olfactory, and/or gustatory stimulation [23]. Olfaction, for instance, is often coupled with all the remaining senses to create its final perception, for example, enjoying your favourite meal. Our brain combines multisensory information to better comprehend our environment [24]. This integration process influences a person's interpretation and the subjective experience that goes with it [25]. Despite the advent of human-machine interfaces in everyday life, the senses used by or produced by these devices are still limited [26]. Typically, human-machine interfaces only stimulate two of our senses, these being vision and audition, and on occasion, touch is also stimulated, with smell and taste being largely ignored. The integration of additional senses with context (i.e., the smell of lavender along with a photo of lavender) can have a significant impact on the enjoyment and sense

of reality [27], consequently effecting the perceived quality of experience. Two means of enhancing the senses in a congruent manner (in a manner that's in agreement with what one would expect in a different sensory modality given a specific input into one sensory modality, such as the smell of lemon and the colour yellow) are considered in this thesis these are natural synaesthesia and crossmodal correspondences to aid in the creation of virtual synaesthesia. These ideologies were chosen as this is how the human brain can naturally combine the different senses. In other words, everyone has crossmodal correspondences, and these correspondences happen automatically. In the case of natural synaesthesia and select few individuals have a form of this phenomenon but this process happens automatically with these individuals.

In this thesis, the term "virtual synaesthesia" is defined as a design paradigm that uses unconscious reasoning to enhance and/or manipulate a multisensory experience without dominating the user's attention. Virtual synaesthesia attempts to accomplish this by considering how the brain naturally integrates information from one sensory modality to another and presenting stimuli that are congruent or incongruent with what the user is expecting in a different sensory modality to another. This ideology should, in theory, reduce the amount of processing the brain needs to do to derive reason out of the presented stimuli. Virtual synaesthesia uses the ideology of natural synaesthesia and crossmodal correspondences. This design paradigm can be employed in multiple areas such as designing human-machine interfaces, enhancing a virtual reality experience or even designing the packaging of a product. Virtual synaesthesia is an emerging field of research that aims to utilise multisensory integration in an overt, low-attention, and transparent fashion making the experience more human-orientated. Virtual synaesthesia takes the premise of real synaesthesia to augment human-machine interaction with more refined multisensorial capabilities leading to better designs, more enriched, and immersive experiences. Such devices could allow individuals to see smells, hear tastes or see beyond the visible spectrum of light via a computerised medium, unlike natural synaesthesia, where this happens automatically and without needing a device.

Despite the numerous cognitive benefits underlying natural synaesthesia, research into this phenomenon outside of cognitive psychology is still in its infancy; concerning the chemical senses (smell and taste), this area remains entirely unexplored in the published literature and to the author's knowledge. The main limitations behind such systems include understanding spatio-temporal throughput of the traditional sensors in humans and developing human-machine interfaces in a manner that best utilises the available bandwidth. In other words, providing too much information to a human user could result in sensory overload, where the user receives more input than what the brain can process. Therefore, utilising design paradigms that consider how the brain would naturally

combine information between senses may prove helpful towards reducing the bottleneck of sensory overlap while simultaneously presenting the same information, albeit in a different manner. The concept of virtual synaesthesia is not entirely new, although practically unexplored. The advantages of virtual synaesthesia over the traditional means of multisensory experience design aim to convey information from one sensory modality to another more intuitive and informatively. The terms artificial and virtual synaesthesia in this work is used interchangeably. Synesthetic applications span across multiple disciplines and are commonly used in marketing [13] and human-machine interfaces [11], [28] but are primarily used as a means to conform to the sensory expectations of an individual. In order to increase the psychological impact, these experiences need to be stimulated in a consistent and congruent manner [29]–[31]. Consistent and congruent stimulation can also maximise the amount of information that can be presented and retained as it will meet what the brain is expecting sensory. However, to do this, the psychophysical aspects need to be explored to find which sensory modalities are more likely to be 'bound' together and, consequently, the best way to express information from one sensory modality to another. An area of cognitive psychology, crossmodal correspondences, embodies this paradigm, albeit with little regard to areas of research outside of the discipline. depicts a conceptual framework for virtual synaesthesia, with the two main outputs being products and applications.

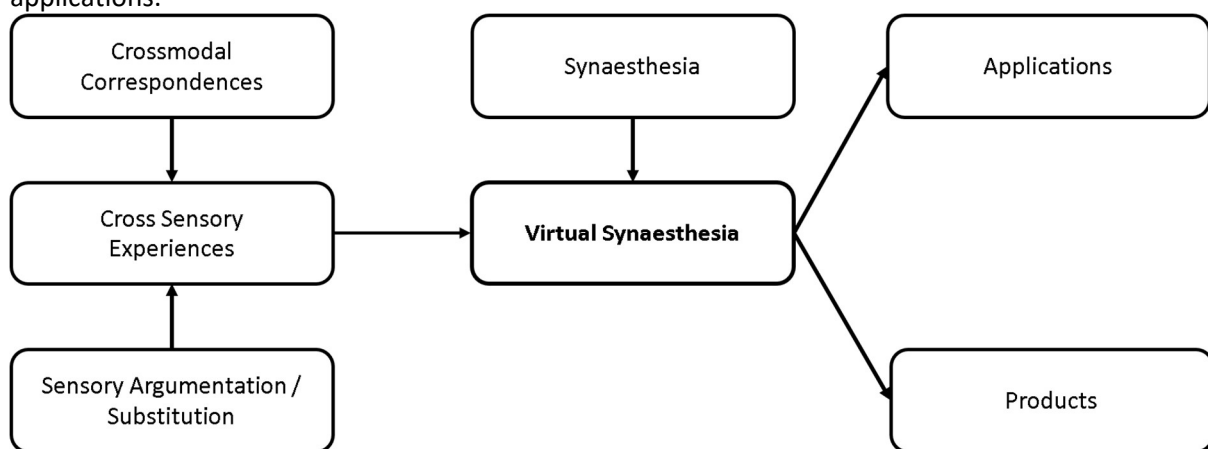


Figure 2. Diagram showing the various aspects of virtual synaesthesia.

From a bottom-up approach, the ideology of virtual synaesthesia can be beneficial to a variety of different areas. For example, product design where the concept of virtual synaesthesia can aid in the design of packaging in a manner that conforms to the sensory expectations of the user. Typically, product designers have the need to stimulate the senses in a semantically congruent manner (i.e., colouring a bottle of perfume the same colour as the target market would associate with the smell, for instance, the smell of lemon and the colour yellow). Designing it in this manner allows the company to benefit by increasing the perceived pleasantness and value of its product. This ideology also extends

to the application domain, where considering the sensory expectations for usage in a colour-sound sensory substitution device led to better performance in an associative memory task and showed higher gains in recognising realistic objects that featured colours [28]. These findings may stem from a lesser effect of sensory overload as the crossmodal bindings between colour-sound are being utilised in a congruent manner resulting in better utilisation of the wearer's unconscious pattern recognition and consequently enhancing their performance. Later in this thesis, the bottom-up design paradigm is used to create a human-machine interface based on the premise of odour-vision synaesthesia.

From a top-down approach, virtual synaesthesia may be helpful with everyday tasks. For instance, Billy Joel and Patrick Stump, lead vocalist for the band Fall Out Boys, both have Grapheme-colour synaesthesia and Chromesthesia (sound-to-colour synaesthesia) [32]. People with sound-colour synaesthesia typically exhibit traits for enhanced memory for sound stimuli [33], as well as enhanced pitch recognition, differentiation, and memorisation [34]. Considering these together, the phenomenology provided by sound-colour synaesthesia may prove useful for musicians and other careers that heavily rely on sound. Taking this conceptual ideology and replicating virtual forms of synaesthesia could, in theory, allow the cognitive benefits behind specific forms of synaesthesia to be replicated in the non-synesthetic population and provide inspiration for the development of semantically congruent human-machine interfaces (applications). For instance, one potential application in this regard could be giving aid to people with Anosmia; by taking inspiration from odour-vision synaesthesia, one could create a device to visualize smells in real-time, which would be beneficial for the wearer to, in essence compensate for their loss of the sense of smell. Another example of an application This could be useful for detecting hazards, such as, off milk or gas leaks. Although should not be considered as a replacement for more reliable measures for detecting gas leaks (i.e., a carbon dioxide detector). Such a device may also be useful for professional wine tasters or perfumers to determine the underlying olfactory notes. Later on, in this thesis the elements needed for the olfactory based top-down approach are explored and uncovered.

In this thesis, a bottom-up approach is utilised to create a human-machine interfaces using the ideology of odour-vision synaesthesia was done to demonstrate the usage of a bottom-up approach and to determine if the underlying cognitive benefits underlying natural synaesthesia a replicable on the non-synesthetic population. The underlying mechanisms needed for an olfactory-based top-down approach are then uncovered and probed. This thesis answers the following research questions:

1. Is it possible to replicate the underlying cognitive benefits of odour-vision synaesthesia? (see Chapter 4)
2. Do people have consistent correspondences between olfaction and an aggregate of different sensory modalities? (see Chapter 5)
3. What is the nature and origin of these correspondences? (see Chapters 6 and 7)
4. Is it possible to predict the crossmodal correspondences attributed to odours? (see Chapter 7)

From these research questions, the hypotheses for the work conducted in this thesis are that some of the cognitive benefits present in natural synaesthesia would still be present using an artificial form of this phenomenon. Secondly, people will have consistent correspondences between odours and the angularity of shapes, the smoothness of texture, perceived pleasantness, pitch, colours, musical genres, and emotions. Thirdly, hedonics, semantics, and the physicochemical features of the presented stimuli will contribute to the nature and origin of olfactory crossmodal correspondences. Finally, crossmodal correspondences will, at least in part, be predictable using the underlying physicochemical features.

1.2 Contributions

The contributions of the thesis are as follows;

- **Virtual Synaesthesia in Human-Machine Interfaces** [35]: As virtual synaesthesia is still in its infancy, it is important to highlight the benefits of considering virtual synaesthesia in human-machine interfaces as a design paradigm. The developed system incorporated the ideology of odour-vision synaesthesia and was used to highlight the potential benefits of implementing an artificial form of this phenomenon.
- **Crossmodal Correspondences of Olfaction** [36]: To further the knowledge of the consistent crossmodal correspondences that exist between odours and different stimuli, some of the associations people have to odours were uncovered. These include the angularity of shapes, the smoothness of texture, the perceived pleasantness, pitch, colours, emotional, and musical genres.
- **Analysis of Olfactory Crossmodal Correspondences** [36], [37]: The mechanisms that drive olfactory crossmodal correspondences are still not fully understood. To further increase understanding, the role between the following dimensions was explored. These include the

knowledge of an odour's identity, the role of pleasant and unpleasant odours, and their physicochemical properties.

- **Predicting The Crossmodal Correspondences Odours Using an Electronic Nose** [38], [39]: Incorporating olfactory crossmodal correspondences into products and applications is not feasible due to costly and time-consuming psychological investigation needed to have been conducted beforehand. To solve this issue, the role of the chemical and physical properties of odours in explaining their underlying crossmodal associations has been explored and shows that it is possible to predict these correspondences using an electronic nose.

1.3 Publications

The following publications are a direct result from [35]–[39] or a follow up work [40]–[43] from the research in this thesis. The publications listed below span multiple disciplines, namely engineering, computer science, psychology, and analytical chemistry.

1.3.1 Journal Publications

- [35] **R. J. Ward**, F. P. M. Jjunju, E. J. Griffith, S. M. Wuerger, and A. Marshall, "Artificial odour-vision synesthesia via olfactory sensory argumentation," *IEEE Sens. J.*, vol. 21, no. 5, pp. 6784–6792, 2020, doi: 10.1109/JSEN.2020.3040114.
- [36] **R. J. Ward**, S. M. Wuerger, and A. Marshall, "Smelling sensations: olfactory crossmodal correspondences," *J. Percept. Imaging*, vol. 4, no. June, pp. 1–12, 2021, doi: 10.2352/j.percept.imaging.2021.4.2.020402.
- [39] **R. J. Ward**, S. Rahman, S. Wuerger, and A. Marshall, "Predicting the crossmodal correspondences of odors using an electronic nose," *Heliyon*, vol. 8, no. July 2021, p. e09284, Jul. 2022, doi: 10.1016/j.heliyon.2022.e09284.
- [40] F. P. M. Jjunju, D. E. Damon, D. Romero-Perez, I. S. Young, **R. J. Ward**, A. Marshall, S. Maher, and A. K. Badu-tawiah, "Analysis of non-conjugated steroids in water using paper spray mass spectrometry," *Sci. Rep.*, vol. 10, no. 1, pp. 1–12, 2020, doi: 10.1038/s41598-020-67484-7.
- [41] S. J. Friston, E. J. Griffith, D. Swapp, S. Julier, C. Irondi, F. P. M. Jjunju, **R. J. Ward**, A. Marshall, and A. Steed, "Consensus Based Networking of Distributed Virtual Environments," *IEEE Trans.*

Vis. Comput. Graph., vol. 2626, no. c, pp. 1–15, 2021, doi: 10.1109/TVCG.2021.3052580.

- [42] S. J. Friston, E. J. Griffith, D. Swapp, S. Julier, C. Ironi, F. P. M. Jjunju, **R. J. Ward**, A. Marshall, and A. Steed, “Quality of Service Impact on Edge Physics Simulations for VR,” *IEEE Trans. Vis. Comput. Graph.*, vol. 27, no. 5, pp. 2691–2701, 2021, doi: 10.1109/TVCG.2021.3067757.
- [43] **R. J. Ward**, F. P. M. Jjunju, I. Kabenge, R. Wanyenze, E. J. Griffith, N. Banadda, S. Taylor, and A. Marshall, “FluNet: An AI-Enabled Influenza-like Warning System,” *IEEE Sens. J.*, vol. 21, no. 21, pp. 24740–24748, 2021, doi: 10.1109/JSEN.2021.3113467.

1.3.2 Conference Proceedings

- [37] **R. J. Ward**, S. M. Wuerger, and A. Marshall, “Visual-odour correspondences are partly explained by chemical features,” in *I-PERCEPTION*, 2021, vol. 12, no. 4, p. 10.
- [38] **R. Ward**, S. Rahman, S. Wuerger, and A. Marshall, “Predicting the colour associated with odours using an electronic nose,” in *1st Workshop on Multisensory Experiences - SensoryX’21*,

1.4 Organisation of Thesis

The organisation of the remainder of this thesis is as follows;

- **Chapter 2** presents an overview of the encompassing aspects of virtual synaesthesia. These include natural synaesthesia, artificial/virtual synaesthesia and the different areas of research that embody this phenomenon, namely multisensory experiences, crossmodal correspondences, and sensory augmentation/substitution systems.
- **Chapter 3** focuses on the experimental methodology used throughout this thesis, namely the L*a*b* colour space and electronic noses.
- **Chapter 4** covers the development of a novel human-machine interface that argues the ideology of odour-vision synaesthesia by transforming odours in the vapour phase into the visual domain using a custom-made electronic nose. The results of this chapter show the sensory augmentation system has the potential to increase human odour identification comparable to that of natural synaesthesia and highlights the prospects for augmenting human-machine interfaces with an artificial form of this phenomenon.

- **Chapter 5** covers the crossmodal correspondences of odours between the angularity of shapes, the smoothness of texture, perceived pleasantness, pitch, colour, emotional, and musical dimensions. The findings of this chapter indicate that people have consistent associations between odours and a variety of different sensory modalities.
- **Chapter 6** covers the nature and origin of correspondences using the underlying hedonic, semantic, and physicochemical features underlying the presented olfactory stimuli. The findings of this chapter indicate that hedonics plays a more notable role in explaining crossmodal correspondences than semantics and that the physicochemical features of olfactory stimuli also play a contributory role.
- **Chapter 7** further probes the link between the physicochemical features playing a role in crossmodal correspondence. The results of this chapter indicate that the crossmodal correspondences of odours can be predicted using their physicochemical features.
- **Chapter 8** discusses the implications of the studies conducted in this thesis, the limitations and benefits, and proposes future work relating to the topics covered in this thesis.

Chapter 2 Background & Related Work

2.1 Introduction To The Background & Related works

Conveying information from one sensory modality to another is a well-established concept, albeit isolated between disciplines. The use of basic sensory substitution solutions (i.e., walking sticks and braille) have shown the importance of conveying information from one sense to another. Despite the unparalleled advantages of these solutions outside of substitution or augmentation of the visual modality, it is relatively unexplored and nominal for the chemical senses.

Human perception of the surrounding world is limited to a thin slice of perception we call our reality. Additional information can be conveyed that is not directly perceivable, either because it is outside our perceivable range or not directly accessible to some individuals; examples include [44], [45] and [46], [47], respectively. In nature, information that is not perceivable by humans still plays a vital role in our survival; honeybees, for instance, use ultraviolet light to find patterns that help them find flowers to pollinate. However, the traditional approaches to convey information from one sensory modality to another typically come with the disadvantage of information overload, where either more information is provided than what the human brain can process or the information is conveyed in a non-meaningful manner leading to months of training to understand the output of the system. The main limitations behind such systems include the understanding of the spatio-temporal throughput of the traditional sensors in humans and the development of brain-machine interfaces in a manner that best utilises the available bandwidth. The idea of augmenting the user's perception through computers can, at least in part, be traced back to Douglas Engelbart [48] where he defines the goals of a conceptual framework as:

- Finding the factors that limit the effectiveness of the individual's basic information-handling capabilities in meeting the various needs of society for problem-solving in its most general sense.
- Developing new techniques, procedures, and systems that will better match these basic capabilities to the needs' problems, and progress of society.

Progressing this ideology, the coupling of the neurological condition known as synaesthesia can provide overt, low attention, and transparent interfaces with the benefits closely resembling the advantages of real synaesthesia. As virtual synaesthesia is an emerging area of research, there is only a small body of research that has been conducted with the exemption of crossmodal correspondences;

the coupling of these areas with the chemical senses is nominal or non-existent. The adaption of virtual synaesthesia is usually accomplished via virtual or augmented reality devices, with very little consideration for the psychological side of the investigation. The idea of "virtual synaesthesia" or "artificial synaesthesia" is a relatively new concept, some prior work in this area includes; [45], [49]–[51]. However, these lack the scientific rigour of an interdisciplinary approach. The remainder of this chapter covers the background for all major aspects of this work with a focus on olfaction where possible. This research focuses on olfaction as its an important emerging area of research and it is not sufficiently explored.

The rest of this chapter provides the background and related works needed to answer the above research questions. It is split into the relevant areas and is organised as follows: Section 2.2 covers the background, causes and mechanisms, as well as related work behind natural synaesthesia. Section 2.3 covers the background and related works for virtual/artificial synaesthesia. Section 2.4 covers the background and related works for multisensory experiences. This topic was covered as this is one of the major domains in which the concept of virtual synaesthesia can be applied. Section 2.5 covers the background, causes and mechanisms, and related works for crossmodal correspondences. This was covered because some of the literature denotes crossmodal correspondences as a weak form of synaesthesia. However, this is mainly covered as it gives an insight into which senses are 'bound' together in the general population. Section 2.6 covers the background and related works for sensory substitution and augmentation systems. This was covered as this is another one of the domains in which the concept of virtual synaesthesia can be applied. A sensory augmentation system is also developed in one of the research chapters. The chapter is then concluded by providing some background information on the technical equipment either developed for or used for the experiments reported in this thesis.

2.2 Olfaction and its Multisensory Experience

2.2.1 Introduction to olfaction and its multisensory experience

Olfaction is the sensation of smell that results from the perception of odours in the vapor phase. Olfaction has many functions, including pheromones, detecting hazards, playing an essential role in taste, and helping to shape our multisensory experience along with the subjective interpretation that goes with it. When volatile molecules enter our nasal cavity, our olfactory receptors detect these molecules, this information is then projected via the olfactory bulb to the olfactory cortex [52]. A

physical and perceptual representation of the odour is formed via a neural signal transmitted in the olfactory pathway [18] and can be described semantically [19] by many types of perceptual qualities (e.g., woody, floral, minty, etc.). This pathway shares a common neural substrate called the limbic system, which deals with mood and emotional processes, namely the Amygdala [53]. Our nasal cavity contains thousands of olfactory receptors [20] that are believed to recognize specific chemical features [21]. Olfactory perception is rooted in the chemical properties of volatile molecules [17]. For instance, odours with low molecular weight, low structural complexity, or containing sulfur are often perceived to be unpleasant [19], [21], [54], [55]. Humans possess thousands of olfactory receptors, which enable us to finely discriminate a wide range of odours. Bushdid *et al.* [56] controversially [20], [57] claim that humans are capable of discriminating more than one trillion odours. The odour ethyl mercaptan can be detected around one part per billion [58], and desensitization to odours can be modulated by attentional factors [59]. This tells us that the human sense of smell is remarkable for detecting and discriminating odours, albeit flawed at identification, even for commonly encountered odours [60]. Odour naming can be a difficult task due to the “tip of the nose” phenomenon [61]. The flawed identification of odours may be attributed to ecological, cultural, or genetic factors; for example, languages containing many smell lexicons (smell-related words) demonstrate improved odour identification (see [22] for a review). Psychophysical evidence suggests that the pleasantness of odours is encoded in the physicochemical structure of odorous molecules [62]. The specificity and limit of detection of the human nose rely on the olfactory receptors' cross-reactivity to produce the final perception of an odour. Olfactory perception and successive neural representations are modulated or influenced by several different factors, such as expectations [63], context [64], multisensory convergence [65], in utero neuroanatomical development [66], and is a heavily learned process [67]. However, a portion of olfactory perception is suggested to be innate and hard-wired [62], [68]–[70]. Our brain constantly combines information from different sensory modalities to better comprehend our surrounding environment [24]. In other words, the presence of olfactory stimuli is usually accompanied by a visual, textural, and/or gustatory experience simultaneously. Our brain will integrate the information from these different sensory modalities. The areas in the brain that include multisensory processing include, but may not be limited to, the superior temporal sulcus, Heschl's gyrus, the inferior frontal gyrus, and the middle intraparietal sulcus [71]. The involvement of various brain areas indicates that multisensory interactions occur at multiple brain processing stages. The human olfactory system has multiple levels of plasticity [72], [73] that reflect a beneficial evolutionary mechanism to reject hazardous compounds. For instance, the odour ethyl mercaptan is often added to propane as a warning agent [58], [74]. Hazardous compounds are also found in fermented food,

and through experience, a person can learn that exceptions exist; for example, kimchi is a fermented Korean dish that can be both healthy and tasty but with a pungent smell. Another example of this with the same premise is the Surströmming herring. This integration process influences a person's interpretation and the subjective experience that goes with it [25]. In other words, when designing multisensory experiences, it is important to consider the information being presented in the other senses rather than focusing on the one of interest. For instance, multisensory semantic congruency has also been shown to influence our decision process, the perceived value, and the perceived quality of experience. Most importantly, incongruency between the actual and expected attributes of an experience could lead to a “disconfirmation of expectation” [75], which results in the experience being perceived as less pleasant [75]. Disconfirmation of expectation is most likely going to occur in multisensory experiences when the input into the different sensory modalities is designed in a unimodal manner instead of considering how the presented stimuli interact and are perceived together. Considering this information together, one means of making the stimuli semantically congruent is crossmodal correspondences, therefore, making it an important metric to consider. The caveat of considering crossmodal correspondences in the design process is that it usually requires extensive human trials to uncover what stimuli are bound together in the different sensory modalities. Due to this it has largely been ignored by the engineering / computer science communities up until recently. More information on multisensory experiences is covered in Section 2.5 as well as crossmodal correspondences is covered in Section 2.6.

The most comprehensively studied aspect of human olfaction is hedonics; pleasantness plays a notable role in olfactory perception. Hedonic determination is arguably the most dominant function of olfaction. All humans can invariably say about odours is whether they are pleasant or not [74]. When ordering a set of odourants based on the variance (principal component scores) of their physicochemical descriptors (i.e., fruity, floral, and aromatic), they also end up relatively ordered in terms of pleasantness [62]. Pleasantness has also emerged as a dominant dimension in multidimensional analyses of perceptual odour spaces [62], [76]. Most literature converges and suggests that pleasantness is a primary perceptual dimension of olfaction. Psychophysical evidence suggests that the pleasantness of odours is encoded in the physicochemical structure of odourous molecules [62], [70], [77], [78], thereby suggesting a link exists between odourous stimuli and crossmodal correspondences. Similarly, in crossmodal correspondences, the main mediating factor is assumed to be hedonics [7], [8], [16], [79], [80], and when considering semantic involvement, knowing what the odour is or not will have a knock-on effect on hedonic (emotional) dimensions [36]. In other words, the primary dimension in both crossmodal

correspondences and human olfaction is suggested to be hedonics and therefore implying a common denominator.

2.2.2 Related Works

The physicochemical features of odours refers to the physical and chemical attributes of olfactory stimuli. This can either be at a molecular level (i.e., atom count, molecular weight ect...) [62] or at a more abstract level, such as the signals obtained from electronic noses [70]. There has been some work relating the physicochemical features of odours to different areas of perception, namely the perceived pleasantness [62], [70], semantic descriptors given to the participants to be rated [78], and "brightness" [81]. "Brightness" was once largely considered an amodal dimension shared across sensory experiences; however, today, it is considered a visual property. A long-standing suggestion is that the perceived brightness or intensity of the stimuli may be used to make crossmodal matches [6], [81]. von Hornbostel believed that "brightness" was a characteristic of all sensory modalities and suggested that these "brightness" judgments were related to the molecular structure [81].

A few studies have attempted to link the physicochemical features of odours to human perception. Haddad *et al.* showed that it was possible to connect the series of electrical signals produced by the MOSES II e-nose to the perceived pleasantness of odours. A neural network with a singular hidden layer and five neurons were used to extract the pleasantness of odourants. The input consisted of manually extracted features (i.e., signal max) [70]. They concluded that their findings might be attributed to a partial innate and hard-wired link in olfactory perception. Wu *et al.* improved upon the model initially presented by Haddad *et al.*, incorporating a non-uniform sampling algorithm as the feature extraction method, adding additional odourants to the dataset, and developing a convolutional neural network for the classification of the perceived pleasantness [77]. There has also been work linking molecular features to odours. Khan *et al.* linked descriptors provided by Dravnieks' *Atlas of Odor Character Profiles*, where \approx 150 olfactory experts ranked 160 odours against 146 verbal descriptors [62]. They found that when ordering physicochemical properties based on their variance, they also get roughly ordered by perceptual pleasantness. This, in turn, allowed them to predict the pleasantness of molecules. Zarzo found that hedonic judgments are correlated with the molecular size indicating that larger molecules containing oxygen are more likely to be perceived as pleasant, and the inverse can be said about sulphur compounds and carboxylic acids [82]. Kerman *et al.* findings suggest that the more complex odours evoked more olfactory notes and more pleasant responses in olfactory experts and naïve subjects [21].

Schiffman *et al.* showed that the perceived intensity of odours could be linked to the two different e-noses (NST 3320 and Cyranose® 320) [83]. Burl *et al.* used an e-nose to predict the perceptual descriptors of odours, for example, "Minty" and "Sour". Their results also revealed that several regression models needed to be developed, as each model was only capable of reliably predicting a few of the descriptors [84]. Overall, these results show that the physicochemical features of odours transduced by an e-nose can be linked to different aspects of perception. However, it is still unknown if the physicochemical features of odours can be linked to crossmodal correspondences to allow for their prediction. The intensity of stimulus has also been shown to produce consistent crossmodal correspondences; odour intensity and the luminance of colour [85], odour intensity and the angularity of shapes [7], taste intensity and pitch [86]. Kemp and Gilbert found that subjects consistently matched colours to odours over time [85]. Their results also indicated that the darker the colour selected by the participants, the higher the perceived intensity. Hanson-Vaux *et al.* findings suggest that both hedonics and the perceived intensity of odours are important factors, with more intense and unpleasant odours associated with an angular shape [7]. Wang, Wang, and Spence explored the role that intensity and hedonics play in explaining the correspondences between taste and pitch [86]. Overall, their results revealed that taste-pitch correspondences are primarily mediated by the quality of the taste stimuli and to a lesser extent, the intensity of the taste. Their results also revealed that these correspondences might be mediated by hedonics. In contrast to the correspondences above, the intensity of the stimuli is a low modal stimulus property, and if intensity does indeed play an important role in crossmodal correspondences, it should, in theory, it should be possible to predict the crossmodal correspondences of an odour using the stimulus properties (physicochemical features). Moreover, it has been shown that it is possible to link the physicochemical features of odours transduced by an electronic nose to the intensity of an odour [78], [83].

Sage and IBM proposed a crowd-sourced challenge entitled DREAM Olfaction Prediction Challenge. The challenge resulted in several models that could predict the intensity, perceived pleasantness and eight of the nineteen semantic descriptors (i.e., "garlic", "fish", and "sour"). These findings confirm the works of prior publications and further highlight that the physicochemical features of odours can be used to predict their perception. Additional mechanisms that could link the physicochemical features of odours to crossmodal correspondence could be complexity or intricacy [8], [21], [87], [88] and hedonic mediation [62], [70], [82]. The notion of intricacy and complexity of the stimuli could be embedded in both the physicochemical features and the perceptual ratings provided by the participants. That is, less complex odours could produce a simpler response in the electronic nose. Comparatively, if less intricate stimuli produced less variance in participants' ratings,

this may be a means of mapping the olfactory stimuli from one space to another. However, the notion of intricacy is a recent addition to the literature presented by Snitz *et al.* [87] and needs further work to confirm its validity. In vision, a predictive property of colour is the wavelength of light. In hearing, the frequency of sound is a predictive property of tone. However, in olfaction, it is not currently possible to predict the smell of a molecule using its molecular structure [89]. This is presumably because the dimensionality of olfactory perceptual space is unknown and olfactory stimuli do not vary continuously in stimulus space [76], [89].

2.3 Synaesthesia

2.3.1 Introduction

Synaesthesia is an idiosyncratic neurological condition that affects approximately 1 in 2000 people [1] and is characterised as both automatic and involuntary [90]. This phenomenon occurs when input into one stimulus provokes a concurrent perception in a second modality, usually different [91]. Sounds, for instance, may trigger the perception of the colour [92], words may produce the perception of taste [93], and smells can produce the perception of both shape and colour [94]. The most common inducers for synaesthesia are linguistic (e.g. words, letters and digits) with the most common concurrent being visual [95]. Synesthetes are consistent in their perceptual experiences weeks or even months later (e.g. [96], [97]) often producing a test-retest accuracy greater than 80% in grapheme-colour synesthetes. The perceptual experiences of grapheme-colour synaesthesia are diverse in the sense that the simultaneous perception of colour superimposed onto the grapheme may vary in both colour and photism [98], meaning these experiences can be perceived in more than one way, being in the mind's eye and projected into an external space. The heterogeneous nature of these findings could be applied to other forms of synaesthesia, such as odour-vision. There are at least 60 types of synaesthesia documented [99], and any permutation of the five senses is theoretically possible. Synaesthesia first came under scientific scrutiny in the 1800s. The early causes and mechanisms behind this neurological condition were that people learnt these crossmodal mappings due to repeated exposure, for example, the colouring in a child's alphabet learning book. For example, in the case of colour-grapheme synaesthesia, early research hypothesised that the coloured overlays superimposed onto the graphemes were learnt from the books and the classrooms in which they were taught. Thus the concurrent synesthetic colour effect was presumed to be aligned with the exposure they had to the colour-grapheme pairing. More hypotheses to explain the causes and mechanisms underlying why synaesthesia occurs have emerged to date. It was not until around 1995 that research

in this area began to gain interest from the scientific community. Even then, the research in this area is predominantly from a psychological perspective. Even from an early stage, it was a common view that synesthetes had certain cognitive benefits in tasks, such as remembering sequences, mathematics, and many other learning challenges. Recently there has been an increase in research looking into the impacts of learning on synaesthesia and now argue that conceptual factors and learning are crucial factors for developmental synaesthesia [100]–[103].

2.3.2 Causes and Mechanisms

The cause of synaesthesia is currently an active research field. The two predominant theories are disinhibited feedback [104] and a reduction in pruning [105]. It may be the case that rare genetic variants [106], [107] result in a reduction in pruning [105] and/or disinhibited feedback [104], allowing individuals to retain their synesthetic perception. Recently it has been shown that the underlying mechanisms may be different for the different forms of synaesthesia [33], which would explain the diversity of the underlying causes and mechanisms. A person may experience synesthetic experiences in a few different ways for instance in the case of developmental synaesthesia; neurological signals always propagate to specific areas in the brain; these signals are backpropagated via feedback connections. Commonly, these signals are 'inhibited' or 'pruned' which prevents synesthetic perception from occurring; however, this may not be the case for some individuals [104], [105]. The synesthetic perception behind developmental synaesthesia occurs consistently and begins during early childhood [108]. It is hypothesised that forms of synaesthesia stem from a genetic basis [106], [107] and is more common in women than men [1], [91]. Synesthetic perception may also be acquired by brain injury [109] or sensory deafferentation (a loss of sensory input from a portion of the body) [108], [110], and temporarily induced by drugs, such as, mescaline or LSD [111]. The most researched form of synaesthesia is grapheme-colour, where graphemes produce a simultaneous perception of colour superimposed on the grapheme. Both the advantages and disadvantages are pertaining to explicit forms of synaesthesia. For instance, in the case of odour-colour synaesthesia, synesthetes have increased odour and colour discrimination [94]. However, the perception will be obtrusive on the synesthete's visual field. Grapheme-colour synaesthesia provides improved recall from simple and paired-associate word lists [3], [112], [113], and controversially have superior recall when recalling large matrices [112], [114]. Showing incongruent colour patches along with a simple equation produces slower reaction times as opposed to a congruent colour patch [115]. Consequently, understanding how multi-sensory integration affects the other senses would prove pivotal to create artificial forms of synaesthesia.

2.3.3 Related Work

The related work of interest pertaining to this thesis are odour-vision synaesthesia. However, due to the fact this form of synaesthesia is rare among synesthetes research has also been conducted among other forms of synaesthesia; odour-vision synaesthesia was of interest as it fits in well with the olfactory theme for the rest of this thesis. Little research has been conducted on odour-vision synaesthesia, albeit not surprising as only 7% of synesthetes have odour-colour synaesthesia [116]. Speed and Majid [94] tested six odour-colour synesthetes and seventeen control subjects on their odour and colour cognition using a series of battery tests. The battery tests consisted of two days of trials with the second day predominantly used to test for consistency over time of the synesthete. Five tests were conducted on both days, with odour-colour associations and odour naming and rating tests being conducted on both. The results revealed that odour-colour synesthetes have enhanced odour and colour discrimination compared to non-synesthetes. The latter paper was used in Chapter 4 to determine if its findings were comparable to that of natural odour-vision synaesthesia. Russel, Stevenson, and Rich [117] performed similar experiments with odour-vision synesthetes. Their findings revealed that hedonics and semantic knowledge of an odour is a dependent factor that contributes towards explaining the concurrent shape/colour visualisation. Due to the sparse literature in regard to odour-synaesthesia the rest of this section explores the cognitive benefits behind colour-grapheme synaesthesia as it is the most widely researched form of this phenomenon and will give some insight into the potential benefits of augmented multisensory experiences with an artificial form of synaesthesia. Dixon *et al.* [115] tested a grapheme-colour synesthete using a modified Stroop test, revealing that incongruent colour patches relating to the individual's perceived experience induces a slower reaction time. Ramachandran and Hubbard [118] performed a series of tests on grapheme-colour synesthetes leading to the conclusion that the synesthetic experience is a sensory effect rather than cognitive. In other words, the synesthetic experience is induced automatically by the brain rather than involving conscious thinking, remembering and/or reasoning. They also showed that graphemes presented in peripheral vision did not induce a concurrent perception which is contradictory to prior findings. Simner *et al.* [119] findings suggest that the most common form of synaesthesia is coloured days, there is no difference between forms of synaesthesia and gender. They also found that the commonness of synaesthesia is eighty-eight times higher (4.4%) than previously assumed in comparison to the standard 0.05%. Colzolo *et al.* [120] attempted to teach colour-grapheme synaesthesia using books with coloured letters. The participants were able to implicitly learn the associations between the colours and the graphemes. Four to six months later, the colour-grapheme associations remained stable and produced a high test-test accuracy. Bor *et al.* [121] taught eight out

of fourteen participants colour-grapheme synaesthesia after a nine-week training period; participants reported synesthetic phenomenological. In their second experiment, twelve out of fourteen participants implicitly learnt the associations. These findings indicate that synaesthesia can be taught to individuals; albeit to an unknown extent, indicating that their integration into human-machine interfaces could potentially teach the subjects the implemented form of synaesthesia. It is important to note that there are two types of synesthetic perception the mind's eye and projected into an external space; the latter is an example of the mind's eye synaesthesia. Mind's eye synaesthesia, in this case, seems to be associative in nature, presenting similarities with crossmodal correspondences, which might even be one in the same. It is highly unlikely that the form of synaesthesia where the concurrent perception is projected into an external space, can be taught, although a couple of papers do make this claim. This is discussed later on in the thesis. Table 1 shows a sample of cognitive benefits of different forms of synaesthesia and could be used as a template to enhance human-machine interfaces with a desired concurrent effect. This is explored in Chapter 4. It is important to note their may be drawbacks for specific forms of synaesthesia; however, in the literature this is rarely covered. Visuo-space synaesthesia also called sequence-space synaesthesia is a condition where an individual perceives a physical position of an ordered list, such as the numbers and dates.

Type of Synaesthesia	Cognitive Benefits	References
Grapheme-colour	Memory Recall (word lists & word pair associations).	[3]
Grapheme-colour	Memory recall (word lists).	[122], [123]
Grapheme-colour	Memory recall (word pair associations).	[112]
Grapheme-colour	Colour recognition and memory.	[123], [124]
Grapheme-colour	Improved vocabulary and academic self-concept in children.	[125]
Grapheme-colour	Enhanced colour-related recall.	[33]
Grapheme-colour	Enhanced autobiography memory.	[4]
Grapheme-colour	Memory performance relating to unconscious knowledge.	[126]
Visuo-space	Enhanced ability to remember meaningful dates.	[127]
Visuo-space	Enhanced ordinal judgments about space.	[128]
Visuo-space	Enhanced cognitive manipulation of time-based information.	[129]
Odour-colour	Enhanced odour and colour discrimination.	[94]
Sound-colour	Enhanced memory for sound stimuli.	[33]
Sound-colour	Enhanced pitch recognition, differentiation, and memorisation.	[34]
Mirror-touch	Enhanced facial expression recognition.	[130]
Mirror-touch	Changes in self-recognition.	[131]
Various	Higher recognition memory.	[33]
Various	Perceptual processing and creativity.	[2]

Table 1. Shows the cognitive benefits underpinning different forms of synaesthesia along with their corresponding references.

2.4 Artificial Synaesthesia

2.4.1 Introduction

Not much research has been done on "artificial" or "virtual" synaesthesia as the area is still in its infancy. However, in recent years interest in this field has slowly been increasing. The field of virtual synaesthesia expands into multiple fields, including computer science, engineering, the arts, marketing, food science, product design, and psychology.

One of the current problems in human-machine interaction is functionality and sensory overload. Functionality overload is when these devices are overloaded with unnecessary features, even though 80% of their users will only use 20% of the provided features [132]. This makes the system unnecessarily complex for the typical consumer. Sensory overload occurs whenever there is more input into a user's senses than their brain can handle. The concept of artificial synaesthesia, among other things, can provide helpful insights towards removing these bottlenecks. It can do this by

providing information in overt and more transparent fashion (easier to perceive) by leveraging the way the brain naturally combines different senses, be it crossmodal correspondences or natural synaesthesia. Although natural synaesthesia isn't experienced by the vast majority it can still provide an insight into which senses are more likely to be 'bound' together especially in the case of developmental synaesthesia. This concept relies on the integration of subtle information to the real-world as efficiently as possible. Artificial synaesthesia can provide information in an overt, low attention, and transparent fashion by providing information from either one sensory modality into another or provide information outside the bounds of traditional perception; it also has the added benefit of, at least in part replicating the cognitive benefits behind natural synaesthesia. Moreover, the main goal of the field is to bridge the divide between the real and virtual to enhance the performance of computers and human-machine interfaces. Bridging this divide will allow for more intuitive interfaces making the overall experience more seamless with reality which should make the overall experience easier to grasp and more informative for the user. A schematic representation of the artificial synaesthesia paradigm is shown in Figure 3. From a basic point of view a human will wear a wearable device of some sort (i.e., mobile AR/VR headset, vibrotactile belt, etc.). The device will feed information to the user and the user may interact with the device. The wearable computer will pull data from sensors that are connected to the wearable computer physically or wirelessly. The sensors could collect information from a different sensory modality than how it is being presented (i.e., displaying olfactory information in a visual medium, or converting vision to haptic). This will then be fed into a synesthetic computing engine to turn the collected data into a concurrent using the ideology of synaesthesia or crossmodal correspondences. This will then be fed back into the main wearable computer component. The output of the synesthetic computing engine is the output displayed to the user. This process will repeat indefinitely while the device is powered on. It is important to note that this ideology goes slightly outside the bounds of traditional synaesthesia and also includes the presentation of information that the human senses may not initially be able to perceive.

Artificial Synaesthesia

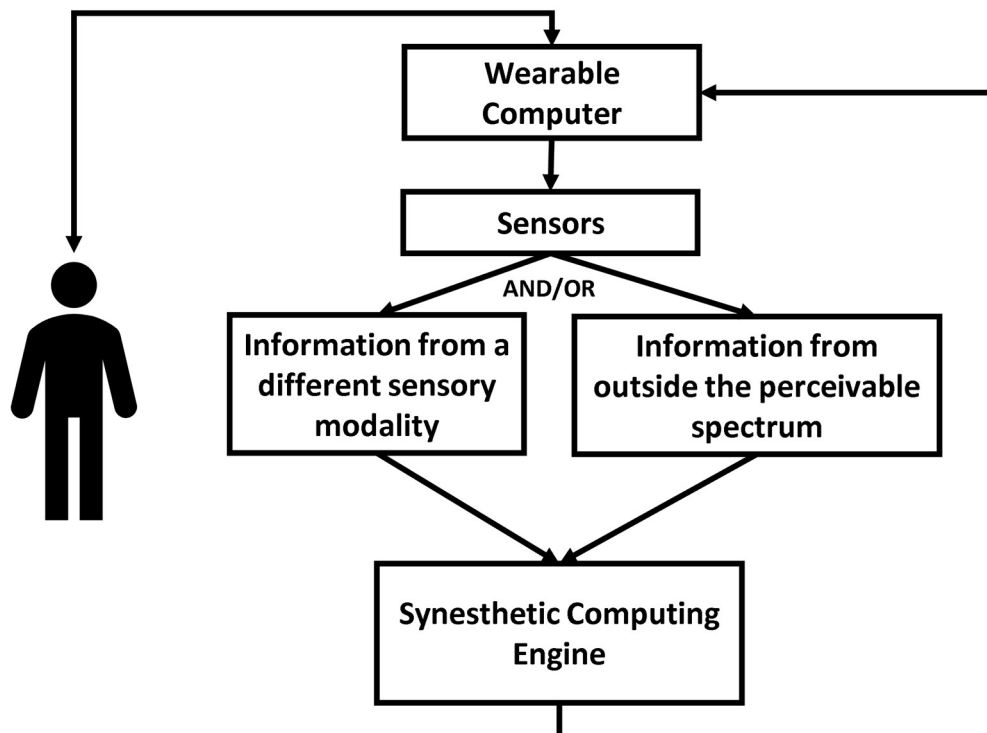


Figure 3. A schematic representation of an artificial synaesthesia device.

