Submission for the award of Master of Research (Marketing)

A Replication and Extension of 'Measuring advertising's effect on mental availability'.

Danae Underwood
Bachelor of Business (Marketing)

Supervision Team:
Dr. Virginia Beal
Dr. Kelly Vaughan
Prof. Rachel Kennedy

Ehrenberg-Bass Institute for Marketing Science
University of South Australia Business School
University of South Australia

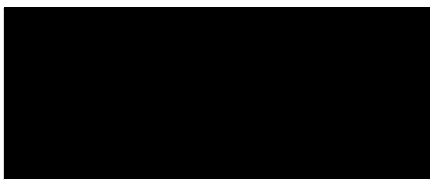
May 2023



DECLARATION

I declare that this thesis presents work carried out by myself and does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university. Nor does it, to the best of my knowledge, contain any materials previously published or written by another person except where due reference is made in the text. All substantive contributions by others to the work presented are clearly acknowledged.

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ABSTRACT

In order for brand advertising to be effective, it has to effect consumer memory (Barnard & Ehrenberg 1997; du Plessis 2005). There are various models and theories that seek to explain how advertising works, the publicity model suggests this is achieved through building and refreshing memory associations with the brand (Sharp 2010a). Being able to retrieve a brand name, or brand-related information from memory in buying situations underpins the concept of mental availability – which is defined as the propensity for a brand to be thought of or noticed in buying situations (Romaniuk & Sharp 2004b; Romaniuk 2013).

The focus of this thesis is on the measurement of mental availability in response to brand advertising, through a differentiated replication and extension of the work of Vaughan et al. (2021) and Vaughan (2016). To measure the effect of brand advertising on mental availability, Vaughan et al. (2021) used the Mental Availability (MA) Metrics. Created by Romaniuk (2013), the four MA Metrics quantify the size of a brand's associative network in consumer memory, relative to category competitors. The metrics are: Mental Market Share (MMS), Associative Penetration (Ab), Association Rate (Aw), and Share of Mind (SoM).

Answering the call from Vaughan et al. (2021) to replicate and extend their findings, this research addressed two methodological limitations of the prior work which utilised cross-sectional secondary data and advertising recognition measures as a proxy for advertising exposure. This research instead collected primary data with forced advertising exposure, and a longitudinal study design with the same respondents pre- and post-advertising exposure for a sample of 3,193 respondents (screened for category use), plus a control group of 217 unexposed respondents. A mid-sized target brand was selected for each category: financial services, on-demand streaming, chocolate, and coffee, and a real world (new to market) advertisement shown to respondents during a distractor task. Respondents were surveyed twice with

brand attribute questions: both pre-advertising exposure, and post-advertising exposure (for the main sample). These questions were used to calculate the MA Metrics at the aggregate level, as well as MMS and a new measure, Number of Associations (NOA) at the individual respondent level.

Key findings of this research include:

- Brand mental availability is affected by advertising exposure at the aggregate brand level, with the biggest change among brand non-users.
- The MA Metrics should be reported separately for brand users and non-users. The Share of Mind metric moves more for brand users, and Associative Penetration moves more for brand non-users.
- There is instability in Mental Market Share and Number of Associations across individuals after exposure to advertising. However, there are consistent, positive increases to these measures (on average) after advertising exposure.
- Using a combination of advertising recognition and correct branding does not sufficiently capture all who recognise an advertisement.

This research demonstrates that the MA Metrics are a suitable tool for measuring change in mental availability for brands following advertising. The patterns of change in the MA Metrics were consistent across the four categories used in this study (a many sets of data design) and with Vaughan (2016) as well as consistent with prior literature on brand usage bias.

As this study is the first of its kind to look at MMS at the individual respondent level, and explore a new measure of Number of Associations (NOA), it builds on the knowledge around the instability of brand attribute measures at the individual level (Barnard et al. 1986; Castleberry et al. 1994; Dall'Olmo Riley et al. 1997; Sharp 2002) and the role of advertising in building and refreshing relevant memories (Hartnett et al. 2021; Sharp 2010a). The exploration of advertising recognition measures as part of RQ3, should lead marketing practitioners and academics to question the suitability of such measures' ability to capture all who have recognised an advertisement.

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CHAPTER ONE

Introduction

The ability to robustly quantify and assess the effect of advertising on consumer memory remains an important discussion within industry and academia. The focus of this thesis is to replicate and extend the previous studies by Vaughan et al. (2021) and Vaughan (2016) which explored the usefulness of the Mental Availability Metrics (Romaniuk 2013) as a way of measuring this effect.

This commencing chapter provides a summary of the core sections of this thesis. It synopsises the research background and problem, study objectives, method, key findings, and contributions. The chapter ends with an outline of the thesis structure.

1.1 Research Background

The role of advertising is said to build and refresh brand memories, working as a form of publicity (Ehrenberg et al. 2002b). For a brand's advertising to be effective, it must therefore affect consumer memory (Barnard & Ehrenberg 1997; du Plessis 2005). Numerous measures exist that are used to evaluate advertising effectiveness such as brand awareness, and brand perceptions – quantifying the effect of advertising on mental availability has had much less investigation (Romaniuk 2013; Vaughan et al. 2021).

Mental availability is defined as the propensity for a brand to be thought of or noticed in buying situations (Romaniuk & Sharp 2004b; Romaniuk 2013, 2016a; Romaniuk & Sharp 2021). This possibility of a brand to come to mind is related to the accessibility of a brand in consumer memory (Romaniuk 2016a). The Associative Network Theories of memory (ANT) underpin the concept of mental availability, with the cognitive model describing human memory as a network of nodes, interconnected by associations or links, cataloguing, and storing information (Anderson & Bower 1980; Collins & Quillian 1969). Brand related nodes within memory can represent information or concepts – these can include brand name, products, colours, logos etc. with each of these nodes able to link to other nodes in the memory creating a network of associations for a brand (Anderson & Bower 1980). These associations assist with the retrieval of information (such as the name of a brand) from memory, through the activation of a cue(s)(Romaniuk 2016a). The more potential cues in memory that are linked to information, the higher the likelihood that the information is successfully retrieved (Romaniuk 2003). In the context of mental availability, a buying situation is the cue that activates brand memories to be retrieved, to bring the brand to mind (Romaniuk 2016a).

Advertising is one way that brand memories and associations can be built or strengthened within consumer memory (Krishnan 1996). Advertising touchpoints

provide the opportunity for consumers to be exposed to brand information and can build a brand's mental availability (Vaughan et al. 2021).

1.2 Research Problem

Having a robust, quantifiable measure of a brand's mental availability was the purpose behind Romaniuk's (2013) development of the Mental Availability (MA) Metrics. The four MA Metrics were created to measure the size of a brand's associative network easily and clearly, relative to category competitors (Romaniuk 2013). The MA Metrics are: Mental Market Share (MMS), Associative Penetration (Ab), Association Rate (Aw), and Share of Mind (SoM) (Romaniuk 2013). This research replicates and extends the work of Vaughan et al. (2021) and Vaughan (2016), who applied these MA Metrics to real-world brand tracking data to examine the effect of advertising on brand's mental availability. This was an exploratory study providing the first empirical evidence, and as such, more is needed to both validate the findings from Vaughan et al. (2021) and Vaughan (2016), in addition to addressing the initial study's limitations. Vaughan et al. (2021) and Vaughan (2016), used secondary tracking data and a cross-sectional design with different respondents surveyed pre- and post-advertising, and without a validated Opportunity-To-See (OTS) for the advertising. To address this, the current research employed primary data, with a longitudinal study design where the same respondents were surveyed pre- and post-advertising exposure and employing a forced advertising exposure to validate OTS.

1.2.1 Research Objectives

The objective of this thesis is two-fold: To further examine the applicability of the MA Metrics as a measure of advertising's effect on memory, namely mental availability, and to understand the impact of the methodological limitations of Vaughan et al.'s (2021) work on the findings.