2.4.2 Related Works

Some forms of artificial synaesthesia have been investigated; Plouznikoff *et al.* [49] created a head-mounted display that replicates grapheme-colour synaesthesia. Their results suggest that short-term memory recall (digit matrices) and visual information search times can be improved with the artificial emulation of synaesthesia. Konishi *et al.* [133] created a suit capable of augmenting the traditional visual, audio paradigm with haptics. This suit has 26 vibrating actuators that are triggered by sound waves. Foner [45] created a system that converts light into sound. This allows for the sonification of both perceivable and not perceivable sources of light, allowing for the detection of camouflage in a forest environment. Kim *et al.* presented flexible thin, filmed inorganic phosphors embedded in an electrically insulating and piezoelectric polymer to simultaneously recognise auditory and visual stimuli to create a platform for realising artificial vision-sound synaesthesia [134]. Xiaochen *et al.* provided a design ideology for multimodal interfaces based on the concept of synaesthesia and claimed that the incorporation of this paradigm would enhance human-machine interaction to be more efficient and natural [135]. They stated that “In the study of multimodal interface design based

on synaesthesia effect it is necessary to understand the formation and composition of each sensory channel so that the corresponding relationship between various channels can be found and utilized to trigger one another". Specifically, here is where envisioning the ideology of natural synaesthesia and crossmodal correspondences comes into play. As this is how the brain combines or merges senses and therefore presents an avenue for enhancing the assimilation of human-machine interfaces and product design. In terms of synaesthetic design, Lee *et al.* explored using the concept of synaesthesia as an interactive design material source for HCI design [136]. They present a card-based tool that allows designers to use the translative property of synaesthesia for ideation. This card-based tool allows you to match an inducer with a concurrent (i.e., sound and colour) as inspiration for your design. They trialled this card system on 10 participants; 90% of the participants agreed that the tool allowed them to create unusual combinations which they would not normally conceive. Although an interesting approach in terms of HCI, this may not be a useful approach in the sense that there would be better mappings from one sense to another (i.e., the sound would be better matched to vision rather than gustation). This could be refined further to provide an agreement percentage between the paired modalities, whereby a higher number would indicate a more robust agreement between the two senses. Merter created a handbook entitled "Synesthetic Approach in the Design Process for Enhanced Creativity and Multisensory Experiences" [137]. They propose using synaesthesia as a multisensory design method to open up new ways of interpreting the design process. They propose a six-step process to archive this, as stated by Merter [137]:

1. *Deconstruction: The product is conceptually deconstructed first into its sensory components, and then to other physical/perceptual components depending on the content and context, through brainstorming, mind-mapping etc. for analysis.*
2. *Identification: The keywords/sensory adjectives are identified for each sensory component, through brainstorming etc., in order to be used for cross-sensory associations.*
3. *Placement: The keywords/sensory adjectives are placed onto the multi-layered cylindrical model in order to be used for sense-based ideation.*
4. *Ideation and Representation: The layers of keywords/sensory adjectives constituting the cylinder are turned to be matched for ideation. Each set of keywords/sensory adjectives is elaborated through the utilization of ideation and representation mediums in order to generate materialized forms of the set of layers.*
5. *Reconstruction: The materialized forms of the layers of the cylinders of different components are cross-matched on a sensory basis to reconstruct the conceptual product, through 2D and 3D mediums.*
6. *Finalization: The concept is finalized in 2D and 3D forms for further development [137].*

Although the work presented by Merter [137] and Lee *et al.* [136] provides a novel insight into designing multisensory experiences, it would be interesting to employ these paradigms in human-machine interfaces. However, one would need to be careful to use permutations of the senses that

would be congruent with each other either semantically or synthetically in order to maximise learning and increase the spatiotemporal throughput of such as device. Most of the work in this area focuses on augmenting human-computer interfaces with information outside of the range of human perception, which is comparable with sensory augmentation devices. This is discussed in more detail in Section 2.6. Most of the literature presented in this section outlines a device for artificially replicating a form of synaesthesia or proposes a “synesthetic” design process. However, they could be better if the rigour of an interdisciplinary was considered, and it would be greatly beneficial if human trials were conducted to determine how well these devices perform, as well as to uncover the extent to which artificial synaesthesia can be replicated rather than the mere creation of a capable device. The work presented by Merter [137] and Lee *et al.* [136] could prove helpful in the creation of artificial synaesthesia. However, one would need to be careful in picking the most optimal concurrent effect. An essential limitation of artificial synaesthesia and all multisensory experiences is that vision usually dominates [138]. This dominating aspect of vision may cause people to realise a mismatch between information from one sensory modality (e.g., olfaction) and vision. Therefore, it would be beneficial to convey cross-sensory information using vision. For instance, one may want to convey the information of odours to a different sensory modality, and the best way to do this would be through vision. In other words, more attention will be paid to the olfactory information presented visually rather than, for instance haptically; albeit this could be rather intrusive if not presented in a subtle manner.

2.5 Multisensory Experiences

2.5.1 Introduction

Multisensory experiences in human-computer interaction (HCI) is an ongoing research field attempting to augment immersive experiences with the five senses (vision, audition, touch, olfaction, and gustation). Our brain constantly combines information from different sensory modalities to better comprehend our surrounding environment [24]. Information from these sensory modalities influences a person’s interpretation and the experience that goes with it [25]. Although various avenues of research have been presented, the two most prominent are the design of interactive experiences that consider the interrelationship between senses such as smell and taste; and total sensory immersion. The work in this area is dominated by only two of the five senses (vision and audition). Recently, researchers have started to investigate the remaining three senses [139], smell [140], taste [141], and, more commonly, touch [142]. To create richer experiences for multisensory experiences, it is

important to understand how the human brain processes this information and how the different senses relate to each other; this is, in part, grounded in the study of crossmodal correspondences [143] the proceeding sections covers the background for this area of research. Covaci *et al.* reviewed how we experience crossmodal correspondences in multisensory media and its relation to the quality of experience (QoE) [144]. QoE is defined in the Qualinet White Paper as “the degree of delight or annoyance of the user of an application or service” [145]. This concept encapsulates the components related to the user’s perception of a certain service and is not a technical metric [144]. QoE is one of the most important factors when designing and creating a multisensorial experience as the impact the experience has on a human observer usually determines the perceived QoE, perceived value [146], and influences our decision process [10]. Therefore, it is important to go beyond the spatio-temporal integration of different types of sensory data and investigate the crossmodal correspondences and semantic basis in order to improve the quality of multisensory experiences. In 2004 Rowe and Jain published the results of a discussion of over thirty leading researchers from a one day workshop [147]. These researchers agreed that multisensory media is a multidisciplinary field (i.e., psychology, art, entertainment, education, and medicine) and proposed three unifying themes. First, a multimedia application or system must encompass a minimum of two correlated media components. Secondly, multisensory media application is interactive and multimodal. Thirdly, these media objects should be used jointly and separately to improve distributed multimedia application to provide transparent delivery of dynamic content as well as application performance [147], [148].

Multisensory experience design considers the different human senses and how they relate to each other. For example, Ranasinghe *et al.* recently proposed “Vocktail” a novel multisensory virtual cocktail used to stimulate the multisensory experience of taste. They used digital smell, colour, and taste to modulate how the experience was perceived and discovered that the combinations of the presented stimuli can be used to deliver a richer experience of flavour. The colour was projected onto the beverage to form a pre-conception of the temperature, fizziness, along with other physical attributes [149]–[151]. Smells were presented as they have a notable role in enjoying and perceiving flavours [152]. More than 80% of the taste experience reflects information delivered by the sense of smell [153]. The authors also used electrical pulses to simulate bitterness, saltiness and sourness while drinking the beverage. As emphasized in [139], multisensory experience design shows great promise on society and markets, creating new products and experiences. The authors then go on to state a few challenges when studying gustatory and olfactory experiences, including intersubject variability, varying olfactory preference over time, and cross-sensory effects. There is also a need to examine the user's perception of the multisensory components [154], as these products/applications' success

depends on the impact it has on human observers [154], [155]. Olfaction in human-computer interaction has recently started to gain interest in both the creation of olfactory displays [156]–[158] and toolkits and frameworks for managing the experience [159], [160] and even conveying information using odours [161]. This indicates that adding olfaction on top of the traditional audio, visual, and tactile feedback is one of the next big steps in multisensory experiences. Obrist, Touch, and Hornbæk discuss opportunities for odours in human-computer interaction based on four hundred and thirty-nine “smell stories” [26]. From this, ten primary categories for stories about smell experiences were derived these are:

1. Associating the past with smell
2. Remembering through smell
3. Smell perceived as stimulating
4. Smell creating desire for more
5. Smell allowing identification and detection
6. Overwhelming power of smell
7. Smell invading private and public spaces
8. Social interaction is affected by the smell
9. Smell changes mood, attitude and behaviour
10. Smell builds up and changes expectations

Overall, this provides an initial baseline in which multisensory experiences involving olfaction can be derived and how smell can affect a multisensorial experience; but also indicates how important the experience of smell can be, making it an important consideration for future technology and research.

2.5.2 Related Work

Not much work has been done with regard to the integration of crossmodal correspondences or synesthetic experiences into human-machine interfaces. Metatla *et al.* [143] investigated the effects of scented 3D printed shapes (“bouba” and “kiki”) on children; their results did not yield any significant tendencies of associating odours to 3D shapes. Furthermore, they did find significant associations between their shapes and odours (lemon and vanilla) and an emotional dimension (arousal). Metatla *et al.* demonstrated that higher engagement could be archived in gameplay by using a congruent audio-visual display and involving estimated vertical elevation [162]. Lin *et al.* found that high degrees of complexity, the colour red, low brightness levels, and high arousal levels are associated with a three-dimensional angular shape. They also showed that a three-dimensional rounded shape is associated

with blue colours, positive valence levels, and high brightness [88]. Covaci *et al.* provided a case study on how we experience crossmodal correspondences in multisensory media and their relation to QoE [144]. They argue that congruent crossmodal correspondences can help enhance QoE by providing insights related to interaction and content production. The authors then go on to explore how levels of excitement vary across different crossmodal congruent conditions by overlaying tactile, olfactory and auditory conditions over videos. These results revealed that the observer's heart rate increases, and more visual attention is given to the relevant features. However, it does not seem to affect the QoE significantly. However, Mesfin *et al.* investigated the use of crossmodally congruent olfactory stimuli in multisensory multimedia [163]. Their results revealed that crossmodally matched media enhances the quality of experience compared to a video-only condition. Ranasinghe *et al.* created a virtual lemonade to digitally change the perception of flavour of a glass of lemonade [164]. This involved using an RGB light emitting diode to change the colour, and a pH sensor to measure how "sour" a plain glass of water was. Electrostimulation was used to adjust the intensity of the sourness of the water. Their results revealed that it was possible to transport the taste perception of lemonade to plain water which archived a similar perception in terms of sourness. Therefore, suggesting that crossmodal congruent stimuli can enhance the QoE. Koizumi *et al.* explored the impact audio has on augmenting food textures by crossmodally changing the auditory properties, thereby changing people's perception of the food they are experiencing [165]. They archived this by using a photo reflector to measure jaw motion and a microphone to analyse chewing sounds; they input the microphone recording into a high pass filter and augmented the volume to exploit the "cross-modality effect". Thereby further showing the potential of integrating crossmodal correspondences into human-machine interfaces. Hoggen *et al.* demonstrated that integrating crossmodally congruent auditory, visual and haptic feedback improved the perceived quality of touchscreen buttons [11]. Finnegan *et al.* showed that incongruent audio-visual crossmodal correspondences could improve distance perception in virtual environments [166].

Design spaces for conveying olfactory information have been proposed by Patnaik *et al.* in [161] with the idea of using olfactory feedback for analytical tasks. They proposed "olfactory marks", which consist of three parts. First is smell glyphs which are images linked to specific real-world examples which are clustered into fragrance classes. Secondly, molecular bouquets, which is the concept that smells or odours are stronger at the initial time of perception, and continuous exposure, will either cause olfactory fatigue or the odours to become perceptually merged. Thirdly, airburst and the concept that air can play two roles when delivering odours, first as a means of conveying the odour and secondly to control the intervals of odours' diffusion. In other words, odours smell more intense

the hotter the environment is, which is one of the factors that can be manipulated to present smells. This design space was later further evaluated by Batch *et al.* [167]. They found that odour intensity and odour type (the identity of the odour) provided poor results. They also investigated temperature and airflow, but again the results weren't too impressive. Maggioni *et al.* [45] identified four key features for an olfactory design space: (i) chemical, (ii) emotional, (iii) spatial, and (iv) temporal. They then proceeded to demonstrate the design space in three separate applications. Overall, their results for incorporating their design space into multimedia show promising results. However, the current caveat of olfaction to convey complex information is still in its infancy and a considerable amount of future research will need to be conducted in order to increase the spatio-temporal throughput and uncover its limitations; although it does show promise towards enhancing human-computer interaction.

Sensory-based studies have started to emerge as a significant influence on traditional multimedia and human-computer interaction. Covaci *et al.* recently investigated how we experience multisensory media congruent with crossmodal correspondences [144]. Their results showed promise towards augmenting multisensory experiences with crossmodal correspondences; specifically, their results showed that visual attention is increased between olfactory and visual content when congruent with crossmodal correspondences. Their results also showed that auditory experiences influence olfactory sensory responses and lessen the effects of the perception of lingering odours. They also provided a case study that argues that given the influence of multisensory media on the quality of experience, one way to maximise this is through multisensory stimulation; interestingly, this argument fits in well with the work presented in this thesis. Ghinea and Ademoye investigated user perception of the associations between video and olfactory media content [27]. Their findings revealed that the association between scent and content has a significant impact on the perceived experience. Yeo *et al.* presented multiple scalable deep artificial neural networks to maximise the user's QoE on the client's side to enhance video quality [168]. This ideology could be coupled with crossmodal correspondences to create a semantically congruent experience to increase the overall QoE [144]. Murrey *et al.* showed that age and gender influenced olfactory and visual media synchronization [169]. Specifically, they found that a maximum skew of five to ten seconds was acceptable when odours were presented before the video and a maximum skew of ten to fifteen seconds when the odours were released after the video. Mesfin *et al.* investigated the use of crossmodally congruent olfactory stimuli in multisensory multimedia [163]. Their results revealed that crossmodally matched media enhances the quality of experience compared to a video-only condition. Koizumi *et al.* explored the impact audio has on augmenting food textures by crossmodally changing

the auditory properties, thereby changing people's perception of the food they are experiencing [165]. Brkic *et al.* state that unpleasant and pleasant odours can alter the way humans perceive a scene [170]. Their results revealed that they could reduce computational costs by rendering a lower-quality scene of a field of grass. The observers were unaware of the difference between the higher and lower-quality scenes when presented with a semantically congruent odour (cut grass). Covaci *et al.* designed a multisensory experience that was designed to be crossmodally congruent and performed experiments that target multiple senses [171]. Overall, they found that designing crossmodally matched multimedia content does not significantly affect the QoE. Raheel *et al.* used physiological sensors (EEG, GSR, PPG, and MLF) for emotion recognition while experiencing multisensory media (tactile, auditory, and visual) [172]. They used tactile-enhanced multimedia clips to simultaneously entice their three sensory modalities in an endeavour to increase the emotional response of the user. Due to the numerous difference that could affect subjective responses (i.e., age, gender, culture ect.), one could propose a real-time emotion recognition system that dynamically changes the content (i.e., virtual reality) to align to the desired emotional response (i.e., fear or pleasantness) and thereby maximising the quality of experience. Raheel *et al.* found that a fusion approach using EEG, GSR, and PPG worked best when coupled with a simple KNN classifier; one would expect further improvements with a better machine learning algorithm (i.e., a deep convolutional neural network). As new technologies are increasingly incorporating more of the five senses and are starting to consider touch, smell, and taste' there is an increasing need to study the user-perceived QoE. Ghinea and Ademoye's findings show that olfaction significantly adds to the user's multimedia and leads to an increased sense of relevance and reality [140]. In the same year, the latter authors also reported that the association between odours and content has a significant impact on user-perceived QoE [27]. Murrey *et al.*'s results suggest that age factors (11%), content factors (10%), and gender (8%) play an important role in user QoE of olfaction enhanced multimedia [173]. Further work by Murray *et al.* further supports the finding the age and gender influence the QoE [174]. Scent type has also been shown to influence QoE where pleasant and unpleasant scent types show significant differences in QoE [175]. Alkasasbeh, Ghinea, and Grønli show that odours can increase user performance in a visual search task (detecting images from a large matrix where the odour is semantically congruent) [176]. Ademoye and Ghinea's results showed that odours of a pleasant and unpleasant nature do not impact assimilation in a negative way [177]. They also showed that the presence of odours do not significantly affect task performance and the inclusion of a performance-based task can help enhance the semantic relationship between the scene and the odours.

2.6 Crossmodal Correspondences

2.6.1 Introduction

Crossmodal correspondences are the consistent associations between different sensory modalities [178]. The goal of this field is to understand the crossmodal binding problem, how does the brain know which stimuli to bind together and which stimuli are bound together? This area of research is not limited to a single domain and is an important factor in any area of research that relies on multisensory integration. Albeit controversial, these correspondences can be considered to be a weak form of synaesthesia [9] and antagonistically [7], [179]. Nevertheless, these associations demonstrate strong correspondences between sensory modalities, despite the explicit evocation (see [6] for a recent review). For example, humans can reliably associate odours with colours, textures, the angularity of shapes, pitch, emotional, and musical ratings, even though they often cannot correctly identify the odour [36]. These associations are often consistent but have a cultural variation bias [180], [181], which may modulate implicit judgements. Stimuli that are congruent either synesthetically or semantically are more likely to be bound together [178], [182]. Like synaesthesia, these associations can occur between a large array of sensory stimuli, including but not limited to: sounds and taste [183], smells and touch [184], [185] and between temperature and colour lightness [186]. These associations play an important part in multisensory integration, both realistically and artificially. Understanding the multisensory integration in humans, that is, how one sense would impact other modalities, will provide a vital new tool that can be used across a large array of applications ranging from marketing to human-machine interfaces. Researchers have known about crossmodal correspondences for decades (i.e., [187]). However, their understanding of their effects and their integration into multisensory experiences is still in its infancy. This is presumable due to the interdisciplinary overlap.

Over the last decade, the field of human-computer interaction has started to capitalise on adding haptic, olfaction, and gustation to enhance multisensory experience design. However, there is no set of clear guidelines to create these experiences, and one of the most important metrics is the quality of experience. QoE can be defined as the degree of delight or annoyance of the user for an application or service [145]. To this end, semantics and crossmodal correspondences play an essential role in enhancing the user's quality of experience [144]. Semantically congruent crossmodal correspondences can help to improve task performance [28] and the perceived pleasantness [188], [189] of a multisensory experience. Semantic congruency has also been shown to influence our decision process [10] and the perceived value [146]. In terms of olfaction, semantic congruency has

also been shown to enhance speeded olfactory discrimination [190] and identification [191]. Semantic congruency plays a vital role in multisensory integration, thus, making crossmodal correspondences an important metric to consider when designing multisensory experiences. Towards this end, it is important to uncover what crossmodal correspondences exist for common aromatic compounds and why these correspondences occur, consequently allowing them to be better exploited during the design process of multisensory experiences.

2.6.2 Causes & Mechanisms

The mechanisms underlying such correspondences have diverse characterisation within the literature. The most frequently deduced mechanisms are hedonics [7], [8], [16], [79], [80], semantics [6], [9], [14], [15], [79], [192], [193], and natural co-occurrence [6], [183], [193] (see [6] for a review). Hedonics refers to the pleasant or unpleasant state induced by the stimuli and includes the subsequent emotional response to the stimuli. In other words, correspondences occur because they elicit a similar emotional response or perception in terms of pleasantness. Semantics refers to knowledge of the identity of the stimuli meaning do these correspondences occur because they know what the presented stimuli are and are associating ratings accordingly, such as between the smell of lemon and the colour yellow. Natural co-occurrence refers to naturally correlated sensory dimensions present with almost everything, such as between the size of an object and how loud it is. Nevertheless, crossmodal correspondences have been demonstrated to influence bias (i.e., providing a red glass filled with white wine can alter the judgement of expert wine tasters [25]) and alter the appearance of physical creations [194]. Meaning these correspondences will be useful in the design of a variety of multisensory experiences, including virtual synaesthesia and sensory substitution/augmentation systems. There are a couple of situations in which these correspondences can be observed, as defined in [6]: between naturally correlated sensory dimensions, such as size and frequency [195] (i.e., the higher the frequency, the smaller the object), pitch and lightness [196] (i.e., the higher the luminance the higher the pitch) and are present in both chimpanzees and humans). Secondly, the neural connections that have been present since birth [6], [197], suggesting that we are all born a synesthete but this ability is usually lost over time. It is suggested that the phenomenology of synaesthesia is present in all individuals in the form of crossmodal correspondences, albeit to a lesser extent and has been defined as 'weak syneasthesia' [9]. An example of such correspondences would be found in commonly used language (i.e., a cool colour, a sweet smell and a sad song). The main difference from these two viewpoints is that crossmodal correspondences requires context and is not automatically invoked in all cases. Although no studies have concluded that the physicochemical features are a

contributory factor towards explaining olfactory crossmodal correspondences, it is somewhat implied in the basis of known correspondences, such as temperature [198] and intensity [85]. The extent of the physicochemical features contributing towards explaining crossmodal correspondences are explored in Chapter 6. All though there isn't a singular given dimension that explains all crossmodal correspondences, the underlying mechanisms seem to be predominantly mediated by hedonics, however some correspondences seem to stem from more of a semantic basis, such as, the correspondences between odour and colour. It is likely that crossmodal correspondences stems from all these mechanisms just with different weighting depending on concurrent correspondence. Stevenson, Rich, and Russell explored the crossmodal correspondences between odours and visual (colour and shape related attributes, such as, a square or a circle), auditory (high pitch, low pitch, loud, or quiet), gustatory (sweet, salty, meaty, etc.), and somatosensory associations (irritancy and pleasantness) [80]. Their results showed that some crossmodal correspondences are mediated by both semantics and perceptual mechanisms but most importantly outline the importance hedonics play in explaining the nature and origin of these correspondences [80]. Their findings also demonstrated that people are generally consistent in reporting their crossmodal correspondence as demonstrated by a high inter-rater agreement two weeks after reporting there first set. However, due to the verbal-based strategy employed in analysing their correspondences this would need to be further investigated and in a more controlled manner to determine the true extent of the nature and origin.

2.6.3 Difference between Crossmodal Correspondences & Synaesthesia

Martino and Marks [9] put forward an influential claim that weak synaesthesia as "cross-sensory correspondences expressed through language, perceptual similarity, and perceptual interactions during information processing". They characterise strong synaesthesia as "vivid image in one sensory modality in response to stimulation in another one". In other words, they claim that weak synaesthesia is crossmodal correspondences/mind's eye synaesthesia and strong synaesthesia invokes a concurrent perception which is stronger than a mere association. There is an overlap between mind's eye synaesthesia and crossmodal correspondences in the literature which suggests that they are the same thing. Some researchers argue that crossmodal correspondences and synaesthesia form a continuum [199] which would explain the interchangeable nature regarding the terminology dependent on the researcher. Here we treat crossmodal correspondences and synaesthesia as separate entities, which is the more modern approach [179]. Although many researchers agree with the claims that were put forward by Martino and Marks, some believe that the similarities between

the two are “superficial” [179] and, therefore should be researched as two separate entities. The differences between crossmodal correspondences and synaesthesia are crossmodal correspondences are a milder form of cross-sensory connections, a form that is non-arbitrary, non-idiosyncratic and does not involve a secondary experience. While synaesthesia is a stronger form of cross-sensory connection, with the experience being idiosyncratic, arbitrary, and involves a secondary experience.

2.6.4 Related Work

A wide array of research has been conducted in olfactory-based crossmodal correspondences largely confirming the existence of certain correspondences. As pointed out by Spence in [6], there has been a recent surge in research in crossmodal correspondences credited to two notable publications by Ramachandran and Hubbard [200], [201] where they replicated the findings of Köhler [202] whereby they found consistent auditory-shape associations between the words “Bouba” and “Kiki” and a round and angular shape, respectively, as depicted in Figure 4. The effect has been dubbed the bouba/kiki effect.

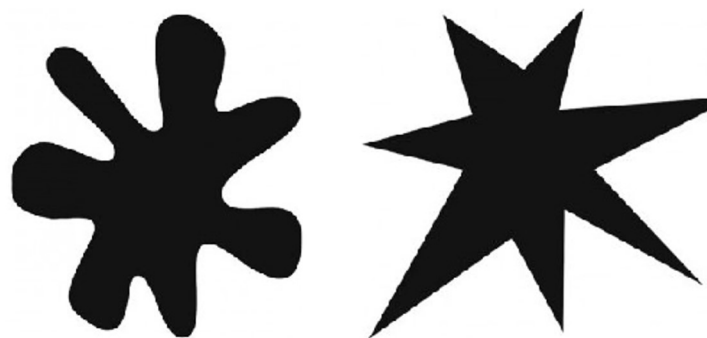


Figure 4. Between 95% to 98% of the population agrees that “bouba” is the shape on the left and “kiki” is the shape on the right.

The rest of this section looks into known olfactory crossmodal correspondences as well as their nature and origin. With regards to the consistent correspondences between odours and shapes Hanson-Vuax *et al.* investigated the perceived angularity of shapes revealing that people do make consistent correspondences between odours and rounded to angular shapes and that hedonics seem to be the main driving mechanism [7]. Kaepler investigated the perceived angularity of shapes and colours of olfactory stimuli confirming that there are consistent correspondences between odours and the angularity of shapes and colours [15]. Participants could freely draw shapes on a graphics tablet, and these shapes were then assigned to different shape dimensions (i.e., big to small and abstract to realistic). Participants could also select colours using a series of linear scales to produce a final colour. Their findings suggest that semantics are the main driving mechanism. Seo *et al.* demonstrated that

certain odours are associated with specific abstract symbols [203]. Two experiments were performed, one asking if the presented odour matches the presented symbol “yes” or “no”; the other used psychophysical and electrophysiological tests using two odours and two of the symbols and a control (no shape) from experiment one. Experiment two presented randomised visual stimuli along with a conjoining odour; participants were asked to rate odour pleasantness and intensity on a one-hundred-point scale. Overall, the literature discussed in this paragraph indicates that people have consistent correspondences between odours and shapes.

Crossmodal correspondences between olfactory-texture correspondences have also been documented. Demattè *et al.* provided a series of cotton fabric swatches with varying degrees of softness to seventeen participants [185]. They were instructed to feel the visually obstructed swatches in a repeated measures setup and were instructed to rate the perceived softness of the swatch on a Likert scale. The results indicated that the presence of odours influences the tactile perception of perceived softness. Lin *et al.* investigated crossmodal correspondences between tangible 3D shapes, colours, and emotions [88]. They found that their participants consistently associated 3D shapes that have varying degrees of complexity with specific colours (red, blue and, the lightness of colour) and emotional dimensions (i.e., arousal). Furthermore, and most importantly, they concluded that designers could not interpolate between two correspondences to determine the correspondences for the object they are designing. However, it still remains to be investigated if they can be predicted using artificial intelligence/machine learning, and Chapter 7 explores this hypothesis. Metatla *et al.* explored the crossmodal correspondences between odours, emotions and 3D shapes in children [143]. Their findings support pre-existing mappings between the odour of lemon being associated with being arousing and angular and the vanilla odour being associated with being calming and smooth. Overall, the literature presented here supports the existence of olfactory-haptic crossmodal correspondences; however, it remains unclear if consistent correspondences exist between odours and how smooth the textures are perceived.

Olfactory-pitch crossmodal correspondences have also been reported. Belkin *et al.* reported crossmodal correspondences between odours and loudness equalised pitch [187]. Their findings indicate that olfactory-pitch correspondences appear to be based on perceptual features (i.e., odour quality) of olfaction rather than the pleasantness or intensity of the stimulus. Crisinel *et al.* explored the crossmodal correspondences between olfaction and both the pitch and instrument class of sounds [16]. Their findings indicate that people have consistent associations between odours and the pitch of musical instruments. They found that the odours associated with the lower pitches (musk, roasted coffee, and ginger cookies) were significantly different from the odours associated with higher pitches

(iris flower and candied orange). They also found that the odours produced a non-random choice of distribution for different musical instruments. The literature here indicates that there should be consistent correspondences between odours and pitch / musical dimensions.

Olfactory-colour correspondences is seemingly one of the most explored dimensions in olfactory crossmodal correspondences. Gilbert *et al.* showed that colour selections differed significantly as a function of emotion and indicated that the expectations of colour for beverages could be elicited based solely on a verbal descriptor [204]. Kemp *et al.* investigated the effects of perceived intensity on colour correspondences [85]. They have shown that the stronger the odour's perceived intensity, the darker the colour associated with it. Michael *et al.* state that visual cues may dominate and guide temperature-related responses [205]. Michael *et al.* go on to explain that this may be attributed to lateralized patterns. That is, red-warming associations are more frequently reported after stimulation to the left nostril, and green-cooling associations are more frequently reported after stimulation to the right [206]. However, this lateralized pattern is only present when the olfactory stimuli are coupled with colours [205], [206]. Kaeppeler's results show that colour-based correspondences occur from a more semantic basis. That is, odours that were rated as more familiar also were associated with very specific colours, and odours, that were rated as less familiar were rather inconsistent in colour selections. The literature here indicates that there should be consistent correspondences between odours and colours.

Olfactory-emotions crossmodal correspondences have also been reported, Levitan *et al.* explored an emotion mediation hypothesis towards explaining the nature and origin between music, odour and emotions [207]. They found that the perceived matches were higher with similar emotional responses and concluded that crossmodal correspondences are mediated by emotions which is generally considered as a form of hedonics. Spence wrote a review paper for the emotional mediation hypothesis explaining crossmodal correspondences involving musical stimuli and concluded that both complex and simple emotional stimuli supports the emotional mediation as one of the key factors [208]. This finding is also embodied in the prior work on olfactory crossmodal correspondences; for examples, see [7], [36].

Temperature-based crossmodal correspondences have also been documented, namely between colour and pitch (see [209] for a review on temperature-based crossmodal correspondences). Wang and Spence demonstrated the existence of crossmodal correspondence between pitch, tempo, and temperature (imagined or physically present) [210]. They found that an imagined cold drink was associated with a higher pitch soundtrack and a significantly faster tempo.

They also found similar results with physically hot, room temperature, and cold drinks. Motoki *et al.*'s results showed the existence of consistent crossmodal correspondences between temperature and colour warmth and lightness, and these correspondences affected the consumers' visual attention [186]. They also found that physical warmth increased attention to light-coloured goods and increased consumer preferences for light-coloured goods under comfortable warmth. Therefore, the literature presented in this paragraph indicates the existence of consistent correspondences between temperature, pitch, and colours.

The presentation of cues from multiple sensory modalities simultaneously can have a profound impact on both perception and behaviour [211]. Marrot, Brochet, and Dubourdieu demonstrated that a white wine that was odourlessly coloured red was described as a red wine by 54 tasters [25], thereby creating a perceptual illusion whereby the tasters ignored the olfactory information. Seo and Hummel reported two experiments investigating the effects of auditory stimulation on the perceived intensity and pleasantness of odours [212]. They reported that odours were perceived to be more pleasant when paired with congruent odours compared to incongruent odours. They also reported that the hedonic valence associated with the sounds could be transferred crossmodally. Unfortunately, they didn't find anything significant with the perceived intensity. Piqueras-Fizman and Spence demonstrated that people have strong crossmodal correspondences to crisps. That is people that grew up in the UK with Walkers crisps, link cheese and onion crisps with the colour blue and the salt and vinegar flavour with the colour green [213]. They showed that the opposite is true for non-Walkers crisp fans, and when shopping for crisps consumers relied on the colouring of crisps for determining the flavour and, unsurprisingly, ended up with the wrong flavour as they blindly relied on the colour. This study demonstrates that incongruity with the expected and actual attributes of a multisensory experience can lead to "annoying" the consumer. Zampini and Spence found that the crispness and staleness were systematically altered by changing the frequency composition and/or the loudness of an auditory cue, thereby changing the perception of a crisp. They found that the overall perception of crispiness and freshness was increased when either the sound level was increased or when paired with higher frequency sounds (2 kHz – 20 kHz). Factors such as this can be exploited in human-machine interfaces, for example, "The Chewing Jockey" [165], a device that uses this principle to enhance the eating experience. Jezler *et al.* demonstrated that the presence of different odours could influence the appearance of physical creations. The features of the physical creations were in alignment with their expected crossmodal correspondences (e.g. the lemon odour biased the creations to have more parts compared to vanilla) [194]. Other than being able to induce bias / create perceptual illusions, semantic congruency has also been demonstrated to be beneficial

in other ways. Dematte, Sanabria, and Spence showed that speeded olfactory discrimination can be archived when coupled with semantically congruent visual features, including colour patches or an outline of the shape the odour corresponds to, such as a strawberry [190]. Osterbauer *et al.* show that the colour cues that modulate olfactory responses have neural correlates in the area of the brain that encodes the hedonic value of smells. Indicating that, at least for colours, semantic congruency increases the perceived pleasantness of the odours. Seo *et al.* showed that as an odour sound pair were rated as more congruent, so was the perceived pleasantness [189]. However, this effect was not found for all of their odours. Laurienti *et al.* demonstrate that semantically congruent multisensory stimuli enhances behavioural performance [211]. In terms of behaviour, semantically congruent multisensory stimuli have been shown to decrease simple reaction times [214]–[216] and lower the threshold of stimulus detection [214], [217], [218]. In terms of perception, the human nervous system goes to great lengths to bind multisensory cues presented close spatiotemporally to create a perceptual gestalt [211]. One example of the end product of multisensory synthesis includes the ventriloquism effect [219]. The ventriloquism effect is an auditory illusion which occurs when sound is misperceived as coming from a source that is moving appropriately when it actually comes from a different invisible source, meaning that an auditory signal can be “pulled” to nearby visual stimuli. The McGurk effect is an illusion where speech sounds are misclassified where the auditory cues in the stimulus conflict with visual stimuli from a speaker's face [220]. As crossmodal correspondences are considered as a sensory expectation, it is loosely coupled with semantic congruency, meaning the congruency and incongruency with crossmodal correspondences could be exploited to create a series of potentially interesting effects which would be useful for human-machine interfaces. For example, as olfactory displays are limited to a small number of smells, it would be beneficial to create an illusion in which it is possible to change the perception of the odours so that they smell like a different object. For instance, the odour linalool is the dominant compound in citrus fruits, therefore, it may be possible to make it smell like lemon, orange and/or pineapple if presented with semantically congruent stimuli (i.e., a virtual lemon). As semantically congruent crossmodal correspondences can enhance user performance in human-machine interfaces [28], they could potentially be leveraged to aid in multisensory activities, for example, the virtual rehabilitation of hemianopia (see [221] for a review). Hemianopia is the partial blindness in half or a quadrant of the visual field; therefore, a virtual rehabilitation method could be developed to enhance oculomotor scanning. This could include presenting visual targets both within the users’ available visual field and slightly outside its bounds. Coupling spatialised audio cues to these targets can aid in the localisation of the target, with pitch being a semantically congruent indicator for the height of the target. This is one of the most robust

correspondences reported to date [6]. To boot, leveraging this crossmodal effect should make the overall experience more pleasant [188], [189], [222], making the repetitive nature of rehabilitation less tedious and more enjoyable.

2.7 Sensory Substitution / Augmentation

2.7.1 Introduction

Sensory substitution is the artificial conversion of one stimulus to another, for example, the conversion of visual stimuli into sound [46] or visual stimuli into tactile feedback [223]. These substitutions systematically convert multiple properties from one stimulus, such as the visual properties (luminance, vertical, and horizontal position), to the auditory properties (pitch, frequency, and amplitude) and are often presented as an abstract representation [224]. One use of the ideology of virtual synaesthesia would be its application in sensory substitution/augmentation systems. For instance, it would be desirable to turn the abstract representation created by typical sensory substitution/augmentation devices into a representational one to make the presentation of information more coherent to improve upon the usability of these devices. Like synaesthesia, these substitutions provide information from one sensory modality to another, albeit through an intermediary device, making the field a suitable framework for creating virtual synaesthesia. One of the first sensory substitution devices can be traced back to [225], where tactile feedback was provided using the video feed of a camera. Sensory substitution could be considered an artificial form of synaesthesia [224], [226] and furthermore, could be used as a complement to artificially expand and create new senses for humans. The term new senses are used here to reflect that the human experience of reality is constrained by biology and refers to the ability to take in new, initially not perceivable information by a human (e.g., radio waves or the infrared spectrum). However, this would utilise at least one of our existing senses just in a new way to convey this information. There is little evidence that these systems create a truly perceptual experience but may lead to a cognitive experience [227], [228]. The main driving factor behind sensory substitution devices is to compensate for the loss of sight by providing concurrent auditory and/or haptic feedback. There have been instances where prolonged, immersive use of a vOICe sensory substitution system [46] has invoked synesthetic-like experiences [229], [230]. Such experiences may be obtained for immediate users of such devices and have the potential to invoke a simultaneous and involuntary perception [229], [231]. This has allowed some blind people to “see” through sound without any technological help after a fixed period; more research needs to be done to confirm this hypothesis, as the author finds this claim

highly unlikely. Ward and Meijer, report that two of the blind users of the vOICe sensory substitution system gained synesthetic phenomenology and argue that the users' previous experience of seeing (i.e., knowledge of a shape) coupled with auditory signal generated resulted in a "visual phenomenology" which is not confined to when the device is being used and claim this is a form "acquired synaesthesia" [229]. However, the extent and validity of their findings need to be further investigated. Work in this area has been predominated with visual-auditory [46], [232], [233] and visual-tactile devices [223], [234] to compensate for the loss of the sense of vision. The work to provide sensory substitution devices between different modalities (not designed to be a replacement for vision) has largely been neglected by the scientific community, mostly due to the fact that the devices are not widely used by the community in which they were originally designed [47] (*i.e., a visual-auditory sensory substitution system are designed for the severely visually impaired*). For instance, "seeing with the brain" [235] and "seeing with the skin" [236]. A notable example outside the traditional norm is a vestibular substitution device [237]. This is a head-mounted device with an accelerometer that provides electro-tactile stimulation to the tongue to aid in head-body postural coordination. The field of sensory substitution and augmentation is rapidly gaining interest in engineering and psychology as these devices can open broad theoretical and experimental perspectives [47]. However, these devices are typically limited to designs to substitute vision often neglecting the other four senses.

As defined in [47], sensory substitution systems typically consist of three components. First, sensor(s) to allow for the conversion of one form of energy into signals that can be interpreted by the second component. Secondly, a coupled electronic system, such as a microcontroller to receive these signals, process them then send them to control the third component. Thirdly, the coordinated activation of a simulator to relay information from the second component to the user. The basic principles behind a sensory substitution/augmentation device are shown *Figure 5*. Sensory substitution and augmentation systems provide an implicit mode of perception [47], meaning they make no call to conscious reasoning concerning the produced sensations. With the concept of virtual synaesthesia and/or crossmodal correspondences this implicit mode perception would become more explicit by considering the way the brain naturally combines and associates the senses in different sensory modalities.

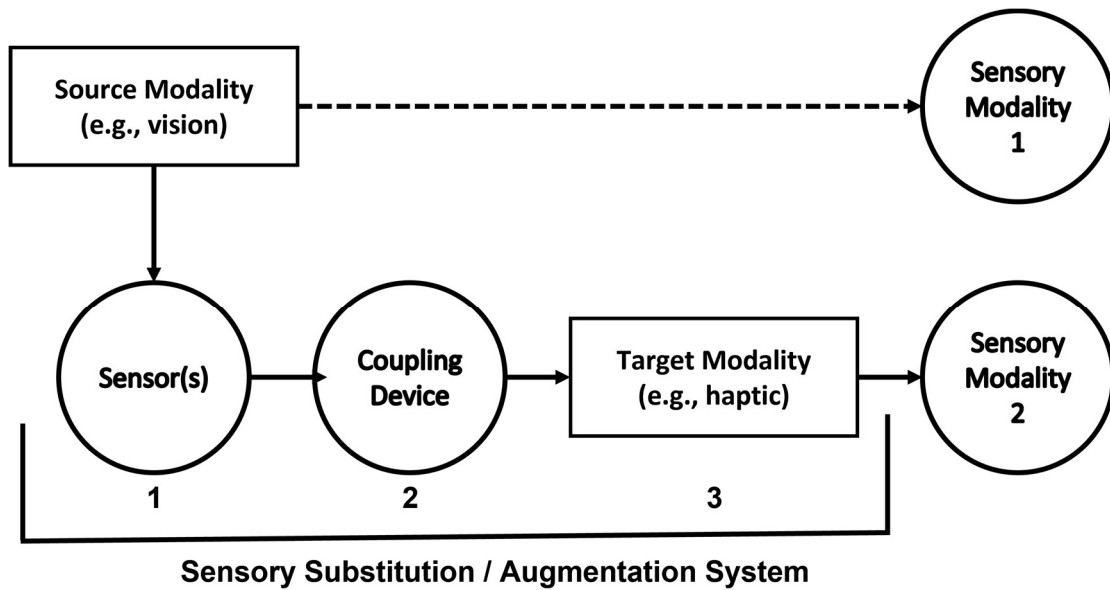


Figure 5. The basic operating principles of a typical sensory substitution/augmentation device. (1) artificial sensors to convert one form of energy to another, (2) a coupled electronic system, and (3) a simulator component to present the information.

There is a growing body of psychological work trying to push the field of sensory substitution toward the goal of augmenting human intellect using artificial synaesthesia; some examples include [224], [226], [238]. Artificial synaesthesia and sensory substitution share specific characteristics but with two distinct goals, one being a compliment to augment human intellect and the latter being a replacement for a lost modality principally visual and, therefore, should be researched in their own right. Both virtual synaesthesia and sensory substitution are sparsely researched when coupled with the chemical senses. Thus, understanding multi-sensory integration and the perception behind olfaction and gustation is vital towards understanding how human-machine interfaces utilising the chemical senses will affect the other modalities and to what extent.