This research will be guided by the questions:

RQ1a: *Are Mental Availability Metrics responsive to brand advertising?*
RQ1b: *How do Mental Availability Metrics move in response to brand advertising at the aggregate level?*

RQ1c: *How do Mental Availability Metrics move in response to advertising for different consumer groups?*
RQ2: *How does mental availability at the individual person level move in response to advertising?*

RQ3: *Is advertising recognition a sufficient measure to capture advertising exposure?*

1.3 Method

Data for this research was collected in November through December 2022 across four categories: two goods and two service categories. This Many Sets of Data (MSoD) approach (Ehrenberg 1990) was used to determine if patterns in one category are repeatable in other categories. The data collected consists of 3, 193 consumers across four categories, in the Australian market. Respondents were surveyed about only one category each.

Data were collected across two time periods (Wave 1 pre-advertising, Wave 2 post-advertising), approximately one week apart using the same respondents in both waves. Wave 1 screened respondents based on category usage and provided an initial measure of the four MA Metrics prior to advertising exposure. In Wave 2, ~790 respondents per category were surveyed again and exposed to the target brand's advertising (one target brand per category), and all four MA Metrics were re-measured. A group of ~55

respondents per category acted as a control group and were not shown the target brand advertising in Wave 2.

The research investigated the change across 16 observations (4 metrics by 4 categories) for RQ1, and where possible, a paired samples t-test was used to examine for statistical significance in the change of the metrics from Wave 1 to Wave 2. To examine individual level change to answer RQ2 and RQ3, the MMS metric was calculated for all individual respondents, for the target brand, and a new measure was introduced – the Number of Associations, or NOA.

1.4 Key Findings & Contributions

This thesis has eight key findings:

Key Finding 1: *Mental availability is affected by advertising exposure at the aggregate brand level.* Change in the MA Metrics was detected for the target brands across all four categories in this research following advertising exposure. Across 16 observations of MA Metrics for the target brands, 14 observations moved in a positive direction following advertising exposure. This was in line with the prior study, but more consistent, where 25 of 40 observations moved in a positive direction in Vaughan (2016). There were far fewer positive changes in the MA Metrics for the target brands in the control group with only 6 of the 16 observations moving in a positive direction, which was anticipated given the target brand's advertising was not exposed to this group.

Key Finding 2: *The biggest change in mental availability is among brand non-users.* This was consistent across the MSoD and supports evidence from wider marketing literature that greater movement is expected among this consumer group (Bird et al. 1970; Burnkrant & Unnava 1995; Krishnan 1996; Romaniuk et al. 2012; Vaughan 2016). Of the 16 target brand level observations for non-users, 15 moved in a positive direction after advertising exposure, while only 10 of the total 16 observations moved in a positive direction for the user group. For the Mental Market Share (MMS)

metric, the average percentage change for the target brands from Wave 1 to Wave 2 was larger for non-users, with an increase of 19.2% compared to only 2.3% for brand users. The pattern of change, whereby non-users saw greater average difference is evident in the remaining three metrics for the target brands – Associative Penetration (Ab) (7.2% for non-users vs -0.7% for users), Association Rate (Aw) (11.9% vs -1.1%), and Share of Mind (SoM) (19.4% vs 6.1%).

Key Finding 3: *The Share of Mind metric captures the change in mental availability for brand users*. Share of Mind (SoM) measures the share of associations for the target brand, from the group of consumers who gave at least one association with the brand. From Wave 1 to Wave 2, the SoM metric increased by 1.7 percentage points. Associative Penetration and Association Rate metrics are already high and therefore can move little, as brand users already have established brand memories and a high number of associations in memory (Krishnan 1996; Zinkhan & Muderrisoglu 1985). As such, they are hitting a ceiling, with limited ability for additional associations to be built from a singular advertising exposure. Then, it is possible that the greater movement seen in SoM for brand users of the target brand is the result of strengthening pre-existing associations in memory and interfering with the ability for other competitor brands to be retrieved from memory.

Key Finding 4: *The Associative Penetration captures the change in mental availability for brand non-users*. The Associative Penetration (Ab) metric saw the most positive change for brand non-users – it measures the percentage of respondents who gave at least one association with the target brand. While all four metrics (on average) increased across the observations for non-users for the target brands, the Ab metric saw the largest increase. This is likely due to target brand's advertising building and/or refreshing the link between advertising messages and the brand, making the brand easier to bring to mind post-ad exposure.

Key Finding 5: *The MA Metrics should be reported separately for brand users and non-users.* As mental availability is greater for brand users due to their existing memory networks, reporting findings for the MA Metrics with users and non-users combined does not accurately show the impact of ad exposure on mental availability for each group. Furthermore, change across the four metrics for these two groups happens differently, primarily Share of Mind for the target brand's users and Associative Penetration leading for non-users. For example, drawing on Associative Penetration (Ab), the change at the aggregate brand level for the target brands was 5.4 percentage points from Wave 1 to Wave 2. However, when looking at the same metric separated for brand users and non-users the nuance in change can be observed. For users, the Ab metric decrease by -0.6 percentage points, with Ab being 94.9% in Wave 1 and 94.2% in Wave 2. While for non-users, there is an average increase of 5.4 percentage points, where Ab was (on average) 69.1 percent in Wave 1 and 74.5 percent in Wave 2. This nuance in change is lost when the two groups are combined.

Key Finding 6: *There is instability in Mental Market Share (MMS) and Number of Associations (NOA) across individuals after exposure to advertising.* At the individual level, over half of respondents saw change (either increase or decline) in Mental Market Share (MMS) for the target brand, and approximately a third of respondents were unstable in the Number of Associations (NOA). This is reflective of the literature on instability in brand attribute measures at the individual level (Brown 1985; Kennedy & Sharp 2002; Rungie et al. 2005; Sharp & Romaniuk 2000; Sharp 2002). Prior studies have shown when measures show stability at the aggregate level, typically this is not reflective of the change among individuals (Dall'Olmo Riley et al. 1997; Sharp 2002). Approximately half of respondents change their responses when surveyed again (Dall'Olmo Riley 2012; Sharp 2002). This is also consistent with the literature around memory and the probabilistic nature of retrieval – there is no guarantee the same information will be retrieved from memory each time (Mitchell 1982; Romaniuk & Sharp 2002).

Key Finding 7: *There are consistent, positive increases in Mental Market Share (MMS) and Number of Associations (NOA) (on average) after advertising exposure.* Even with instability present at the individual level, after exposure to the target brand's advertising, these two measures do see an average increase – MMS sees a positive 2.9 percentage points change, and NOA increases by 0.6 associations, almost one association. The control group declined for both measures for the target brands – MMS decreased (on average) by -1.1 percentage point, and NOA by -0.2 associations, remaining essentially stable.

Key Finding 8: *Using a combination of advertising recognition and correct branding does not sufficiently capture all who recognise an advertisement.* Even with validated OTS and forced advertising exposure, not all respondents can correctly identify the brand within the advertisement. On average among brand users, 56% were classified into the sub-group that Recognised And Correctly Branded the target brand's advertisement, and 49% of non-users were classified into the same sub-group. While capturing (on average) half of these consumer groups, the remaining half were either able to recognise the advertisement but could not correctly identify the target brand (24% of users, 29% of non-users) or did not recognise the advertisement at all (20% of users, 22% of non-users). Based on widely used recognition measures where advertising recognition is used in conjunction with correct brand identification (for recent examples: Crommelin et al. (2014) and Vaughan et al. (2021)), these consumers would not be captured by this measure.

Contributions

The results of this thesis contribute to the body of knowledge on the MA Metrics and their use as a tool to measure the effect of advertising on a brand's mental availability (Vaughan 2016; Vaughan et al. 2021). As a differentiated replication of Vaughan et al. (2021) and Vaughan (2016), the results of this thesis found at the aggregate brand level, the MA Metrics across this study and Vaughan (2016) largely follow the same pattern,

with positive increases after advertising exposure for the target brands. While there is more consistent positive change in the MA Metrics in this research, it demonstrates that the limitations of Vaughan et al. (2021) and Vaughan (2016) did not affect the MA Metrics' ability to measure change in mental availability after a brand has advertised. Similarly, the patterns found by Vaughan (2016) across the different consumer groups are evident in this research. Brand users see far less consistent positive change in the metrics for the target brands after exposure to advertising. The brand non-users, across both studies, saw consistent, positive increases post-advertising for the target brand.

These consistencies suggests that brand tracking data will not limit the MA Metrics' ability to identify and measure change in a brand's mental availability after advertising. Similarly, while forced exposure in this study does appear to result in greater positive change in the MA Metrics, compared to using recognition as a proxy for advertising exposure in Vaughan (2016), the overall pattern across both studies were consistent. Additionally, this is the first work (to the author's knowledge) to explore the MA Metrics at the individual level to understand the source of change for the target brand at the aggregate level. It showed that there is instability in MMS and NOA at the individual level, which adds to the breadth of knowledge within the brand attribute literature space (Dall'Olmo Riley 2012; Sharp 2002; Sharp & Romaniuk 2002a, 2002b).

For marketing practice, the results of this study demonstrate the use of the MA Metrics to measure advertising effects to marketing professionals. With the same patterns of change evident in this research as in Vaughan et al. (2021) and Vaughan (2016), it suggests that brand tracking data is sufficient for brands to explore and measure the effect of advertising on mental availability, using the MA Metrics. Additionally, this study calls into question the efficacy of advertising recognition as a proxy for advertising exposure. It suggests if marketing practitioners consider those 'exposed' to only be the respondents who recognise an advertisement and correctly identify the brand, they are potentially missing a large proportion of respondents who

were in fact exposed. This study found about half of respondents who were exposed to the target brand's advertising, were not categorised as recognising the advertisement. One way this could be addressed in future advertising effectiveness studies is with the use of a prompted brand list to capture the correct brand aspect of the ad recognition measure, rather than a brand recall approach.

Furthermore, with 80% of the consumer dataset used in this research (on average) comprising of brand non-users, it speaks to the importance of advertising to the entire market, not just a sub-set of brand users who already have many, pre-existing associations in memory.

1.5 Thesis Structure

This thesis begins by discussing the background literature, Part A of Chapter Two describes mental availability and how human memory works. Part B details how advertising works, followed by Part C which explores how advertising's effect on memory can be measured, including a discussion of the research being replicated and extended (Vaughan 2016; Vaughan et al. 2021).

Chapter Three outlines the research questions, with Chapter Four outlining the method used in the research, including how the methodological limitations of the study being replicated and extended are addressed.

Chapter Five details the data analysis process used to answer all five primary research questions, while Chapter Six reports the results. Key findings from this research are detailed in Chapter Seven.

The final chapter (Chapter Eight) concludes this thesis, and details implications for marketing practice and academia. Additionally, limitations as well as future research are suggested.

CHAPTER TWO

Literature Review

The purpose of Chapter Two is to overview the literature relevant to this thesis, to support the need for the research questions this thesis sets out to answer (which are detailed in Chapter Three). This chapter is divided into three key parts.

Part A introduces and defines the concept of mental availability. It overviews how human memory works, with reference to mental availability and discusses how these concepts apply to brands. This section also introduces category entry points as a memory cue, and how these relate to mental availability.

In Part B, two primary models of how advertising works are introduced, with discussion on the differences between each model. This is followed by an overview of key factors that make advertising effective, in regard to memory.

Part C examines some of the traditional measures used to evaluate advertising effectiveness, including advertising recognition and recall. A new set of measures, the Mental Availability Metrics, are introduced, along with a summary of the research that is being replicated and extended in this thesis.

2.1 PART A: Mental Availability

Part A introduces the concept of mental availability and how this differs from brand salience. It includes a discussion of the Associative Network Theories of Memory, as these theories underpin the concept and measurement of mental availability.

2.1.1 Defining Mental Availability

Mental availability is the propensity for a brand to be noticed and/or thought of in buying scenarios (Romaniuk & Sharp 2004a, 2004b). Mental availability relates to the accessibility of a brand in consumer memory, and how easily it can come to mind in a buying situation (Romaniuk 2013, 2016a). Alongside mental availability is physical availability (namely distribution and accessibility of goods and services), the second way in which brands are said to compete (Sharp 2010b). For brands, building both mental and physical availability is what underpins brand growth (Sharp 2010b).

Brand salience is a term which for many people refers to top-of-mind brand awareness from a category prompt. While not completely synonymous with the newer term of mental availability, these are similar concepts. Where brand salience and mental availability differ are in reference to the cues uses. Brand salience draws on a single category cue, while mental availability considers the breadth of brand associations across many cues related to buying or using a category (further detail on brand associations can be found in section 2.1.3.1) (Bogomolova & Romaniuk 2010; Romaniuk & Sharp 2004b). As such, the term mental availability will be used throughout this thesis. This is to avoid confusion with using the more limited term of brand salience (being top-of-mind awareness).

To understand why researchers evolved the concept of salience to mental availability, it is vital to understand how human memory works and impacts brand choice. The

following section will discuss this with particular emphasis on the Associative Network Theories.

2.1.2 How Human Memory Works: Associative Network Theories of Memory

The concept of mental availability is underpinned by the Associative Network Theories of memory (ANT) (Anderson & Bower 1980). First introduced by Collins (1969) and Anderson (1973), ANT is a cognitive model that explains human memory works as a series of interlinking nodes, cataloguing, and storing information. ANT is one of the oldest theories of memory with the most empirical backing, making it widely cited and accepted within literature (Anderson & Bower 1980; Holden & Lutz 1992; Romaniuk 2013; Vaughan et al. 2021).

As expressed in ANT, human memory is comprised of nodes, representing pieces of information or concepts – such as colours, names, shapes, dates, and including brand information. Connected nodes are things thought about or processed in memory together, forming links or associations in memory (Anderson & Bower 1973). Meaningful associations help reduce the cognitive effort of memory retrieval, by connecting nodes to other important information such as important dates, or a person (Carlston 2007). Brand information can be stored in the same way. A brand such as Cadbury may come to mind for a shopper from a range of internal or external associations (associative links) including seeing the colour purple, hearing the Phil Collins song "In the Air Tonight" used in the well-known gorilla drumming advertisement, or thinking about past gifts. Such associative links can be created when the brand is directly or indirectly interacted with e.g., receiving Cadbury as a gift or seeing advertising (more on this is in section 2.1.3.1). There are a range of dimensions related to learning, storage, and retrieval within human memory for brand information. This following section will discuss these additional dimensions.

2.1.3 Encoding, Storage, & Retrieval

Prior to brand associations and links forming, human memory undergoes a three-step process which involves learning, storing, and then the retrieval of the information learned. These three stages of memory processing are encoding, storage, and retrieval (Anderson & Bower 1980; Anderson et al. 1988).

The initial stage, encoding, is the learning and interpreting of information (Anderson & Bower 1980). At this preliminary stage when new information is encountered, existing information already stored within memory is used to help understand and contextualise the new information (Anderson & Bower 1980; Tulving & Thomson 1973). One might know some characteristics of a cat – such as having fur, whiskers, and two ears – but when seeing a picture of a cat, new information like a breed of cat, or types of fur (short or long) can also be connected in memory to previously encountered information of cats. Information that is repeatedly encountered (read: exposed to) can have a 'priming' effect (Neuman 2006). For example, repeatedly seeing images of a cat can help to encode the information learned about cats more effectively in memory.

The encoding process works the same when learning about brands. The information that one is exposed to such as the brand's logo, colours, or products all help to form connections within memory (to encode the brand in memory). Repetition of exposure to such information can help to ensure efficiency and effectiveness when processing brand information into memory in the future (Hintzman & Block 1971). It is possible, then, this could impact the probability of future product choice, and purchasing (Berger & Fitzsimons 2008; Nedungadi 1990) – more on this later in this section.

Following from the learning stage, the storage stage sees the information being retained in memory (Anderson & Bower 1980). When the information is still being processed in memory, it is still possible to lose the information as it is considered 'fragile', or 'not set,' while the links and associations are being built (Phelps 2004). It is

suggested the consolidation of the information can take time. Some theorise that the brain is waiting on emotional stimuli before 'setting' the associations with this new information (Phelps 2004). A known factor impacting the storage of information is the number and strength of pre-existing links in memory. The human brain stores information more effectively when there are established associations (Lang et al. 2013; Phelps 2004). du Plessis (2005) suggests the likelihood of neurons connecting to form an association is directly related to how many times in the past these neurons have connected through repetition. Neurons are more likely to connect if they are 'familiar' with one another (e.g., jointly presented in advertising) – therefore exposure, and even familiarity with brands makes new information more likely to be successfully stored through co-presentation.