2.7.2 Related Work

Due to the nature of the components of a sensory substitution system, there is a very diverse number of potential sensory substitution systems. However, to the author's knowledge, nobody has published a device dedicated to olfaction substitution or augmentation; therefore, the rest of the section covers some of the most popular sensory substitution/augmentation devices. Meijer created "the vOICe" [46] that converts multiple visual properties (luminance, vertical and horizontal position) to auditory properties (pitch, frequency, and amplitude), which is consequently presented to a human user. Prolonged usage of the "the vOICe" sensory substitution device has apparently invoked synesthetic-like experiences [229], [230] in some individuals. The vOICe has also been subject to investigations in

the psychology community. Auvray *et al.* investigate the extent to which people could master this device after prolonged usage [239]. Their results revealed that participants could use an auditory representation of a visual scene for object recognition, locomotor guidance, pointing and localisation. While slightly contradictory to the latter paper, where Merabet *et al.* found that usage of the vOICe in blind subjects actually impairs the user's ability to identify objects [240], they conclude that this is because of a crossmodal disruptive effect because the subject is late blind. Ward and Meijer report that two blind users of the vOICe sensory substitution device obtained a visual phenomenology through immersive and long-term usage of the device in terms of years [229]. This phenomenology is triggered when using the sensory substitution device, and once established, the mappings between the visual and auditory domains are not confined to when the device is being worn and are arguably a form of artificially acquired synaesthesia. This phenomenon could prove useful to augment human intellect with more refined multisensorial capabilities to create new 'senses' for humans over time. Although more research is needed to determine the extent to which this is possible, this paradigm neatly fits into the concept of virtual synaesthesia and is one of the very ambitious goals of the field. Ward and Wright present a review of the relationship between sensory substitution and synaesthesia and argue that sensory substitution exhibit the same characteristics as natural synaesthesia [224]. Their argument for this is as follows "Both are associated with atypical perceptual experiences elicited by the processing of a qualitatively different stimulus to that which normally gives rise to that experience". They also make an important remark regarding the distinction that sensory substitution shares the same characteristics, but they don't need to share the pathways (artificially or neurologically). They claim that the inducing/substitution modality in sensory substitution is not lost making it comparable to natural synaesthesia. Their second hypothesis is that it should be possible to induce the phenomena in expert users in the substituting modality even when the stimuli is not produced by the sensory substitution device. They also state that developmental synaesthesia may be better understood by comparing the two. The ideology presented in this review paper, in part aligns with the paradigm of virtual synaesthesia, specifically, they state that sensory substitution matches the schema for synaesthesia, with the substituting sense acting as the synaesthetic inducer and the substituted sense as the resulting synaesthetic concurrent". Kerdegari *et al.* [241] created a tactile helmet for firefighters which presents navigation commands via tactile feedback. This uses an ultrasound sensor to provide depth information sequentially relaying information to the actuators situated inside the helmet of the firefighter. Kerdegari *et al.* also compared haptic and auditory feedback for navigation in a low visibility environment [242]. Their results revealed that haptic feedback leads to a lower route deviation than auditory feedback. Novich and Eagleman investigated

the best method for relaying haptic feedback presented to the lower back [243]. They found that space-time patterns gave the highest information transfer rate, and the motors were best placed at a minimum of 6 centimetres apart. Many locations on the skin have been investigated to find the optimal location for providing tactile feedback [244]–[246]; due to the large density of mechanoreceptors in the fingertips, tactile stimulation in this area has been proven to be a good location [247]. Keeley outlines a few criteria that he considers necessary and sufficient for distinguishing between sensory modalities, including physical stimulation (i.e., pressure, light, and electrical), neurobiology (the sensory organ and their connection to the brain), and dedication (the organ has been adapted through evolution to respond to certain stimuli) [248]. Keeley then extends this concept to sensory substitution and argues that users of sensory substitution systems can detect visual information that does not constitute vision. Narumi *et al.* presented the MetaCookie+, a pseudo-gustatory display that leverages crossmodal principles of vision (e.g. projecting the image of a Jaffa cake over a plain cookie) and olfaction (e.g. the smell of chocolate) to change the user's perception of taste (a plain cookie) [249]. Devices such as this are what this thesis envisions, however, a deeper understanding of crossmodal principles and how they affect our multisensory experience is needed to truly understand and consequently exploit to create such systems, more so for olfactory-based devices.

2.8 Electronic Nose

An electronic nose (e-nose) is an array of gas sensors where each sensor in the array has limited capability of detection, and its specificity comes from the number of sensors. This array of sensors is used to detect chemicals/odours in the environment. The first conceptualisation of this device came from Persaud and Dodd [250] in 1982; they often rely on a pattern recognition system for the characterisation and classification of gaseous compounds [251] in the vapour phase. The basic principle of an e-nose is to convert the "chemical footprint" into a series of electrical signals. These signals are usually indicated by a change in resistance. It is often beneficial to also have a temperature sensor as gaseous compounds have different volatilities at different temperatures and are therefore reflected in the signal obtained by the e-nose. A diagram of the architecture of a generic e-nose is shown in Figure 6; some architectures also incorporate membranes to filter out specific gases.

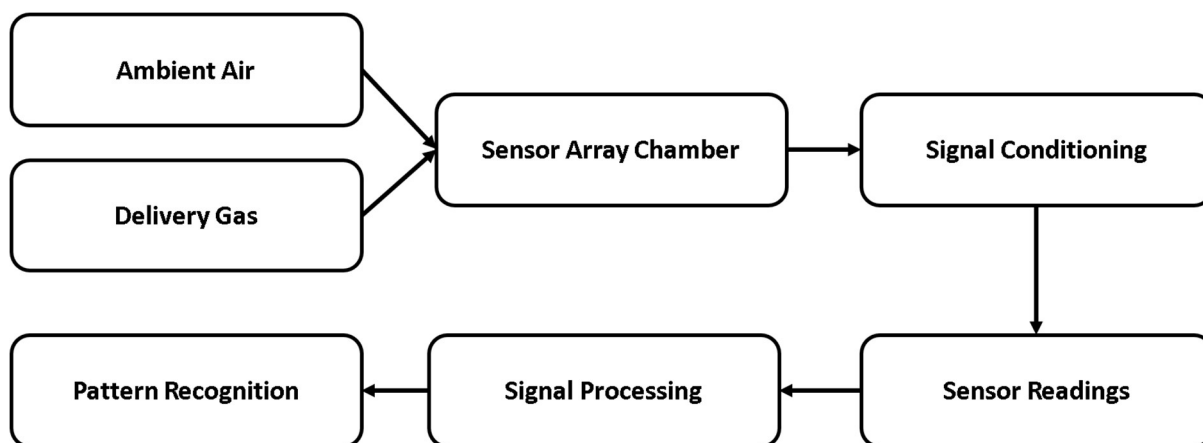


Figure 6. A diagram showing the architecture for a generic e-nose.

E-noses are, more often than not, fine-tuned to solve a specific problem (i.e., wine classification [252], diabetes diagnosis [253], and lung cancer screening [254]) which entails different configurations in the sensors in the array. The main disadvantage of using an e-nose is that quantification is not generally possible without calibration; even then limited to only being able to quantify the gas(es) in which the calibration was performed. Moreover, e-noses have the advantage of being portable over the gold standard (mass spectrometry). When designing the sensor array for an e-nose it is of the utmost importance to design an array consisting of specific sensors for the target compounds of interest. Hence, allowing for the development of an array with no redundant sensors while still being able to capture as much of the “chemical footprint” as possible. The benefit of this is that it is a cost-saving measure that also reduces the complexity of the developed e-nose in the hardware, software development as well as subsequent data analysis.

E-noses have proven useful for the detection and characterisation of volatile organic compounds [255], which would make them ideal for usage with essential oils. Russo *et al.* tested the effectiveness of an electronic nose system to detect bergamot essential oil in terms of quality and genuineness [256]. They used an ISE Nose 2000 (ISE, Pisa, Italia) coupled with a sensor box of twelve metal-oxide sensors. Overall, the e-nose could reliably discriminate between industrial cold-pressed bergamot essential oil, bergamot essential oil with no deterpenation, and bergamot essential oil deterpenation when visualised with principal component analysis. Rasekh *et al.* used an e-nose for the identification of herb and fruit-based essential oil [257]. They used the MAU-9 e-nose that contained nine sensors, and again their e-nose could discriminate between six essential oils when visualised with principal component analysis. These findings indicate that e-nose technology has the capability of picking up the “chemical footprint” of aromatic essential oils. The specific sensors used

in the arrays are diverse (i.e., [256]–[258]) even for the classification of the same type of solution, although temperature and humidity sensors seem to be commonly used, as these factors would affect the response of most chemical sensors. The diversity of sensors selected in the literature could be attributed to the fact that a lot of the ingredients in essential oils are closely kept company secrets to prevent replication from competitors. The ingredients would also vary from brand to brand and scent to scent. However, one common overlap between custom-made e-noses and essential oils is the use of a temperature sensor and the use of the MQ series of gas sensors. Essential oils can also create secondary air pollutants caused by a reaction to the air, including formaldehyde (HCHO) and secondary organic aerosols [259]. It has also been shown that essential oils can have a negative impact on air quality [260]. Considering these results, the e-nose presented in Section 3.2 and Section 3.3 was designed to contain a temperature, humidity, air quality, HCHO, and sensors from the MQ series.

2.9 Mass Spectrometry

Mass spectrometry is an analytical tool that is used to measure the mass-to-charge ratio (m/z) of ions. The results are usually presented in the form of a mass spectrum, typically consisting of intensity on the y-axis and the m/z on the x-axis. Mass spectrometry is often used to quantify known compounds, identify unknown components using molecular weight determination, and determine the chemical properties and structure of molecules. Every mass spectrometer has three main components: an ionization source, a mass analyser, and an ion detection system. The ionization source converts molecules into the vapour phase allowing the molecules to be manipulated by magnetic and electrical fields. There are a variety of different ionisation techniques, including desorption atmospheric chemical ionization (DAPCI); this is an ambient ionization technique. DAPCI-MS is a plasma-based ionisation technique that uses solvent ions and high-velocity gas to ionise the analytes in a sample. DAPCI-MS allows for both non-volatile and volatile compounds to be analysed for more sensitive and efficiency of low polarity compounds [261]. Figure 7 shows a generic schematic for DAPCI-MS. The mass analyser separates and sorts ions according to their m/z ratio. The ion detection system measures the ions then sends them to a data system along with their relative abundances; an example mass spectrum is shown in Figure 8. Due to the large sensitivity and specificity of mass spectrometry it is considered the gold standard for chemical analysis and have been used in a wide range of

applications, including but not limited to nitroaromatic explosives [262], essential oils [263], protein identification [264], biological tissues [265], and microorganisms [266].

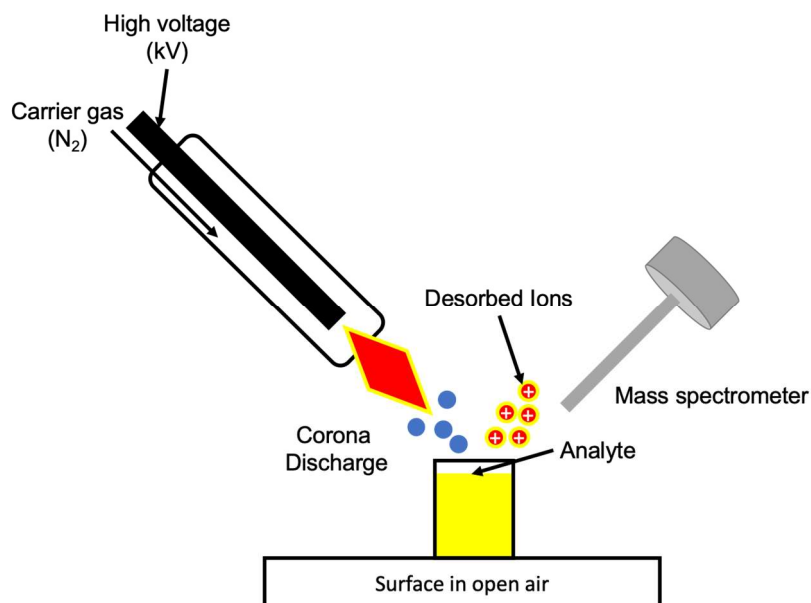


Figure 7. DAPCI mass spectrometry general schematic.

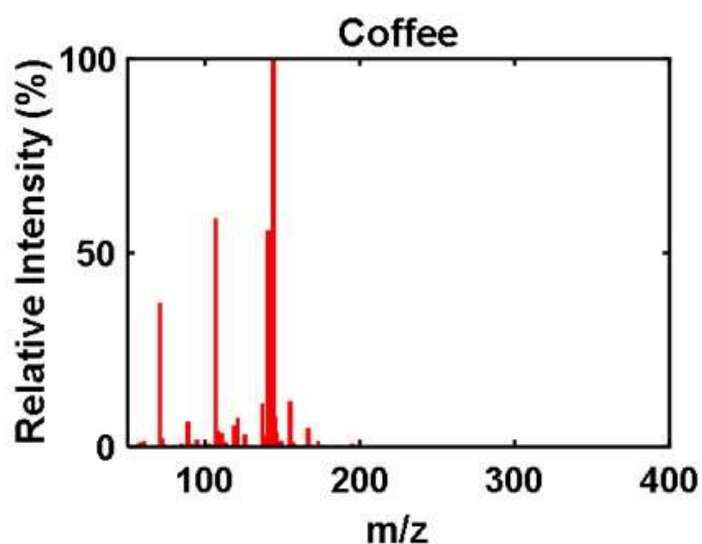


Figure 8. Example mass spectrum showing the relative intensity and m/z for coffee essential oil.

2.10 Conclusion

In this section, the backgrounds and related works are given for the areas umbrellaed by the concept of virtual synaesthesia. These include natural synaesthesia, multisensory experiences, crossmodal correspondences, and sensory substitution/augmentation. Natural synaesthesia and crossmodal correspondences were covered, as this is where the ideology of virtual synaesthesia stems from. Multisensory experiences and sensory substitution/augmentation were covered as these are a couple

of domains needed that make virtual synaesthesia possible and areas it could be applied to. The background is also covered the remaining methodology used in this thesis, namely electronic noses and mass spectrometry.

Virtual synaesthesia is a new paradigm aiming to enhance human-machine interfaces with more refined multisensorial capabilities by presenting information to the user more informative and intuitively. Among other advantages, virtual synaesthesia should be able to replicate the same cognitive benefits as its natural counterpart, although training or long-term usage of a compatible device may be required. This paradigm may also prove helpful towards presenting complex information in a more intuitive manner to enhance multisensory experiences with more refined capabilities, including increased assimilation. However, this area is still in its infancy and would require a significant amount of work to be conducted to confirm these hypotheses. Virtual synaesthesia takes some of its ideology from natural synaesthesia.

A brief review of the causes and mechanisms and related works behind natural synaesthesia is covered in Section 2.3. Although synaesthesia was first documented in 1812 by Georg Sachs [267], research into this phenomenon is in its infancy due to a lack of interest by the psychology community. This is presumably because synesthetes are very rare, and finding multiples of people with the same form of synaesthesia would be a difficult task, especially with the rarer forms of synaesthesia, such as odour-vision and because most people with synaesthesia think their experience of reality is normal and are unaware of their condition and therefore go undiagnosed. Synaesthesia is a unique way of a synesthete perceiving their surroundings with numerous cognitive benefits. The philosophy behind artificial synaesthesia to augment human intelligence would benefit all areas of science, from identifying patterns in large matrices to generalised learning. The effects of synaesthesia are not always beneficial; for instance, it has been shown to induce slower reaction times when coupled with incongruent stimuli [97]. Here is where the concept of virtual synaesthesia can help when designing multisensory experiences, as congruency between stimuli is one of its core values. Coupling virtual synaesthesia into human-machine interfaces can grant a window into perception and thought. This will allow for the development of systems where the cross-modality space-time throughput can be utilised in a congruent and efficient manner bypassing the bottleneck of attention and potentially improving learning. Consequentially allowing for the development of more refined multisensorial experiences. In other words, it may be possible to reduce the bottleneck of conveying information in a multi or cross-sensory manner by considering how the brain naturally 'binds' multisensory information rather than relying on arbitrary mappings between one sensory modality to another. Although the concept of natural synaesthesia can prove beneficial if utilised correctly, it is not present

in most of the population. Although they should be researched as separate entities it is important to consider how other means of how the brain combines information, one that is present in the general population (crossmodal correspondences).

Crossmodal correspondences are the consistent associations people have between stimulus features in different sensory modalities. An introduction and related works for crossmodal correspondences is covered in Section 2.6. Crossmodal correspondences have been characterised in the literature as a weak form of synaesthesia and are an important addition to the concept of virtual synaesthesia as it considers how different sensory modalities are 'bound' together with inclusion of the general population. The literature for crossmodal correspondences supports the hypothesis that there should be consistent crossmodal correspondences between odours and the angularity of shapes, physical textures, temperature, pitch, musical, and emotional dimensions. The nature and origin towards explaining olfactory crossmodal correspondences has diverse characteristics with multiple hypothesis being semantics (knowledge of the identity of an odour), hedonics (pleasantness / emotions) and natural co-occurrence (indirectly learnt from our environment, such as the size of an object and how loud it is). Presumably the nature and origin of crossmodal correspondences most likely stems from all these mechanisms, with some contributing more than others. Based on the existence of known correspondences, such as temperature [198] and intensity [85] this somewhat implies that the physicochemical features should, at least in part, help to explain the nature and origin of olfactory crossmodal correspondences. This hypothesis is explored in more detail in Chapters 6 & 7. In addition, there is an emerging area of literature, mainly from a psychology perspective that demonstrates the benefits of manipulating the sensory expectations whereby both congruency and incongruency would be advantageous towards manipulating a multisensory experience towards a desired outcome.

The nature of virtual synaesthesia entails that the experience is multisensory or, at a minimum, contains multiple sensory modalities. The background and related works for multisensory experiences in human-computer interaction are covered in Section 2.5. Research in this area is rapidly gaining interest in investigating multisensory perception and how it affects human-computer interaction, however, incorporating the chemical senses into multimedia applications is still in its infancy compared to vision, audition, and haptics. In terms of olfaction-enhanced multimedia, the addition of scents is proving to be a great addition in improving the quality of experience and the designs of multimodal interfaces. Overall integrating crossmodal correspondences in the designs of multisensory experiences is gaining interest, albeit limited. Understanding the cognitive processes across all sensory modalities could play a vital role in developing more refined multimodal interfaces

that better considers human perception [171], [268]. Hence the concept of virtual synaesthesia will prove useful towards this end. The sensory experience perceived by humans is rather limited in the sense that we only perceive a small portion of it. Loosely speaking, sensory substitution/augmentation opens up opportunities to expand upon and build new “senses” for humans. Making the field a suitable test bed for the preliminary exploration of virtual synaesthesia. That is, if we take the paradigm of virtual synaesthesia and apply it to a sensory substitution or augmentation system, it may be possible to exploit the benefits underpinning natural synaesthesia or crossmodal correspondences. One use of virtual synaesthesia could be the subtle presentation of information between the real and virtual worlds while minimising functional and sensory overload, providing an overt, low-attention human-machine interface using real-world information. Current sensory substitution/augmentation systems provide an implicit mode of perception, however, coupling the ideology of virtual synaesthesia can help provide an explicit mode of perception which would greatly benefit these systems in terms of improving the amount of retained information while minimising the amount of the redundantly presented information. As the work in this thesis focuses mainly on olfaction, it is important to uncover the hows and why’s of olfactory perception.

Olfactory perception is a complex process that involves contributions from a variety of different factors, such as expectations [63], context [64], multisensory convergence [65], in utero neuroanatomical development [66], and is a heavily learned process [67]. Unlike vision, where the wavelength of light is a predictable property of colour, and in hearing, frequency is a predictive property of tone, there is no predictive property of how molecules will smell. However, hedonic determination is arguably the most dominant function of olfaction. Psychophysical evidence suggests that the pleasantness of odours is encoded in the physicochemical structure of odorous molecules [62], [70], [77], [78]. This link could potentially be exploited to predict different aspects of perception, including pleasantness, intensity, and semantic descriptors. It is still unknown to what extent this is possible. For example, is it possible to predict the crossmodal correspondences of odours using their physicochemical features? Most of the literature converges to the controversial statement that this is possible due to a partly innate and hard-wired link in olfactory perception. However, at the time of writing, this is only a theory, and more research is needed to confirm or reject this hypothesis.

The next chapter (Chapter 3) covers the experimental setups and methodology used throughout this thesis.

Chapter 3 Experimental Setups & Methodology

3.1 Introduction

This chapter includes the different parts of the experimental setups used throughout this thesis which are described in detail. The first method was the development of the electronic nose (e-nose) used to uncover the chemical footprint of odours. As described previously, an e-nose consists of an array of gas sensors coupled with a pattern recognition system. These sensors physically interact with particles and produce a potential difference in the electronic circuit by changing the resistance of the material inside the sensor and measuring using the output voltage. Different gas sensors have different sensing materials inside the sensor that respond to a specific gas(es). The voltage value generated by the sensor can estimate the concentration and type of the gas. However, most odours contain multiple compounds that make up their composite odour. Therefore, a carefully selected array of sensors is typically required to capture the entire smell and not just a specific element of it. A pattern recognition system is required to make sense of the signals generated by the e-nose; for example, given a series of ten different signals, the pattern recognition system could differentiate between presented odour (i.e., this is the smell of pineapple) and in some cases quantify specific gases (i.e., this odour contains 30 ppm of alcohol). Figure 9 shows an example sensor responses from the sensors in the e-nose; this is the type of data presented to the pattern recognition system. Notice how the sensor responses change over time; some responses will have a small change over time (i.e., temperature), while others exhibit a larger change (e.g., MQ5 and Air Quality).

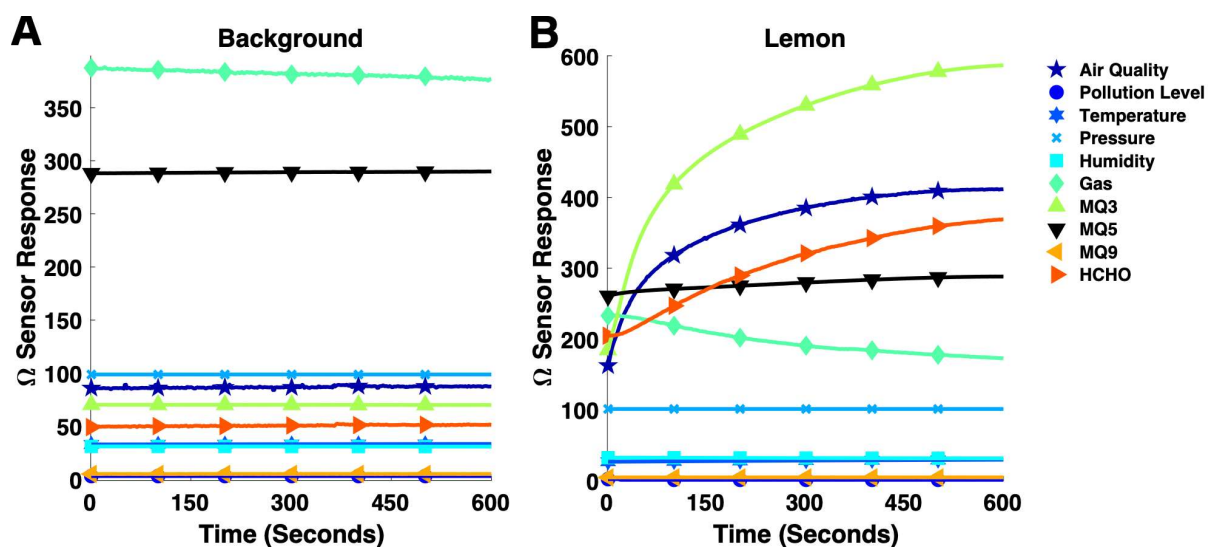


Figure 9. Example e-nose responses for no odour (A) and for lemon essential oil (B).

The $L^*a^*b^*$ colour space, also referred to as the CIE Lab colour space, is a standardized and device-independent way of representing colours. This colour space expresses colour as three channels: L^* for perceptual lightness between the values of 0 – 100, a^* red – green with values typically ranging from -127 to 127, and b^* yellow – blue again with values typically ranging from -127 to 127. The $L^*a^*b^*$ colour space was designed to be perceptually uniform where a numerical change in colour aligns with a similar perceptual change and covers the entire range of colour perception (see [269] for more information) and is the reason why this specific colour space was chosen. Figure 10 shows a sample of the $L^*a^*b^*$ colour gamut.

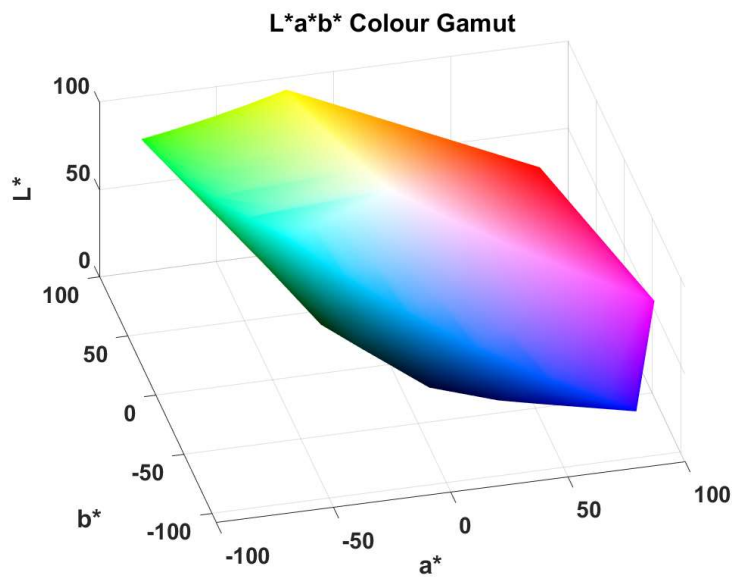


Figure 10. $L^*a^*b^*$ colour gamut in sRGB colour space.

The rest of this chapter is organised as follows; section 3.2 covers the first version of the electronic nose. Section 3.3 covers the second and improved version of the electronic nose used throughout this thesis.

3.2 Electronic Nose

An e-nose was developed to uncover the 'chemical footprint' of the aromatic solutions to be used for the purpose of this thesis. The e-nose consists of five commercially available gas sensors: MP503, BME680, MQ3, MQ5, and WSP2110 (Seeed Studio) and is designed to detect a wide range of chemicals, as shown in Table 2. The sensor array was connected to an Arduino MKR1000 microcontroller, chosen for its wireless capabilities and controlled using custom software. This array of sensors was mounted in a chamber using a custom-made backplate, and the averaged output resistance of each sensor was taken as the response. This information is then sent to the mobile

computing engine using user datagram protocol (UDP) \approx every 125 ms. The schematic for the e-nose is shown in Figure 11. The circuit for the e-nose is shown in Figure 12; note that this version of the e-nose did not include the MQ9 sensor. This e-nose was used in Chapter 4 to emulate odour-vision synaesthesia. See Section 2.8 for justification of these sensors.

Gas Sensor Name	Detection Range (ppm)	Most Sensitive Gases	Sensor Output Name
MP503	10 – 1,000	Alcohol & Smoke	Air Quality & Temperature
BME680	0 – 500	IAQ (Indoor Air Quality)	Humidity, Pressure &, Gas
MQ3	0.05 – 10	Alcohol & Benzine	MQ3
MQ5	200 – 10,000	LPG, Town gas, Natural Gas, Alcohol, & Smoke	MQ5
WSP2110	1 - 50	Toluene, Methanol, Benzene, Alcohol, & Acetone	HCHO

Table 2. Gas sensors with their range of detectable gases. The information in this table was obtained from the corresponding sensors' datasheet. NOTE: The sensors may also be able to detect gases other than those listed in the table.

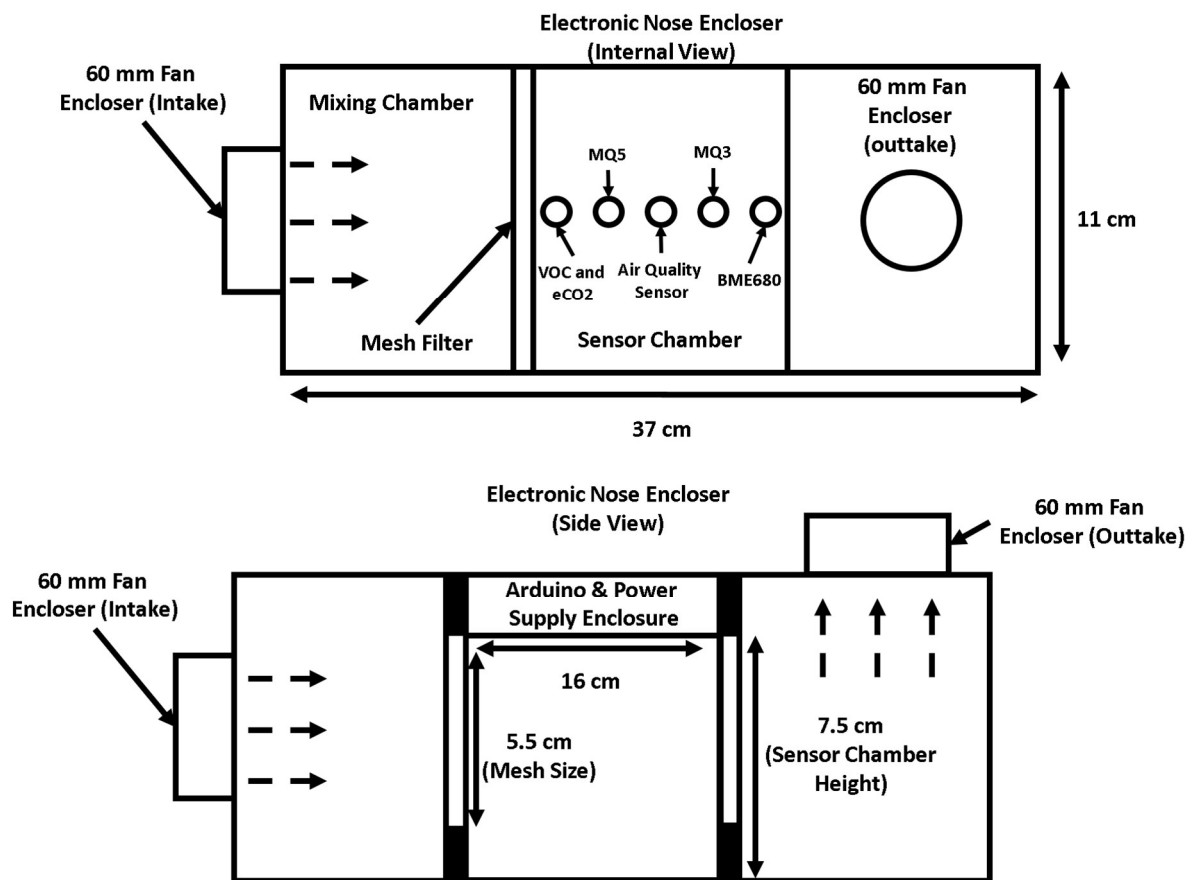


Figure 11. Schematic for the electronic nose (e-nose) used for odour detection and recording in chapter 4.

3.3 Electronic Nose V2

Building upon the electronic nose presented in the section above, an MQ9 gas sensor was added, and the container was changed to a custom 3D printed, and sealable container made using PLA. This additional sensor was added to improve upon the e-nose's range of detection. The full list of sensors used in this revision of the e-nose is shown in Table 3, and the photo of the experimental setup is shown in Figure 13. The circuit for the e-nose is shown in Figure 12. This version of the e-nose was used for the experiments performed in Chapter 5 and Chapter 6. See Section 2.8 for justification of these sensors.

Gas Sensor Name	Detection Range (ppm)	Most Sensitive Gases	Sensor Output Name
MP503	10 – 1,000	Alcohol & Smoke	Air Quality & Temperature
BME680	0 – 500	IAQ (Indoor Air Quality)	Humidity, Pressure & Gas
MQ3	0.05 – 10	Alcohol & Benzene	MQ3
MQ5	200 – 10,000	LPG, Town gas, Natural Gas, Alcohol & Smoke	MQ5
MQ9	10-1000 CO 100-10000 Gas	Carbon Monoxide, Coal Gas and Liquefied Gas	MQ9
WSP2110	1 - 50	Toluene, Methanol, Benzene, Alcohol & Acetone	HCHO

Table 3. Gas sensors used in version 2 of the electronic nose.

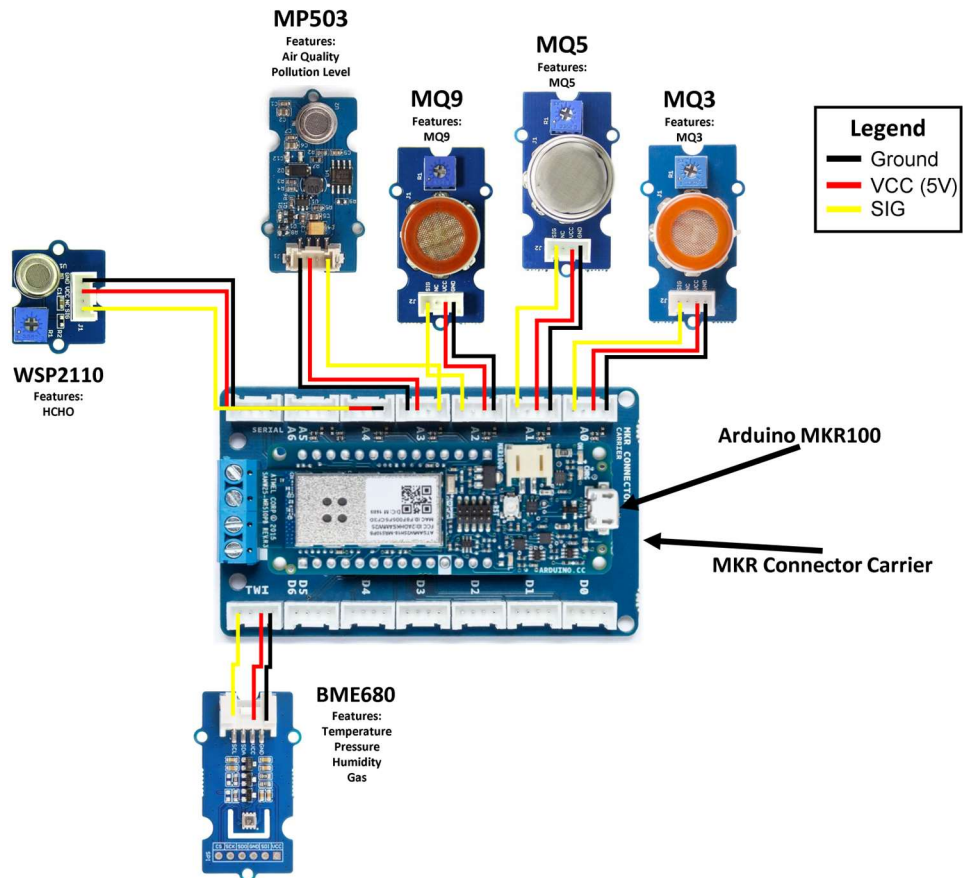


Figure 12. Circuit schematic for the e-nose used throughout this thesis.



Figure 13. Photo of version 2 of the electronic nose used for the recording of different odours.

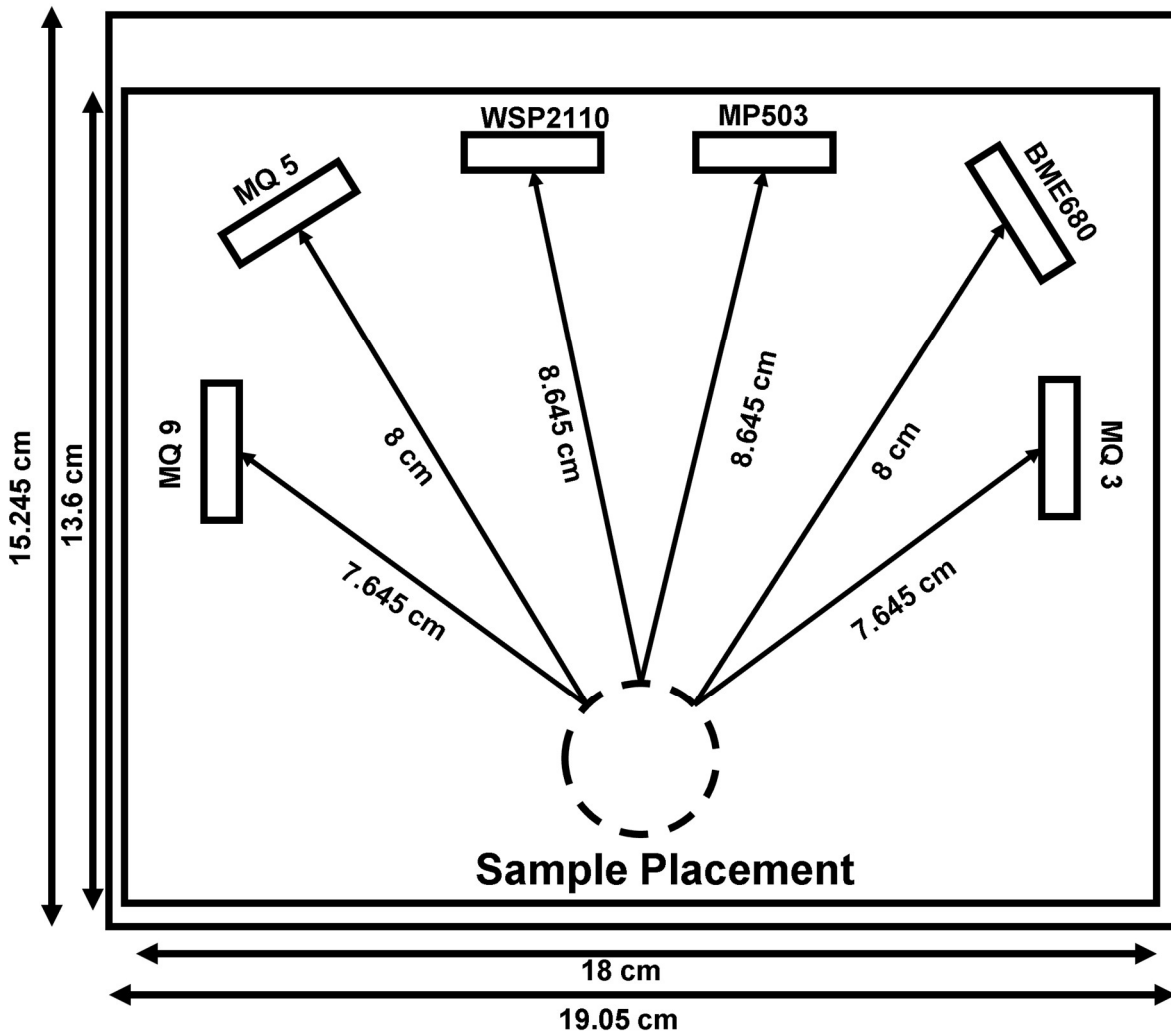


Figure 14. Schematic for version two of the electronic nose used for odour detection and recording in chapters 6 & 7.

3.4 Human Trials

Before any human trials were conducted, Ethical approval was obtained from the Health and Life Sciences Research Ethics Committee at the University of Liverpool. This was the ethical approval used for all the human trials in this thesis, and confirmation of approval can be found in the appendix Section 9.1. Ethical approval was obtained before any trials involving humans were conducted. Before anyone participated in any experiments, they were first given a participant information sheet (see the appendix). This sheet was kept as vague as possible so as not to provoke any bias before the beginning of each trial (i.e., not giving the list of the exact odours used in the experiment beforehand so they do not make any inferred decisions on the possible identity of the odour). Finally, directly before

participation the participants signed a consent form to satisfy the ethical procedure (see the appendix).

3.5 Conclusion

In this chapter, the methodology behind electronic noses and the L*a*b* colour space was discussed; both of these methods have been used in multiple chapters in this thesis. The specifics of the two iterations of the e-nose, including the comminution protocol used, the sensors used in the array, and schematic representations of the e-noses, are covered. The general information underlying the human trials conducted in this thesis is also given. More details on the specifics of each human trial are covered in the respective chapter. Considered together, the information presented in this chapter should allow for all of the experimental setups to be replicated when considered with the relevant information from the corresponding chapter. The following chapters utilise the information reported in this chapter as a means to an end to conduct and answer research questions; therefore, it is important to articulate the underlying methodology to make the findings reproducible.

Chapter 4 Virtual Synaesthesia in Human-Machine Interfaces

4.1 Introduction

This chapter focuses on utilising a top-down paradigm of virtual synaesthesia to create a human-machine interface that loosely mimics odour-vision synaesthesia. Using this top-down approach, the benefits of implementing an artificial form of synaesthesia into human-machine interfaces were explored to determine if the paradigm can create a device with some of the same cognitive benefits as its natural counterpart. As the area of virtual synaesthesia is still in its infancy, the potential benefits, challenges, and limitations of implementing virtual forms of this phenomenon still need to be investigated. However, successfully integrating the paradigm of virtual synaesthesia should, in the long run, be able to make human-machine interfaces more natural and efficient.

To test the potential of incorporating an artificial form of synaesthesia into a human-machine interface, an augmented reality device was created to loosely mimic odour-vision synaesthesia. Odour-vision synaesthesia was chosen for exploration as more attention is given to the more dominating sense [138] and is comparable with the literature [94]. Focusing on odour-vision synaesthesia in this chapter also allows it to fit in around the olfactory theme in the rest of this thesis. An e-nose and an odour generator have been developed to generate and detect odours for visualisation. Details about the custom-made odour generator and electronic nose can be found in Sections 4.2 and 3.2, respectively.

The experimental setup for the experiments performed in this chapter is shown in Figure 15, and has three major components: (A) an active odour source (olfactory display), (B) an odour detector (e-nose) and (C) a mobile computing engine with a pattern recognition system and a visualiser. First, an odour is released into the environment (A), a custom olfactory display was developed to release odours into an open environment. This is then transduced by the e-nose (B) and sent to the mobile computing engine (C) via a UDP (User Datagram Protocol) connection. The mobile computing engine, in turn, will generate a 2D abstract shape that represents the current odour, assign a colour to it using the random forest machine learning algorithm and then display it to the user in real-time.