The final stage in memory processing is retrieval. Information that has been learned and stored can be recalled and moves from long-term memory into working memory (Lang 2000). The recollection or retrieval of information from storage is achieved by the activation or triggering of a cue (Nedungadi 1990; Romaniuk 2016a). The brand relevant concepts that are encoded, stored, and then retrieved from long-term memory after the triggering of a cue are brand associations (Keller 1993). Cues, and how they are used within the process of retrieval of brand associations from memory will be discussed in further detail in the following section.

2.1.3.1 Importance of Cues

Understanding general knowledge about how information is retrieved from memory gives marketers insights into the sorts of cues that can activate brand relevant memories.

The retrieval of a brand name from memory is achieved through the activation of a node which works as a cue, functioning as a connection point for all other relevant associations (du Plessis 2005). Cues can be any number of pieces of information, such as names, places, dates, or an event. Once a node has been activated, it is possible for other information or nodes, that are connected via associated links, to come to mind.

The relative 'strength' (whether the node has been established and reinforced in memory) and the 'recency' (how recently the cue was activated) of the cue effects the likelihood of the brand information being retrieved (Knitsch & Young 1984; Nedungadi 1990).

One type of cue that is important for marketing is a category entry point, or CEP. These are used by consumers in a buying scenario (Romaniuk 2016a) and can be likened to distribution outlets within the mind (Romaniuk 2003). The more distribution outlets linked to the brand (in memory), the higher the likelihood the brand will be thought of, or noticed, when a CEP cue is encountered. The following describes CEPs in more detail.

2.1.3.2 Cues: Category Entry Points (CEPs)

CEPs are thoughts which can be grouped into common reasons why or situations in which a consumer could/might buy from a category – they are the thoughts before a consumer transitions into becoming a category buyer (Romaniuk 2016a). As internal or external motivations behind the purchase, they help the consumers' mind retrieve the brand (or relevant brands) when in a purchasing scenario. An example of a CEP for the carbonated beverages category could be 'something to drink with dinner. This example CEP is shown in Figure 1 as an example of a cue and associated links in memory. 'Something to drink with dinner' is the initial cue CEP, which has been activated in memory (in this example). If the associations within the consumers memory are strong enough and have been activated recently enough, this can spread and activate other associations throughout the memory network, demonstrating the idea of spreading activation (Collins & Loftus 1975). As demonstrated in Figure 1, the cue 'something to have with dinner' can activate the 'refreshing' node, which then could activate the brand 'Solo', or could directly activate the brand Coca-Cola, meaning both brands have a chance of being retrieved.

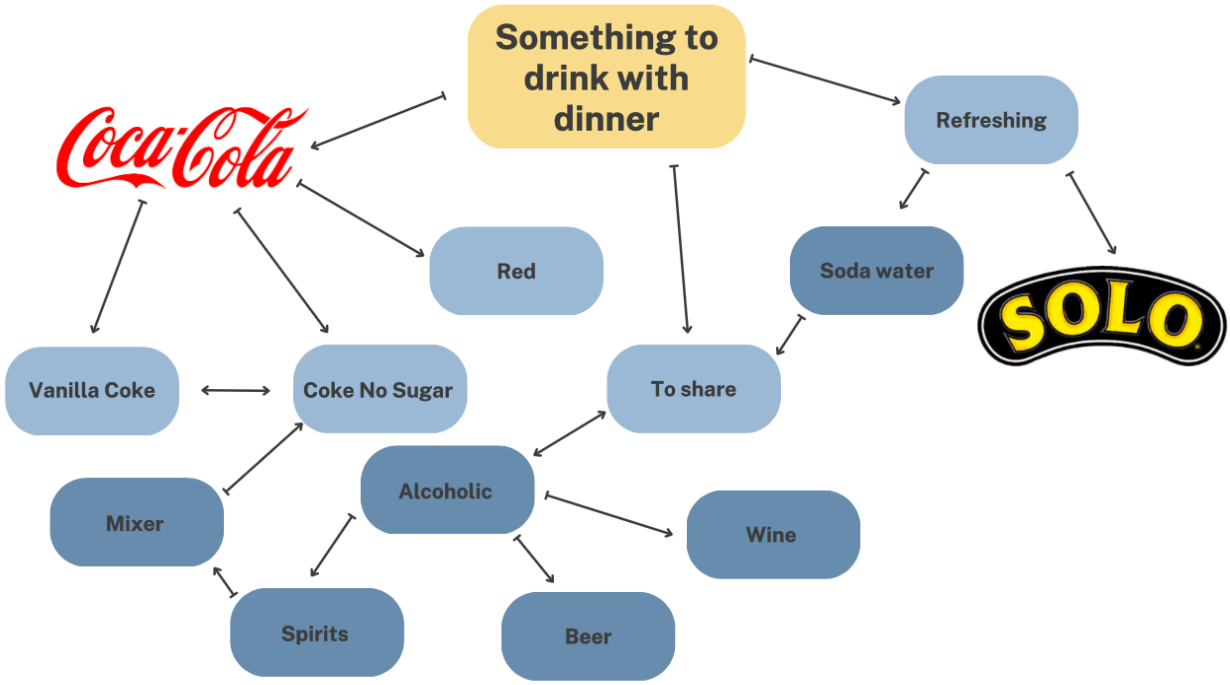


Figure 1: Simple illustrative example of a network of memory associations.

The ability for the cue to help retrieve information is dependent on several factors. The further away the stimuli are within the network (i.e., Solo is further in the memory network from the CEP cue than Coca-Cola which has a direct association), strength of the associations (how often the association is activated), and freshness of the links in memory (how recently the association has been activated) can affect whether the information is retrieved (Anderson et al. 1988; Franzen & Bouman 2001).

It is important to understand the retrieval of information from memory is known to be probabilistic, with no guarantee or certainty that the same information will be retrieved each time (Mitchell 1982; Romaniuk & Sharp 2002). To demonstrate, consider you have seen a person at a party. They're very familiar to you, you recognise their face or other aspects of their appearance, but you cannot remember their name in this instance. Your inability to retrieve their name from memory while recognising other aspects of the person is considered to be retrieval failure, and this can happen with brand memories too (Sharp & Romaniuk 2002b). The concept of probabilistic retrieval will be expanded upon in the following section.

2.1.4 Factors Impacting Brand Retrieval

When discussing brand information retrieval from memory, it is imperative to understand there are several factors that can impact this process, as noted in both cognitive psychological and marketing literature (Burnkrant & Unnava 1995; Krishnan 1996; Romaniuk et al. 2012).

With respect to this research, direct brand experience through brand usage is one of the key phenomena documented within marketing literature which impacts retrieval (Bird et al. 1970). Brand users tend to possess a more established network of associations for the brands they use, compared to non-users of the same brands, due to direct brand experience (Bird et al. 1970; Burnkrant & Unnava 1995; Krishnan 1996; Romaniuk et al. 2012). Previous brand usage – or usage bias - can increase the probability the brand will be retrieved for brand users. The familiarity that brand users have with a brand can mean they have stronger and fresher relevant memory structures (Craik & Lockhart 1972; du Plessis 2005; Wyer 2008), in turn increasing the chances that a cue encountered will activate associations in memory linked to the brand, more easily bringing the brand to mind (Keller & Davey 2001).

The number and the strength of associations linked to a brand in memory can also impact retrieval (Romaniuk et al. 2012). A higher number of associations is known to contribute to a higher possibility of retrieval (Romaniuk 2003, 2013). The more mental pathways to (or associations with) the brand, the more opportunities for the brand to be retrieved when a cue or CEP is encountered. It is important to note these factors can, but are not guaranteed, to ensure brand retrieval from memory. Recalling information from memory is said to be probabilistic, with no guarantee or certainty that the same information will be retrieved each time (Mitchell 1982; Romaniuk & Sharp 2002; Sharp 2002).

The most important factors in the building and strengthening of these memory structures and brand associations is repetition and exposure to co-presented information. It is imperative that increasing both the quantity of the associations, as well as the quality or strength of the associations with a brand is considered a priority for brands (Kennedy 2016). Along with direct brand experience, in-direct brand experience such as being exposed to a brand's advertising (Vaughan et al. 2021) or hearing positive word-of-mouth has also been said to assist in the building and strengthening of a brand's memory structures. Keller (1987) notes how the proximity of advertising exposure to when the consumer is at a point-of-purchase could help consumers to retrieve brand information from memory, but also assist in brand choice (Ephron 1995; Ephron 1997).

2.1.5 The Importance of Mental Availability in Purchasing Scenarios

Some suggest consumers choose brands based on the first one that will satisfy their needs (Elrod et al. 2004). Others assume that the process requires the consumer to evaluate their need for the product as well as alternatives, search for information, and finally make their purchase decision (Doran 2000). While other literature suggests that brands that receive more attention (Gidlöf et al. 2017; Janiszewski et al. 2013; Milosavljevic et al. 2012), or a brand that a consumer is more familiar with (Alba & Marmorstein 1987; Park & Stoel 2005) is more likely to be chosen.

Despite differing views, similarity across these possible factors to brand choice is memory – previous interactions with a brand through a multitude of different avenues allow the information to be processed in memory, to help drive brand choice (Alba & Marmorstein 1987; Nguyen 2017). This underpins the concept of mental availability, which is about having a brand accessible within memory.

To understand how a brand could become mentally available to buyers, Nedungadi (1990) and Franzen (2001) describe two stages of cognition. These stages are brand consideration (evocation) and brand evaluation.

- The brand consideration phase is characterised by the narrowing down of possible brand alternatives to a smaller, brand consideration set. Brands that are more prominent within the consumer's mind, due to the number and strength of associations held, are more likely to be evoked within this phase (Franzen & Bouman 2001). A limitation of this process is it assumes that consumers may only choose from the brands that are active in memory at that time, and not seek out alternatives that may be accessible within their wider memory.
- During the second phase of brand evaluation, the brands that have been narrowed down in the brand consideration phase become a part of a smaller group of brands, forming the consumer's 'choice set' (Franzen & Bouman 2001). Brands within the choice set are usually part of the consumers personal repertoire of brands (Sharp & Romaniuk 2002b). Consumers are typically more familiar with these brands due to previous usage, and these brands are usually more mentally available (Sharp & Romaniuk 2002b).

Though these two stages are simplistic representations of memory and brand choice (as cognition is far more complex than a two-step model, that does not take into consideration other factors like emotion (du Plessis, 1994b)), it highlights the importance of mental availability in buying situations. Those brands with higher accessibility within memory, that are recalled during the consideration stage, and then considered at the evaluation stage have a higher chance of being bought (Romaniuk & Sharp 2003). Given brands that have more presence in memory have a higher propensity to come to mind (du Plessis 2005) this demonstrates the role of mental availability. There is little need to seek out other brand options when there are typically available alternatives within memory, that require far less cognitive effort to retrieve (Heath 1999).

2.2 PART B: How Advertising Works

Part B introduces two different, broad models of advertising, persuasion and publicity, with a discussion on each, as it is crucial to understand the effect of advertising on memory. This is followed by an examination of key factors that can make brand advertising effective.

2.2.1 Different Models of Advertising

Within the advertising literature there are differing views on how advertising works. There are numerous theories that have offered explanation for how advertising can affect consumers. Among them are the attitude and attitude toward the ad formation theories, elaboration likelihood model, signalling, information processing, and persuasive argument theory (Kenworthy & Sparks 2016). Each of these have immediate relevance to how advertising can work. However, this following chapter focuses on two of the popular broad classes of thought – persuasion and publicity models – which offer contrasting views. A key purpose of acknowledging these different schools of thought is to highlight an important similarity for this research, that is for advertising to be effective, it must affect consumer memory (Barnard & Ehrenberg 1997; du Plessis 2005). Given mental availability and memory are intrinsically tied, it is pertinent to understand how advertising can affect memory.

2.2.1.1 Advertising via Persuasion

There are those that see advertising as a tool to persuade indecisive consumers to buy a brand they have seen advertised (Barry & Howard 1990; Jones 1990; Meyers-Levy & Malaviya 1999; Strong 1925a; Strong 1925b). Some of the literature around the persuasion model suggest that advertising can be used to manipulate unsuspecting consumers, changing their brand preferences almost unconsciously (Jones 1990). Information Processing (IP) Theory suggests that advertising is a tool that can be used

to persuade customers to adopt the advertised brand (Heath & Feldwick 2008). It is proposed this can be done with clear messaging and assuming the advertisements are processed at high levels of attention (Heath & Feldwick 2008; Meyers-Levy & Malaviya 1999). The AIDA (Awareness-Interest-Decision-Action) (Barry & Howard 1990; Strong 1925a; Strong 1925b) and DAGMAR (Defining Advertising Goals for Measured Advertising Results) models have also been used historically to explain the way that advertising works and is processed by consumers. These theories explain the learning and processing of advertising by consumers as a linear, step by step process (Meyers-Levy & Malaviya 1999), though these theories fail to reflect how consumer minds typically work and process advertising.

2.2.1.2 Advertising via Publicity

Other academics suggest advertising instead works as a reminder, or publicity for a brand (Ehrenberg et al. 2002a). The role of advertising then is to build and refresh brand memories, thereby maintaining or increasing a brand's mental availability (Sharp 2010a). Comparing to the persuasive models of advertising that suggest consumers are highly attentive to advertising, this theory acknowledges that consumers typically process advertising at low levels of attention (Heath 2000). Consumers mostly do not view learning about brands as highly important (Heath 1999). Despite the lower level of attention given to most advertisements, they are still able to work through memory activation or strengthening brand memories (Wright 2016).

There are other mechanisms that seek to explain how advertising works – these include Bond theory, signalling, and priming (Sharp 2010b), which is similar to the publicity model.

Bond theory suggests that the mere existence of a brand's advertising informs the consumer about the brand. Their advertising suggests that the brand is a safe, stable brand to purchase from due to the brand's ability to spend on advertising (Nelson

1974; Sharp 2010a). Advertising can also help with the status signalling of a brand – it can be used to inform consumers about what the brand is like (Nelson 1974). For example, advertisements for a brand suggesting exclusivity or luxury can show consumers what to expect from that brand and its products when encountering it in purchasing scenarios (Sharp 2010a). Priming is concerned with building exposure for a brand, and this can be done through advertising. Priming proposes that consumers tend to find brands that they are more familiar with, more favourable (Sharp 2010a; Wyer 2008).

2.2.1.3 Reflection on Persuasion and Publicity

Despite the different beliefs of how advertising functions (across researchers and conditions), the commonalities between these theories and mechanisms suggest that for advertising to work (and work effectively) it must affect consumer memory (Barnard & Ehrenberg 1997; du Plessis 2005).

Where these theories differ is how memory is affected by brand advertising. The persuasion model assumes that consumers are aware and actively processing the message or information within an advertisement, and that this then shapes or changes their buying behaviour (Heath & Feldwick 2008). In contrast to this, the publicity model emphasises that advertisements and brand information is typically not a priority - as such, brand information gets less attention and processing (Heath 2000). These competing (and occasionally complementary) theories show how conversations within the advertising space continues to circulate around understanding how brand advertising works. Whether consumers need to pay active attention to advertising (or not), or view advertisements as a marker of a successful brand, memory is the thread linking advertising to brand choice (Hartnett et al. 2021; Sharp 2010a).

The publicity model (which this thesis focuses on throughout) assumes that advertising works through refreshing brand memories, rather than through persuasion (Barnard & Ehrenberg 1997). Given this assumption, it is expected that advertising exposure increasing relevant memories could be tested. As discussed in Chapter 2,

Part A, the theory of mental availability is able to be quantified and tested using four MA Metrics – all of which provide insight into the size of relevant associations held with brands in consumer memory. These metrics allow for the change in these associations or links with these relevant memory structures to be directly measured. Then, if advertising were to work as academics who support the publicity school of thought suggest (i.e., Ehrenberg et al. 2002a, Sharp 2010a), then testing consumer mental availability after advertising exposures should see a change in these relevant associations or memories.