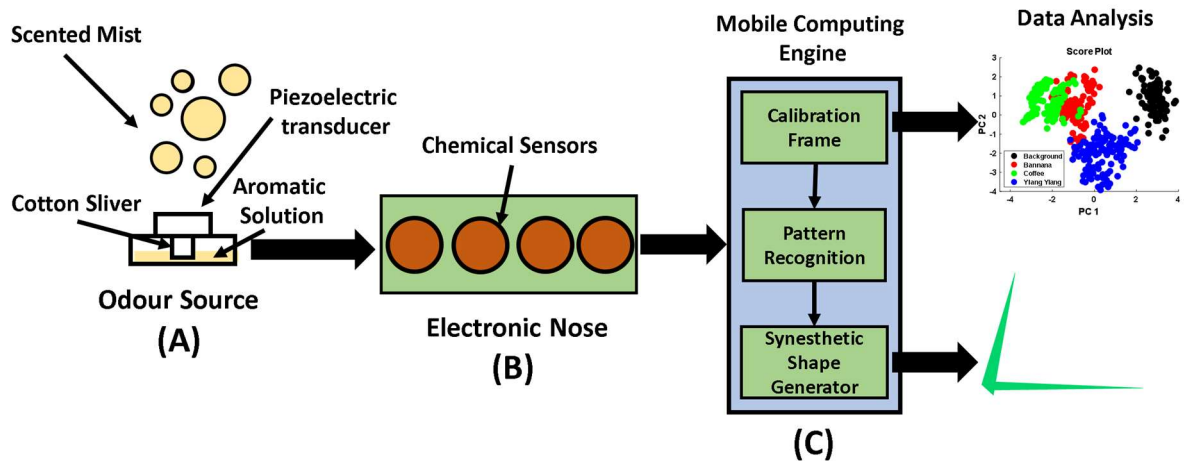


Figure 15. Schematic representation of the experimental setup for the synesthetic visualisation of odour sources.

In this chapter, the following research question was asked; is it possible to replicate the underlying cognitive benefits of odour-vision synaesthesia? It is hypothesised that some, if not all, of the underlying cognitive benefits behind natural synaesthesia would carry over if artificially emulated. The work for this chapter is published in the IEEE Sensors journal [35]. This chapter is organised as follows. Section 4.2 covers the odour generation method used to create the odours for the e-nose to detect. Section 4.3 covers a comparative analysis of the most suitable method for detecting odours and tests to determine the limit of detection of the e-nose. Section 4.4 covers essential oil and gas sensor relationship testing using principal component analysis. Section 4.5 covers the pattern recognition aspect of the system. Section 4.6 covers the visualisation of the odours. Section 4.7 and 4.8 covers the human trials of the developed method to determine if the cognitive benefits behind odour-vision synaesthesia are, at least in part, replicable.

4.2 Odour Source / Aroma Generation Method

A small olfactory display was created to release odours into the environment, as shown in Figure 16. This utilises a piezoelectric transducer to turn the aromatic solution into a fine mist which is supplied to the transducer via a cotton sliver. The transducer (Seed Studio [270]) consists of a piezoelectric plate that heats the aromatic solution using ultrasound and has a frequency of 105 ± 5 kHz. This creates a vertical bottom-up diffusion when supplied with a liquid, creating a fine mist. The aromatic solution was left sitting for 10 minutes before the odour was released, giving time for the cotton sliver to absorb enough of the aromatic solution for a continuous stream. A mount was created to house

the cotton sliver and transducer. The custom olfactory display is depicted in Figure 16. Now that it is possible to programmatically generate different odours it is important to uncover the most optimal method for detecting the created stimuli.

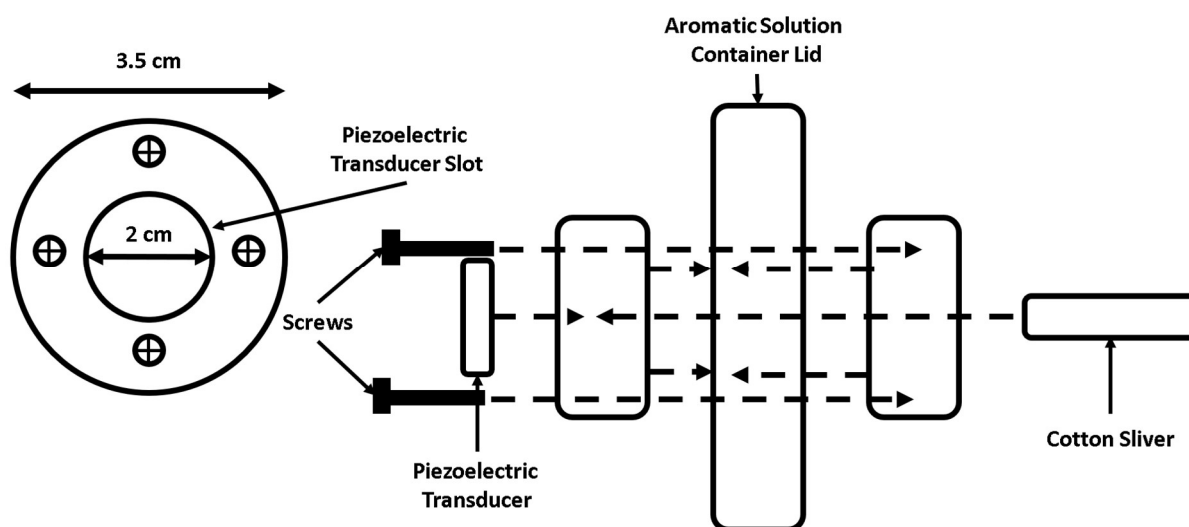


Figure 16. Schematic for the piezoelectric transducer-based olfactory display used to generate different odours.

4.3 Optimal Odour Detection Method

First, solutions were created consisting of 0.5 mL of the respective aromatic oils or model compounds and 4.5 mL of deionised water with a ratio of 1:9 (v/v). In total, 19 unique mixtures were created: three for the model compounds (phenyl alcohol, methyl butyrate, and allyl hexanoate) and sixteen for the aromatic oils (banana, black pepper, cedarwood, caramel, coffee, eucalyptus, fudge, lemon, lime, orange, patchouli, tea tree, vanilla and ylang ylang). Some aromatic essential oils were selected due to a perceptual overlap (perceived to smell similar by a human (coffee, toffee, and caramel)). To determine the optimum detection method, sample model compounds (phenyl alcohol, methyl butyrate, and allyl hexanoate) were first detected in the open environment using tandem mass spectrometry (MS/MS) in positive ion mode with DAPCI (desorption atmospheric pressure chemical ionisation) coupled to the mass spectrometer (see Figure 17). These compounds were chosen due to their presence in a wide variety of odours. DAPCI-MS was selected as it is non-invasive, real-time, able to analyse complex mixtures, does not require toxic reagents and has no secondary pollution [271]. The active compounds (m/z) of interest were isolated and detected using collision-induced tandem mass spectrometry (MS/MS) [272].

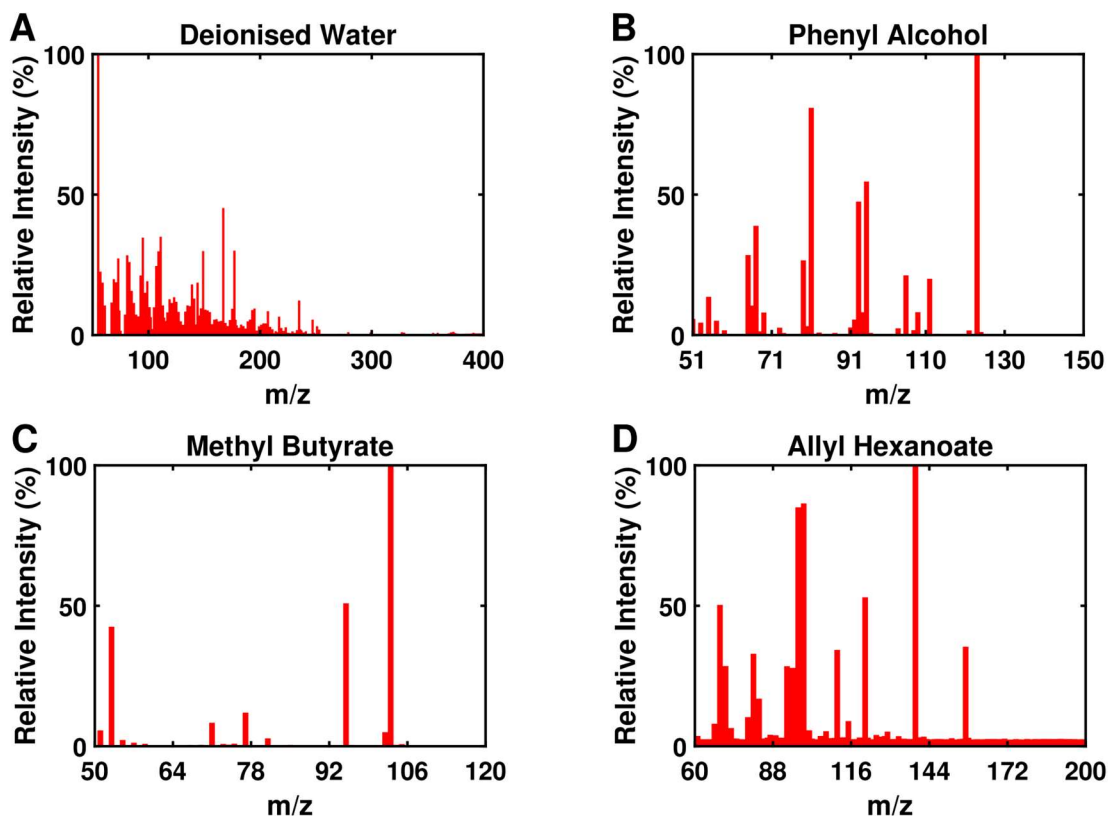


Figure 17. Positive ion mode DAPCI-MS collision induced (CID MS/MS) mass spectras; phenyl alcohol (B) (Mw 122), methyl butyrate (C) (Mw 102) and ally hexanoate (D) (Mw 156), protonated ion molecules $[M+H]^+$ at m/z 157, 117, 152 and 103.

From Figure 17 we can see that the DAPCI-MS can detect the standard model compounds with high specificity and sensitivity, meaning it will have a wide range of detection. Next representative mass spectrums of the aromatic samples were recorded (banana, coffee and ylang-ylang) and are shown in Figure 19. For this experiment, $\approx 10 \mu\text{L}$ of the aromatic solutions were spotted onto a piezoelectric transducer. These samples were recorded to allow for a comparison with the developed e-nose system. The range of detection experiment for the e-nose consists of 500 ppm of the model compounds in deionised water and is shown in Figure 18. The range of detection experiments for the e-nose shows us that the sensors can detect and therefore characterise a wide variety of chemicals and not just the samples used in the confines of these experiments.

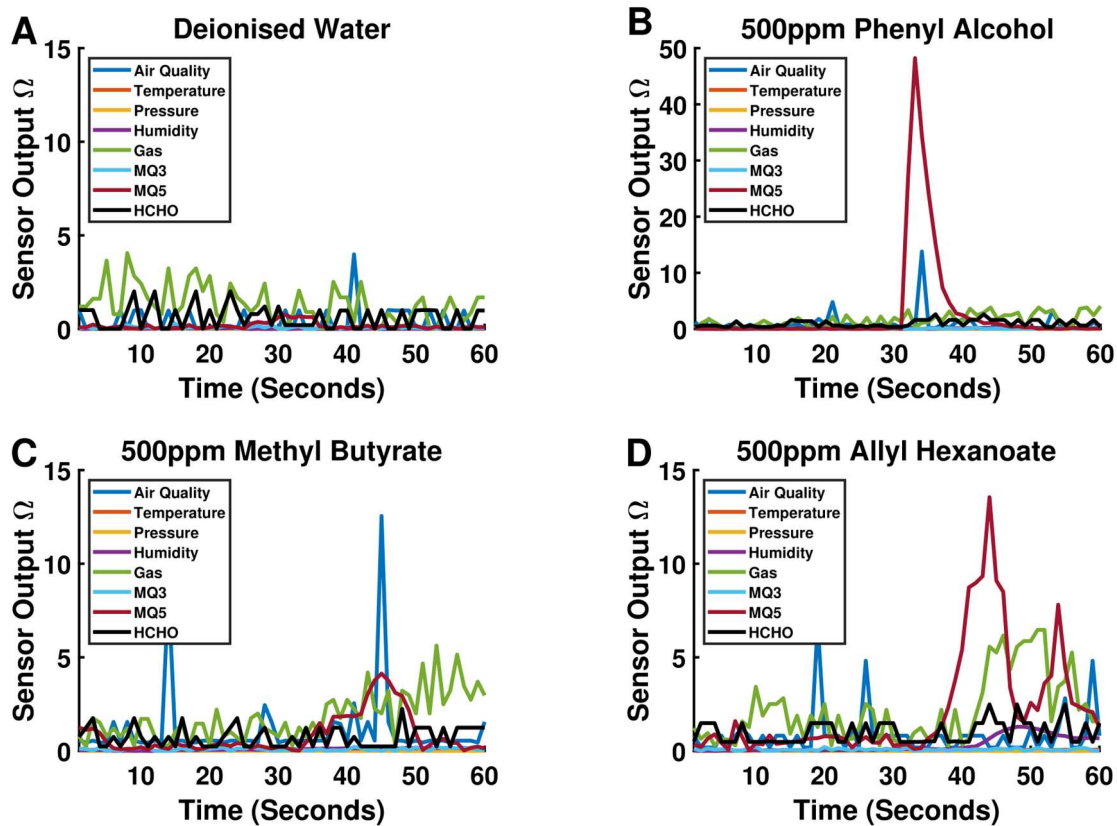


Figure 18. Sample e-nose responses for the standard model compounds and deionised water, samples were spotted on the piezoelectric transducer for the limit of detection.

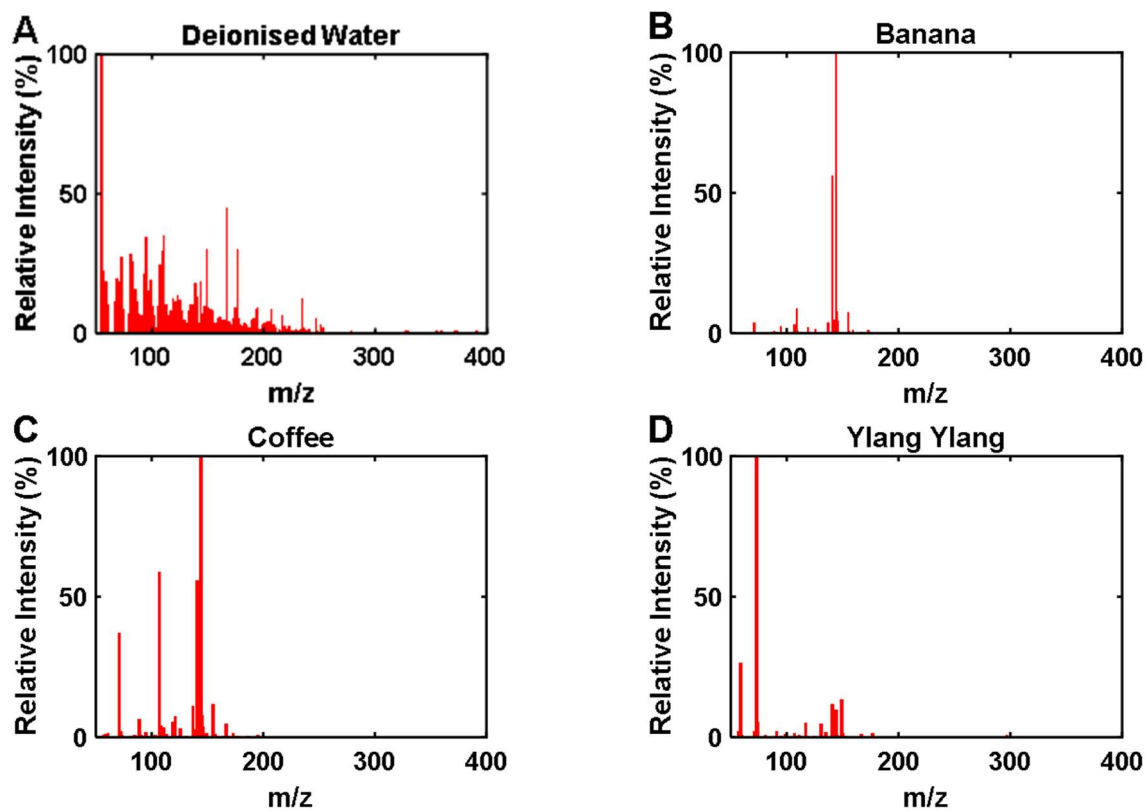


Figure 19. Sample mass spectrums for deionised water (A) and the essential oil samples (B – D).

Based on both Figure 18 and Figure 19 it is evident that the e-nose can detect a wide range of chemicals but is unable to quantify without calibrating the sensors on specific chemicals. Compared to DAPCI-MS, the e-nose has less sensitivity and specificity, making DAPCI-MS inherently the better choice for quality of data. However, it lacks in other ways. The e-nose was chosen to be the device for the rest of the experiments because, unlike the mass spectrometer, it is low-cost, lightweight, portable, and provides access to the data in real-time. Moreover, the data provided by the e-nose is sufficient for the task at hand. As the physicochemical features of the odours transduced by the e-nose will provide enough information to the user. Whereas, if information from a mass spectrometer was presented to a naïve user, this would result in functional and sensory overload (too much information to make meaningful sense out of it).

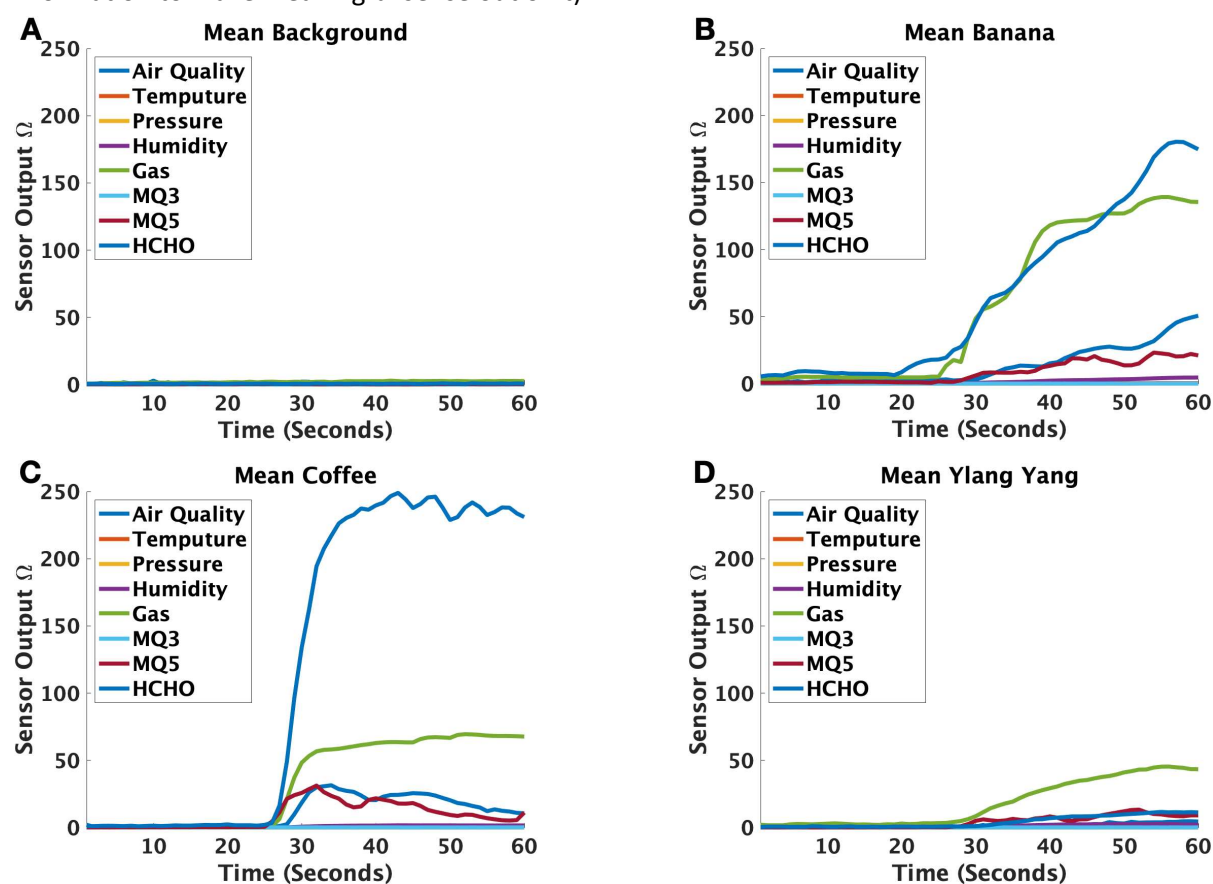


Figure 20. Sample e-nose recordings no odour (A) and the aromatic oil samples (B – D). The process to atomise the aromatic solution started at the 20 second mark.

After deciding the e-nose to be the optimal method for the rest of the experiments, another five recordings were collected for banana, black pepper, cedarwood, caramel, coffee, eucalyptus, fudge, lemon, lime, orange, patchouli, tea tree, vanilla, and ylang-ylang. These recordings resulted in 85, 60-second long recordings prepared for the rest of the experiments in this chapter. Now that it is possible to get a “footprint” of a given odour, it would be beneficial to explore how well the e-nose

can discriminate between odours and which sensors contribute towards the discrimination of the odours.

4.4 There Is Sufficient Overlap Between The Odours In The Physicochemical Space

Principal component analysis was then conducted on the aromatic samples for banana, coffee and ylang-ylang. This was undertaken to determine how much of an overlap there is between the odour recordings and to uncover to what extent each of the values (sensor responses) produced by the e-nose contribute towards the detection of the aromatic samples. A dataset was constructed; first, to reduce the noise from the signal, a moving average filter was then applied, and the median value was taken for each sensor over one-second intervals. Next, the first thirty-five seconds were removed, as the releasing of the odour occurred at the twenty-second mark, as shown in *Figure 20*; additionally, another fifteen seconds were removed to allow for the odour to build up in the environment. The dataset was then logged and normalised using z-score normalisation using the population standard deviation and standardised against the gas sensors (independent features). The first three principal components explain 80.21% of the total variance, 43.24%, 22.08%, and 14.87%, respectively. The first two principal components are shown in *Figure 21A*, and the first two loadings are shown in *Figure 21B*. It is important to note that the intensity of the odour, in this case, is an arbitrary factor in this PCA and was not used in generating the shapes, as this information would typically be unavailable. The intensity, in this case, was an arbitrary value known at the time of recording the odours. The intensity was included to analyse its relation to the other components included in the analysis as well as determining the influence it would have in the generation of the shapes and the colour profiles and is not a response from one of the sensors.

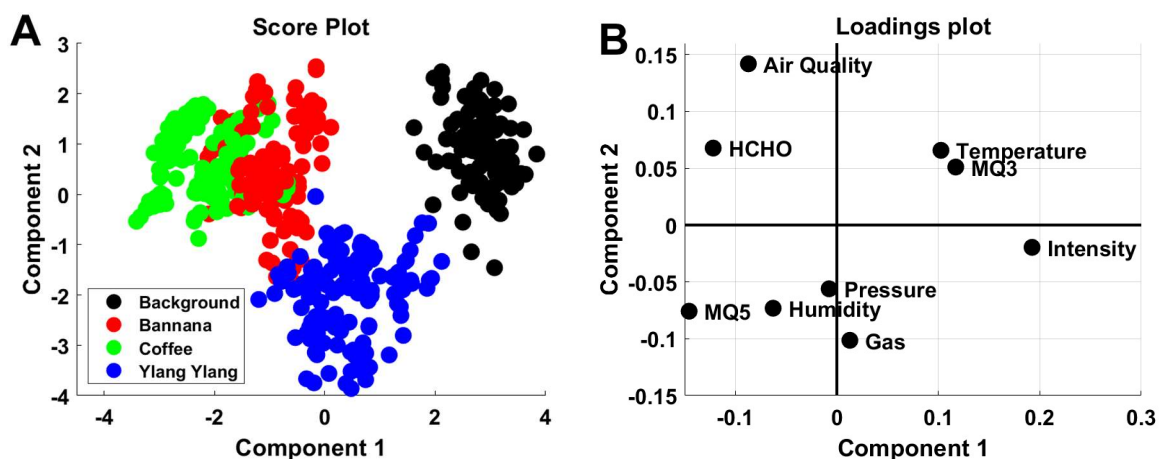


Figure 21. Score plot (A) of 3 different odours and the background response from the e-nose after pre-processing. Loadings (PCA coefficients) plot (B) shows the correlation coefficients.

From Figure 21A, we can see that there is a small overlap between the model odours; this small overlap will allow for the creation of distinct and consistent colour profiles. Having no overlap will provide colours that are not distinct enough. Meaning that the similar odours that are unseen to the pattern recognition component (i.e., orange and lemon), the generated colour profiles that may be too consistent to differentiate one odour from another (i.e., the colour profiles for orange and lemon will be almost identical and hard to tell apart). However, too much overlap would result in colour profiles that are not consistent enough (too much variation to make meaningful sense out of); a little overlap will be the optimal middle ground towards these two issues. This overlap requirement is meant for odours unseen to the system where there are a potentially infinite number of possible odours and odour permutations, so a little bit of overlap, but not too much, will help discriminate chemically similar odours that are unseen to the system. From Figure 21B, we can see that intensity plays the most significant role in explaining the variation in the x-axis (see Figure 21A), suggesting that the stronger each odour becomes, the more distinguishable they are to the e-nose. It also indicates that intensity makes the most contribution to the colour and shape variation of the system. It also shows that the BME680 sensor (air quality) is the most sensitive sensor in the array for the detection of the aromatic solutions (the air quality is the furthest sensor response from (0, 0) using Euclidean distance even though it is one of the weakest components on the first component). Now that it has been tested which sensors contribute and the extent of the overlap between the odours in order to generate the colour profiles needed for the coloured shape, a pattern recognition system needs to be developed.

4.5 Distinct Colour Profiles Can Be Created Using The Random Forest Classifier

A pattern recognition system was developed to generate the colour profiles. Ten of the aromatic recordings (banana, caramel coffee, eucalyptus, lemon, orange, patchouli, tea tree, vanilla, and ylang-ylang) and the background (no odour) were used to train the pattern recognition system with the remaining five (black pepper, cedarwood, fudge, lime, and pine) used for testing the colour profiles as these were odours unseen during the training stage. A dataset was constructed following the same process presented in Section 4.4. A variety of machine learning algorithms were then tested on the dataset to determine which one performs the best for the classification of odours. All algorithms were trained and tested in accordance with 50-fold cross-validation.

Algorithm	Accuracy Rating (%)
Fine Tree	86.4
Linear Discriminant	46.7
Support Vector Machine	95.0
K-Nearest Neighbour	88.6
Random Forest	95.57

Table 4. Table showing the accuracy of five different machine learning algorithms tested.

The algorithms shown in Table 4 were considered as they are commonly used for the classification of data from e-noses, this is because they are sufficiently lightweight enough to be deployed in sparse resource environments [273]–[275], in this case a mobile phone. The discrimination ability of the system could be improved by calibrating the sensors in the array to detect specific gases and/or including a more gas sensors. As the random forest algorithm had the highest accuracy rating in the test case, it was used for the generation of the colour profiles. The sample colour profiles for the odours (black pepper, cedarwood, fudge, lime, and pine) were not used to train the classifier and are shown in Figure 22.

Ten equally spaced apart points were taken from the outside of a cylindrical representation of the $L^*a^*b^*$ colour space at ($L^* = 70$). This colour space was chosen for its perceptual uniformity allowing for the selection of colours equally spaced apart perceptually. The colours were assigned to the output of the classifier based on a one-to-one mapping of the classification output. Additionally, the colour black was assigned to be that of the background class. The information in Figure 22 shows that diverse and unique colour profiles can be generated for unknown odours. However, as typical with the gas sensor responses and machine learning algorithms, there is noise in the generated colour

profiles (colours with a small frequency (%). Now that a pattern recognition system has been developed to generate colour profiles depending of the underlying physicochemical features a visual stimuli needs to be developed to house the colour. More information could be presented to the user at any given point in time if this shape was dynamic (e.g., a shape the morphs to represent the current odour(s)).

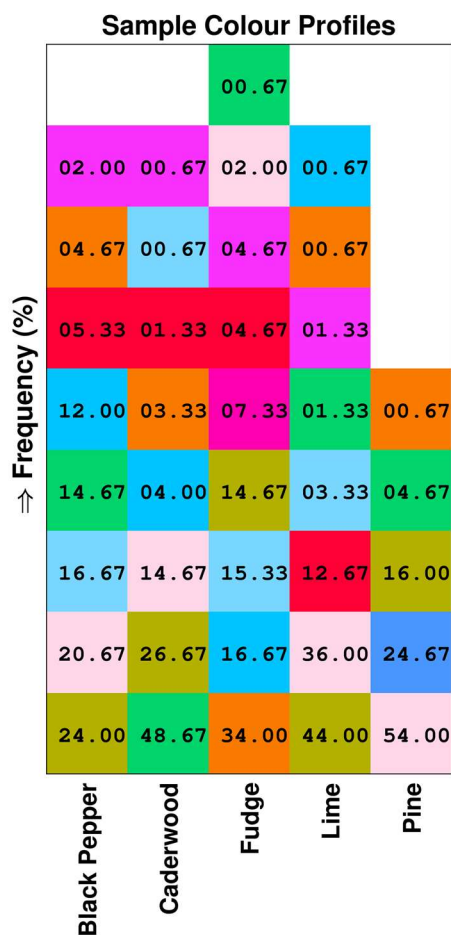


Figure 22. Sample colour profiles for unknown odours. The frequency of each colour is the number of how many times the colour occurred in 150 seconds of recordings, indicated as a percentage.

4.6 Consistent Shape Stimuli Can Be Generated Using A Custom Equation

To visualise odour sources in real-time, the e-nose transmits packets of information to the mobile computing engine; the mobile computing engine then creates a visual representation of the odour source (a coloured abstract shape) and superimposes it onto a live feed from the subjects' camera. The augmented reality aspect is then combined with a stereoscopic view of the real-world (AR/VR), allowing the user to move around the environment unhindered. The AR / VR device is shown in Figure 23A with the e-nose and olfactory display element shown in Figure 23B.

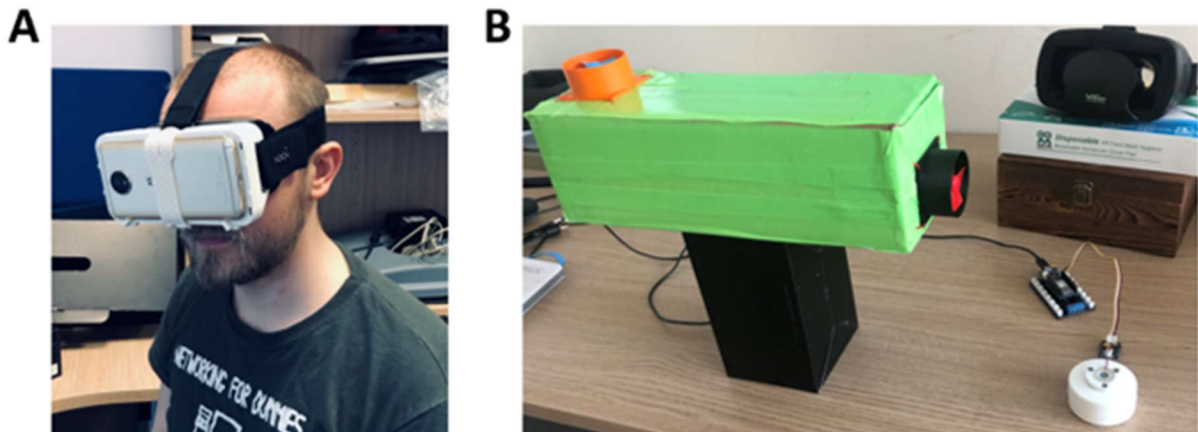


Figure 23. (A) An image of a user wearing the system. (B) Image of the e-nose with the olfactory display.

The visualiser is shown in Figure 23A fuses the data from the e-nose shown in Figure 23B and the pattern recognition element to create a 2D abstract shape that represents the current odour source. This used the processed e-nose responses and was designed for the ambient visualisation of odours to loosely resemble real odour-vision synaesthesia, to show the potential of augmenting a synthetic form of this phenomenon into human-machine interfaces. To generate the vertices the following algorithm is applied to the e-nose responses.

$$x_i = \frac{1}{1 + \sigma_i \sin \frac{2\pi i}{\frac{m_1 m_2}{9} + \frac{\sigma_i}{2}}}, \text{ for } i = 1, 2, 3, \dots, n \quad (1)$$

Equation 1. The final equation to generate the location of the x vertices.

$$y_i = \frac{1}{1 + \sigma_i \tanh \frac{2\pi i}{\frac{m_1 m_2}{9} + \frac{\sigma_i}{2}}}, \text{ for } i = 1, 2, 3, \dots, n \quad (2)$$

Equation 2. The final equation to generate the location of the y vertices.

Where n is the number of sensor responses from the electronic nose, σ_i is the current value from sensor(i), m_1 and m_2 is the index location for the first and second-largest values in the vector,

respectively. x_i and y_i correspond to the vertex coordinates centred around the origin on a Cartesian plane. To create Equation 1 and Equation 2, the standard equation for a 2D radar (spider) plot was modified, which is one of the traditional graphs for plotting e-nose responses. This equation was altered to provide to create more visually distinct shapes and to align it with natural odour-vision synaesthesia, or at least as close as possible. The equations for an empty radar plot with equal values is shown in Equation 3 and Equation 4.

$$x_i = \sin\left(\frac{2\pi i}{n}\right), \text{ for } i = 1, 2, 3, \dots, n \quad (3)$$

Equation 3. The equation to generate the location of the x vertices equally spaced from the centre.

$$y_i = \cos\left(\frac{2\pi i}{n}\right), \text{ for } i = 1, 2, 3, \dots, n \quad (4)$$

Equation 4. The equation to generate the location of the y vertices equally spaced from the centre.

Where n is the number of sensors, it was then required to constrain the size generated shape to be within the unit square so the vertices of the shape do not go off the edge of the screen, leading to Equation 5 and Equation 6.

$$x_i = \frac{1}{1 + \sin\left(\frac{2\pi i}{n}\right)}, \text{ for } i = 1, 2, 3, \dots, n \quad (5)$$

Equation 5. The equation to generate the location of the x vertices equally spaced from the centre but within the unit square.

$$y_i = \frac{1}{1 + \cos\left(\frac{2\pi i}{n}\right)}, \text{ for } i = 1, 2, 3, \dots, n \quad (6)$$

Equation 6. The equation to generate the location of the y vertices equally spaced from the centre but within the unit square.

It was then desired to incorporate the responses from the e-nose in order to create a representative shape based on the currently presented odour. Based on Equation 5 and Equation 6, this led to Equation 7 and Equation 8.

$$x_i = \frac{1}{1 + \sigma_i \sin\left(\frac{2\pi i}{n}\right)}, \text{ for } i = 1, 2, 3, \dots, n \quad (7)$$

Equation 7. The equation to generate the location of the x vertices, within the unit square but considering the sensor responses.

$$y_i = \frac{1}{1 + \sigma_i \cos\left(\frac{2\pi i}{n}\right)}, \text{ for } i = 1, 2, 3, \dots, n \quad (8)$$

Equation 8. The equation to generate the location of the y vertices, within the unit square but considering the sensor responses.

Where σ_i is the current value from sensor(i). The equations were adjusted further to make the generated shapes more unique and more “synesthetic”. This led to Equation 7 and Equation 8 being adjusted to create Equation 9 and Equation 10.

$$x_i = \frac{1}{1 + \sigma_i \sin\left(\frac{2\pi i}{\sigma_i}\right)}, \text{ for } i = 1, 2, 3, \dots, n \quad (9)$$

Equation 9. The equation to generate the location of the x vertices within the unit square, considering the sensor responses and modified to be more synesthetic and unique.

$$y_i = \frac{1}{1 + \sigma_i \tanh\left(\frac{2\pi i}{\sigma_i}\right)}, \text{ for } i = 1, 2, 3, \dots, n \quad (10)$$

Equation 10. The equation to generate the location of the y vertices within the unit square, considering the sensor responses and modified to be more synesthetic and unique.

However, an issue has arisen whereby some vertices appear to be dominating the others in terms of magnitude (points in 2D space very far away from the others). Therefore, the equations were further adjusted to reduce this artefact this led to Equation 11 and Equation 12.

$$x_i = \frac{1}{1 + \sigma_i \sin\left(\frac{2\pi i}{\frac{m_1 m_2}{9} + \frac{\sigma_i}{2}}\right)}, \text{ for } i = 1, 2, 3, \dots, n \quad (11)$$

Equation 11. The final equation to generate the location of the x vertices.

$$y_i = \frac{1}{1 + \sigma_i \tanh\left(\frac{2\pi i}{\frac{m_1 m_2}{9} + \frac{\sigma_i}{2}}\right)}, \text{ for } i = 1, 2, 3, \dots, n \quad (12)$$

Equation 12. The final equation to generate the location of the y vertices.

Where m_1 and m_2 is the index location for the first and second-largest values in the vector (an array of sensor responses at a given point in time). Equation 11 and Equation 12 are the final equations and the ones used to create the shapes outlined below.

The visual representation of the odours consists of using the pattern recognition system to generate the colour of a shape and a custom algorithm to generate the vertices. A sample output for

one of the generated shapes is shown in Figure 25B-D, with A showing the output of the system on the mobile phone. Each half of this image shows the view for the left and right eye separately. These two images will be perceptually merged into one while wearing the AR/VR headset. The generated shape is then superimposed onto the user's visual field, allowing them to move around unhindered while viewing the generated synesthetic shape.

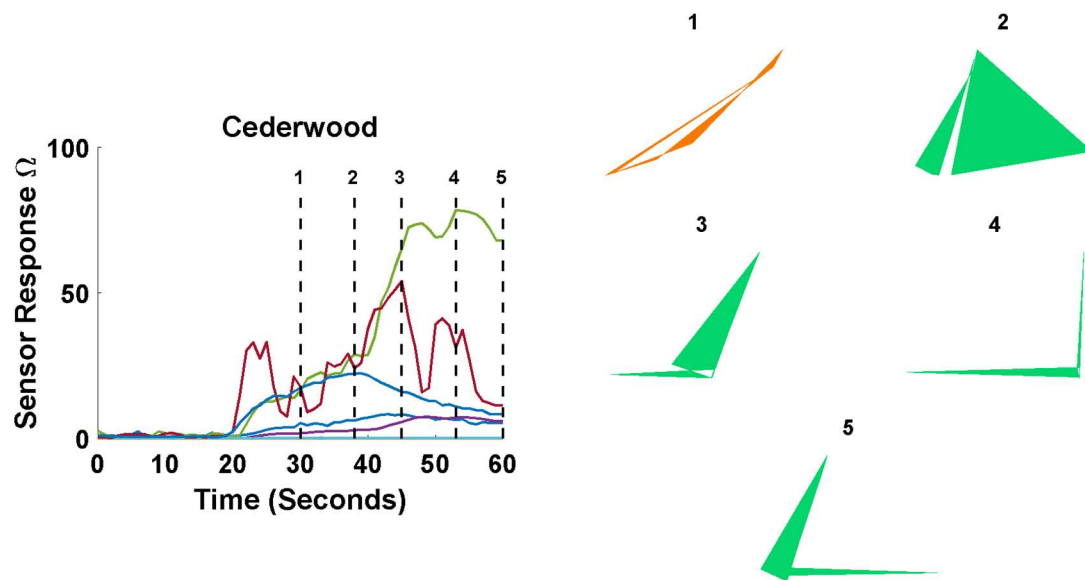


Figure 24. Sample shapes and colours generated over time with a rising intensity for the cederwood aroma. 1 - 5 shows the coloured shape generated at 30, 37, 45, 52 and 60 seconds respectively.

The role that intensity plays in the generation of the shapes was further investigated (see Figure 24). This shows the evolution of the shape, over time with a rising intensity. The vertical lines denote the time each shape on the right-hand side of the graph was generated from the recording. It is important to note that it would be quite difficult to associate which lines contribute to which sensor feature and the shape was designed to represent the odour as a whole instead of its individual elements, comparable to natural synaesthesia. This revealed that as the intensity of the odour increases, the more consistent the colour and generated shapes become. This compliments the findings from Figure 21, which suggests that the intensity of the odour is the most influential factor. Now that the elements system has been designed and tested it would be beneficial to test the device on humans to see how well the device works and to investigate if the cognitive benefits underlying natural odour-vision synaesthesia are transferable to a human-machine interface. Now that the system has been developed it is important to test the device on humans to determine how well the system performs to test to see if the hypothesis that some of underlying cognitive benefits behind natural synaesthesia (e.g., odour-vision synaesthesia) could be replicated via a computerised medium.

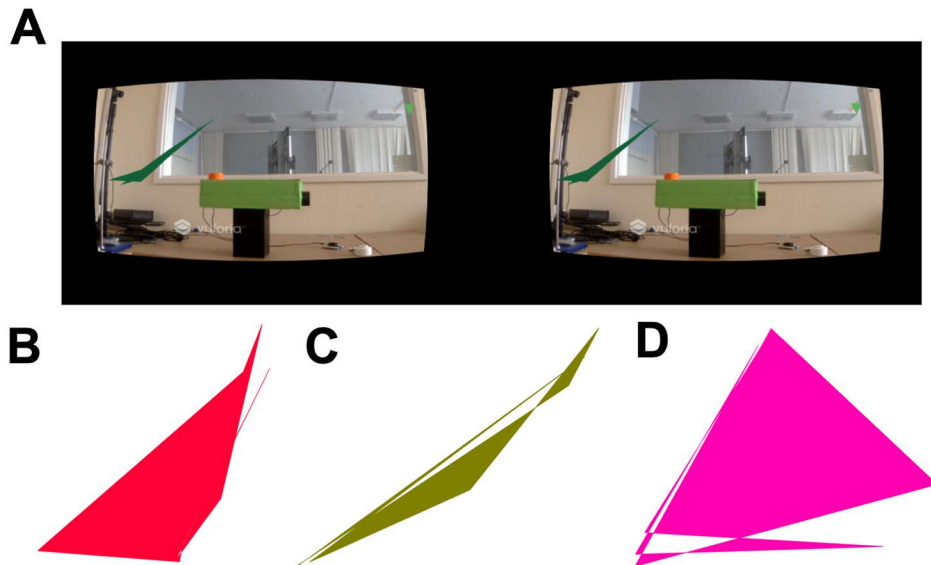


Figure 25. Sample output of the system while recording the aroma cedarwood. (B, C, D). Sample shape generated by the system for banana, coffee and ylang ylang respectively.

4.7 Virtual Odour-Vision Human Trails Process

Before conducting any human-trials a selection process was considered to ensure the integrity of the experiments. No participants reported any impairment that could affect their sense of smell (i.e., cold, flu, or anosmia). This criterion was checked twice once via e-mail communication during the participants statement of interest to participate and once physically before the experiment started. Participants were also provided with an information sheet so they knew what was involved in the experiment before coming in. Participants were briefed about potential allergens and breaks (a minimum of a 10-minute break halfway through, or if the participant felt like they have a reduced sense of smell). They were instructed not to wear any scented deodorant/perfume on the day of the experiment. No other limitations were imposed on the human trials conducted within this chapter.

4.8 Using The System Significantly Increases Olfactory Identification

To test the hypothesis that implementing an artificial form of synaesthesia into a human-machine interface could artificially reproduce some of the underlying cognitive benefits of natural synaesthesia, an offline version of the system was developed consisting of pre-generated shapes; this was done to reduce environmental contamination (so the trials could be conducted within a reasonable timeframe). The samples used in this experiment were placed in a clear polypropylene test tube;

consisting of 200 μL of the prepared solution placed on a 3 x 1 cm cotton sliver, placed in the test tube, covered in white tape to avoid any associations to the odours based on colour, and numbered. A total of 27 samples (9 triplet grouplets) were prepared for the experiments. Participants were presented with triplets of odours and performed a basic odour identification task; this was performed first without the shapes generated by the system and once with the shapes generated by the system. Twelve participants (8 males and 4 females, mean age = 36) took part in the experiment. The experiment took roughly 20 minutes to complete. The participants took a 10-minute break halfway through the experiment to prevent olfactory fatigue. This led to the experiment consisting of three blocks; two ten-minute blocks of experiments with a ten-minute block in between the experiment blocks. Ethical approval was obtained from the University of Liverpool and conducted following the standards set in the Declaration of Helsinki for Medical Research Involving Human Subjects. Participants gave written consent before taking part in the experiment.

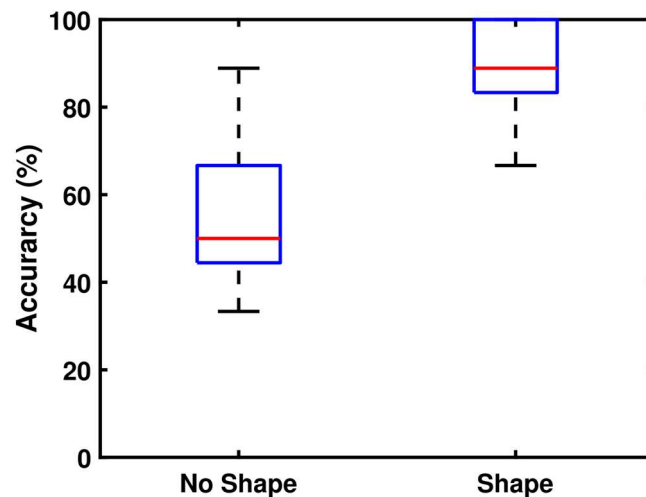


Figure 26. Boxplot showing the median (red line), the minimum and maximum values (black horizontal lines) and 25th and 75th percentiles indicated by the bottom and top edges (blue box) respectively.

The results shown in Figure 26 shows that the artificial emulation of odour-vision synaesthesia can enhance human olfactory identification. In this experiment, there was a mean increase in olfactory identification by 33.40% when the participants were shown the shapes with the odour. To determine if this result was statistically significant, a one-tailed paired t-test was conducted. This revealed that the use of the synesthetic shape in conjunction with their sense of smell increased odour identification more than without using the shape (i.e., just their sense of smell $t(11) = -5.84$, $p < 0.001$). It is worth noting that although participants were instructed to use their sense of smell along with the visual aid, we cannot be sure if they solely used one sense as opposed to both (i.e., just using their sense of smell while being provided with the visual aid). The findings reported in this section answered the research question for this chapter.

4.9 Chapter 4 Summary

In this chapter, the research question was asked; is it possible to replicate the cognitive benefits of a natural form of synaesthesia in a human-machine interface? It was hypothesized that some, if not all, of the underlying cognitive benefits, were replicable. The findings in this chapter, specifically the findings of the human trials (Section 4.8), provide supporting evidence for the hypothesis and answers the research question. The potential of augmenting an artificial form of synaesthesia in a human-machine interface was analysed and exemplified. The optimum means for transducing chemicals in the open environment was chosen (e-nose). This was selected due to it being lightweight, portable, and real-time access to the data, compared to an in-situ Xevo triple quadrupole mass spectrometer (TQ MS) (Waters Corporation, Manchester, UK). The mass spectrometer using DAPI did provide higher sensitivity and specificity, but this was not required for the task at hand. Experiments were performed to make sure that the e-nose could detect and therefore characterise chemicals outside the confines of the aromatic samples used in these experiments. A novel human-machine interface was then developed utilising a top-down approach of virtual synaesthesia. The goal of this chapter was to exemplify the benefits of augmenting human-machine interfaces with a synthetic form of this phenomenon and was exemplified with the 33.40% increase in olfactory identification. PCA was conducted on the recordings obtained by the custom-built e-nose revealing that there is a small overlap between different odours, which would allow the generation of distinct and consistent colour profiles. It also suggested that intensity will be the most influential factor in the generation of the colours and shapes. Next, five pattern recognition algorithms were tested, with the Random Forest algorithm achieving the highest accuracy rating and therefore able to generate the most consistent colour profiles. The evolution of the generated shapes over time and with a rising intensity was tested, complimenting the findings from the PCA that showed that the intensity is the most influential factor; showing that the stronger the intensity of an odour the more consistent the colour and shape variations become. Human trials were conducted to test the hypothesis that augmenting human-machine interfaces with synthetic forms of synaesthesia can provide the same benefits as its natural counterpart. The tests revealed that even without training, the system could enhance human odour identification, therefore providing support for this chapter's hypothesis. Prolonged usage of the system will need to be conducted to determine if it can also improve colour discrimination, however the results from these experiments do demonstrate that the underlying cognitive benefits behind synaesthesia can, at least in part be replicated using human-machine interfaces. The limitations of the work conducted in this chapter include the number of participants (12), although the findings do indicate a large performance increase when using a complimentary shape and their sense of smell, a

more robust number to for the performance increase would be obtained with more participants. Although this device was created using a bottom-up approach for virtual synaesthesia the stimuli being presented could be presented in more meaningful manner, the colours and shapes for instance could align with the wearers olfactory crossmodal correspondences to reduce the amount of processing the brain needs to do make reason out of presented stimuli. The next chapter will focus on exploring the mechanisms (olfactory crossmodal correspondences) needed for a bottom-up approach of virtual synaesthesia to determine what correspondences exist for olfactory stimuli. The work presented in this chapter (Chapter 4) could be improved upon by uncovering the stimuli that people would correspond to a given odour. Therefore, the next chapter will focus on uncovering the correspondences.

Chapter 5 Crossmodal Correspondences of Olfaction

5.1 Introduction

This chapter focuses on weak synaesthesia (the consistent correspondences people have towards odours). The novelty of this chapter is to characterise people's crossmodal correspondences between odours and a variety of different sensory modalities. An interactive graphical user interface was developed to record the participants' responses to determine if people have consistent associations between odours and different sensory dimensions. The sensory dimensions explored are the angularity of shapes, smoothness of texture, perceived pleasantness, pitch, colours, musical genres, and emotions. Participants were presented with odours that were placed in a clear test tube, covered in white tape, and numbered one through ten in a random permutation. This was done to avoid any adverse associations and to hide any visual stimuli that could influence the participant's decision on the identity of the odour (i.e., the colour of the essential oil). The experimental setup to analyse people's crossmodal correspondences is shown in Figure 27.

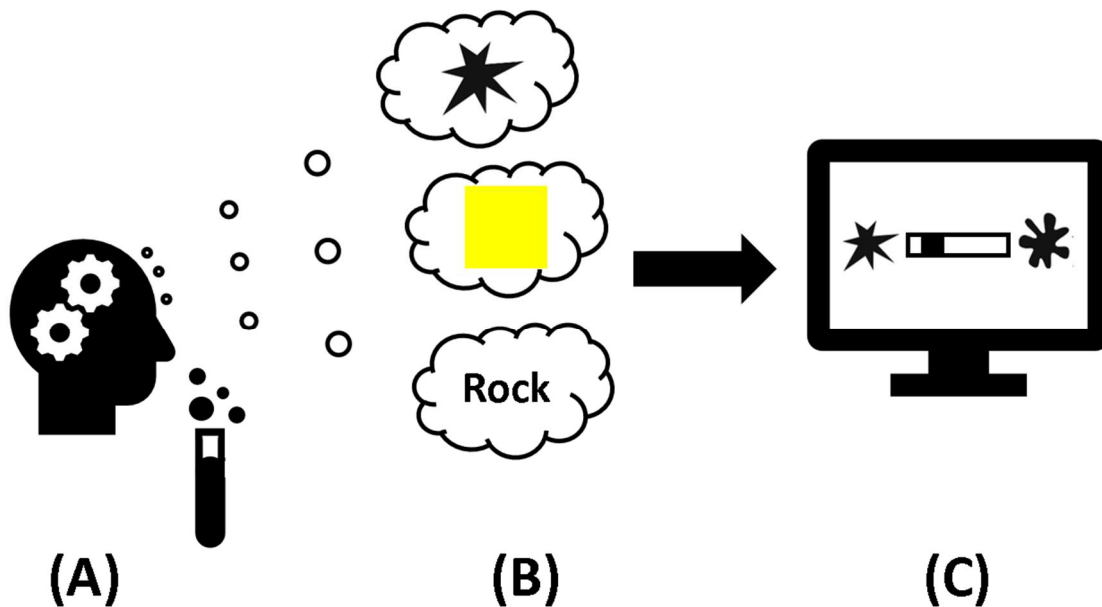


Figure 27. Schematic setup to extract people crossmodal associations. (A) Participant smelling an odour. (B) Participants mental representation of an odour. (C) Graphical user interface to save the participants crossmodal associations.

This chapter answers the research question do consistent correspondences exist between odours and the angularity of shapes, the smoothness of texture, perceived pleasantness, pitch, colours, musical genres, and emotions. The colour and shape modalities were explored to enhance the olfactory sensory augmentation presented in Chapter 4; the other sensory modalities were

explored to increase the number of potential use cases from the research conducted in this chapter. It is hypothesised that consistent correspondences will occur in all crossmodal dimensions. The research conducted in this chapter has been published in the *Journal of Perceptual Imaging* [36]. This chapter is organized as follows: Section 5.3 – 5.5 covers the materials and methods for this chapter. Section 5.6 covers tests to see if consistent correspondences exist between odours and the angularity of shapes, smoothness of texture, perceived pleasantness, and pitch. Section 5.7 covers tests to determine if consistent correspondences exist between odours and musical and emotional dimensions. Section 5.7 covers tests to see if consistent correspondences exist between odours and colours. Section 5.8 covers a discrimination task to determine how familiar the presented odours were to the participants. The chapter is concluded with a summary of the results and findings.

5.2 Odours

Ten different odours were used; five from Miaroma™ (black pepper, lavender, lemon, orange and peppermint) and five from Mystic Moments™ (caramel, cherry, coffee, freshly cut grass, and pine). These specific odours were selected to have an overlap with prior literature (e.g., [7], [14], [15], [143], [189], [192]) and are also commonly used in immersive olfaction-enhanced experiences (e.g., [27], [170], [175]). Additionally, two different brands of essential oil brands were selected to give a more diverse chemical profile amongst the odours (see Chapters 6 & 7 for justification). Odours were stored at $\approx 2.5^{\circ}\text{C}$ to minimise oxidation. The prepared samples consist of 4 mL of the respective essential oil and are removed from and placed back into the fridge at the same time to ensure approximately uniform evaporation.

5.3 Participants

Sixty-eight participants were recruited from the population of the University of Liverpool (45 females and 23 males; mean age of 26.75 and a standard deviation of 12.75). Participants were recruited via mass emails, posters, and using the University of Liverpool's EPR (Experiment Participation Requirement). Participants recruited from the EPR system did so in exchange for class credit. No participants reported any issues that might affect their sense of smell (e.g., cold or flu). Participants were instructed not to wear any scented body sprays on the day of the experiment or participate if they have any known allergies. No other restrictions were imposed on the recruitment criteria, and was

not restricted to specific demographics (e.g., nationality ect...). Participants were first briefed about potential allergens and breaks (a ten-minute break halfway through or if they felt like they had a reduced sense of smell) and then briefed about the task. Participants were placed in a lightproof anechoic chamber; the lighting in the chamber was kept consistent by using the daylight setting on the overhead luminaire. The experiment was conducted under the standards set in the Declaration of Helsinki's standards for Medical Research Involving Human Subjects. Participants gave written informed consent before taking part in the experiment.

5.4 Apparatus

All results were obtained through a graphical user interface programmed in MATLAB R2018b. During the experiment, participants were placed in a lightproof anechoic chamber equipped with an overhead luminaire (GLE-M5/32; GTI Graphic Technology Inc., Newburgh, NY). The lighting in the room was kept consistent by using the daylight simulator of the overhead luminaire. The speakers were JBL Desktop speakers; the colour stimuli were shown on a calibrated EIZO ColourEdge CG243W monitor. The results were analysed using MATLAB R2018b.

5.5 Tasks & Stimuli

Participants were instructed to associate a given odour with a value along each of the following dimensions: visual shapes (angularity), textures, pleasantness (using a Likert scale), pitch, musical genres, and emotions. For the musical genres and emotions, participants were asked to select the most dominant choice. The aromas were presented in a random order (determined by a random number generator in MATLAB), and all associations were assessed in the same order for a given aroma. Participants were presented with the stimuli for as long as was necessary for them to make their decision. At the end of the experiment, participants were asked to identify the odour from a precompiled list (classification task). A neutral option was available for four experimental tests (visual shapes, texture, pleasantness) and the emotion task. However, participants were strongly discouraged from using this option. Before the experiment commenced, participants were required to provide basic preliminary answers, such as their name, gender, and age, as shown in Figure 28.

Participants full name:

What is your gender? Gender
 Male
 Female

How old are you?

Which country have you spent the most time in?
 Afghanistan
 Albania
 Algeria
 Andorra
 Angola
 Antigua & Deps
 Argentina

Please select your favourite genre of music:
 Classical
 Country
 Jazz
 Metal

Done

Figure 28. Graphical user interface for collecting the preliminary information.

5.5.1 Shape Stimuli

A nine-point Likert scale was constructed with a rounded shape, "bouba", and an angular shape, "kiki", on the scale's left and right side, respectively. Similar to an earlier experiment performed by Hanson-Vaux *et al.* [7]. The midpoint of the nine-point scale (5) was neutral (no opinion). The anchors on each side of the scale were the images used in Hanson-Vaux *et al.* and are shown in Figure 29. The number in the top left-hand side indicates what odour to present to the participant.

8

Please select a number from the scale;
 Is the odour more like the image to the left or to the right?

1 2 3 4 5 6 7 8 9

Done

Figure 29. The graphical user interface for collecting information about the shape stimuli.

5.5.2 Texture Stimuli

A nine-point Likert scale was constructed with the words "smooth" and "rough" on the left and right side, respectively. Participants were supplied with physical representative textures to aid them in their decision, with silk being a representative of smooth and sandpaper being a representative of rough. Only two texture samples were provided to the participants. The midpoint of the nine-point scale (5) was neutral (no opinion). Participants felt the textures at least once during the questions' first appearance. Participants could feel the physical textures again if they felt they needed to. The graphical user interface to collect information about the texture stimuli is shown in Figure 30.

8

What does the odour feel like, is it more; rough or smooth?

1 2 3 4 5 6 7 8 9

Rough Smooth

Done

Figure 30. The graphical user interface for collecting information on the texture stimuli.

5.5.3 Pleasantness

A nine-point Likert scale was constructed, ranging from very unpleasant on the left side to very pleasant on the right side. The centre of the scale (5) was used as neutral (no opinion). The graphical user interface used for collecting the pleasantness ratings is shown in Figure 31.

8

How pleasant was the odour?

1 2 3 4 5 6 7 8 9

Very Unpleasant Very Pleasant

Done

Figure 31. Graphical user interface for collecting the pleasantness ratings.

5.5.4 Pitch Stimuli

The full range of audible frequencies (20 Hz to 20 kHz) was implemented using a slider where movement from left to right corresponded to an increase in frequency. Every time the slider was adjusted, the respective frequency was played, producing a sinusoidal tone lasting 1 second in length. Due to the large volume of potential selections, participants were played a sample from each end of the scale, followed by a sample halfway between these two points. If the current pitch did not match the odour, a lower or higher pitch was selected (approximately halfway between the last two frequencies) as indicated by the participant. During the initial tones being played at either end of the scale, the range of frequencies the participants could hear was determined by selectively increasing the frequency on the lower end and decreasing the frequency on the upper until the participant could hear the tone. Eight participants did not complete the pitch question; therefore, we only used the results for the sixty who did the pitch-related analyses. This was because this question was added to the experiment at a later point. The level for the pitch stimuli is shown in Figure 32, and the graphical user interface for collecting information on the pitch ratings is shown in Figure 33.

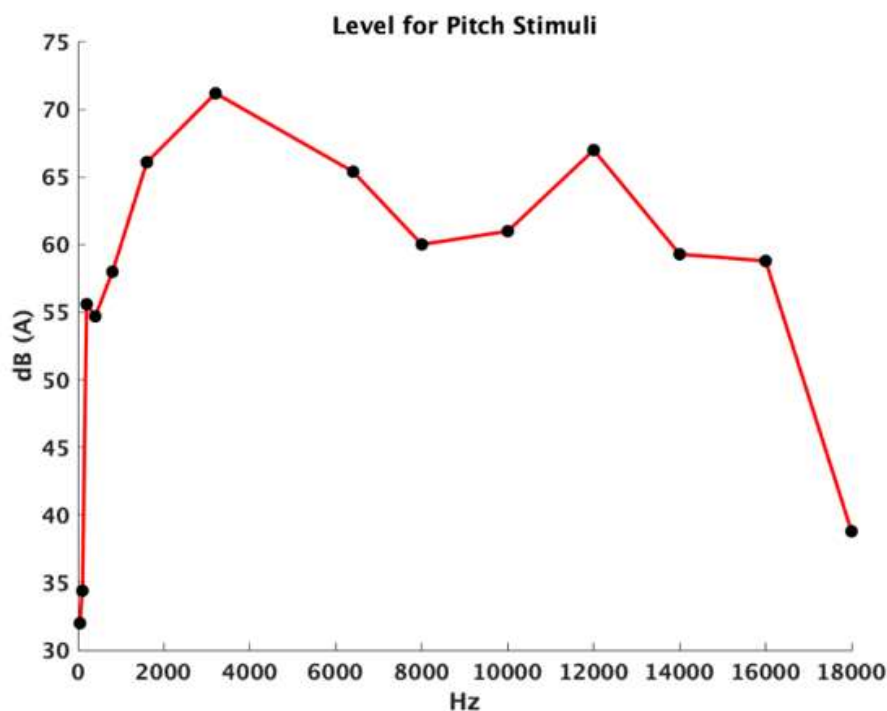


Figure 32. The level in dB (A) for the presented pitch stimuli at specified frequencies. Black dots denote the sampling points.

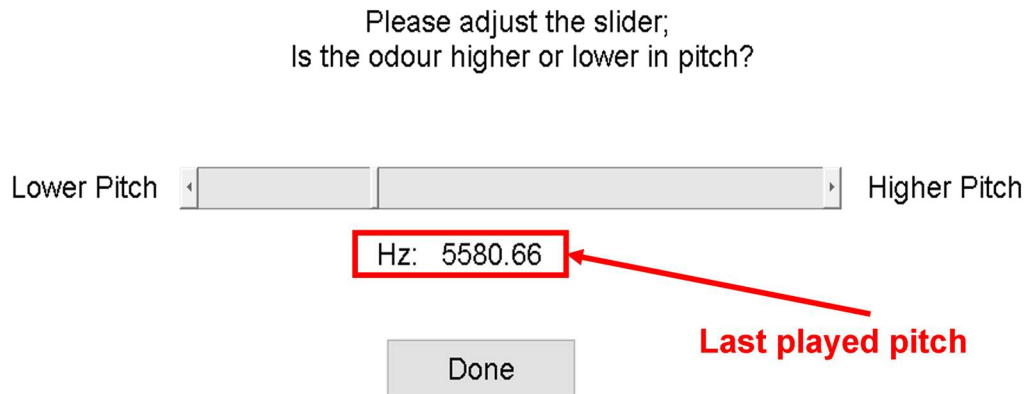


Figure 33. Graphical user interface for collecting the pitch ratings.

5.5.5 Music Stimuli

Seven different music genres - classical, country, heavy metal, jazz, rap, classic rock, and soul, were presented to the participants. Six were selected from [276], with one added due to its vast popularity (soul). Each sample was 15 seconds in duration, normalized to -3 dB (relative to the peak amplitude), and played at the same volume across participants. The stimuli were trimmed using Audacity software. Participants had to listen to each sample at least once during the questions' first occurrence; the order was subject to the participant's preference. The musical excerpts used in this experiment can be found in Table 5; the graphical user interface to collect the musical genre ratings is shown in.

Genre	Artist	Title	Start Time	YouTube Link
Soul	Ben E. King	Stand By Me	0:41	https://www.youtube.com/watch?v=hwZNL7QVJjE
Classical	Mozart	Eine Kleine	0:05	https://www.youtube.com/watch?v=oy2zDJPIgwc
Heavy Metal	Slayer	Angel Of Death	0:14	https://www.youtube.com/watch?v=TnRZhLRv6eM
Jazz	Frank Sinatra	Fly Me To The Moon	0:07	https://www.youtube.com/watch?v=mQR0bXO_yI8
Rap	Eminem	Sing For The Moment	0:30	https://www.youtube.com/watch?v=D4hAVemuQXY
Rock	The Rolling Stones	Paint It Black	0:13	https://www.youtube.com/watch?v=O4irXQhgMqg
Country	Johnny Cash	Falsom Prison Blues	0:00	https://www.youtube.com/watch?v=s_NLlOiD1Wo

Table 5. Details of musical excerpts; each excerpt lasts for 15 seconds. After extraction, each clip was normalized to -3 dB (relative to the peak amplitude).

Is this odour more;
Classical, Country, Jazz, Metal, Rap, Rock or Soul?

Genre and Sample Audio

Classical
 Country
 Jazz
 Metal
 Rap
 Rock
 Soul

Figure 34. Graphical user interface to collect the musical genre ratings.

5.5.6 Colour Stimuli

The CIE L*a*b* colour space was used because of its perceptual uniformity. Participants could slide through 101 linearly interpolated slices from the L* channel of the colour space, increasing or decreasing the lightness. Only colours that fit in the sRGB colour gamut were shown. This removed the limitations of earlier studies that let participants choose from a small selection of colours. The graphical user interface for collecting information about the participants' colour associations is shown in Figure 35.

8

Please select the colour that best represents the odour.

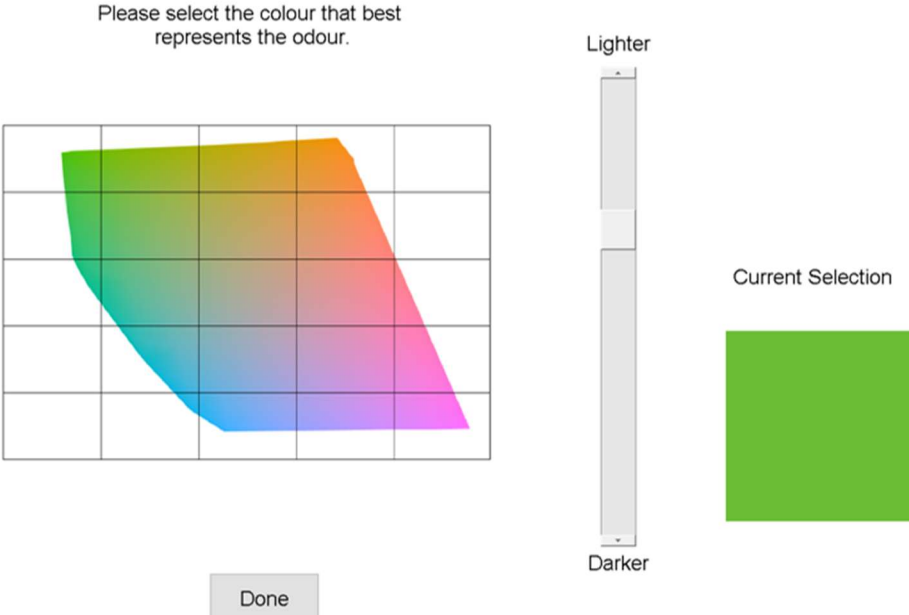


Figure 35. Graphical user interface for collecting information about the participant's colour associations.

5.5.7 Emotion Stimuli

A subset of emotions from the Universal Emotion and Odour Scale [277] was included. These were – angry, aroused, bored, calm, disgust, excited, happy, sad, and scared. An option for neutral (no opinion) was also available. The graphical user interface to collect information on the participant's most dominant emotion is shown in Figure 36.

8

How does this Odour make you feel?

If you selected something else,
please specify.

Emotions

Neutral

Happy

Sad

Angry

Aroused

Scared

Disgust

Calm

Bored

Excited

Something Else

Figure 36. The graphical user interface to collect information on the participants' most dominant emotion.

5.5.8 Classification Task

A list of different aromas was compiled consisting of the ten odours used in this experiment and an additional eleven (banana, coconut, eucalyptus, fudge, honey, musk, pineapple, rose, strawberry, toffee and vanilla). These were presented in alphabetical order. The extra eleven odours were included so that observers were less likely to base their decision on previously presented odours when identifying the current odour. The classification task was presented after the participants went through the questions for each odour (See Sections 5.5.1 - 5.5.7). The graphical user interface to collect information on what the participant thought the odour was is shown in Figure 37.

If you can identify the odour,
What was it?

Figure 37. The graphical user interface to collect information on what the participant thought the odour was.

5.6 The Angularity, Smoothness, Pleasantness & Pitch Ratings Are Non-Random

The participant's ratings for the angularity of shapes, smoothness of texture, perceived pleasantness and pitch were first standardised using z-score normalisation; ratings were centred around the grand mean of the respective scale. Separate one-way repeated measures ANOVA's (Greenhouse-Geisser corrected, $\alpha = 0.05$) were then conducted on the mean z-score ratings for the angularity of shapes, smoothness of texture, perceived pleasantness, and pitch. This was done to see if the presence of different odours influenced the ratings (i.e., are the ratings different if the aroma of caramel is presented as opposed to lemon?). This revealed that the odours significantly affected all ratings: angularity of shapes ($F(7.09, 475.52) = 16.59, p < 0.001, \eta^2 = 0.19$), smoothness of texture ($F(7.98, 534.87) = 5.53, p < 0.001, \eta^2 = 0.07$), perceived pleasantness ($F(6.97, 467.23) = 10.48, p < 0.001, \eta^2 = 0.13$) and pitch ($F(8.58, 406.788) = 10.23, p < 0.001, \eta^2 = 0.148$). Post-hoc one-sample t-tests were then conducted to determine which odours induced a non-random distribution (significantly different from the scale's grand mean of 0). The significantly 'angular' odours are lemon and peppermint. The significantly 'rounded' odours are coffee and caramel (see Figure 38A). The significantly 'rough' odour was black pepper, with caramel being the significantly 'smooth' odour (see Figure 38B). The

significantly ‘pleasant’ odours are orange and lemon. The significantly ‘unpleasant’ odour was black pepper (see Figure 38C). The significantly ‘lower pitch’ odours are coffee and caramel. The significantly ‘higher pitch’ odour was peppermint (see Figure 38D). The hypothesis that consistent crossmodal correspondence would be obtained between odours and the angularity of shapes, smoothness of texture, perceived pleasantness, and pitch were both tested and met. A complete set of calculations for these tests are shown in Table 6 - Table 9. Rows in bold indicate significant findings ($p < 0.005$). Now that we know the angularity, smoothness, pleasantness, and pitch ratings induced a non-random distribution, it is essential to uncover if the musical genre and emotional ratings are also non-random.

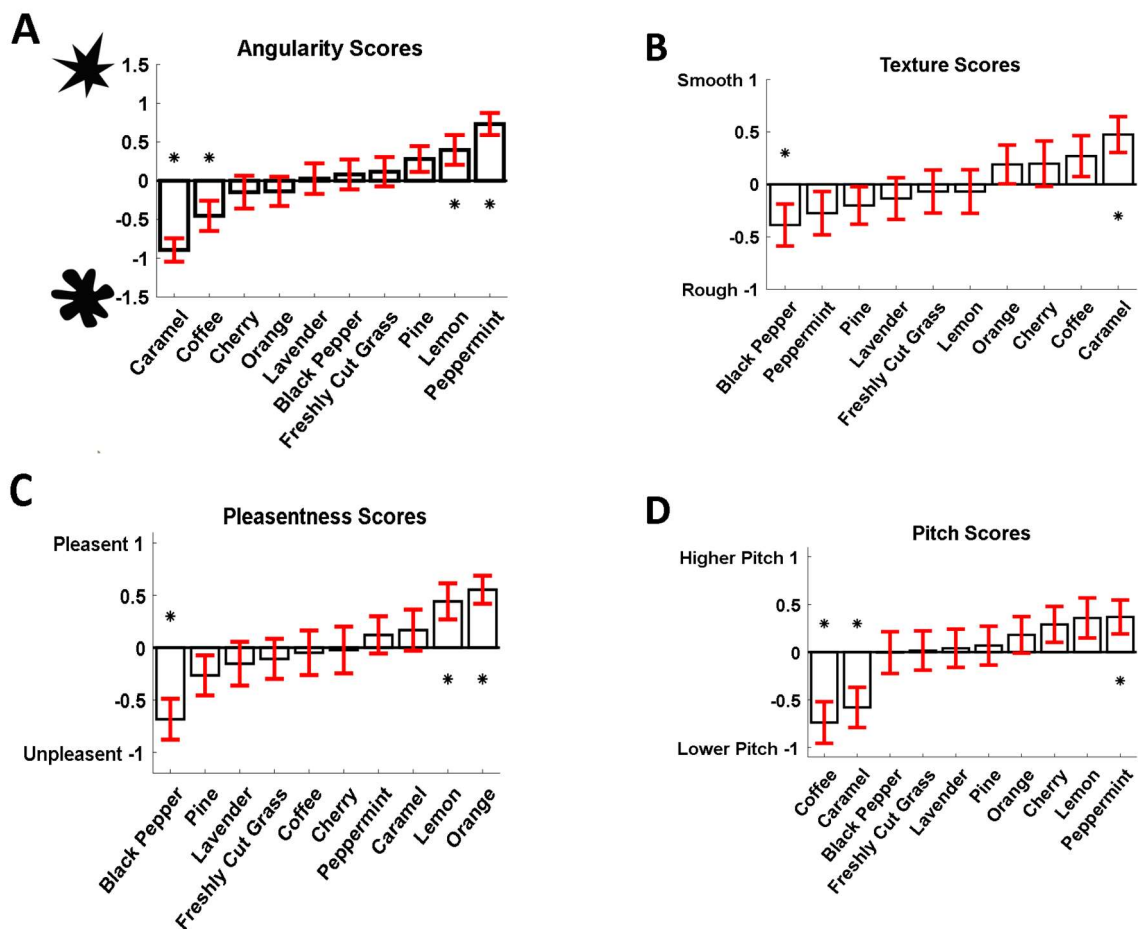


Figure 38. (A – C) Mean scores for the ten odours after z-score normalization. Asterisks mark the odours that are significantly different from the scale's original grand mean of 0. Errors bars show a 95% confidence interval of the respective odour. (D) shows the information as (A – C) but it is the of \log_2 of the original ratings.

5.6.1 The angularity of shapes t-test results

Odour	df	t	p
Black Pepper	67	0.6951	0.4894
Caramel	67	-9.8827	< 0.0000
Cherry	67	-1.1686	0.2467
Coffee	67	-3.8740	0.0002
Freshly Cut Grass	67	1.0181	0.3123
Lavender	67	0.2331	0.8164
Lemon	67	3.4372	0.0010
Orange	67	-1.2052	0.2324
Peppermint	67	8.6109	<0.0000
Pine	67	2.8009	0.0067

Table 6. One sample t-test results for the angularity of shapes.

5.6.2 The smoothness of texture t-test results

Odour	df	t	p
Black Pepper	67	-3.2265	0.0019
Caramel	67	4.6475	<0.0000
Cherry	67	1.5191	0.1334
Coffee	67	2.3011	0.0245
Freshly Cut Grass	67	-0.5569	0.5794
Lavender	67	-1.1314	0.2619
Lemon	67	-0.5489	0.5849
Orange	67	1.7155	0.0909
Peppermint	67	-2.2170	0.0300
Pine	67	-1.8779	0.0647

Table 7. One sample t-test results for the smoothness of texture.

5.6.3 The perceived pleasantness t-test results

Odour	df	t	p
Black Pepper	67	-5.8434	< 0.0000
Caramel	67	1.4215	0.1598
Cherry	67	-0.1715	0.8644
Coffee	67	-0.3840	0.7022
Freshly Cut Grass	67	-0.9409	0.3501
Lavender	67	-1.2255	0.2247
Lemon	67	4.2785	0.0001
Orange	67	6.8718	< 0.0000
Peppermint	67	1.1367	0.2597
Pine	67	-2.3113	0.0239

Table 8. One sample t-test results for the perceived pleasantness.

5.6.4 The pitch t-test results

Odour	df	t	p
Black Pepper	59	-0.0407	0.9676
Caramel	59	-4.6077	< 0.0000
Cherry	59	2.5700	0.0127
Coffee	59	-5.6494	< 0.0000
Freshly Cut Grass	59	0.1313	0.8960
Lavender	59	0.3394	0.7355
Lemon	59	2.8444	0.0061
Orange	59	1.5813	0.1192
Peppermint	59	3.4745	0.0010
Pine	59	0.5631	0.5755

Table 9. One sample t-test results for the perceived pitch.

5.7 The Musical Genres & Emotions Ratings Are Non-Random

First, the participant's ratings were converted into percentiles for the musical genres and emotions (see Figure 39A and Figure 39B). To determine if the presence of different odours influenced the participant's selections, chi-squared tests of independence were conducted on the musical and emotional ratings. This revealed that the odours impacted the emotional ($\chi^2(90) = 187.54, p < 0.05$, Cramer's $V = 0.17$) and music genre ratings ($\chi^2(54) = 138.20, p < 0.05$, Cramer's $V = 0.18$). To determine which of the stimuli were different from chance selection, chi-squared tests for goodness of fit were conducted (Bonferroni corrected, $\alpha = 0.005$). This revealed that all odours were significantly different from chance selection for the emotional dimensions. The odours – black pepper, caramel, freshly cut grass and orange were significantly different from a chance selection for the genre association task. All odours were significantly different for the emotional association task. Table 10 & Table 11 shows the complete set of values for the musical and emotional dimensions, respectively; rows in bold indicate significance. The hypothesis that musical and emotional correspondences exist between odours was both tested and met. Now that it is known that the musical and emotional ratings induced a non-random distribution, it is important to determine if the same holds for the colour ratings.

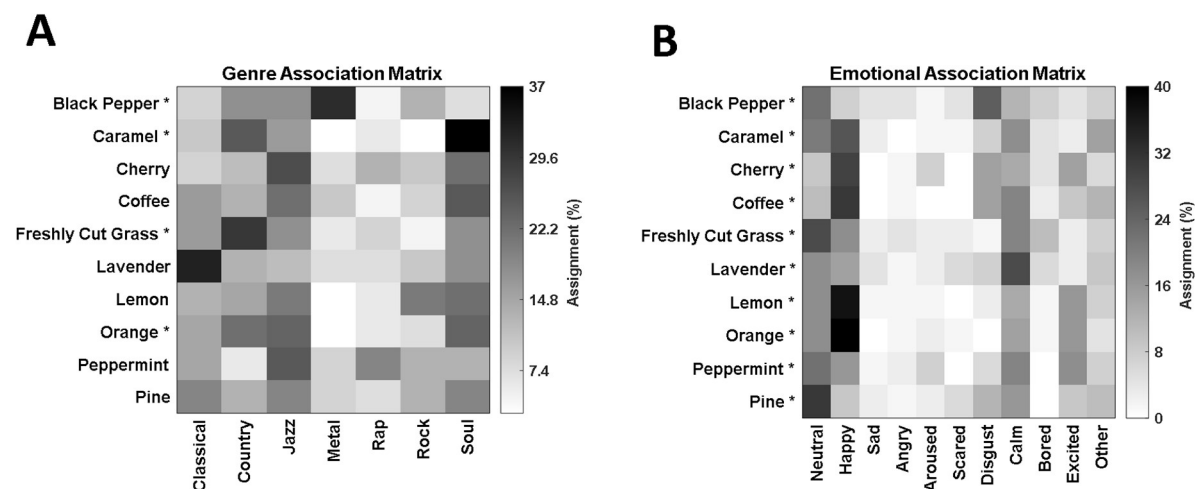


Figure 39. Asterisks mark the odours that are significantly different from chance selection. (A) Association matrix between the ten odours and the seven musical genres. (B) Association matrix between the ten odours and the 11 possible emotional selections.

5.7.1 Emotion's chi-squared tests for goodness of fit results

Odour	df	χ^2	p
Black Pepper	10	43.6178	< 0.0000
Caramel	10	62.7061	< 0.0000
Cherry	10	56.2355	< 0.0000
Coffee	10	71.7649	< 0.0000
Freshly Cut Grass	10	57.2061	< 0.0000
Lavender	10	47.8237	< 0.0000
Lemon	10	94.4120	< 0.0000
Orange	10	111.5592	< 0.0000
Peppermint	10	50.0884	< 0.0000
Pine	10	56.8825	< 0.0000

Table 10. Chi-squared test for goodness of fit to see which odours differ from chance selection in the emotion association task.

5.7.2 Musical Genre chi-squared tests for goodness of fit results

Odour	df	χ^2	p
Black Pepper	6	22.5889	0.0009
Caramel	6	46.0602	< 0.0000
Cherry	6	14.7651	0.0222
Coffee	6	15.3828	0.0175
Freshly Cut Grass	6	21.5595	0.0015
Lavender	6	21.7653	0.0013
Lemon	6	16.2064	0.0127
Orange	6	22.7948	0.0009
Peppermint	6	11.4709	0.0749
Pine	6	7.1473	0.3074

Table 11. Chi-squared test for goodness of fit to see which odours differ from chance selection in the musical genre association task.

5.8 The Colours Ratings Are Non-Random

To analyse the colour ratings, a novel algorithm was developed. This algorithm was developed because in the relevant literature; the authors let participants select the colour correspondences using a finite set of predefined colours. However, this approach is both time-consuming and would not result in an accurate representation of the participant's colour correspondences. Therefore, we allowed participants to select a colour from the $L^*a^*b^*$ colour gamut by interactively moving through this colour space by adjusting the L^* variable. First, 343 interpolated colours were extracted from the hull of the $L^*a^*b^*$ colour gamut (see *Figure 40A*). Additionally, three shades of grey were added to the interpolated set. Next, the colour each participant had selected for each of the odours was taken and mapped onto to the perceptually closest colour. The perceptually closest colour was determined by the lowest ΔE 2000 error. ΔE 2000 is the distance between two colours with higher values indicating a greater distance between two given colours. These colours are used as a representative colour selection shown in *Figure 40B*. The median hue angles from the perceptually closest colours are shown in *Figure 40C*. To determine if the lightness of the selected colour were significantly different from the scale's midpoint and default colour slice from the $L^*a^*b^*$ colour gamut of 50, one-way t-tests (test value = 50, Bonferroni corrected, $\alpha = 0.005$) were conducted. This revealed that all odours except for black pepper and coffee were significantly different (see Table 12). A chi-squared test of independence was conducted on the binned ($N = 15$) hue angles to see if the selected colours were significantly different from a chance selection. This revealed that the colour selections are significantly different from chance selection ($\chi^2(126) = 588.95$, $p < 0.05$, Cramer's $V = 0.31$). To determine which odours produced consistent colour profiles, Rayleigh's z tests (Bonferroni corrected, $\alpha = 0.005$ ($0.05 / 10$)) were conducted on the hue angles for the commonly selected colours (*Figure 40B*). This revealed that the colour profiles caramel, cherry, coffee, lemon, and orange are non-random, thereby supporting the hypothesis of consistent crossmodal odour-colour correspondences. Now that we know that the colour ratings induced a non-random distribution, it is important to determine how well the participants could identify the odours as this may have an impact on the ratings they were assigning to the crossmodal ratings presented in this chapter.

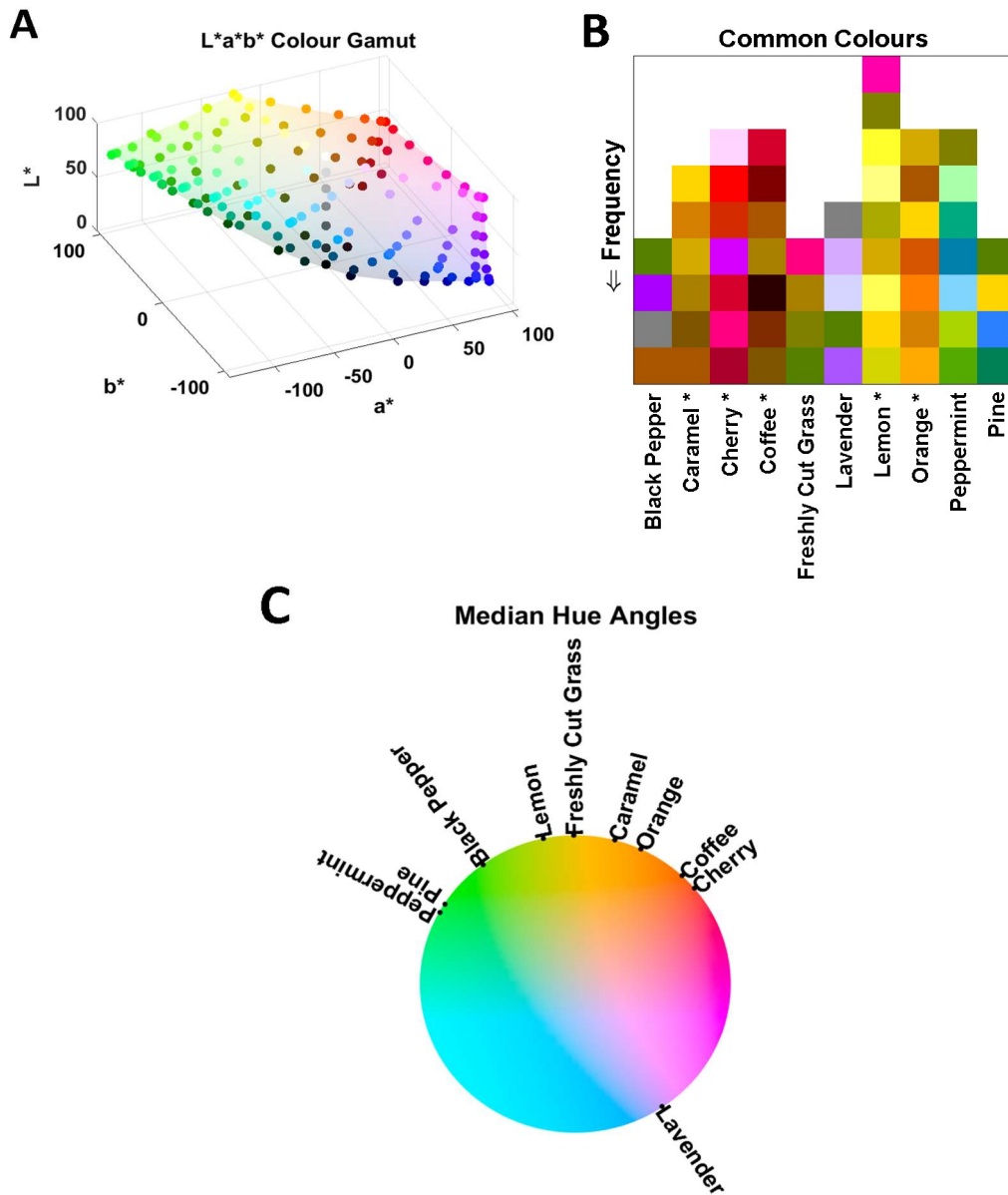


Figure 40. (A) L*a*b* colour gamut showing the interpolated points used to determine the perceptually closest colour. (B) Common colours selected by the participants where each colour has been mapped more than twice. Colours at the bottom of the graph occurred more often. (C) Cylindrical representation of the L*a*b* colour space showing the median hue angle of the commonly selected hues for each odour.