2.2.2 Effective Advertising

The focus of 'effective advertising' in this thesis is not on sales effective advertising, but on the memory effects of advertising, and the factors that can influence the effect of advertising on memory and mental availability.

It can be difficult to isolate the effects of advertising on a brand's sales or mental availability when other activities or externalities such as price promotions, competitor advertising, and economic conditions must be considered (Hartnett et al. 2016). There are, however, four factors (reach, branding, creative, and message) that are considered to be important in creating effective (sales or memory) advertising (Biel & Bridgwater 1990; du Plessis 1994a; Eisend & Tarrahi 2016; Hartnett et al. 2016). These will be discussed in further detail in this section.

2.2.2.1 Reach

Advertising can only impact the memory of those who have seen the advertisement (this requires an OTS) (Romaniuk 2016b). In relation to mental availability, reaching as many category users as possible is the ideal strategy for ensuring maximum visibility to a brand's advertising (Binet & Field 2013; Ephron 1997; Romaniuk 2016b). Evidence from real-world, single-source studies sees the greatest change on a brand's

sales is when advertising exposures move from zero to one (McDonald, 1969, 1997; Reichel and Wood, 1994; Roberts, 1999; Romaniuk 2021; Taylor et al. 2009; Wood, 2009). This is not to say additional exposures have no impact, as it can bring extra sales, but the greatest impact (on average) is after the initial advertising exposure - with subsequent exposures having diminishing returns (Jones 1995; Taylor et al. 2013). The implications being media plans should prioritise reach over frequency, which in turn for mental availability will spread the advertising ability to affect more category users' memory.

2.2.2.2 Branding

Branding relates to the presence of the brand in any marketing communications such as advertising. Branding helps to link the advertising efforts to the correct brand – as without effective branding, it is possible for advertisements to be misattributed to competitors (Kennedy et al. 2000), or not be linked to a brand at all (Romaniuk 2009; Teixeira et al. 2010). Essentially, rendering the advertisement useless as it cannot have a chance to strengthen and/or build new memory associations for those exposed. As Romaniuk (2009) suggests, branding is the most important component of an advertisement – without branding, an advertisement just becomes a movie.

Displaying the brand can be through direct branding by explicitly showing or saying the brand name, or using a number of different brand cues, such as the logo, font, pack shots, colours, or ad styles to signal the brand (Romaniuk & Hartnett 2010a, 2010b; Teixeira et al. 2010). To ensure branding within TV advertisement is executed in the most effective way, it is best to brand early and brand often (Romaniuk 2009; 2021). Romaniuk's (2009) suggest the following strategy of effective direct branding in advertisements:

- *Using dual mode:* This is a combination of both audio and visual branding.
- *Higher visual branding frequency:* Showing the brand often, throughout the duration of the advertisement.

- *Branding early within the advertisement:* Displaying the brand within the initial seconds of the advertisement.

Branding strategies help to anchor the advertising to the correct brand, and therefore influence brand mental availability.

2.2.2.3 Creative

Creative, which can include anything from humour, voiceover, or showing a product has often been a self-purported way of grabbing consumer attention (Bellman et al. 2019). As noted earlier, advertising is typically given low levels of attention (Heath 2001; Heath 2007; Singh & Rothschild 1983), with brands having to compete with competitors for attention (Hartnett 2011). Creative can therefore work for a brand to help gain attention of their advertising, but it is important any creative does not overwhelm other elements within the ad, like branding (Franzen 1994; Sutherland & Sylvester 2000).

There are numerous creative devices that may be utilised when creating an ad. Music, speaking or non-speaking characters, and informational appeals are just three of many that can be used to help 'sell' a particular product or brand within an advertisement (Hartnett et al. 2016). Some of these, such as psychological benefits and humour have been seen to have positive effects on sales when used as a creative device within an advertisement (Hartnett et al. 2016; Williams et al. 2022). Though, it must be noted there is no perfect formula for creating a 'sales effective' advertisement (Hartnett et al. 2016; Stewart & Koslow 1989).

Emotive content, or emotional advertising, is another creative tool that can be utilised to create more 'effective' advertising on memory. Emotional content is seen to require less of a cognitive load to process (Heath et al. 2009; Nicks & Carriou 2016). With a less of a cognitive load, Heath (2009) believe this lower effort of processing and attention could serve advertisers, as the information is 'automatically' processed. Emotional

stimuli can make the information easier to process (Heath et al. 2009; Nicks & Carriou 2016).

Another creative element is creating likeable advertising. Ad likability has been posited to help consumers more efficiently and effectively process advertising and its content, and as such, could result in less 'screening out' of advertisements (du Plessis 1994b; Haley & Baldinger 1991; Smit et al. 2006). The main dimensions of a likeable ad are: entertaining, energetic/stimulating, relevant, empathetic, and familiar (Kennedy et al. 1995; Kennedy & Romaniuk 1997; Stavrinos et al. 2016). There is a degree of overlap here with two emotional elements that are suggested to assist with the cognitive processing of advertisements. These are again, tools that can be used to help with creating a more effective advertisement, and better help to link the advertisement to the brand in memory, making it more accessible.

2.2.2.4 Message

Some suggest that a message within an advertisement is anything that isn't the brand name (Laczniak et al. 1989), or something that can work to suggest the purchasing of that brand (Noth 1987). The advertising messages that are particularly relevant to this research are brand attributes, of which CEPs are a type of, which are frequently communicated by brands. Brand attributes, and CEPs, have been found to be present within the minds of consumers when making purchasing decisions (Holden 1993; Romaniuk 2003). Brand attributes can be divided into three types:

- Product category (i.e., soft drinks, chocolate, banks),
- functional/beneficial attributes (i.e., low in sugar, smaller pack size), and finally,
- purchase and consumption situations (i.e., when I want to treat myself) (Holden 1993; Romaniuk 2003) – of which are most related to CEPs.

Such brand attributes provide the opportunity for consumers to build or refresh connections in memory between the brand and existing relevant memories that can impact choice at the next category purchase. In other words, they are key to building and refreshing a brand's mental availability, by reinforcing associations between the brand and possible cues that may be encountered in buying situations.

2.3 PART C: Measuring the Effect of Advertising

Part C concludes this Chapter Two and examines the different measures of advertising effectiveness such as recall, recognition, and biometric attention measures used to understand the effect of advertising on memory. This section also properly introduces the Mental Availability (MA) Metrics, with a detailed look at the specific research this thesis is replicating and extending.

2.3.1 Measures

2.3.1.1 Advertising Recall and Recognition

Advertising recall measures can be divided into two types: aided, and unaided. Aided recall typically uses a category cue and asks respondents to list brands from that category they have seen advertising for recently (Till & Baack 2005). Unaided recall does not use a category cue, but rather simply asks respondents to list as many brands as possible they have seen in a TV show they watched, for example (Till & Baack 2005).

Advertising recognition, on the other hand, uses visual aids as a cue. Respondents are shown an advertisement (that is de-branded) and asked if they remember seeing/hearing it recently (du Plessis 1994a). Typically, respondents who recognise the ad are also asked which brand the advertisement was for (Crommelin et al. 2014; Vaughan et al. 2021). Additionally, relying on correct brand identification can be

limiting when advertising is not usually processed at the high involvement level (Heath & Nairn 2005).

The use of a visual cue can result in higher recognition scores due to it being an easier cognitive task, than recall (Vaughan et al. 2016). This ease of recognition creates less usage bias against brand non-users, as more non-users can retrieve the advertising memory (Vaughan et al. 2016). This means marketers can achieve a more accurate measure of advertising awareness, than compared to ad recall approaches which show larger usage biases (du Plessis 1994a; Hammer & Riebe 2006; Vaughan et al. 2016).