5.8.1 The lightness of colour t-test results

Odour	df	t	p
Black Pepper	67	1.5619	0.1230
Caramel	67	3.9341	0.0002
Cherry	67	3.4126	0.0011
Coffee	67	-2.2315	0.0290
Freshly Cut Grass	67	3.4385	0.0010
Lavender	67	4.5279	< 0.0000
Lemon	67	14.6296	< 0.0000
Orange	67	11.8555	< 0.0000
Peppermint	67	6.6110	< 0.0000
Pine	67	3.6706	0.0005

Table 12. One sample t-test results to determine if the selected lightness values were significantly different from the range's midpoint and default slice of 50.

5.8.2 The commonly selected colours Rayleigh's z-test results

Odour	z	p
Black Pepper	0.9721	0.4025
Caramel	5.7906	0.0005
Cherry	5.3279	0.0018
Coffee	6.2289	0.0004
Freshly Cut Grass	2.1595	0.1125
Lavender	1.4393	0.2473
Lemon	6.6732	0.0003
Orange	6.6345	0.0002
Peppermint	3.2245	0.0336
Pine	0.7061	0.5214

Table 13. Rayleigh's z-tests to determine which odours produce a non-random colour profile.

5.9 The Participants Had Poor Olfactory Discrimination

For this task, the participants were required to identify what the presented odour was by selecting an odour from a pre-compiled list of 23 different odours along with an option for “cannot identify”. Categorically correct discrimination was achieved 62.94% of the time by picking the correct odour from an odour in the same category. To determine if the selection was categorically correct, the fragrance classes outlined in [76] were used. Exact discrimination was achieved 45.74% of the time by correctly identifying the current odour. The top three misclassified odours were: caramel (20.59%), pine (13.24%), and black pepper (10.29%). The top three correctly classified odours were peppermint (82.35%), lemon (80.88%), and orange (61.76%); the discrimination matrix is shown in Figure 41. This tells us that the knowledge of the identity of the odour may play a role in explaining the nature and origin of crossmodal correspondences. This hypothesis is further explored in the next chapter (Chapter 6).

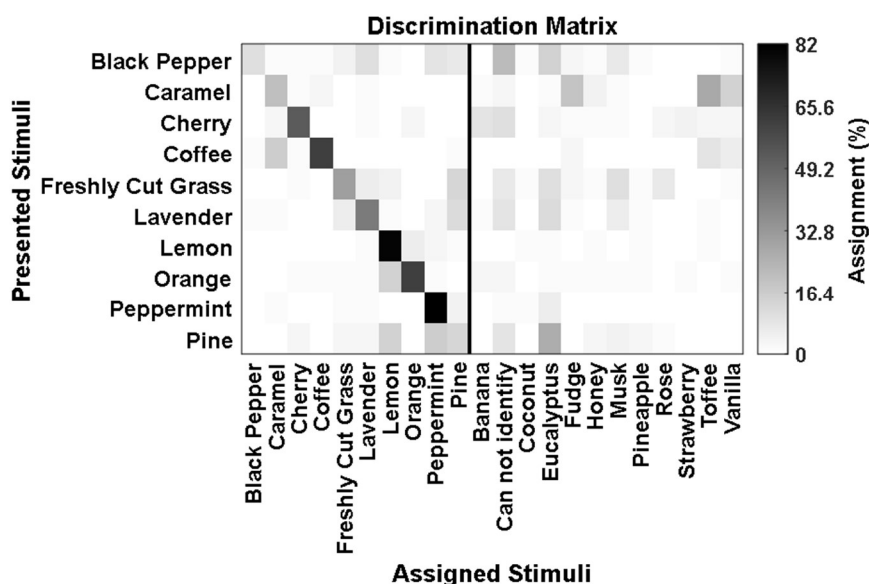


Figure 41. Discrimination matrix for the 10 odours, along with an additional 12 misclassifications. Any options that were never selected have been removed from the graph.

5.10 Chapter 5 Summary

This chapter tested the hypothesis that people have consistent correspondences between odours and the angularity of shapes, smoothness of texture, perceived pleasantness, pitch, colours, musical genres, and emotions. Evidence to support this hypothesis was obtained using one-way repeated measures ANOVA's and posthoc one sample t-tests; significant findings were uncovered, with the

odours caramel and coffee being significantly associated with a rounded shape and the odours lemon and peppermint being significantly associated with an angular shape. For the smoothness of texture, the odour of black pepper is significantly rough, and the odour of caramel is smooth. For perceived pleasantness, the black pepper odour is significantly unpleasant, with the lemon and orange odours being significantly pleasant. For the pitch ratings, the odours of coffee and caramel are significantly associated with a lower pitch, with peppermint being significantly associated with a higher pitch. A Chi-squared test of independence was conducted on the binned hue angles of the colour selections to see if the selected colours were significantly different from chance selection. This revealed that the colour selections were non-random. A new algorithm was then developed to determine the perceptually closest colour. This algorithm maps the colours selected by the participants to a set of pre-defined colours, thereby compressing the perceptual space but allowing for small variations in colour, including hue and lightness. Using Rayleigh's z-tests showed that the odours of caramel, cherry, coffee, lemon, and orange for the commonly selected colours produced non-random colour profiles. Using chi-squared tests of goodness of fit on the musical ratings revealed that the odours of black pepper, caramel, freshly cut grass, and orange induced a non-random distribution. For the emotional selection task, all odours induced a non-random distribution. When considered together, these findings support the hypothesis that consistent crossmodal correspondences would be obtained between odours and the angularity of shapes, smoothness of shapes, the perceived pleasantness, pitch, colour, musical and emotional dimensions. The findings reported in this chapter are important because it reports a previously unknown crossmodal correspondence (the smoothness of texture). More importantly, it allows for the analysis to uncover the nature and origin of these associations, which is reported in the next chapter. The limitations of the work conducted in this chapter are the number of crossmodal dimensions explored. That is, the potential number of use cases is limited as more crossmodal correspondences could have been explored (i.e., temperature and weight). As we have uncovered that these correspondences exist in the general population, for them to be efficiently utilised for virtual synaesthesia, we will need to understand why these correspondences occur, such that we know the limitations of using them for virtual synaesthesia. Consequently, allowing for their exploitation (i.e., to make the procedurally generated stimuli for the olfactory sensory augmentation developed in the last chapter more meaningful to the user) in a variety of different areas, including human-machine interfaces and multisensory experiences. This is explored in the next chapter (Chapter 6).

Chapter 6 Analysis of Olfactory Crossmodal Correspondences

6.1 Introduction

This chapter focuses on exploring the nature and the origin of the correspondences uncovered in Chapter 5. The underlying hedonic, semantic, and physicochemical dimensions were explored to quantify the role they play in explaining olfactory crossmodal correspondences. The hypothesis is that hedonic and semantic involvement will play a role in explaining the nature and origin of these associations and that the physicochemical features of the olfactory stimuli will also be a contributory factor. The underlying perceptual data used in this chapter was initially obtained in Chapter 5 and used Version 2 of the developed e-nose (see Sections 3.3 & 3.4) to extract the physicochemical features of the olfactory stimuli. The experimental methodology for this chapter is depicted in Figure 42.

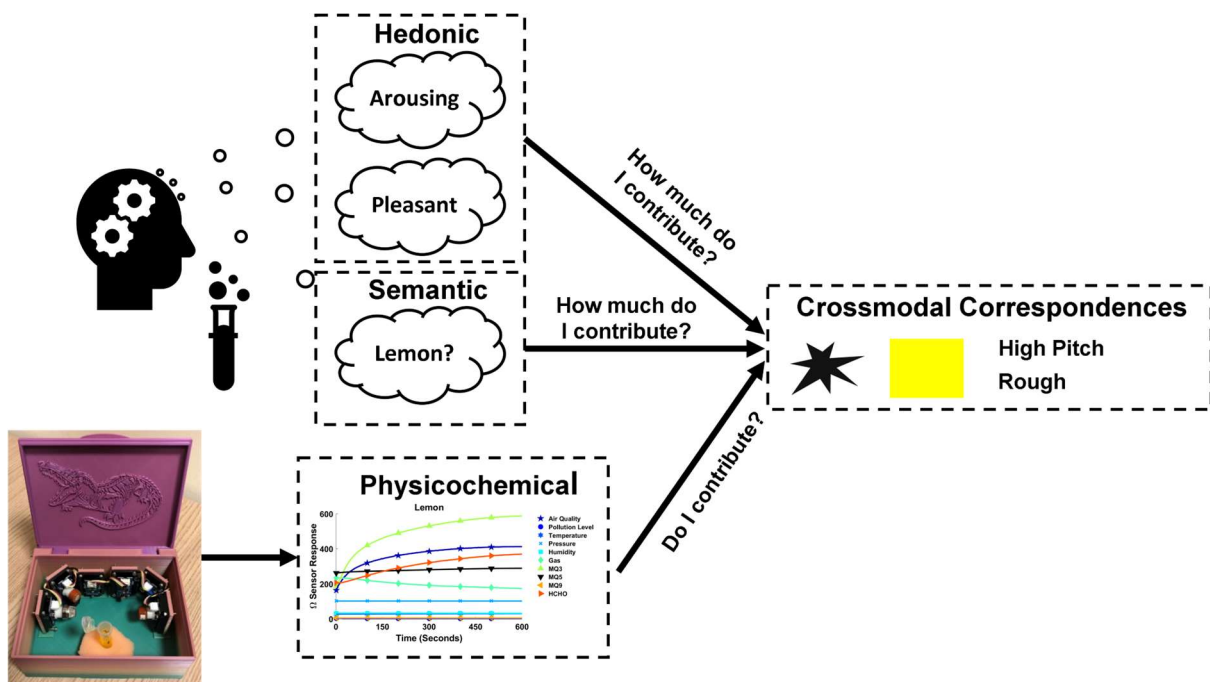


Figure 42. Experimental methodology diagram for Chapter 6.

This chapter answers the research question what is the nature and origin of olfactory crossmodal correspondences? It is hypothesised that semantics, hedonics, and the underlying physicochemical features will play a role in explaining their nature and origin, with hedonics contributing more than semantics and the physicochemical features. The research conducted in this chapter has been published in the Journal of Perceptual Imaging [36] and the i-Perception Journal [37]. This Chapter is organised as follows. Section 6.3 covers a principal component analysis of the odours

in the perceptual space. Section 6.4 then tests to see if semantic involvement affects the perceptual ratings for the angularity of shapes, the smoothness of texture, the perceived pleasantness and pitch. Section 6.5 then tests to see if semantic involvement affects the emotional and musical correspondences. Section 6.6 concludes the semantic involvement analysis with the colour correspondences. Section 6.7 then explores the role that the hedonic dimension of emotions plays in explaining crossmodal correspondences. Section 6.8.1 then performs PCA coupled with a k-means cluster analysis to visualise the relationship between the odours. Section 6.8.2 then quantifies the overlap between the odours in the perceptual and physicochemical data in the physical space. Section 6.8.3 then proves that the physicochemical features of the olfactory stimuli are a contributory factor in crossmodal correspondences.

6.2 Odour Recordings

The prepared solutions consisted of 4 ml of the respective essential oil. Five were from Mystic Moments™ (caramel, cherry, coffee, freshly cut grass, and pine), and five were from Miaroma™ (black pepper, lavender, lemon, orange, and peppermint). Each solution was placed in the same position for all the recordings to negate distance-based sensor bias. Each recording was 10 minutes in duration, with 100 prepared in total for the experiments; ten recordings were prepared for each of the odours. Before any of the recordings were used in the analysis, they first underwent pre-processing to reduce the dimensionality and remove signal noise from the generated signals. The pre-processing involved taking the mean over 1-second intervals creating a 600 x 10 matrix. The signal for each sensor response was then smoothed using a 3-point moving average. The median value from each sensor for each recording was then used for the analysis; this resulted in a final dataset of 100 x 10. One row for each recording and one column for each feature from the e-nose, excluding the time component.

6.3 Semantics and Hedonic Should Play a Role In Explaining The Nature And Origin of Olfactory Crossmodal Correspondences

PCA was first conducted on the mean angularity of shapes, smoothness of texture, perceived pleasantness, the colour dimension (L^*); along with the discrimination accuracy (%) for each odour and the percentiles for the musical genres and emotional dimensions. The ratings for the discrimination accuracy, pitch, colour dimension (L^*), musical genres and emotions were rescaled to

be between 1 and 9, and then standardised. The first three principal components consist of 33.32%, 25.44% and 12.88% of the total variance. The first two principal components are shown in Figure 43A. These show the perceptual similarity between the odours. For example, (lemon, cherry and orange), (coffee and caramel), and (lavender, freshly cut grass and pine) archived similar ratings in most but potentially not all dimensions. The loadings matrix shown in Figure 43B shows us how each of the underlying features influences the principal components. The most important piece of information in the loadings plot is that “Discrimination Rate” has a strong loading on the first component (furthest from 0 on the x-axis). Thus, suggesting that the discrimination rate is an influential factor in crossmodel correspondences. Moreover, the negative loadings of “Country”, “Bored”, and “Calm” on the discrimination rate component tell us that the knowledge of the identity of the odour mainly affects the hedonic dimensions (emotional and musical). The negative loadings of the hedonic dimensions on the “Angularity”, “Smoothness”, “Pleasantness”, and “Pitch” suggest that they are mainly influenced by hedonic dimensions rather than the discrimination rate. Now that we have discovered the hedonics play the dominate role in explaining the nature and origin of olfactory crossmodal correspondences, it is important to conduct further tests as PCA is a rather subjective analysis. Therefore the role that the knowledge of the odours identity and hedonics play is further explored in the proceeding sections.

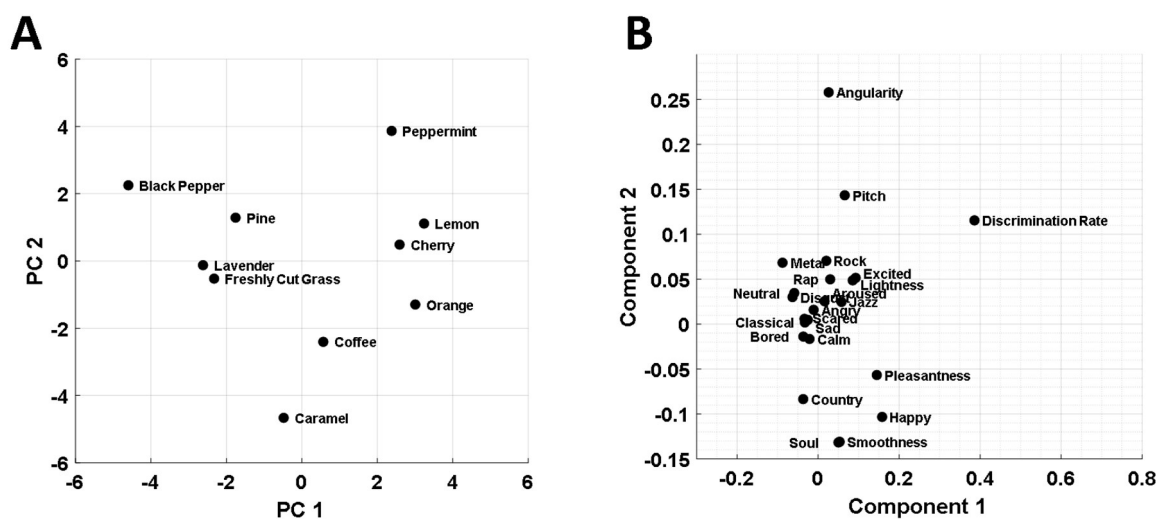


Figure 43. (A) Score plot of the perceptual ratings for each odour. (B) Loading's plot is showing the correlation coefficients for each of the dimensions used in the PCA.

6.4 Knowledge Of the Odours Identity Does Not Affect The Angularity, Smoothness, Pleasantness, and Pitch Ratings

To determine the extent of semantic involvement on the underlying perceptual data the z-scores for the angularity of shapes, smoothness of texture, perceived pleasantness and pitch were split into two datasets, dependent on if the participants correctly identified the odour or not (see Figure 44). Separate two-way repeated measures ANOVA (Greenhouse-Geisser corrected, $\alpha = 0.05$) were conducted using the odours and discrimination (correct vs. incorrect) as within-subjects factors. This revealed that the main effect for identification was not significant for the angularity ($F(1, 6) = 3.19$, $p = 0.124$, $\eta^2 = 0.347$), smoothness ($F(1, 6) = 0.123$, $p = 0.738$, $\eta^2 = 0.020$), pleasantness ($F(1, 6) = 0.142$, $p = 0.74$, $\eta^2 = 0.18$) or pitch ($F(1, 6) = 0.540$, $p = 0.50$, $\eta^2 = 0.119$). Therefore, indicating that the knowledge of the odour's identity does not significantly affect the ratings for the angularity of shapes, smoothness of texture, perceived pleasantness, or pitch. Now that has been discovered that knowledge of the odours identity doesn't affect the angularity, smoothness, pleasantness, or pitch ratings it is important to determine if it affects the musical genre and emotional ratings.

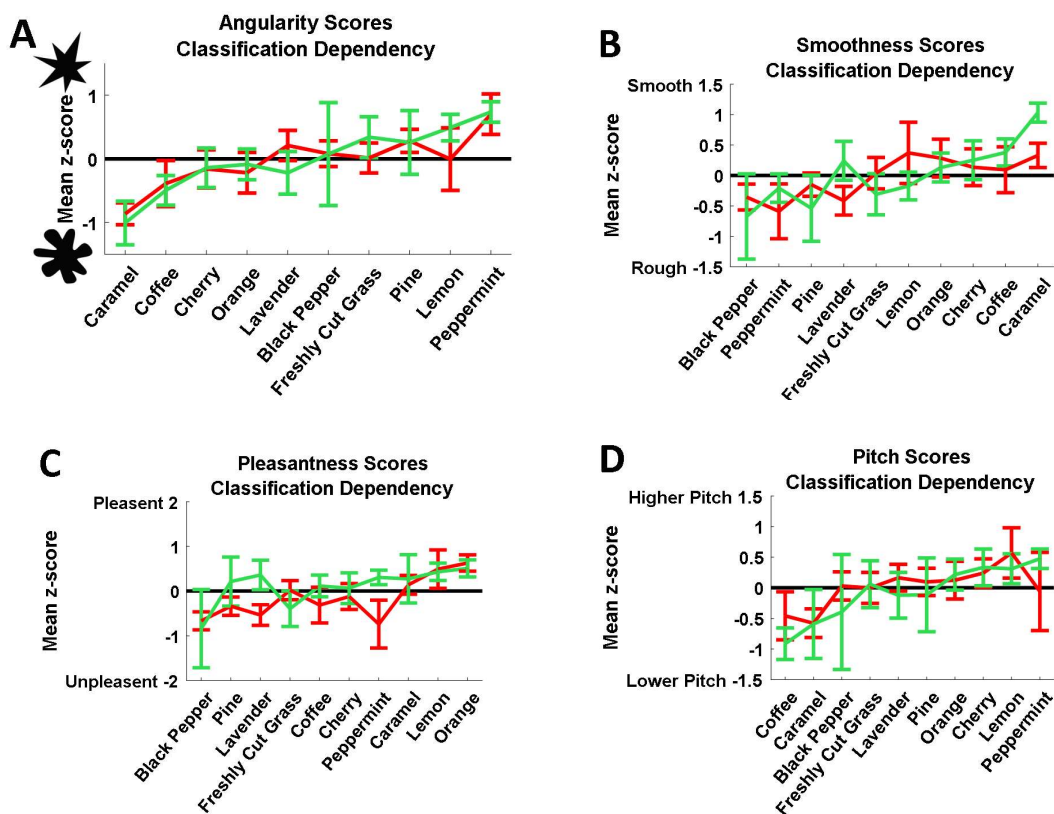


Figure 44. Mean z-scores asterisks denote odours where there is significant variation between the correct and incorrect ratings. The green markers denote correct classification, and the red markers denote incorrect classification. The error bars show the 95% confidence interval.

6.5 Knowledge Of the Odours Identity Does Affect The Musical Genres & Emotional Ratings

To determine if knowledge of an odour's identity affected the musical genre and emotional ratings, chi-squared tests of independence were conducted on the relative assignment percentages between the correct and incorrect proportions expressed as percentiles. The musical genres and emotional dimensions are represented as percentiles as its underlying data are categorical and not numerical. One-sample t-tests (Bonferroni corrected, $\alpha = 0.005$ ($0.05 / 10$)) were conducted to determine if incorrect and correct proportions were significantly different from 0 (no change). This revealed that lavender and freshly cut grass were significantly different for the genre ratings (see Table 14). For the emotional dimensions, the odours of black pepper, caramel, cherry, freshly cut grass, lavender, and lemon are significantly different (See Table 15. One sample t-test results to determine which odours for the emotional dimensions were significantly different from 0 (no change).. Now that it was determined that knowledge of the identity of the odour did affect the musical and emotional ratings, it is important to determine if it also affects the colour ratings.

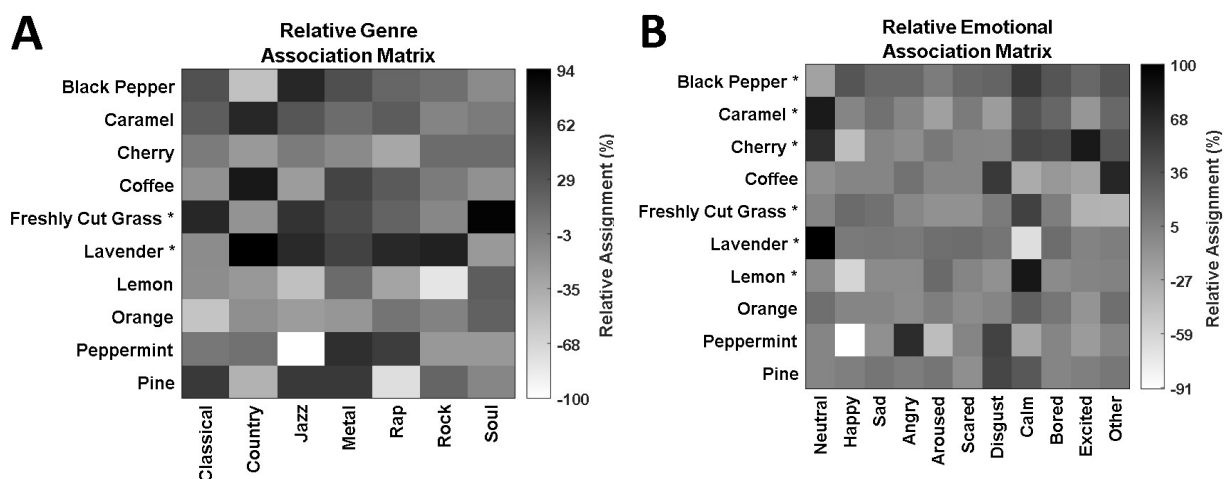


Figure 45. (A) Relative association matrix between the ten odours and the seven genres. (B) Relative association matrix between the ten odours and the 11 possible emotional selections.

6.5.1 Musical genre proportions t-test results

Odour (Correct vs Incorrect)	df	t	p
Black Pepper	6	3.5062	0.0127
Caramel	6	3.9241	0.0078
Cherry	6	2.9417	0.0259
Coffee	6	3.0648	0.0221
Freshly Cut Grass	6	4.5139	0.0040
Lavender	6	4.8174	0.0029
Lemon	6	3.5837	0.0116
Orange	6	2.2539	0.0651
Peppermint	6	3.2182	0.0182
Pine	6	3.1941	0.0187

Table 14. One sample t-test results to determine which odours for the musical genres were significantly different from 0 (no change).

6.5.2 Emotional proportions t-test results

Odour (Correct vs Incorrect)	df	t	p
Black Pepper	10	7.9480	< 0.0000
Caramel	10	4.3374	0.0015
Cherry	10	3.9749	0.0026
Coffee	10	3.0553	0.0121
Freshly Cut Grass	10	3.8407	0.0033
Lavender	10	4.8719	0.0006
Lemon	10	4.0871	0.0022
Orange	10	3.3323	0.0076
Peppermint	10	3.1004	0.0112
Pine	10	3.2735	0.0084

Table 15. One sample t-test results to determine which odours for the emotional dimensions were significantly different from 0 (no change).

6.6 Knowledge Of The Odours Identity Does Affect The Colour Ratings

The algorithm outlined in Section 5.8 Section was conducted on the correct and incorrect datasets to determine if knowledge of the odour's identity affected the colour ratings. Chi-squared tests for goodness of fit (Bonferroni Corrected, $\alpha = 0.005$) were conducted on the observed proportions (correct vs. incorrect for the commonly mapped colours, see Figure 46). This revealed that the proportions for black pepper, cherry, lemon, peppermint and pine were significantly different (see Table 16). Comparing Figure 46A and Figure 46B, we can see that the generated colour profiles are more consist with common odours and for the uncommon odours, the generated colour profiles are more diverse, meaning that knowledge of the odour's identity does influence the ratings, but these correspondences still occur if they do not know what the odour is. The assumptions that knowledge of an odour's identity would affect the participant's colour assignments were both tested and met. Now that it was uncovered that knowledge of the identity of the odour affected the colour ratings, musical, and emotional ratings but not the angularity of shapes, smoothness of texture, perceived pleasantness, and pitch ratings. To answer the rest of the hypothesis, the role of hedonics and the physicochemical features play in explaining the nature and origin of crossmodal correspondences still needs to be explored and therefore is covered in the rest of this chapter.

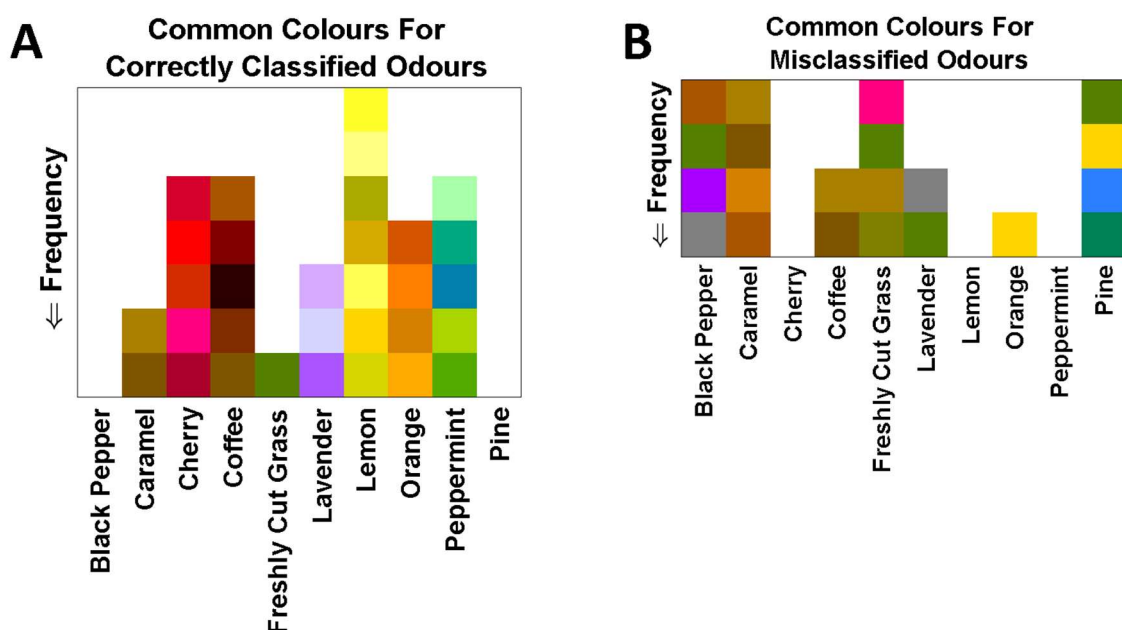


Figure 46. Common colour selections where each colour has been (A) correctly classified and (B) incorrectly classified. Each colour had to have been mapped more than twice for it to be deemed a common colour. Colours at the bottom of the graph occurred more often.

6.6.1 Chi-squared tests for goodness of fit on the observed colour proportions results

Odour (Correct vs. Incorrect)	df	χ^2	p
Black Pepper	1	8.0000	0.0047
Caramel	1	2.6666	0.1025
Cherry	1	10.0000	0.0016
Coffee	1	4.2857	0.0384
Freshly Cut Grass	1	4.8000	0.0285
Lavender	1	1.2000	0.2733
Lemon	1	14.0000	0.0002
Orange	1	4.8000	0.0285
Peppermint	1	10.0000	0.0016
Pine	1	9.0000	0.0047

Table 16. Chi-squared test results for the goodness of fit tests to determine if the proportions of the generated colour profiles are significantly different.

6.7 Hedonics Plays a Role in Explaining the Nature and Origin Of Olfactory Crossmodal Correspondences

This analysis was conducted on the unstandardized but scaled mean values for each odour. Before checking the VIF (Variance Inflation Factor) values, the hedonic dataset (emotion and musical) was split into two. This was done to avoid having too many independent variables. Next, the VIF (Variance Inflation Factor) values were checked for both the emotional and musical sets to test for multicollinearity. This revealed that moderate multicollinearity exists in the musical set (all VIF values > 10), and thus was excluded from the analysis. The VIF values were also checked for the emotional dataset indicating that bored, calm, happy, and sad VIF values were > 10 and therefore excluded from the analysis. The significance level for inclusion into the models was set at 0.05, and the results are shown in Table 17.

Independent Variables	Dependent Variables	Stats (Estimated Coefficient, Standard Error, t-value, p-value)
Angry, Aroused, Scared, Disgust, and Excited	Angularity	Intercept (-8.76, 3.37, -2.6, $p = 0.04$) Angry (5.44, 2.02, 2.69, $p = 0.036$) Scared (3.34, 1.52, 2.20, $p = 0.070$) Excited (-2.12, 0.60, 3.57, $p = 0.011$) Modal Summary ($R^2 = 0.76$, $F(3, 9) = 6.46$, $p = 0.026$)
Angry, Aroused, Scared, Disgust, and Excited	Smoothness	Intercept (13.58, 1.57, 8.67, $p < 0.001$) Angry (-3.43, 0.94, -3.64, $p = 0.010$) Scared (-2.27, 0.71, -3.21, $p = 0.018$) Excited (-0.72, 0.28, -2.61, $p = 0.039$) Modal Summary ($R^2 = 0.81$, $F(3, 9) = 9.08$, $p = 0.012$)
Angry, Aroused, Scared, Disgust, and Excited	Pleasantness	Intercept (31.26, 6.16, 5.08, $p = 0.007$) Angry (-21.04, 5.55, -3.79, $p = 0.022$) Scared (-18.45, 5.06, -3.65, $p = 0.021$) Disgust (-0.95, 0.09, -10, $p < 0.001$) Excited (0.58, 0.13, 4.33, $p = 0.012$) Angry*Scared (0.58, 0.13, 4.33, $p = 0.026$) Modal Summary ($R^2 = 0.98$, $F(5, 9) = 67.6$, $p < 0.001$)
Angry, Aroused, Scared, Disgust, and Excited	Pitch	Intercept (1.40, 0.72, 1.94, $p = 0.087$) Excited (1.01, 0.39, 2.57, $p = 0.033$) Modal Summary ($R^2 = 0.45$, $F(1, 9) = 6.62$, $p = 0.033$)
Angry, Aroused, Scared, Disgust, and Excited	Correct Discrimination Rate	Intercept (-289.09, 173.76, -1.66, $p = 0.14$) Scared (248.57, 148.79, 1.67, $p = 0.14$) Excited (237.04, 101.42, 2.134, $p = 0.05$) Scared*Excited (-186.25, 90.74, -2.05, $p = 0.08$) Modal Summary ($R^2 = 0.82$, $F(3, 9) = 9.25$, $p = 0.01$)
Angry, Aroused, Scared, Disgust, and Excited	Lightness	Intercept (7.17, 0.60, 11.80, $p < 0.001$) Disgust (-0.79, 0.233, -2.38, $p = 0.045$) Modal Summary ($R^2 = 0.41$, $F(2,9) = 5.65$, $p = 0.045$)

Table 17. Stepwise linear regression results. Note: some of the models have selected some emotional dimensions where their contributions are not significant.

The information shown in Table 17 shows us that the hedonic variables are the most influential factor for predicting crossmodal interactions. Significant relationships have been found between a subset of our hedonic dimensions and the angularity of shapes, smoothness of texture, perceived pleasantness, pitch, lightness of colour (L^*) and the correct discrimination rate. Now we know that hedonics plays a role in explaining the nature and origin of the olfactory crossmodal

correspondences, it is important to determine if the physicochemical features also play a role in explaining the nature and origin of crossmodal correspondences.

6.8 The Physicochemical Features of The Presented Stimuli Play a Role in Explaining The Nature And Origin Of Olfactory Crossmodal Correspondences

6.8.1 The odours in the perceptual and physicochemical spaces are reasonably similar

PCA was then conducted on the perceptual and chemical data to visualize the interrelationship of the odours in the two spaces. To prepare the datasets for PCA, both the pitch ratings and colour dimensions were rescaled between 1 and 9. Z-score normalization was then conducted on both datasets separately; the population standard deviation and mean of all the dataset were used for the perceptual dataset. For the chemical dataset, the z-score normalization used the population standard deviation and the mean of the columns. The distance between two points indicates how similar two odours are in their respective space, with the closer points indicating a higher degree of similarity. Based on inspection of the scree plots, the first two components for both the perceptual and chemical data were kept; no rotations were performed as we wanted to keep the two spaces as comparable as possible. The perceptual dataset's first two components explain 79.13% of the total variance, 48.15%, and 30.98%, respectively, and is shown in *Figure 47A*. The first two components for the physicochemical dataset explain 75.56% of the total variance, 51.06% and 24.49%, respectively, as shown in *Figure 47B*.

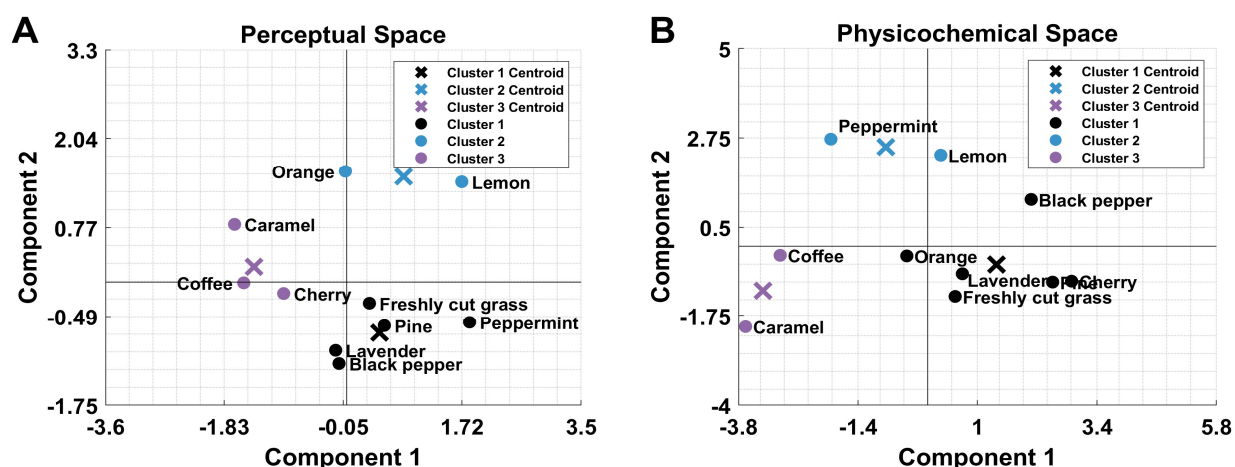


Figure 47. Principal components in (A) perceptual space and (B) chemical space. Both score plots are based on the PCA correlation matrix.

To determine the groups that archived similar perceptual/chemical scores, k-mean cluster analysis was conducted on all the principal component scores. This process produces clusters based on feature similarity, where each cluster contains similar principal component scores across all

dimensions. In Figure 47, the cross marker denotes the centre location of the clusters; the filled circles indicate the principal component score, with the colour representing the cluster grouping determined by k-means cluster analysis. From Figure 47A, we can see that (caramel, coffee, and cherry), (orange and lemon), and (freshly cut grass, lavender, pine, peppermint, and black pepper) obtained comparable scores making them perceptually similar. From Figure 47B, we can see that (coffee and caramel), (peppermint and lemon), and (black pepper, lavender, freshly cut grass, orange, pine, and cherry) have comparable scores, making them similar in physicochemical space. Comparing the cluster groupings from Figure 47A with Figure 47B, we can see moderate overlap in the physicochemical and perceptual spaces with (coffee and caramel), and (lavender, freshly cut grass, pine, and black pepper) are in the same cluster in both cases. Therefore, showing a moderate overlap between odours in the perceptual and physicochemical spaces which implies that a reasonable degree of similarity exists between these two spaces. To further analyse the overlap between these two spaces, a Procrustes analysis was used as this algorithm allows for quantification of the overlap between two spaces.

6.8.2 The odours in the perceptual and physicochemical spaces overlap by 49%

A Procrustes analysis was performed to determine how closely the odours are related between the chemical and perceptual space in the physical space. The algorithm fits the points between the perceptual and chemical space using the best shape-preserving Euclidean transformations matching the physicochemical and perceptual spaces to the physical space. As multidimensional scaling (MDS) provides relative points in space, a Procrustes analysis can be performed on the resulting matrix [278], [279] with the goodness of fit criterion defined as the sum of squared errors. The output consists of the distance of points in space where lesser values indicate a better fit, with zero being a perfect fit and one being entirely dissimilar. The dataset was pre-processed in the same manner as performed in the exploratory factor analysis above. A scree plot showing ordination stress was constructed to determine how many dimensions are required to explain the data sufficiently (*Figure 48A*). This revealed that the first two dimensions are sufficient for the visualization of both the physicochemical and perceptual dimensions. Therefore, we decided to plot the MDS maps in two dimensions. Looking at both the PCA scores plots (*Figure 48*) and the MDS maps (*Figure 48C & Figure 48D*), we can see that the perceptual and physicochemical spaces are visually similar. One thousand simulations from a random location with uncorrelated coordinates and an appropriately scaled p-dimensional normal distribution were run using the three dimensions to determine how similar these two spaces are. The goodness of fit was calculated for each pair of MDS solutions (mean = 0.51, min = 0.43, max = 0.60,

see Figure 48B), where a value of 0 indicates a perfect alignment. This revealed a 49% ($1 - 0.51 * 100$) similarity on average between the physicochemical and perceptual spaces in the physical space, meaning that perceptually similar odours are also similar in the physicochemical space to about 49%. Now it is known that there is a reasonable degree of overlap between the two spaces, it is important to uncover which of the physicochemical features are important towards explaining this overlap.

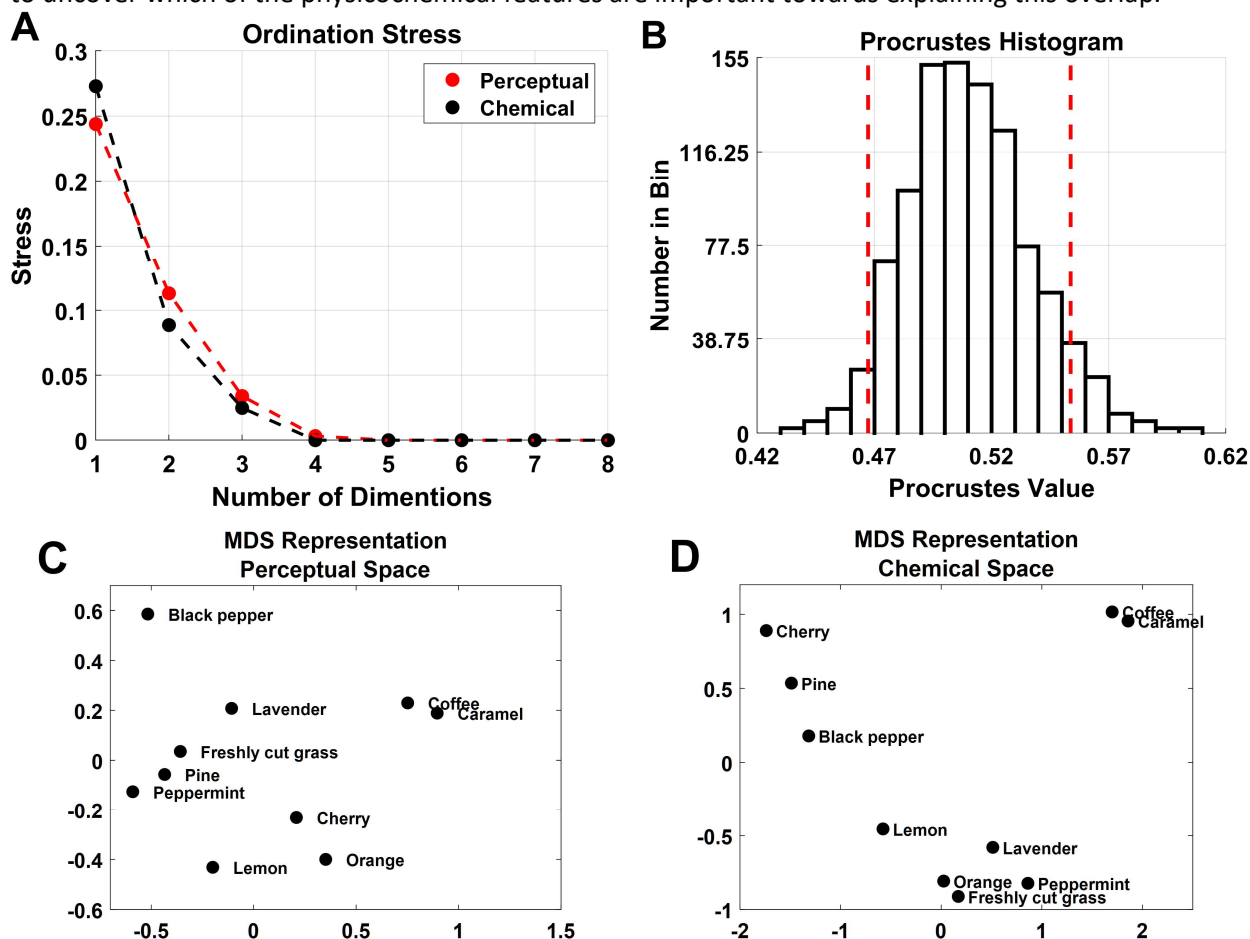


Figure 48. (A) Ordination stress scree plot. (B) Histogram plot of 1000 generated Procrustes values using a random location with uncorrelated coordinates and from a scaled p -dimensional normal distribution. The vertical dashed lines indicate a 95% confidence interval. (C) Example MDS plot of the perceptual space. (D) Example MDS plot of the chemical space. The shape of the MDS plots will vary based on the initial random start location.

6.8.3 The physicochemical features correlated with olfactory crossmodal correspondences

To determine which features were important towards explaining the findings reported in the last section, a series of Pearson correlations were performed to determine if specific physicochemical attributes were correlated with the underlying perceptual data (see Table 18). The correlations were performed on the raw perceptual ratings and the mean physicochemical features. The physicochemical features used in this analysis are air quality, temperature, pressure, humidity, gas,

MQ3, MQ5, MQ9, and HCHO. The level of significance was Bonferroni corrected to the number of physicochemical features ($0.05 / 9 = 0.0056$).

Perceptual dimension	Statistics Name (rho, p-value)
Angularity of shapes	Air Quality (0.2989, < 0.0001) * Temperature (-0.1986, < 0.0001) * Pressure (-0.0752, 0.0501) Humidity (0.1658, < 0.0001) * Gas (-0.2971, < 0.0001) * MQ3 (0.1755, < 0.0001) * MQ5 (0.1053, 0.0060) MQ9 (-0.0191, 0.6186) HCHO (0.2452, < 0.0001) *
Smoothness of texture	Air Quality (-0.1924, < 0.0001) * Temperature (0.0343, 0.3721) Pressure (0.0552, 0.1503) Humidity (-0.0672, 0.0798) Gas (0.2289, < 0.0001) * MQ3 (-0.1184, 0.0020) * MQ5 (-0.892, 0.0199) MQ9 (-0.0397, 0.3016) HCHO (-0.1436, 0.0002) *
Perceived pleasantness	Air Quality (-0.1164, 0.0024) * Temperature (-0.1630, < 0.0001) * Pressure (0.0224, 0.5603) Humidity (0.0675, 0.0787) Gas (0.1359, 0.0004) * MQ3 (-1174, 0.0022) * MQ5 (-0.1791, < 0.0001) * MQ9 (-0.1219, 0.0014) * HCHO (-0.0631, 0.1001)

Perceptual dimension	Statistics Name (rho, p-value)
Pitch	Air Quality (0.2224, < 0.0001) * Temperature (-0.1017, 0.0127) Pressure (0.0567, 0.1656) Humidity (0.1353, 0.0009) * Gas (-0.1518, 0.0002) * MQ3 (0.1774, < 0.0001) * MQ5 (0.1080, 0.0081) MQ9 (-0.0158, 0.6985) HCHO (0.2470, < 0.0001) *
L*	Air Quality (0.1184, 0.0020) * Temperature (-0.1711, < 0.0001) * Pressure (-0.0627, 0.1022) Humidity (0.1284, 0.0008) * Gas (-0.1439, 0.0002) * MQ3 (0.0460, 0.2314) MQ5 (-0.1004, 0.0088) MQ9 (-0.0339, 0.3772) HCHO (0.1300, 0.0007) *
a*	Air Quality (-0.0535, 0.1635) Temperature (0.2361, < 0.0001) * Pressure (0.2905, < 0.0001) * Humidity (-0.1037, 0.0068) Gas (0.2648, < 0.0001) * MQ3 (0.0788, 0.0400) MQ5 (0.1686, < 0.0001) * MQ9 (0.0932, 0.0151) HCHO (0.0487, 0.2051)

Perceptual dimension	Statistics Name (rho, p-value)
b*	Air Quality (-0.1036, 0.0068) Temperature (-0.1447, 0.0002) * Pressure (0.0773, 0.0438) Humidity (0.1430, 0.0002) * Gas (0.0920, 0.0164) MQ3 (-0.0903, 0.0185) MQ5 (-0.2600, < 0.0001) * MQ9 (-0.2434, < 0.0001) * HCHO (-0.0606, 0.1144)

Table 18. Pearson correlation results for all perceptual dimensions. The degrees of freedom for all perceptual dimensions except for pitch is 678. The degrees of freedom for the pitch correlations is 598. Rows in bold indicate significant coefficients.

From Table 18, we can see that the analysed olfactory crossmodal correspondences are significantly correlated with at least four physicochemical features. This indicates that the physicochemical features of the olfactory stimuli influence crossmodal correspondences. The “Air Quality” sensor detects a wide range of harmful gases for indoor air conditions. It is also a significant feature on all perceptual dimensions, excluding the hue of colour (a* and b*) indicating that the quality of the stimuli will influence crossmodal correspondences. Out of the five perceptual dimensions where “Air Quality” is significant, in four of them, the feature “HCHO” is also significant, suggesting that the secondary gas formaldehyde is predominantly responsible. Temperature, humidity, and pressure will interact in complex ways to determine the intensity of the odour. It is important to note that it is not possible to rule out the involvement of the other physicochemical features in contributing to intensity. Here we will focus on the physical temperature, humidity, and pressure as aspects of intensity, as these three features would be a constant underlying all odours. With the exception of the smoothness of texture, either “Temperature,” “Pressure,” and/or “Humidity” is significant, indicating that along with the quality of stimuli, the intensity is also a contributory factor. For the perceived pleasantness, the odours that had a lesser response for “Air Quality,” “Temperature,” “MQ3,” “MQ5,” and “MQ9” but had more volatile organic compounds that affect air quality (“Gas”) in the range of 1 ~ 50 ppm were more pleasant. These results indicate that the perceptual dimensions for the angularity of shapes, perceived pleasantness, pitch, and the colour dimension (L*) were affected by both the quality and aspects of intensity. The smoothness of texture seemed to be affected by quality factors but not intensity. The colour dimensions (a* and b*) seemed to be affected by aspects of intensity but not quality. The physicochemical features provided by the

e-nose are a composite of the entire smell; therefore, it would be ideal to see how the physicochemical features impact olfactory crossmodal correspondences as a whole instead of its individual elements; consequently, we proceeded to create generalized linear mixed models. We that we know that there is a overlap between the odours in the perceptual and physicochemical spaces and that the physicochemical are correlated with the perceptual dimensions it was decided to how much the physicochemical features contribute to the perceptual dimensions as a whole rather than its individual elements.

6.8.4 Olfactory crossmodal correspondences should be predictable

The generalized linear mixed-effect models (GLMM) were created using the raw perceptual ratings as the dependent variable and the mean physicochemical features of each odour as the independent variables. The physicochemical features used in this analysis are air quality, temperature, pressure, humidity, gas, MQ3, MQ5, MQ9, and HCHO. Each model was only fitted to one perceptual dimension at a time resulting in seven different models. First, multicollinearity was tested for in the chemical dataset. This revealed multicollinearity between Air Quality (VIF = 16.8302) and MQ3 (VIF = 17.0148); therefore, we decided to remove the MQ3 feature from the dataset. The VIF values were rechecked after removing the MQ3 feature revealing no multicollinearity (all VIF values are less than 5) in the physicochemical dataset. We then proceeded to fit the GLMM's (Bonferroni corrected for the number of models ($\alpha = 0.0071$)) treating the participants and the odours as a random factor. Coefficients with a p-value greater than our Bonferroni corrected alpha were not included in Table 19.

Model	Model fit statistics (Log-likelihood (LL), Akaike information criterion (AIC), Bayesian information criterion (BIC), Conditional R^2 (C- R^2), Marginal R^2 (M- R^2))					Coefficients (Name, Estimate, SE, t-stat, p-value)
	LL	AIC	BIC	C- R^2	M- R^2	
Angularity of shapes	3064.6	3118.9	- 1520.3	0.18	0.18	Air Quality (0.1141, 0.30, 0.25, 1.20, 0.23) Temperature (-0.4315, -1.30, 0.22, -5.87, p < 0.0001) Pressure (-0.0006, -0.002, 0.17, -0.01, 0.99) Humidity (-0.2057, -0.56, 0.29, -1.91, 0.06) Gas (-0.1852, -0.55, 0.24, -2.32, 0.02) MQ5 (0.1188, 0.35, 0.24, 1.41, 0.16) MQ9 (0.0049, 0.014, 0.27, 0.05, 0.96) HCHO (0.0817, 0.25, 0.23, 1.08, 0.28)
Smoothness of texture	-1481.3	2986.5	3040.8	0.10	0.06	Air Quality (-0.0174, -0.04, 0.23, -0.17, 0.86) Temperature (0.1157, 0.31, 0.21, 1.5, 0.13) Pressure (-0.0309, -0.08, 0.15, -0.52, 0.60) Humidity (-0.0083, -0.02, 0.270, -0.07, 0.94) Gas (0.2416, 0.65, 0.22, 2.88, 0.0040804) MQ5 (-0.1514, -0.39, 0.23, -1.72, 0.08) MQ9 (-0.0468, -0.12, 0.25, -0.46, 0.64688) HCHO (0.0897, 0.24, 0.22, 1.13, 0.26)

Model	Model fit statistics (Log-likelihood (LL), Akaike information criterion (AIC), Bayesian information criterion (BIC), Conditional R^2 (C- R^2), Marginal R^2 (M- R^2))					Coefficients (Name, Estimate, SE, t-stat, p-value)
	LL	AIC	BIC	C- R^2	M- R^2	
Perceived pleasantness	-1464.7	2953.4	3007.7	0.20	0.10	Air Quality (0.2123, 0.50, 0.22, 2.26, 0.02) Temperature (-0.0632, -0.17, 0.20, -0.87, 0.39) Pressure (-0.1257, -0.33, 0.15, -2.26, 0.02) Humidity (-0.0346, -0.08, 0.26, -0.32, 0.75) Gas (0.4488, 1.21, 0.21, 5.67, p < 0.0001) MQ5 (-0.5238, 1.37, 0.22, 6.29, p < 0.0001) MQ9 (0.0434, 0.11, 0.24, 0.45, 0.65) HCHO (0.3892, 1.07, 0.21, 5.19, < 0.0001)
Pitch	-5940.9	11906	11958	0.36	0.09	Air Quality (0.1027, 604.62, 526.36, 1.15, 591, 0.25) Temperature (-0.1502, -1008.1, 464.84, -2.17, 0.03) Pressure (-0.0506, -331.43, 346.18, -0.96, 0.34) Humidity (0.0604, 362.68, 608.66, 0.60, 0.55) Gas (0.0971, 650.94, 504.67, 1.29, 0.20) MQ5 (-0.1142, -738.1, 511.84, -1.44, 0.15) MQ9 (0.0954, 593.13, 569.5, 1.04, 0.30) HCHO (0.2923, 1989.6, 485.74, 4.09, p < 0.0001)

Model	Model fit statistics (Log-likelihood (LL), Akaike information criterion (AIC), Bayesian information criterion (BIC), Conditional R^2 (C- R^2), Marginal R^2 (M- R^2))					Coefficients (Name, Estimate, SE, t-stat, p-value)
	LL	AIC	BIC	C- R^2	M- R^2	
L*	-2953.5	5931	5985.3	0.25	0.16	Air Quality (0.3856, 8.43, 1.99, 4.23, p < 0.0001) Temperature (0.0087, 0.21, 1.76, 0.12, 0.90) Pressure (-0.2808, -6.83, 1.31, -5.21, p < 0.0001) Humidity (0.2376, 5.29, 2.30, 2.30, p = 0.0218) Gas (0.4562, 11.36, 1.91, 5.95, p < 0.0001) MQ5 (-0.6921, -16.60, 1.94, -8.57, p < 0.0001) MQ9 (0.3046, 7.03, 2.16, 3.26, p = 0.0012) HCHO (0.5197, 13.13, 1.84, 7.14, p < 0.0001)
a*	-3248.6	6521.2	6575.5	0.22	0.17	Air Quality (-0.1820, -6.12, 3.12, -1.96, 0.0503) Temperature (0.3154, 12.09, 2.76, 4.39, p < 0.0001) Pressure (0.0649, 2.43, 2.05, 1.18, 0.2378) Humidity (0.4316, 14.79, 3.61, 4.10, p < 0.0001) Gas (0.2671, 10.23, 2.99, 3.42, 0.0007) MQ5 (0.0506, 1.87, 3.04, 0.61, 0.5388) MQ9 (0.2255, 8.01, 3.38, 2.37, 0.0180) HCHO (0.0869, 3.38, 2.88, 1.17, 0.24)

Model	Model fit statistics (Log-likelihood (LL), Akaike information criterion (AIC), Bayesian information criterion (BIC), Conditional R^2 (C- R^2), Marginal R^2 (M- R^2))					Coefficients (Name, Estimate, SE, t-stat, p-value)
	LL	AIC	BIC	C- R^2	M- R^2	
b*	-3339.7	6703.4	6757.6	0.25	0.23	Air Quality (0.6529, 25.87, 3.61, 7.18, p < 0.0001) Temperature (0.3255, 14.70, 3.18, 4.62, p < 0.0001) Pressure (-0.072, -3.18, 2.37, -1.34, p = 0.18013) Humidity (-0.1385, -5.59, 4.17, -1.34, p = 0.18016) Gas (0.4794, 21.63, 3.46, 6.26, p < 0.0001) MQ5 (-0.8851, -38.48, 3.50, -10.98, p < 0.0001) MQ9 (-0.4705, -19.69, 3.90, -5.05, p < 0.0001) HCHO (0.3337, 15.28, 3.33, 4.59, p < 0.0001)

Table 19. Generalized linear mixed model results for all perceptual dimensions. The degrees of freedom for all coefficients in the table is 671, with the exception of the pitch model, where the degrees of freedom is 591. Marginal R2 is the variance explained by the fixed factors, and conditional R2 is the variance explained by the entire model [280]. The Wilkinson model formula used is: Perceptual dimension $\sim 1 + \text{Air Quality} + \text{Temperature} + \text{Pressure} + \text{Humidity} + \text{Gas} + \text{MQ5} + \text{MQ9} + \text{HCHO} + (1 | \text{Participant ID}) + (1 | \text{Odour ID})$. Significant predictors are highlighted in bold.

The results from Table 19 confirm the findings from the Pearson correlations and tell us that physicochemical features are a contributory factor towards explaining people’s crossmodal associations. That is, when treating the participants and the olfactory stimuli as a random effect, significant coefficients were found in all of the generated models. These models also show that between 6% - 23% variance is explained by the fixed effects (physicochemical features), providing further support for the claim that the physicochemical features are an influential factor in olfactory crossmodal correspondences. This suggests that olfactory crossmodal correspondences can be predicted using the underlying physicochemical features. The extent to which olfactory crossmodal correspondences can be predicted is covered using a more rigorous method in covered the next chapter.

6.9 Chapter 6 Summary

This chapter answered the research question what is the nature and origin of olfactory crossmodal correspondences? It is hypothesised that semantics, hedonics, and the underlying physicochemical features will play a role in explaining their nature and origin, with hedonics contributing more than semantics and the physicochemical features. The hedonic, semantic, and physicochemical relationships underlying olfactory crossmodal correspondences were explored. This revealed involvement from all three mechanisms, including a novel mechanism (physicochemical). First, PCA was conducted on the underlying perceptual dimensions (angularity of shapes, smoothness of texture, perceived pleasantness, pitch, the lightness of colour, emotional, and musical dimensions). This suggests that there is more hedonic involvement than semantic, with semantic involvement mainly affecting the hedonic dimensions suggesting more of a “knock-on” effect rather than direct involvement. Each individual perceptual dimension was then analysed for semantic involvement using separate two-way repeated measures ANOVA’s revealing that the ratings for the angularity of shapes, smoothness of texture, perceived pleasantness, and pitch are not affected by knowledge of the identity of the odour. One sample t-tests revealed that the ratings for odours of freshly cut grass and lavender are affected by knowledge of the odour’s identity for the musical dimensions. A series of one-sample t-tests also revealed that for the emotional dimensions, the odours of black pepper, caramel, cherry, freshly cut grass, lavender, lemon, and peppermint induced a non-random distribution. Chi-squared tests for goodness of fit were conducted on the proportions for the commonly selected colours for the correctly classified and the misclassified colour profiles. This revealed that the proportions for black pepper, cherry, lemon, peppermint, and pine were significantly different. Next, a series of stepwise linear regression models were created to determine the impact the hedonic dimensions (emotions) have on explaining olfactory crossmodal correspondences. This revealed that the hedonic dimensions significantly affected all of the core sensory modalities.

The physicochemical features' role in explaining the nature and origin of olfactory crossmodal correspondences was then explored. A perceptual and physicochemical space was first constructed then PCA was used to visualise the similarity between the odours in the physical spaces coupled with a k-means cluster analysis. This revealed that the perceptual and physicochemical spaces are quite similar, with six out of ten odours grouped into the same clusters in both cases. To quantify the relationship between the odours in the perceptual and physicochemical spaces in the physical space, a Procrustes analysis was performed. This revealed that the odours in the perceptual and chemical spaces are similar to the degree of 49%.

Next, it was determined if any physicochemical features correlated with the perceptual dimensions. This revealed that the perceptual dimensions for the angularity of shapes, perceived pleasantness, pitch, and colour dimension (L^*) were affected by both the quality and aspects of intensity. The smoothness of texture seemed to be affected by quality factors but not our aspects of intensity. The colour dimensions (a^* and b^*) seemed to be affected by aspects of intensity but not quality. Considering these results together, we can see the perceptions dimensions are correlated with a variety of physicochemical features and demonstrates that they, at least in part, contribute towards explaining the nature and origin of olfactory crossmodal correspondences. A series of generalized linear mixed models were then created using the physicochemical features of the odours and the raw perceptual data from sixty-eight participants. These models generated significant coefficients in all cases and explained between (6% - 23%) of the variance explained by our fixed factors (physicochemical features). The fact it was possible to do this suggests that not only is there a relationship between olfactory crossmodal correspondences and the physicochemical features of the stimuli, but we can use these features to predict their crossmodal perception. Coupling the findings from the Pearson correlations with the generalized linear mixed models results led to the conclusion that the physicochemical features are a contributory factor due to involvement from intensity, odour quality, and the complexity/intricacy of the underlying stimuli. Considering these findings together answered the research question of what is the nature and origin of olfactory crossmodal correspondences?

The findings reported in this chapter are important because it explores the impact of hedonics and semantics together towards explaining the nature and origin of crossmodal correspondences, which in prior literature is usually done separately. The findings in this chapter also introduces the concept that the physicochemical features of odours play a contributory role towards explaining the nature and origin of the correspondences which is a consistently overlooked aspect of prior work. Now we have a better understanding to why these correspondences occur, with hedonics, semantics, and the olfactory stimuli's physicochemical features playing a role in explaining the nature and origin. It was also uncovered that hedonics plays a greater role than semantics. In other words, it is more important for the stimuli to be perceived as either pleasant or unpleasant than for the user to know the identity of the olfactory stimuli. It is important to probe the extent of the physicochemical feature's contribution and to investigate how we could utilise the uncovered correspondences for stimuli that the crossmodal correspondences have not been uncovered for. This could allow for the determination of what the crossmodal correspondences are for a given stimuli in real-time for potentially unknown stimuli which would be greatly beneficial for human-machine interfaces, such as the one presented in

Chapter 4, however in order to do this machine learning algorithms need to be developed to predict the crossmodal correspondences are for unknown stimuli. The limitations of the work conducted in this chapter include the limited sample size, specifically after splitting the ratings into two datasets based if they could identify the odour or not. This led to small samples, as low as thirteen for some odours which could led to a false positive or negative for the results reported in Section 6.4 – 6.6. Another limitation of this research chapter is that the musical data collected in Chapter 5 were highly multicollinear was impossible reliably analyse their contribution towards their role in hedonics. The final limitation of this chapter is as both the musical and emotional data collected in Chapter 5 were multiple-choice. The role the physicochemical features play in explaining the emotional and musical dimensions was not analysed and, therefore, presenting an avenue for future research.

Chapter 7 Predicting The Crossmodal Correspondences of Odours Using an Electronic Nose

7.1 Introduction

This chapter focuses on predicting the crossmodal correspondences of odours using the physicochemical features transduced by an e-nose. The novelty of the research presented in this chapter is to determine if it is possible to predict the crossmodal perception of odours, thereby eliminating the need for extensive psychological tests, enabling more refined multisensorial experiences to be developed, and to determine if there is a systematic and predictable link between the physicochemical features of odours and crossmodal correspondences. To determine if it was possible to predict the crossmodal correspondences attributed to smell, two different brands of essential oils were used to present chemical diversity to the underlying physicochemical features. Data on the crossmodal perception of odours (the angularity of shapes, smoothness of texture, perceived pleasantness, pitch, and colours) for various essential oils were used from Chapter 5. E-nose responses were collected for the different odourants using the same brand and volume as the perceptual data. The odours used in the confines of these experiments were chosen as they are commonly used in perfumes and olfaction-enhanced multimedia. Robust predictions of the human perception of odours are crucial for constructing an artificial olfactory system and industrial quality control applications and designing multisensorial experiences where assessments must be made in accordance with human perception. The experimental methodology for this chapter is shown in Figure 49.

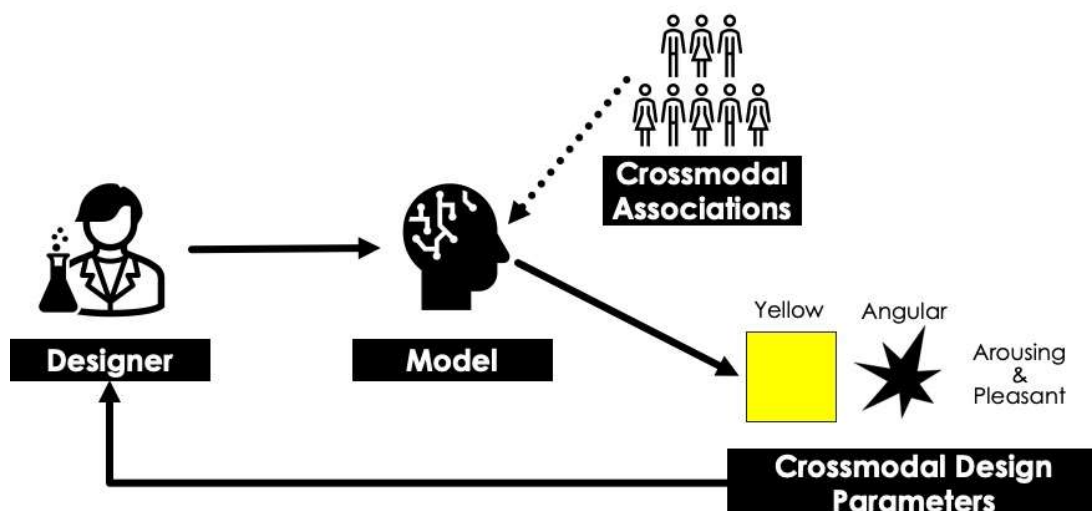


Figure 49. The experimental methodology used for predicting crossmodal olfactory perception.

This chapter answers the question is it possible to predict olfactory crossmodal correspondences using the stimuli's physicochemical features? It is hypothesized that olfactory crossmodal correspondences, will at least in part, be predictable. The research conducted in this chapter is published in the Heliyon journal [39]. This chapter is organised as follows: Section 7.2 covers the origin of the data in this chapter has come from as well as outlying the data pre-processing steps that have taken place. Section 7.3 covers a short analysis on perceptual outlier removal. Section 7.4 covers a multivariate analysis of variance to determine which of the underlying physicochemical features to use in training the regression models. Section 7.5 covered a short analysis of the most optimal regression algorithm to use for predicting the crossmodal perception of odours using their underlying physicochemical features. Section 7.6 contains the optimisation of parameters of the algorithm that performed best in Section 7.5 and includes the results of the regression analysis of predicting the crossmodal correspondences of odours using the underlying physicochemical features transduced by version two of the developed e-nose. Section 7.7 determines how robust the correlations uncovered in Section 7.6 are. This chapter is concluded with a short summary of the findings.

7.2 Data pre-processing steps

For this chapter, the perceptual data from Chapter 5 was used along with the chemical data initially collected in Chapter 6. The pre-processing of the perceptual data included the removal of perceptual outliers. Any values outside the range of ± 1.5 std of the mean value were considered outliers and replaced with the mean value. Any detected outliers were excluded from the second mean calculation. The median values of the perceptual data were used to train and test the artificial intelligence models reported below. The pre-processing for the chemical data is the same as reported in Chapter 6. This includes taking the mean over one-second intervals, followed by a three-point moving average filter. The median value for each of the physicochemical features for each of the recordings was used in the analyses reported below.

7.3 The perceptual space does not change too much with outlier removal

To determine if the removal of the perceptual outliers influenced the perceptual dimensions, PCA coupled with k-means cluster analysis was used. Z-score normalization was then conducted on the

perceptual data containing the outliers and the perceptual data without the outliers separately; the population standard deviation and mean of all the dataset was used for the perceptual dataset. The perceptual dataset with the outlier's first two components explains 79.13%, 48.15%, and 30.98%, respectively, and is shown in *Figure 50A*. The perceptual dataset without the outlier's first two components explains 83.01% of the total variance, 51.63%, and 31.37%, respectively, and is shown in *Figure 50B*.

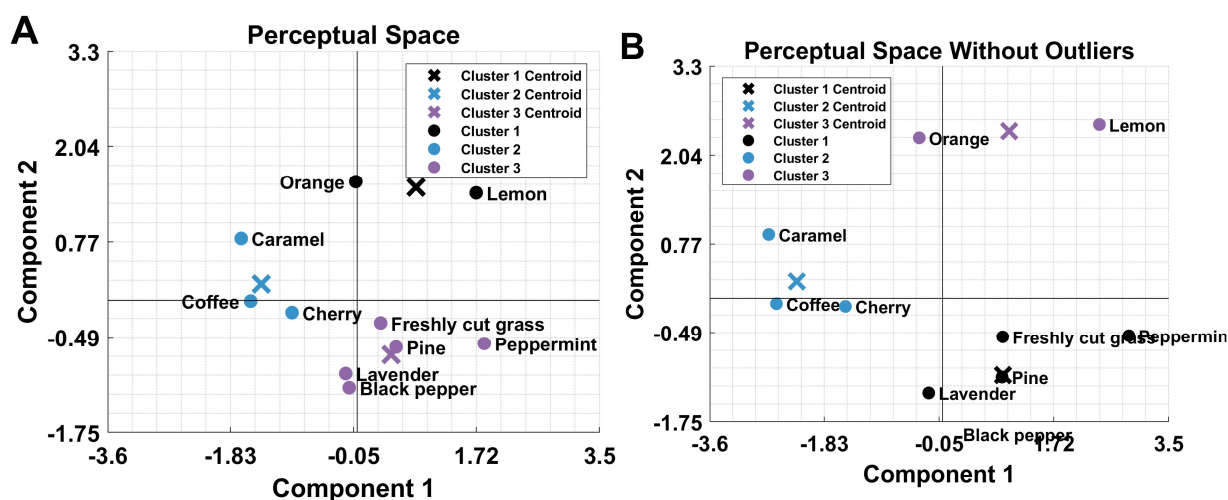


Figure 50. Score plots for the perceptual space for (A) with the outliers and (B) without the outliers.

The crosses in Figure 50 denote the centre locations of the clusters; the filled circle's location denotes their principal component scores, with the colour denoting the cluster grouping. Comparing Figure 50A with Figure 50B, we can see that the odours are still grouped into the same clusters. The variance explained in the perceptual space with the outliers is 79.12% and 83.01% without the outliers. Considering these together, we can see the underlying data is not impacted too much by removing the outliers. PCA with outlier removal captured slightly more of the underlying variance in the first two components suggesting that removing the outliers would be more optimal. That is, when the outliers were removed, there was slightly less variance in the underlying data, so PCA will be able to explain more of the variance in its first two components. It has not affected the responses enough to separate the odours from the respective clusters, which indicates the underlying integrity is still intact. Now that it is known that the perceptual space doesn't change too much with the outlier removal, it was decided to check to see if all the physicochemical features still contribute.

7.4 All sensors still contribute after outlier removal

To determine which features would contribute to the final models, a multivariate analysis of variance (MANOVA) was first conducted with the e-nose features as the dependent variable and the identity of the odour as the independent variable. This revealed that there is a statistically significant difference in the features (e-nose sensor responses) based on the presented odour ($F(81, 538.9) = 37.74$, $p < 0.0001$, $R^2 = 0.85$). To determine which features differ for the presented odour, one-way univariate ANOVAs were conducted on the presented odours. This revealed that all features significantly differ (Bonferroni corrected) depending on the odours (all p-values < 0.005): air quality ($F(9, 90) = 91.98$), pollution level ($F(9, 90) = 22.70$), temperature ($F(9, 90) = 26.90$), pressure ($F(9, 90) = 65.83$), humidity ($F(9, 90) = 22.84$), gas ($F(9, 90) = 29.91$), MQ3 ($F(9, 90) = 51.93$), MQ5 ($F(9, 90) = 42.35$), MQ9 ($F(9,90) = 20.79$), and HCHO ($F(9,90) = 54.30$). These results indicate that all the sensors respond to one or more of the gases in the essential oils and that these responses are different for each of the features depending on the presented essential oil. Therefore, it was decided to use all the features when training the regression models.

7.5 Gaussian process regression performs the best out of tested algorithms

To determine the optimal regression algorithm to predict people's crossmodal correspondences, four different algorithms were tested: linear regression, support vector machine, random forest, and Gaussian process regression (GPR) using fifty-fold cross-validation. GPR had the lowest root-squared mean error in all cases, see Table 20. Therefore, it was decided to proceed with GPR but with hyperparameter optimisation.

Perceptual Dimension	Algorithm	Root Squared Mean Error
Angularity of shapes	Linear Regression	0.4858
	Support Vector Machine	0.2977
	Random Forest	0.4049
	Gaussian Process Regression	0.2323
Smoothness of texture	Linear Regression	0.2550
	Support Vector Machine	0.1768
	Random Forest	0.3712
	Gaussian Process Regression	0.1235
Perceived pleasantness	Linear Regression	0.5991
	Support Vector Machine	0.3143
	Random Forest	0.5114
	Gaussian Process Regression	0.2156
Pitch	Linear Regression	542.75
	Support Vector Machine	356.76
	Random Forest	462.08
	Gaussian Process Regression	345.78
L*	Linear Regression	6.2475
	Support Vector Machine	2.6561
	Random Forest	6.8510
	Gaussian Process Regression	2.2396
a*	Linear Regression	7.3990
	Support Vector Machine	4.3430
	Random Forest	5.7468
	Gaussian Process Regression	4.2879
b*	Linear Regression	14.9140
	Support Vector Machine	9.1155
	Random Forest	13.6230
	Gaussian Process Regression	6.2969

Table 20. Regression algorithm results. Rows in bold denote the algorithm with the lowest error for each tested correspondence.

7.6 Gaussian process regression hyperparameter optimisation and predicting olfactory crossmodal correspondences

It was decided to optimize the kernel function for each of the models were optimised by selecting the function that best represented the underlying data by iterating through the selection of hyperparameters and selecting the hyperparameters that best expressed the underlying data, see Table 21.

Perceptual Dimension	Kernel Function	Standardized
Angularity of shapes	Exponential	False
Smoothness of texture	Matern 32	False
Perceived pleasantness	Rational quadratic	True
Pitch	Matern 52	False
L*	Squared exponential	True
a*	Exponential	True
b*	Squared exponential	True

Table 21. Optimal model hyperparameters for each developed model. All possible combinations of the basis, kernel functions and standardized input were tested. The parameter combinations in the Table are the ones that archived the lowest root-squared mean error.

Pearson correlations were used to calculate the within and between odour correlations. The human-human correlation between the participant's responses and the median ratings was calculated. This revealed correlations of ($r = 0.55, p < 0.0001$) for the angularity of shapes, ($r = 0.35, p < 0.0001$) for the smoothness of texture, ($r = 0.43, p < 0.0001$) for the perceived pleasantness, ($r = 0.39, p < 0.0001$) for pitch, ($r = 0.56, p < 0.0001$) for the colour dimension L*, ($r = 0.57, p < 0.0001$) for the colour dimension a* and ($r = 0.60, p < 0.0001$) for the colour dimension b*. To test the quality of the models on unseen odours, a leave-one-odour-out approach was used. The models were trained ten times using all the recordings for nine of the odours, and leaving out all the recordings for one odour, the odour that was left out was used for testing. This resulted in a 90 x 10 matrix for training and a 10 x 10 matrix for testing for every iteration. This was repeated ten times until all the odours had been tested in an unseen state. The human-machine correlations were then calculated using the median ratings, and machine regression ratings, a slope of 1 indicates perfect machine performance and a slope of 0 means that a relationship does not exist between the predicted v. actual ratings. This revealed a correlation of ($r = 0.71, p < 0.0001$) for the angularity of shapes, ($r = 0.82, p < 0.0001$) for the smoothness of texture, ($r = 0.2, p < 0.0484$) for the perceived pleasantness, ($r = 0.70, p < 0.0001$)

for pitch, ($r = 0.59, p < 0.0001$) for the colour dimension L^* , ($r = 0.44, p < 0.0001$) for the colour dimension a^* and ($r = 0.42, p < 0.0001$) for the colour dimension b^* .

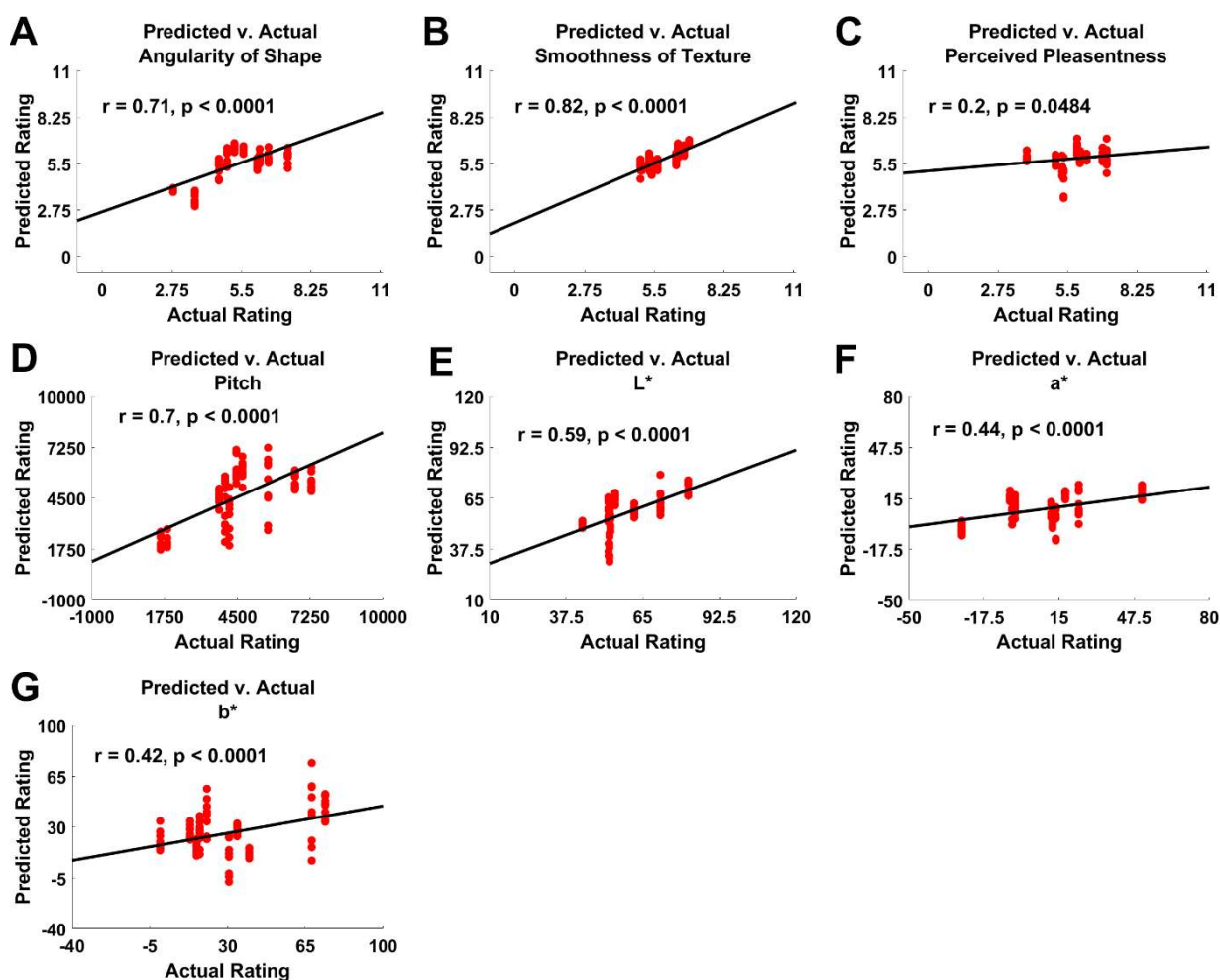


Figure 51. Predicted v. actual plots for (A) the angularity of shapes, (B) the smoothness of texture, (C) the perceived pleasantness, (D) pitch, (E) the colour dimension L^* , (F) the colour dimension a^* and (G) the colour dimension b^* .

From Figure 51, it can be seen that for some of the sensory modalities, the predictions correlated well with the human ratings ($r > 0.50$). The sensory modalities that correlated well are the angularity of shapes, the smoothness of texture, pitch and the lightness of colour. The sensory modalities that did not correlate well are the perceived pleasantness and the colour dimensions (a^* and b^*). These findings indicate that the correspondences people have towards odours can be robustly predicted (all p -values < 0.0001 except for the perceived pleasantness) using the underlying physicochemical features.

7.7 The findings are robust

To further investigate the statistical robustness of the findings, the perceptual data associated with a given odour was randomly shuffled one hundred times for each perceptual dimension, and the regression analysis was repeated. For example, the response values for lemon now might be the response values for black pepper. The average prediction rates dropped for all perceptual dimensions to ($r = -0.16$, $p = 0.11$) for the angularity of shapes, ($r = -0.04$, $p = 0.15$) for the smoothness of texture, ($r = -0.18$, $p = 0.15$) for the perceived pleasantness, ($r = -0.14$, $p = 0.14$) for pitch, ($r = -0.04$, $p = 0.23$) for the colour dimension L^* , ($r = -0.12$, $p = 0.20$) for a^* , and ($r = -0.19$, $p = 0.14$) for b^* . These findings reflect the model's ability to predict the crossmodal correspondences of odours rather than the reported correlations being obtained due to its internal structure.

To test if these results were significantly impacted by the removal of the perceptual outliers, the prediction analysis was repeated with the inclusion of the perceptual outliers. This resulted in a moderate change in the correlation coefficient in the perceived pleasantness from ($r = 0.20$, $p > 0.05$) to ($r = 0.09$, $p > 0.05$), L^* from ($r = 0.59$, $p < 0.0001$) to ($r = 0.46$, $p < 0.0001$), and a^* from ($r = 0.44$, $p < 0.0001$) to ($r = 0.35$, $p = 0.0003$). A small change was noticed in the angularity of shapes ($r = 0.71$, $p < 0.0001$) to ($r = 0.64$, $p < 0.0001$), smoothness of texture from ($r = 0.82$, $p < 0.0001$) to ($r = 0.79$, $p < 0.0001$), pitch surprisingly increased from ($r = 0.70$, $p < 0.0001$) to ($r = 0.75$, $p < 0.0001$), and b^* did not change at all ($r = 0.42$, $p < 0.0001$) to ($r = 0.42$, $p < 0.0001$). The correlations for the angularity of shapes, the smoothness of texture, pitch, and the lightness of colour are still significant with the inclusion of the outliers, revealing that the results were only slightly influenced by the removal of the outliers.

7.8 Summary

In Chapter 6, a principal component analysis coupled with k-means cluster analysis was conducted, and the similarity between the odours used in the experiments investigating the physicochemical and perceptual spaces was explored. This revealed a $\approx 60\%$ overlap between the two spaces in the physical space, which indicates that there is a reasonable degree of consistency between the two spaces, and a relationship between the physicochemical features and the crossmodal perceptual ratings exists. The results from Chapter 6 suggest that olfactory crossmodal correspondences should be predictable using their underlying physicochemical features and was the main motivation behind this chapter as this could be deployed on the device created in Chapter 4, among other things. In this chapter, different regression algorithms – linear regression, support vector machine, random forest, and Gaussian

process regression were trained and tested using fifty-fold cross-validation. Gaussian process regression gave the lowest error in all cases suggesting that out of the four tested algorithms, Gaussian process regression best captured the relationship between the physicochemical features transduced by an e-nose and their crossmodal ratings. An e-nose was then aligned to the crossmodal perceptual axis of olfaction, revealing that it is possible to predict the crossmodal correspondences of odours using their physicochemical features, even if the odour was unseen to the generated models. The models for perceived angularity of shapes, smoothness of texture, pitch, and lightness of colour archived good correlations ($r \geq 0.50$, $p < 0.0001$) and could be robustly predicted. Although the hue of colour (a^* and b^*) could be robustly predicted, their correlations were not overwhelming ($r < 0.50$). The perceived pleasantness in our case could neither be robustly predicted ($p = 0.484$) nor captured a decent amount of variance ($r = 0.20$); this suggests that a larger sample size of odours might be needed to be able to predict the perceived pleasantness [70], [77]. The static robustness of these findings was then investigated by randomizing the perceptual data revealing that the obtained correlations were attributed to the model's ability to predict the crossmodal correspondences of odours rather than the internal structure of the underlying data. Finally, it was tested if removing the outliers affected our findings by retraining the models without outlier removal, leading to the conclusion that the results were not significantly influenced by the removal of the outliers. In this chapter, we learnt that it is possible to predict the crossmodal correspondences attributed to odours using an electronic nose. The findings reported in this chapter are important as it confirms that the link between the physicochemical features of odours is a contributory factor which was uncovered in the prior chapter and demonstrates that there is a systematic and predictable link between the physicochemical features of odourous stimuli and crossmodal correspondence. More research needs to be conducted to uncover the extent to which the physicochemical features contribute towards explaining our crossmodal perception; for instance, if an e-tongue was used as opposed to an e-nose, does the same finding also extend to crossmodal taste dimensions and is it still possible to predict olfactory crossmodal correspondences for novel stimuli (smells never encountered by the people assigning the ratings). The limitations of these findings is the number of crossmodal perceptual dimensions explored. That is if more models were created on more olfactory crossmodal correspondences, then it would increase the number of potential use cases and uncovers if it is actually possible to predict that specific crossmodal correspondence. Another limitation is the amount of variance left in the underlying data after the removal of the perceptual outliers, specifically for the smoothness of texture. It is possible that the correlation coefficient obtained for this dimension may not be a true reflection of the models predictive abilities. Another limitation is the number of odours these models were

trained; albeit an improvement would be expected but models only being trained on nine different odours at a given point in time is not a true reflection of the distribution of scale for crossmodal correspondences, that is, if a larger variance of the reported crossmodal correspondences was captured the ability for the model's ability to predict crossmodal correspondences is anticipated to be improved. This chapter utilises the finding from Chapter 6 that suggests that a predictable link exists between olfactory crossmodal correspondences to confirm the suggestive data and to create predictive models that could be used to enhance the perceptual performance of the olfactory sensory augmentation devices presented in Chapter 4.