2.3.1.2 Brand Attribute Measures

The measurement of brand attributes has been prevalent in both marketing industry and academia for some time (Brown 1985; Kennedy & Sharp 2002; Rungie et al. 2005; Sharp & Romaniuk 2000; Sharp 2002). Largely, the focus has been on testing of attributes associated with a given brand, for example the attribute may be "*tastes good*". This is used as an indicator of future buying behaviour (arising from a 'positive attitude'), with little evidence to support this (Barwise & Ehrenberg 1985; Kennedy & Sharp 2002; Singh & Dall'Olmo Riley 2021). One limitation that has been documented within the literature is the instability of such measures at the individual level (Barnard et al. 1986; Castleberry et al. 1994; Dall'Olmo Riley et al. 1997; Exner et al. 1978; Sharp 2002). Typically, this temporal variability in attitude and brand image measures is seen upon re-testing, where approximately half of respondents say the same thing the next time (Dall'Olmo Riley 2012; Katona, 1979; Sharp 2002).

2.3.1.3 ARS Persuasion Metric

The ARS Persuasion Metric, created by RSC The Quality Measurement Company, is used to identify an advertisement's likelihood or ability to have a positive impact on brand sales (Phillips & Stanton 2004). The ARS Persuasion measure examines whether persuasion of an advertisement and choice is related to the attention given to it. While

a suitable measure to understand the effect of a brand's advertising on sales, it does not offer a way to examine the effect on memory for a given brand's associative network.

2.3.1.4 Neuromeasures & Emotional Response

Neuromeasures in advertising research look at how different areas of the brain are activated or change (typically through EEG) when reacting to an advertising stimulus (Crites & Aikman-Eckenrode 2001; Rossiter et al. 2001). Such measures are limited, often not being scalable and some suggesting emotional states such as irritation have an effect on the readability and applicability of results (Ciceri et al. 2019).

Another measure, the emotional response measure, discussed in Stout & Leckenby (1986) (and more recently in Bellman (2017)) has three dimensions (experiential, empathetic, and descriptive), and was put forward as a more effective way to measure the impact of advertising, rather than relying on a 'cognitive response,' particularly at low-involvement levels of processing (Stout & Leckenby 1986). However, this measure relies on ad recall and attitude to advertising and does not offer further insight into the associations linked to a given brand (Kennedy & Northover 2016).

While advertising recall and recognition measures are useful for detecting the trace of advertising in memory, brand attribute measures useful when explored at the aggregate level, ARS persuasion metrics demonstrate the link between advertising and attention, and neuromeausres and emotional response do show change in EEG – none of these advertising effectiveness measures are sufficient for providing insight into the size of a brand's associative network. What they fail to do, is measure the effect of advertising on the broader network of associations that are linked to a brand (Vaughan et al. 2021). This, however, can be achieved through utilising the Mental Availability (MA) Metrics (Romaniuk 2013; Vaughan et al. 2021).

2.3.2 Mental Availability Metrics

The Mental Availability (MA) Metrics, created by Romaniuk (2013) provide the ability to measure and assess a brand's mental availability through giving insight into the brand's network of associations. They function similarly to more widely used brand performance metrics (BPMs), being Market Share, Penetration, Average Purchase Frequency and Share of Category Requirements (Romaniuk 2013). Where the four BPMs allow a brand to compare and measure sales within their category, the MA Metrics measure the breadth and number of associations, relative to the brand and their category (Romaniuk 2013).

The four MA Metrics developed by Romaniuk (2013) are:

> **Mental Market Share (MMS):** The brand's share of associations from total category associations.
>
> **Associative Penetration (Ab):** The percentage of consumers who have at least one association linked to the brand. This is taken from the total sample.
>
> **Association Rate (Aw):** The average number of associations, given by those who have at least one association with the brand.
>
> **Share of Mind (SoM):** The share of associations for the brand, from consumers who have at least one association with the brand.

The specific calculations for each MA Metric can be found in section 5.5 of Chapter 5.

2.3.2.1 Mental Availability Metrics: Recent Studies

Since the MA Metrics were published by Romaniuk (2013), there has been one study to date that specifically used the four metrics as a measure of advertising's effect on a

brand's mental availability – the work of Vaughan et al. (2021). Other academics (Anesbury et al. 2020; Stocchi et al. 2016; Stocchi et al. 2020) (as recent examples) have used the Mental Availability Metrics to some extent within their studies, however, Vaughan et al. (2021) is the primary work which uses all four metrics and seeks to explore their efficacy as advertising effectiveness measures.

Vaughan et al. (2021) found the MA Metrics are an appropriate measure to assess and quantify advertising's effect on a brand's network of memory associations. This is primarily due to the way the MA Metrics themselves were designed – it measures whether there is an association with the brand, not the strength or degree of that association (Romaniuk 2013). The metrics also allow for comparison across brands within a market or competitive set (Romaniuk 2013; Vaughan et al. 2021).

The studies by Vaughan et al. (2021) and Vaughan (2016) used secondary data, collected as part of brand-tracking surveys during 2012-2015. Data were collected from the Australian, UK, and US markets. A spectrum of categories was represented, with data from CPG and financial services, employing the MSoD approach as suggested by (Ehrenberg 1990). There were eight different target brands measured across the categories. Two waves of data were collected, pre- and post-advertising, with the second wave in-field when the target brands had active advertising. Campaigns were on-air prior to Wave 2 between two and eight-weeks. Respondents were asked brand attribute and advertising recognition questions in both waves of data collection providing a benchmark prior to advertising activity. Those respondents who reported to have seen the advertisement (claimed exposure) and could correctly identified the target brand, were classified as being aware of the advertising. The respondents were split into brand user and non-user groups, to account for usage bias in results.

The studies found that at the aggregate level MA Metrics do respond when a brand advertises, showing the potential use of the MA Metrics in assessing the impact of advertising on consumer memory (Vaughan et al. 2021; Vaughan 2016). More

specifically, it was found that when both brand users and non-users are aware of a brand's advertising, the MA Metrics are greater (Vaughan et al. 2021). The greatest magnitude of change from Wave 1 to Wave 2 in the MA Metrics was when brand advertising reached the brains of category buyers who are brand non-users (Vaughan 2016).

Despite Vaughan et al. (2021) and Vaughan's (2016) findings, that the MA Metrics moved in a positive direction in the second time period (after brand advertising had occurred) for the target brand, which demonstrated that advertising could affect a brand's mental availability, the study had a number of limitations. The data used was not collected for the express purpose of testing the four MA Metrics, and a cross-section sample of respondents were used across the two waves of comparison, making it difficult to truly benchmark the MA Metrics pre- and post-advertising exposure and the impact of advertising on consumer memory. There was also only claimed advertising exposure, with no guarantee of respondents seeing the target brand's advertising execution.

This research sets out to address the limitations of the prior studies (Chapter 4, Part B, section 4.2.1.1 covers the limitations of the study in more detail), as well as to robustly test the usefulness of the MA Metrics to assess the impact of advertising on a brand' mental availability across a different range of conditions.

2.4 Chapter Summary

This chapter discussed the concept of mental availability, human memory works, and the advertising literature that is relevant in answering the research questions this thesis aims to answer (outlined in the next chapter).

Part A introduced and defined the concept of mental availability, with an exploration of how human memory works to encode, store, and retrieve brand information. Why mental availability is important to a brand, and within purchasing scenarios was examined.

Part B discussed the two primary models of advertising, persuasion and publicity, and contrasted their differences. Factors such as creative and branding to make advertising effective were also explored.

Finally, Part C deliberated on the various measures available to marketers to measure advertising's effect on memory. The limitations of these measures were discussed, and the MA Metrics examined as alternate set of metrics to assess advertising's effect on a brand's network of associations. The prior studies being replicated and extended as the foundation for this research was also briefly introduced.

CHAPTER THREE

Research Questions

This chapter outlines the five core research questions this study aims to answer. Appropriate literature is drawn on to support the use of these questions in further evaluating the MA Metrics as measures of advertising effectiveness on memory.

3.1 Research Questions 1a & 1b

As part of the replication and extension of Vaughan et al. (2021) and Vaughan's (2016) work, the first research question (RQ1a) will investigate whether there are aggregate-level changes in a brand's MA Metrics when a brand has advertised. Literature, and more notably (to this research in particular) the study of Vaughan (2021), and Vaughan (2016) suggest that brand advertising has an effect on mental availability, by refreshing and building the brand's network of associations in consumer memory (Barnard & Ehrenberg 1997; du Plessis 2005; Ehrenberg et al. 2002a).