The next chapter (Chapter 8) discusses the work conducted in this thesis, including a summary of the findings for all chapters, the interpretation of the results as well as the limitations and the benefits of the conducted research.

Chapter 8 Discussion & Future Work

8.1 Introduction

In this thesis, the concept of virtual synaesthesia has been proposed. Virtual synaesthesia is a human-orientated design process to aid in multi-sensory integration in an overt, low-attention, and transparent fashion. It does this by considering how the brain combines senses in two domains, natural synaesthesia and the consistent correspondences present in most of the population (crossmodal correspondences). It uses this as a design paradigm to aid in the creation of multisensory experiences, where there is a need to express information cross-sensory. Virtual synaesthesia aims to augment multisensory experiences with more refined multisensorial capabilities leading to better designs, more enriched, and immersive experiences. The concept of virtual synaesthesia can be used in various areas, including but not limited to multisensory experiences, the arts, product design, human-machine interaction, and the entertainment domains. The practical and commercial relevance of the work conducted in this thesis has started to attract the attention of advertisers, marketers, the food sector, and, very recently, multisensory media [144]. This interest stems from the need to convey information about the olfactory and gustatory attributes of the experience by matching the attributes of the stimuli in different sensory modalities [281] and the removal of the bottleneck of conducting expensive and extensive human trials to uncover what the olfactory crossmodal correspondences for a given odour are. In order to demonstrate the benefits of virtual synaesthesia and uses this paradigm in the area of olfaction, several important have arisen and have been answered in this thesis and are as follows:

1. Is it possible to replicate the cognitive benefits behind natural synaesthesia in a human-machine interface? (see Chapter 4)
2. What are, if any, are the crossmodal correspondences between odours and different sensory modalities? (see Chapter 5)
3. What are the underlying driving factors for olfactory crossmodal correspondences? (see Chapter 6)
4. Is it possible to predict olfactory crossmodal correspondences using the stimuli's physicochemical features? (see Chapter 7)

The rest of this chapter is organised as follows: Sections 8.2 and Section 8.3 summarises Chapter 2 and 3, respectively. Sections 8.4–8.6 summarise the findings, interpret the results, and acknowledge

the limitations and benefits of the conducted research for their respective chapter. This chapter is then concluded by discussing some areas of exploration for future research.

8.2 Background & Related Work

In Chapter 2, a comprehensive review of virtual synaesthesia was conducted. The review includes the concept of virtual synaesthesia and gives a detailed description of the areas related to its elements. An in-depth description of natural synaesthesia, including an introduction to the area, the causes and mechanisms behind the phenomenon, and the related works in this area, is given. The sparse background literature with respect to virtual/artificial synaesthesia is covered, followed by the background and related works for a subset encompassing areas of research regarding the engineering, computer science, and psychology disciplines. The terms virtual/artificial are used interchangeably within the related literature and in this thesis. An introduction into multisensory experiences, crossmodal correspondences, and sensory substitution/augmentation is then given, followed by a related works section for the respective areas of research. The theory behind the experimental setups used in this thesis (electronic noses and mass spectrometry) is also covered. The findings of this chapter indicate that virtual synaesthesia is practically unexplored but has numerous potential advantages that need to be explored further. There are numerous cognitive benefits behind natural synaesthesia that would greatly benefit human-machine interfaces under the assumption that natural synaesthesia can be artificially replicated. The ideology of natural synaesthesia and crossmodal correspondences can also grant a window into thought and perception, allowing for a design paradigm that considers how the brain combines senses either in the population (crossmodal correspondences) or in a select few of the population (natural synaesthesia). One area of interest for the concept of virtual synaesthesia is generic multisensory experiences. This is the main area of work this thesis envisions the concept of virtual synaesthesia being used. The term multisensory experiences are used loosely here and encompasses any area where the design or consideration of more than one sense is required. The concept of virtual synaesthesia for multisensory experience design could be used to increase the spatiotemporal throughput of the experience in a manner that stimulates the different senses in a way that would be more intuitive for the user. Prior research has shown that conforming to senses in a congruent and crossmodal manner can influence our decision process, including increasing the perceived pleasantness [188], [189] the perceived value [146], improving speeded olfactory discrimination [190], increasing identification rate [191], and finally improving the spatiotemporal throughput of a human-machine interface that lead to improved task performance

[28]. These are some advantages the concept of virtual synaesthesia could embody. It is anticipated that more advantages will arise when the area of virtual synaesthesia has been researched more. Another area in which the concept of virtual synaesthesia could be applied too is sensory substitution/augmentation systems typically, these devices present arbitrary mappings from one sense to another (i.e., the video feed from a camera (vision) to vibrotactile feedback) as demonstrated by Hamilton-Fletcher, T. D. Wright, and J. Ward [28] aligning the concurrent feedback to align with crossmodal correspondences can help to improve performance in these systems, therefore applying the concept of virtual synaesthesia when these devices are being created, should, in theory, aid in improving the spatiotemporal throughput from one sense to another.

8.3 Experimental Setups & Methodology

In Chapter 3, a detailed description of the experimental setup used in Chapters 4, 6, and 7 is given. To transduce the physicochemical properties behind aromatic essential/fragrant oils, an array of six gas sensors that produce ten different features was used to detect these aromas in the vapour phase. The transduced features are the physical and chemical characteristics of an odour; most of these gas sensors represent the physicochemical features of the presented chemical with a change in resistance. These electrical signals can consequently be used for a variety of different purposes, including characterising, discriminating, and predicting attributes of the presented odours. Two versions of an electronic nose are presented in this chapter: one for the real-time visualisation of odours and the other to characterise/predict people's correspondences towards odours. Additionally, a brief overview of the $L^*a^*b^*$ colour space was given along with reasoning for why this specific colour space was chosen (perceptual uniformity).

8.4 Virtual Synaesthesia in Human-Machine Interfaces

In Chapter 4, a novel human-machine interface was developed, implementing the ideology of odour-vision synaesthesia. This chapter answered the following research question is it possible to replicate the cognitive benefits behind natural synaesthesia in a human-machine interface? It was found that it was possible to replicate the cognitive benefits behind a natural form of synaesthesia (odour-vision). To provide an answer to this question, a device was created that transduced odours into a two-dimensional abstract shape that represented the current odour source in real-time, the device

consisted of three main components: (1) an active odour source, (2) a custom-made electronic nose to gather physicochemical information about the current odour(s), and (3) a mobile computing engine for characterisation, classification, and visualisation of an odour in real-time. An offline version of the system was then developed and tested on twelve individuals from the population of the University of Liverpool. Participants were asked to complete an odour identification task using (1) just their sense of smell and (2) both their sense of smell and a complimentary visual stimuli (a pre-generated abstract shape). The results revealed a significant improvement in a simple olfactory discrimination task. Olfactory discrimination had a mean increase of 32.40% when a smell was coupled with a complimentary shape representing the current odour demonstrating that the system has the potential to increase human odour identification comparable to that of natural synaesthesia, thus highlighting the prospects for augmenting human-machine interfaces with an artificial form of this phenomenon. The novelty of this chapter is two-fold first, the demonstration of utilising a bottom-up approach of virtual synaesthesia to develop an application. Secondly, it shows the underlying cognitive benefits behind a natural form of synaesthesia (odour-vision) are, at least in part, transferable to a human-machine implementation. Augmenting a human-machine interface with virtual forms of synaesthesia is still a practically unexplored area, and more research needs to be conducted to determine the true extent to which it can be beneficial, albeit the cognitive benefits should, to a reasonable degree, align with its natural counterpart. For example, if someone has sound-colour synaesthesia, then they should have, enhanced memory for sound stimuli [33], enhanced pitch recognition, differentiation, and memorisation [34]; some, if not all, benefits could be replicated artificially with a human-machine interface, although long term usage may be required.

The developed artificial odour-vision synaesthesia system exhibits the same characteristics as its natural counterpart. Firstly, it is perceived to be in the subject's personal space via a wearable AR/VR system which projects a view from the real world using a mobile phone camera. Secondly, it is passive and involuntary as the system processes all odours within the range of the sensors, which are consequently displayed to the user in the form of an abstract shape. Thirdly, the colour and shape are reasonably stable over time, albeit there is a small room for error in the machine learning component (the colouring of the shape) and noise in the generated signals. Not much work has been done in terms of virtual synaesthesia, and the work in this section is some of the first empirical evidence that integrating an artificial form of synaesthesia into human-machine interfaces can be beneficial. The potential implications for virtual synaesthesia could be extensive and are not necessarily limited to human-machine interfaces but multisensory experiences in general. It could provide insights into new "senses" for humans, allowing for comparisons between real synesthetes and artificial synesthetes

which could ultimately help to refine multisensory experiences with more refined capabilities. The limitations of the research conducted in this chapter are the number of participants (twelve); although it is evident there is quite a large difference between the two conditions (smell with no shape and smell with a complimentary shape) for scientific robustness, the desired number of participants for a two-sample t-test would be twenty-two. Additionally, the shape and colour of the generated shape could be matched to the wearers respective crossmodal correspondences. It wasn't towards the end of the research conducted in this thesis that it was discovered that the physicochemical features transduced by an e-nose could be linked to crossmodal correspondences. Therefore, it would be beneficial to enhance the design of this system by adding in the regression models obtained in Chapter 7 or adding in a calibrations phase which adjusts the generated models to be more in favour of the wearer's crossmodal correspondences rather than generalised crossmodal correspondences. The benefits of the work conducted in this chapter include some of the first empirical evidence that augmenting a human-machine interface with an artificial form of synaesthesia can both be a worthwhile endeavour and demonstrate that the underlying cognitive benefits of its natural counterpart are, at least in part reproducible. The benefits of the findings of this chapter, although more research needs to be conducted around this theme, could be used as inspiration to develop human-machine interfaces and multisensory experiences using the concept of virtual synaesthesia. The device itself could be used to better understand the physicochemical features of odours via a synesthetic representation. The device could also be developed further using the crossmodal correspondences uncovered in Chapter 5 and the predictive models from Chapter 7, which could allow for the tuning of novel odourants to match with the crossmodal correspondences, which would make the overall perception to be perceived as more pleasant. The anticipated impact of this work extends into multiple domains (e.g., sensory augmentation/substitution and cognitive marketing) but shows some benefits of considering the concept of virtual synaesthesia and making multisensory experiences more human-orientated. As well as the ideology, the implementation of a truly 'synesthetic experience' can be beneficial for human-machine interfaces, which will hopefully lead to its paradigms utilisation in both the products and application domains.

8.5 The Crossmodal Correspondences of Olfaction & Analysis of Crossmodal Correspondences

In Chapter 5, the existence of 'weak synaesthesia' (the non-arbitrary but consistent correspondences present in most individuals) was explored. To answer the question, what are, if any, are the

crossmodal correspondences between odours and different sensory modalities? Specifically, this chapter tested to see if people have correspondences between odours and the angularity of shapes, perceived pleasantness, pitch, colours, emotions, and musical dimensions. In addition to these sensory dimensions, a novel sensory modality was explored, the smoothness of texture. The results revealed that people have consistent crossmodal correspondences towards odours and the aforementioned sensory modalities. Crossmodal correspondences are starting to gain traction in designing multisensory experiences as well as a variety of different areas (i.e., product design). Therefore, uncovering the extent to which consistent crossmodal correspondences exist for different odours will help in the design process and in creating perceptual illusions. The limitations of the work conducted in Chapter 5 are the quantity of the uncovered crossmodal correspondences or more specifically, its knock-on effect on Chapter 6. In Chapter 6, the nature and origin of crossmodal correspondences were explored. Although a large variety of olfactory crossmodal correspondences was explored, it is not a complete list of known olfactory correspondences. Therefore the degree of involvement from the explored mechanism may vary if more or a complete list of olfactory crossmodal correspondences were uncovered. The benefits of the work conducted in Chapter 5 include a deeper understanding of how different senses are 'bound' to olfaction. The results from this chapter could be used as a psychophysical framework to aid in the design or development of interactive experiences involving olfaction, such as product design. It has been shown that changing the packaging of products can change the consumers' perception of the item within [13]. Therefore, tailoring an experience to fit around the user's sensory expectations would be greatly beneficial in a variety of domains. The novelty of the work conducted in Chapter 5 includes the exploration of novel sensory modality, the smoothness of texture and its usage in Chapters 6 and 7.

In Chapter 6, the question what are the underlying driving factors for olfactory crossmodal correspondences using the perceptual data collected in Chapter 5. To answer this question the physicochemical properties behind the stimuli presented in Chapter 5 were explored; semantic and hedonic dependencies were also investigated. The results revealed that the hedonic factor has a larger involvement than semantics, and a new aspect, the physicochemical features, is also a contributory factor towards explaining the nature and origin of these correspondences. The crossmodal perceptual dimensions (angularity of shapes, the smoothness of texture, perceived pleasantness, pitch, and colours) were found to be significantly correlated to various physicochemical features linked to aspects of intensity and odour quality. Snitz *et al.* proposed a quantitative and robust method for measuring intricacy that depends on more intricate stimuli evoking a larger variance in the perceptual responses of participants. The notion of intricacy and complexity of the stimuli could be embedded in

both the physicochemical features and the perceptual ratings provided by the participants and is another plausible reason for explaining the physicochemical features contributing to olfactory crossmodal correspondences. That is, less chemically complex odours would have produced a simpler response in the electronic nose. Comparatively, if less intricate stimuli produced less variance in the perceptual data, this may be a means of mapping the olfactory stimuli from one space to another. It is important to note that the involvement from other mechanisms cannot be ruled out: for example, results from a series of Pearson correlations revealed that there could be contributions from the quality of the olfactory stimuli as well as intensity. Moreover, it has been demonstrated that the characteristic response patterns provided by an electronic nose can encapsulate aspects of perceived intensity [83], which could also be reflected in the participant's crossmodal ratings. While it is generally recognized that olfactory perception is strongly shaped by context, experience, and learning, our findings suggest that a predictable and systematic link exists between the physicochemical features of odourous stimuli and olfactory crossmodal correspondences.

The rules governing these correspondences need to be fully understood because by understanding how these correspondences occur, they can be better exploited when designing multisensory experiences. Crossmodal correspondences have been proven beneficial in a variety of different applications, mainly in the form of semantic congruency, but includes but not limited to: enhancing the perceived pleasantness via semantic congruency [188], [189], [222], improving user performance in human-machine interfaces [28], speeded olfactory discrimination [190], and increased discrimination rate [191]. A study by Piqueras-Fizman & Spence has shown that people have strong crossmodal associations with products [213], and incongruency with these sensory expectations “annoys” the consumer [13]. Considering these findings, there are a series of advantages towards incorporating crossmodal correspondences into the multisensory design process, as well as disadvantages for not considering them. There is an increasing need to examine the user’s perception of the multisensory components [154] for multisensory experiences. These products/applications’ success depends on the impact it has on human observers [154], [155]. Presenting olfactory information in a meaningful way can enhance its reality, clarity, and enjoyment [27]. Recent work in multisensory experiences branches away from solely the technical challenges, with more focus on enhancing the perceived quality of experience. This includes, but is not limited to, synchronisation [282]–[284], scent type [175], and impact of information recall [177], [285]. When designing applications or packaging of a product, it is important to conform to the user’s sensory expectations to enhance the perceived quality of the experience. Little work in this area considers how different sensory modalities affect each other and the impact this has on immersive and interactive

experiences. Very recently there has been a push to merge crossmodal correspondences into areas of computer science and engineering (i.e., [11], [143], [162]). In Chapters 5, 6, and 7, the olfactory stimuli used in our experiments were aromas commonly used in perfumes and in olfaction-enhanced multimedia (e.g., [27], [170], [175]). These odours were selected due to an overlap with prior literature (e.g., [7], [14], [15], [143], [189], [192], [286]). Thus, providing a psychophysical framework to aid in the design or development of multisensory involving olfaction. The limitations of Chapter 6 include the number of participants, specifically to determine if semantics played a role in the collected dataset was split in two (correct identification v incorrect). In some cases (i.e., peppermint), the incorrect dataset was rather on the small side (thirteen). Therefore, there may be some bias in the findings regarding the contributions of semantics due to the number of incorrect answers for some of the odours. The benefits of the work conducted in Chapter 6 include a deeper understanding of how and why olfactory crossmodal correspondences occur. Once we understand the driving mechanism behind these correspondences, we gain a deeper understanding of how our brain works and a gain a greater understanding of how olfactory crossmodal correspondences can be exploited. The work in Chapter 6 also, for the first time, suggests that the physicochemical features of odours partly explain our crossmodal perception. The same may also extend to taste. The novelty of the work conducted in this chapter includes the exportation of the semantic and hedonics properties to determine which one plays a greater role and the exploration of the physicochemical features of the presented stimuli. These findings could be used to align a multisensory experience to the user's olfactory sensory expectations, which could be used in cognitive marketing (i.e., the design of a perfume bottle) or the development of an olfactory-based virtual reality application (i.e., a virtual store or to merely enhance the perceived pleasantness of the olfactory attributes). The findings from Chapter 6 also suggest that a systematic and predictable link exists between the physicochemical features of an odour and olfactory crossmodal correspondences, which would be useful for uncovering the crossmodal correspondences of odours in real time. This would be useful applications that could have unknown stimuli being present, for example, the sensory augmentation system presented in Chapter 4. This concept is explored more in the next section.

8.6 Predicting The Crossmodal Correspondences of Odours Using an Electronic Nose

In Chapter 7, the physicochemical link underlying our crossmodal correspondences was further examined to determine if it is possible to predict people's crossmodal correspondences towards odours. Five different machine learning methods were tested to determine which one produced the

lowest error in terms of regressing the perceptual data using the physicochemical features; Gaussian Process Regression provided the lowest error in all cases. Thereafter, the Gaussian Process Regression hyperparameters were then optimised for each of the perceptual dimensions (the angularity of shapes, the smoothness of texture, the perceived pleasantness, pitch, and colours). Each of the generated models was then tested using a leave-one-odour-out approach to determine if the models could predict the crossmodal perception of odours even if the model has never seen that odour before. This revealed that it was possible to predict olfactory crossmodal correspondences and further supports the claim of the physicochemical features of odours and that it is a contributory factor to crossmodal correspondences.

In vision, a predictive property of color is the wavelength of light. In hearing, the frequency of sound is a predictive property of tone. However, in olfaction, it is not currently possible to predict the smell of a molecule using its molecular structure [89]. This is presumably because the dimensionality of olfactory perceptual space is unknown and olfactory stimuli do not vary continuously in stimulus space [76], [89]. Compared to vision and audition, predicting olfactory percept requires significantly more information rather than a particular attribute; even then, there is still substantial room for improvement. In Chapter 7, the physicochemical features of odours were transduced using a custom e-nose, transmitted it to a receiver, and predicted. It was demonstrated that the correspondences a person would have towards an odour could be predicted even if the odours were unseen by the models. Consequently, suggesting that a systematic and predictable link exists between the physicochemical features of odours and their crossmodal correspondences. This finding further implies that the correspondences people have towards odours are, at least in part, encapsulated in the physicochemical features and, therefore, can be captured by a machine. The findings show that it is possible to predict the crossmodal correspondences of odours using the stimuli's physicochemical features. The main perceptual axis of olfactory perception is pleasantness [287] which the e-nose signals could be partially encapsulating [70]. However, the model that was created for the perceived pleasantness did not correlate well, suggesting that if the perceived pleasantness were partially encapsulated in the underlying signals, its contribution would be minimal. It is also possible that the e-nose signals may encapsulate aspects of intensity [83]. Other possible reasons for explaining this finding include The perception of odours is a complex process that involves both learnt and innately tuned components [62]. It is important to emphasize the limitation of the findings; olfactory perception and successive neural representations are modulated or influenced by several different factors, such as expectations [63], context [64], multisensory convergence [65], and is a heavily learned process [67]. However, a portion of olfactory perception is suggested to be innate and hard-

wired [62], [68]–[70], which the results of Chapter 7 could reflect, as the dominant aspects of olfactory perception will not be reflected in the physicochemical features. For example, it has been shown that newborn babies with no exposure to culture or learning are averse to unpleasant odours [69], and rats are averse to the smell of predators even if they are bred for several generations in a predator-free environment [68]. Other plausible explanations for the uncovered mapping between the physicochemical features and crossmodal correspondences include but are not limited to – intensity [78], [83], [288], complexity or intricacy [8], [21], [87], [88], and odour quality [187], [289]–[291]. The perceived intensity of the stimuli can be expressed as a logarithmic function of stimuli concentration [292]. In the case of hedonic mediation, a few studies have linked the molecular properties [21], [62] and the physicochemical features [70], [77] of odours to their perceived pleasantness. The work presented by Khan *et al.* provided an alternative view that the pleasantness of odours could be partly explained by the physicochemical properties of the odours molecules and the fact that the electronic nose can assess hedonic valence as documented in Chapter 7 and in earlier works [70], [77]. The limitations of research conducted in this chapter include the degree of variance in the underlying perceptual data, specifically the smoothness of texture. Although it was highly correlated ($r = 0.82$), after the removal of the perceptual outliers, there was only a small amount of variance remaining, resulting in it being highly correlated. Another limiting factor again is the number of models created, which imposes a limitation on the use cases. For instance, olfactory-weight and olfactory-temperature crossmodal correspondences could also have been explored, and consequently having predictive models created for them which increases their potential use cases. The benefits of the findings from Chapter 7 include models for the real-time classification of crossmodal human perception of olfactory discrimination. This could allow for the fine-tuning of stimuli in different sensory modalities to align with the sensory expectations of the user given an undefined or unknown olfactory stimuli. Another benefit of the work in this chapter is that it confirms the findings uncovered in Chapter 6 and confirms a relationship exists between the physicochemical features and olfactory crossmodal correspondences, which is an important advancement towards explaining the nature and origin of these correspondences. The novelty of the work conducted in this chapter is that it shows that a systematic and predictable link exists between olfactory crossmodal correspondences and the physicochemical features of the presented stimuli. This link was suggested in Chapter 6 but is confirmed in Chapter 7. This finding could be used to help design multisensory experiences, such that the experience is tailored around the olfactory attributes as there is a systematic and predictable link; one could simply predict the crossmodal dimensions rather than conducting rigorous human trials. It is important to note the latter idea is not meant or suitable as a substitute in an academic context or in

a situation where it may be detrimental to the health of an individual. There is also room for error in the accuracy of the crossmodal predictions meaning there is no guarantee that the “correct” rating would be obtained, especially for the models with a low correlation coefficient and incongruency with the user's sensory expectations and reduce the overall pleasantness of the experience and will induce a slower reaction time. Nevertheless, now it is uncovered that a systematic and predictable link exists, and more robust models with less room for error could be developed. These models should typically include more stimuli and their respective correspondences, and the crossmodal ratings could be collected from individuals from the same culture.

8.7 Virtual Synaesthesia

Considering the work conducted in this thesis, the concept of virtual synaesthesia was proposed as a design paradigm. A top-down approach of this paradigm was utilised initially to create an olfactory sensory augmentation device using the premise of natural synaesthesia (see Chapter 4). It was revealed that the cognitive benefits underlying natural synaesthesia, at least in part, overlapped with a virtual form of this phenomenon. Sticking to the olfactory theme of this thesis, a bottom-up approach of virtual synaesthesia was considered; however, the underlying mechanisms to accomplish this task needed further exploration to be viable. Therefore the work conducted in this thesis branched out to olfactory crossmodal correspondences for inspiration of which senses are ‘bound’ to olfaction (see Chapter 5). To properly utilise crossmodal correspondences in multisensory experiences, it is vital to understand why and how these correspondences occur (see Chapter 6). Different types of multisensory experiences have different requirements, such as the need to uncover the crossmodal correspondences of unknown stimuli in real-time; this would be beneficial for the device created in Chapter 4 to make the system design more intuitive for the user. This more intuitive design would take the concept of virtual synaesthesia to provide crossmodally congruent stimuli in real-time using stimuli detected by sensors (i.e., odours (gas sensors) or sound (microphone)). If we take the device presented in Chapter 4 as an example, this device creates a synesthetic coloured shape stimuli that represents the current odour source. General crossmodal correspondences could be uncovered between odours, colours, and shapes. Predictive models, in turn, could be created to predict the shape and colour the stimuli needs to be in order to be crossmodally congruent (see Chapter 7). The limitations in this thesis regarding virtual synaesthesia is that this concept is still in its infancy, meaning very little research has been conducted in this area. The work conducted in this thesis aims to shed more light on this area of research and hopefully will increase the research interest

in virtual synaesthesia. Another limitation was that the underlying research needed to create a bottom-up approach for this design paradigm needed further research; this research was conducted in Chapters 5, 6, and 7; however, these findings remain not investigated in terms of making a bottom-up approach that utilises olfaction. There have been a few devices in the literature made to date that utilise that, at least in part, utilise the concept of virtual synaesthesia, such as Konishi *et al.* synaesthesia suit [133] and Foner's light sonicifier [45]. However, most of these devices remain untested on human's so in terms of demonstrating the system works as intended and the underlying ideology works remains an area of significant interest for the area of virtual synaesthesia. However, devices that utilise the paradigm of virtual synaesthesia could be a useful platform for future research. In terms of replicating the cognitive benefits behind natural synaesthesia, a study by Plouznikoff *et al.* [49] results suggest that short-term memory recall (digit matrices) and visual information search times can be improved with a virtual form of colour-grapheme synaesthesia. Coupling the findings from Chapter 4 suggests that creating virtual forms of synaesthesia can provide some of the underlying cognitive benefits behind natural synaesthesia, thereby demonstrating the usefulness of virtual synaesthesia in human-machine interfaces. The extent to which this is possible, however, is still unknown and needs further investigation. Overall, the concept of virtual synaesthesia looks promising avenue to explore to make multisensory experiences more human-orientated and seamless. Virtual synaesthesia could, in theory, also contribute to the research of natural synaesthesia by allowing the comparison between virtual and natural synesthetes; this could include mnemonic techniques, search strategies, and the effect of prolonged synaesthesia on the underlying cognitive elements. In the case of the work conducted in Chapter 4, it was shown that olfactory discrimination was increased, prolonged exposure to the system is needed to determine if users can acquire increased colour discrimination, which could be compared to natural synaesthesia. If an acceptable overlap occurs between natural and artificial synesthetes ($\geq 70\%$), artificial synesthetes could be used as a research platform for the rarer forms of synaesthesia. Although a couple of studies have concluded that it was possible to create "artificial synesthetes" via prolonged use of a sensory substitution device, this is a bold claim and warrants further exploration by other researchers for validation. The main limitation of the work regarding virtual synaesthesia in this thesis is that this work barely scratched the surface of virtual synaesthesia, a lot more research needs to be conducted in this area to determine its practicality and validity. The potential benefits of considering virtual synaesthesia as a design paradigm include a more human-orientated design that considers which senses are 'bound' together, which could lead to more refined multisensory experiences leading to better designs, more enriched, and immersive experiences. In theory, virtual synaesthesia should help reduce the bottleneck of

attention and potentially improve learning by reducing the amount of processing the brain needs to do to make meaning out of a given stimuli.

In terms of incorporating the ideology of 'virtual synaesthesia' into applications and products from a user experience perspective, a few considerations must be met. First, will it be useful, that is, under some circumstances utilising the concept of virtual synaesthesia can be quite useful, such as its use for sensory augmentation and substitution systems where there is a need to convey information crossmodally. In another context applying the paradigm may not be useful at all. For instance, if you simply designing a multisensory experience solely for entertainment purposes, conforming to the user's sensory expectations can enhance the perceived pleasantness and overall enjoyment. However, there will be a threshold in this instance and extending beyond that threshold may induce a negative reaction to the experience. Secondly, would the experience be useable after considering the paradigm of virtual synaesthesia, in some cases, it would be quite easy to go over the top when designing the experience, such as a virtual reality experience, which again may induce an undesirable negative reaction to the experience. That is, it would be beneficial to limit how much of the experience is altered using a synesthetic design. Finally, does considering the concept of virtual synaesthesia add value to the experience, in other words, is it important to consider how the brain combines senses for the specific multisensory experience? If yes, then the concept of virtual synaesthesia should be considered. If not, then it may be redundant to consider the paradigm for the specific scenario. Although not limited to, this thesis envisions the use of virtual synaesthesia mainly being used in the context of sensory substitution/augmentation systems (i.e., [28], [35]), cognitive marketing (i.e., [293], [294]), and the arts. However, from a broad perspective, the concept of virtual synaesthesia will be useful in other areas, such as creating perceptual illusions (i.e., [25], [295]).

8.8 Virtual Synaesthesia and Responsible Innovation

The concept of virtual synaesthesia and multisensory experiences, in general, presents a plethora of opportunities both in academia and industry. However, these needs should be met responsibly [23] as they can affect our minds and body (i.e., [25], [295]–[297]). Velasco and Obrist [23] state three "laws" for multisensory experiences:

1. Multisensory experiences should be used for good and must not harm others.
2. Receivers of a multisensory experience must be treated fairly.
3. The someone and the sensory elements must be known.

These “laws” focus on debating and acknowledging: the what (the impression), the why (the rational/reason), the who (the someone), the when (the event), and the whom (the receiver). They state that the third law consists of two parts; who is crafting the multisensory experience, and secondly, what sensory elements do we select and why? They also state a call for transparency in this law regarding what knowledge guides the design, who designs it, and what sensory elements are chosen to craft an experience. As the concept of virtual synaesthesia is inherently multisensory, the responsible innovation framework put forward by Velasco and Obrist would apply in the context of virtual synaesthesia. An unintentional consequence of virtual synaesthesia is that it embodies rule three. That is, one of the aims of virtual synaesthesia is to make multisensory experiences more transparent by drawing upon the mechanisms of natural synaesthesia and crossmodal correspondences. This overt augmentation would allow a user to transparently access information from one sensory modality to another to make the experience more human-orientated. It also has the additional benefit of determining what sensory elements to use and why. Detour aside, it is important to iterate that the concept of virtual synaesthesia is still in its infancy, meaning a significant amount of further work will need to be conducted to confirm its validity and viability. As such, any work conducted in this thesis should not be used in mission-critical scenarios that could have a profound impact on an individual. As an example, consider the predictive models created in Chapter 7 This chapter explored to answer a very specific research question and was suggested as an advancement for the olfactory sensory augmentation created in this thesis. In the case of the work conducted in this thesis, these models were created for use as a augmentation and not a substitution. As with all machine learning algorithms, there is room for error, meaning that very careful consideration is needed before utilising it in a multisensory experience, as, at some point, it will produce wrong and potentially misleading information. Before utilising the concept of synaesthesia, consideration of the three “laws” above is needed to ensure responsible innovation. In fact, for responsible innovation, all multisensory experiences should conform to the “laws” above and is not limited to virtual synaesthesia.

8.9 Future Research Directions

The area of virtual synaesthesia is still in its infancy with regard to its methodology, understanding, and exploitation. Based on the research conducted in this thesis, there are a few areas of research that can be conducted further. Some of these are described below.

8.9.1 Synaesthesia and human-machine interfaces

In Chapter 4, a human-machine interface was developed using the ideology of odour-vision synaesthesia. The results show the potential of augmenting multi-sensory experiences with an artificial form of this phenomenon in terms of enhancing human cognition. The extent of this, however, remains to be investigated; for instance, is it possible to replicate the cognitive benefits of other forms of synaesthesia other than odour-vision? To what extent can the cognitive benefits be replicated? How can the replication of this phenomenon help with everyday tasks? Finally, through virtual synaesthesia, we gain the possibility of psychologically exploring artificial synesthetes.

8.9.2 Crossmodal correspondences

Chapter 5 investigated a wide variety of crossmodal correspondences between odours and the angularity of shapes, smoothness of texture, perceived pleasantness, pitch, colours, emotional, and musical dimensions were explored. The area of crossmodal correspondences has been well explored from a psychology perspective, but little has been done in areas of computer science and engineering. For example, exploring the effects, crossmodal correspondences could have on multi-sensory experiences (i.e., multisensory experience design in the context of XR); being able to robustly predict these correspondences may make research of their usage in the computer science/engineering disciplines more attractive. As the associations are shared across observers, further work is needed to determine these associations' stability over time [7], [298]. These interactions could be used to determine how crossmodal correspondences affect the perceived quality and pleasantness of cyber-physical entities, such as 3D printed food and experiences in virtual reality. Future research could explore how employing crossmodal correspondences into human-machine interfaces could benefit multimodal setups [144], which could be advantageous for people with disabilities [299]. This would involve designing a human-machine interface that considers multimodal interaction patterns, such as crossmodal correspondences. Furthermore, the integration of colour-sound correspondences in a human-machine interface has been shown to enhance user performance [28], thereby demonstrating the need for crossmodally congruent interfaces.

8.9.3 Predicting crossmodal correspondences

In Chapter 6, a relationship was uncovered between the physicochemical features of odours and their reported crossmodal correspondences. In Chapter 7, different machine learning models were created to predict crossmodal correspondences. The work developed in these two chapters

could be considered to be a building block for the digital transmission of smell. In theory, the transmission of odours would require recording an odour to reproduce (e.g., intensity over time), deciphering odour composition, transmitting, and reproducing it at the other end. However, the synthesis of odours is currently technically limited. Thus, deciphering the odour along the perceptual axis and aligning different sensory modalities to match the user's sensory expectations could generate a similar percept, even if the odour(s) or physical configurations at either end of the transmission points are not identical. Interestingly this ideology could be used to fine-tune interactive and immersive experiences to suit a particular desired outcome. For example, changing the colour of a drink affects our perception of the product, shaping the aroma, taste, or flavour [150]. In other words, it is possible to shape the multisensory perception of products and experiences towards a more favourable or desired outcome, such as enhancing the perceived pleasantness or creating perceptual illusions. The work reported in Chapter 7 could be improved upon by including a larger sample size of odours along with their crossmodal correspondences to enhance the reliability of the generated models. Additionally, more robust and reliable models can be obtained by developing the models to suit singular nationalities and cultures, as they are an influential factor towards explaining crossmodal correspondences (i.e., [198], [300]). Finally, although it was demonstrated that it is possible to align an e-nose to the crossmodal perceptual axis of olfaction for commonly encountered odours, it remains to be investigated if this is still the case with novel odourants.

8.9.4 Virtual synaesthesia

In this thesis, the ideology of virtual synaesthesia as a design paradigm was disclosed and discussed, and two design patterns emerged a bottom-up approach and a top-down approach. At the moment, these two approaches along with the concept of virtual synaesthesia, are still in their infancy, therefore, more research is needed to determine their validity. More forms of virtual synaesthesia other than odour-vision could be explored, including but not limited to sound-colour, lexical-gustatory, colour-grapheme, visio-space, and auditory-tactile. The ideology of synaesthesia gives us a doorway to determine which senses or more likely to be 'bound' together and how, therefore, is not limited to just human-machine interfaces but also other areas, such as product design and multisensory art. Consequently, expanding this approach for research in different disciplines. Congruency with the expected sensory attributes has been shown to improve the perceived pleasantness and task performance of a given experience. However, incongruency has been shown to induce larger reaction times but is a solemnly researched area, with the literature mainly focusing solely on the benefits of crossmodal congruency. In other words, the concept of virtual synaesthesia

may induce negative effects if done incorrectly, but more research needs to be conducted to determine the best way to create the experience, along with any benefits or drawbacks that may arise. The work in this thesis has demonstrated some potential benefits in regard to augmenting human-machine interfaces with the concept of virtual synaesthesia. It would be interesting to determine the benefits and drawbacks in regard to generic multisensory experiences.

8.10 Concluding Remarks

This thesis set out to answer four research questions; first, is it possible to artificially replicate the cognitive benefits behind a natural form of synaesthesia; this question was answered in Chapter 4. It was found that the cognitive benefits behind natural odour-vision synaesthesia were, at least partially replicable, demonstrated by a sizable increase in olfactory identification. To further improve upon the device presented in Chapter 4 and, similarly, any multisensory experience that plans to or utilises olfaction, the question of if consistent crossmodal correspondences exist between odours and different sensory modalities was answered in Chapter 5. It was found that people do have consistent crossmodal correspondences between odours and the angularity of shapes, the smoothness of texture, perceived pleasantness, pitch, colour, emotional and musical dimensions. However, to fully utilise crossmodal correspondences in multisensory experiences, it is important to understand their nature and origin; this is explored in Chapter 6. It was found that hedonics contributes more than semantics, and the physicochemical features of odours also play a role in explaining the nature and origin of olfactory crossmodal correspondences. Finally, now it is known the physicochemical features of odours play a contributory role. The question of if olfactory crossmodal correspondences can be predicted using the stimuli's physicochemical features arose; this is answered in Chapter 8. It was found that olfactory crossmodal correspondences could be predicted using the physicochemical features of the odours; this could be implemented in the device presented in Chapter 4 to uncover the shape and the colour associated with an arbitrary odour in real-time, thereby presenting more meaningful stimuli back to the wearer. Along with the presentation of the ideology of virtual synaesthesia, providing answers to these research questions is the novel contributions of this thesis. It is envisioned that the beneficiary of the work conducted in this thesis, albeit not limited to, is anyone designing a multisensory experience, more so if the experience uses olfaction but with consideration of the responsible innovation and the applicability of virtual synaesthesia.

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Chapter 9 Appendix

Ethics Approval



Health and Life Sciences Research Ethics Committee (Psychology, Health and Society)

1 May 2019

Dear Prof Wuerger

I am pleased to inform you that your application for research ethics approval has been approved. Application details and conditions of approval can be found below. Appendix A contains a list of documents approved by the Committee.

Application Details

Reference: 5131
Project Title: How does the brain combine different senses?
Principal Investigator/Supervisor: Prof Sophie Wuerger
Co-Investigator(s): -
Lead Student Investigator: -
Department: Psychological Sciences
Approval Date: 01/05/2019
Approval Expiry Date: Five years from the approval date listed above

The application was **APPROVED** subject to the following conditions:

Conditions of approval

- All serious adverse events must be reported to the Committee (ethics@liverpool.ac.uk) in accordance with the procedure for reporting adverse events.
- If you wish to extend the duration of the study beyond the research ethics approval expiry date listed above, a new application should be submitted.
- If you wish to make an amendment to the study, please create and submit an amendment form using the research ethics system.
- If the named Principal Investigator or Supervisor leaves the employment of the University during the course of this approval, the approval will lapse. Therefore it will be necessary to create and submit an amendment form within the research ethics system.
- It is the responsibility of the Principal Investigator/Supervisor to inform all the investigators of the terms of the approval.

Kind regards,

Health and Life Sciences Research Ethics Committee (Psychology, Health and Society)

iphsrec@liverpool.ac.uk

0151 795 5420

Appendix - Approved Documents

(Relevant only to amendments involving changes to the study documentation)

The final document set reviewed and approved by the committee is listed below:

Document Type	File Name	Date	Version
Participant Consent Form	Consent Form - Multisensory processing	01/03/2019	1
Advertisement	Debrief - Multisensory processing	01/03/2019	1
Risk Assessment	risk assessment multisensory	26/03/2019	0.3849
Participant Information Sheet	Participant Information Sheet – Multisensory Processing	25/04/2019	24

Figure 1. A copy of the ethical approval used for the human trials conducted in this thesis.

Participant Information Sheet



Participant Information Sheet

Study Title

How does the brain combine different senses?

Invitation

I would like to invite you to take part in a research study. Before you decide you need to understand the research being done and how it would affect you. Please take time to read the following information carefully. Ask questions if anything you read is not clear or would like further information.

Our senses perform a very important in our everyday life's, from viewing the world around us to determining if food is fit for human consumption. This study looks into developing a better understanding of how the human brain combines input from different senses.

What's Involved?

You will be given scented essential oils to smell. You will need to sniff these oils and answer some questions presented via a graphical user interface on a computer screen. During the course of the experiment, you will be in a controlled environment, and given access to the essential oils, there will be a person in the room with you to provide you with instructions and assistance if needed. All information collected will be stored under the regulations of the Data Protection Act 1998 and will not be shared with any third parties.

On the day of the trial, we request that do not wear any perfume, Eau de toilet or any other strong smelling substances. Free refreshments will try and be acquired for your efforts.

Are there any risks in taking part?

As essential oil's use extracts from plants and/or fruits there are allergens you need to be aware off (see further information section for a list of potential allergens). The trial will take place in a controlled environment this environment is about the same size as a large elevator, so there may be a risk of claustrophobia, however, if this does occur, you can leave the room at any time during the trial.

How long will it take?

Approximately 30 to 40 minutes.

How will my information be kept confidential?

All information collected during the course of this research will be kept strictly confidential. Your data will be collected using a computer program, these results will be logged to the computer's hard drive. There will be no information stored which will link you to the results, these results will also be kept on an encrypted hard disk. This information will be used to determine if there is consistency of correspondences between olfaction and other sensory modalities and will not be shared with any third parties.

Do I have to take part?

It is up to you decide if you want to take part. However, we hope you do, we will also try and provide at the end of the trail.

What will happen to the results of the research study?

The results from this study will be published in a conference or journal, there will be no identifiable information recorded or published that will link you the results.

Refreshments

Refreshments might be provided for your efforts and time.

Further Information and contact details

It is not advised to take part in the study if you have allergens.

If you have any questions, please feel free to contact me at: ryan.ward@liverpool.ac.uk

Figure 2. A copy of the information sheet given to each participant before any experiments involving humans.

Consent form



Consent Form

Title of Project: How does the brain combine different senses?

Principal Investigator/Supervisor: Professor Sophie Wuerger

1. I hereby confirm I have read and understand the information sheet for the above study. I have had the opportunity to read and consider the information, ask questions and have had these questions answered satisfactorily.
2. I understand that my participation is voluntary and that I am free to withdraw at any time without reason.
3. I hereby confirm I have no known allergies to any of the following: Caramel, Cherry, Coconut, Honey, Lavender, Musk, Orange, Peppermint, Pineapple or Vanilla.
4. I understand there may be risk of claustrophobia and I understand I can leave the room at any time if this does occur.
5. I agree for my responses to be recorded and kept accordingly as indicated in the Data Protection Act 1998. I understand that my personal information will not be shared with any third parties and will only be used in the confines this study.
6. I agree to take part in the above study.

_____	_____	_____
Name of Participant	Date	Signature
_____	_____	_____
Name of Person taking consent.	Date	Signature

Figure 3. A blank copy of the consent form given to the participants before any participation.