The previous studies were exploratory in investigating advertising's effect on mental availability; therefore, it is critical to advance knowledge with further empirical research to validate the findings and confirm whether repeatable patterns are found. Notably, understanding if the MA Metrics can be used to capture the effect of advertising on a brand's mental availability, which leads to the first research question this thesis seeks to answer:

RQ1a: *Are Mental Availability Metrics responsive to brand advertising?*

To explore the MA Metrics in further detail, it is important to understand in which direction each of the four measures move, if they do at all, within this study. Vaughan (2016) found that the MA Metrics moved at the aggregate level following advertising. Through employing new methodology and using primary data in this research design (see more detail on method in Chapter 4), the second research question aims to examine how the MA Metrics respond at the aggregate level, and how this compares across new methodological conditions. This will build on the findings of the previous study (Vaughan 2016) and examine if any repeatable patterns arise between the studies, and within the many sets of data (MSoD) of this research.

RQ1b's purpose is to understand any potential impacts the adjustments in methodology could have on the MA Metrics. It allows for an examination of the MA Metrics and how they are responsive to brand advertising, and in which direction each metric moves across the MSoD. This is in addition to exploring the usefulness of the MA Metrics as a tool with which to measure the effect of short-term advertising exposure and explore the differences or similarities between this study and Vaughan (2016). As such, it leads to the second research question:

> **RQ1b:** *How do Mental Availability Metrics move in response to brand advertising at the aggregate level?*

To better compare with the results from Vaughan (2016), there are four sub-questions, with which the results at the aggregate level for all four MA Metrics will be examined:

> **RQ1b.1:** *How does a brand's Mental Market Share (MMS) metric change with a recent advertising exposure?*
>
> **RQ1b.2:** *How does a brand's Associative Penetration (Ab) metric change with a recent advertising exposure?*
>
> **RQ1b.3:** *How does a brand's Association Rate (Aw) metric change with a recent advertising exposure?*
>
> **RQ1b.4:** *How does a brand's Share of Mind (SoM) metric change with a recent advertising exposure?*

3.2 Research Question 1c

Usage bias, wherein brand users typically have a higher number of associations in memory than non-users, is well documented within marketing literature (Romaniuk et al. 2012; Sharp et al. 2001; Vaughan et al. 2021). This is due to the direct experience users have with a brand – the brand is considered to be more personally relevant and familiar to users than compared to non-users (Keller 1993).

This leads to RQ1c, which will examine any differences in the MA Metrics between different consumer groups of brand users and brand non-users, again at the aggregate level across this study and Vaughan (2016). While Vaughan (2016) found that the MA Metrics for brand non-users moved more than for brand users, on average, as this research is a replication of this exploratory study, this research question aims to uncover whether the same pattern is evident under different conditions, by answering the question:

> **RQ1c:** *How do Mental Availability Metrics move in response to advertising for different consumer groups?*

Following the same structure as RQ1b, RQ1c is also divided into four sub-questions whereby the results for the MA Metrics are explored across brand users and brand non-users:

> **RQ1c.1:** *How does a brand's Mental Market Share (MMS) metric change with a recent advertising exposure for different consumer groups?*
>
> **RQ1c.2:** *How does a brand's Associative Penetration (Ab) metric change with a recent advertising exposure for different consumer groups?*
>
> **RQ1c.3:** *How does a brand's Association Rate (Aw) metric change with a recent advertising exposure for different consumer groups?*

RQ1c.4: *How does a brand's Share of Mind (SoM) metric change with a recent advertising exposure for different consumer groups?*

3.3 Research Question 2

Stability of measures across the marketing discipline has been the topic of conversation for some time (Barnard et al. 1986; Castleberry et al. 1994; Dall'Olmo Riley et al. 1997; Sharp 2002). The perceived stability of brand image and attitude data seen at the aggregate level, whereby results change little over time for a large group, but when explored at the individual level there is variation in responses. This variation at the individual level was proposed by Katona (1979) to be the result of learning new information between time period one and time period two. Even testing across disciplines, where measures of memory are examined years on from an initial study (Exner et al. 1978), the measures lack temporal consistency.

This instability of measures at the individual level leads to the next research question this thesis sets out to answer. Where RQ1a and RQ1b seek to examine the MA Metrics at the aggregate level (where more stability in the metrics is to be expected as per Sharp & Romaniuk 2002a, 2002b), RQ2 will examine the effect of brand advertising on mental availability at the individual level, across all four categories:

> **RQ2:** *How does mental availability at the individual person level move in response to advertising?*

To better explore this question, RQ2 is divided into two sub-questions. The MMS metric for each individual will be calculated and explored, providing each respondent's share of associations for the target brand. RQ2a.2 will examine the actual number of associations (NOA), a new metric not previously investigated, each individual provides to the target brand following advertising exposure, across the four categories.

> **RQ2a.1:** *How does a brand's Mental Market Share (MMS) metric change with a recent advertising exposure within individuals?*

RQ2a.2: *Does the number of associations (NOA) a brand receives change with a recent advertising exposure within individuals?*

3.4 Research Question 3

One of the limitations of Vaughan et al. (2021) and Vaughan's (2016) study this research aims to replicate and extend the evidence for is the use of advertising recognition as a proxy for advertising exposure. Vaughan (2021) used secondary, brand-tracking data and were fielded when the target brand had an advertising campaign on-air. While attempts were made to confirm OTS by asking respondents which TV shows they had watched, for example, and compared these with the media schedule for the target brands, the researchers were unable to verify if respondents had actually been exposed to a given advertising execution. As a proxy for validated advertising exposure, Vaughan (2016) rather used advertising recognition and asked if respondents remembered seeing a specific advertisement (and for which brand it was for). While recognition measures are not uncommon in advertising effectiveness studies, the purpose of this research question (and largely, the research itself) is to build on the initial work of Vaughan et al. (2021) and Vaughan (2016), to uncover the suitability of an advertising recognition measure working as a proxy for validated exposure. It aims to explore whether self-reported measures of recognition, in conjunction with correct branding recall (as used by Vaughan (2021)) serves as an appropriate measure, across both brand users as well as brand non-users. Which leads to the final question this thesis seeks to answer:

> **RQ3:** *Is advertising recognition a sufficient measure to capture advertising exposure?*

3.5 Chapter Summary

The five core research questions that this thesis sets out to answer were discussed in this chapter. The purpose of the questions to understand how brand advertising affects brand mental availability at both the aggregate and individual levels and across different consumer groups, and how these results compare to the original study being replicated and extended.

CHAPTER FOUR

Research Method

This chapter discusses the importance of empirical generalisations and replications as the cornerstones of robust marketing science. It is followed by the methodological limitations of the original studies of Vaughan et al. (2021) and Vaughan (2016) and a detailed description of the research design and method used to collect data in this research.

The chapter consists of four main parts. Part A outlines empirical generalisations. It is followed by Part B, which discusses the study being replicated and extended, and the methodological limitations of the work that will be addressed by this research. Part C describes the operationalisation of the independent and dependent variables of this study. Finally, Part D details the survey elements and data collection.

4.1 PART A: Empirical Generalisations & Marketing Science

Empirical generalisations (emp gens) are the cornerstone of robust science and can be defined as a pattern between two or more variables that is seen to exist across numerous contexts or scenarios (Uncles & Wright 2004). These relationships, or patterns, are often described using mathematical models, charts, or symbols (Bass 1995). These persistent patterns can be considered law-like but may not always hold under all conditions, which are referred to as boundary conditions (Bass 1995).

The importance of emp gens within all scientific fields, including marketing science, cannot be understated. As Hanssens (2018) suggests, understanding emp gens in marketing can help to make marketers' lives easier through clarifying empirically supported evidence and patterns, that in turn inform brand related marketing decisions.

To contribute to the robustness of the results from this thesis, a many sets of data (MSoD) approach was implemented. Employing MSoD, instead of a single set of data (SSoD), can help to ensure better internal validity of results (assuming the results are not the result of other external factors outside of what is being tested) (Ehrenberg 1990) and offers the opportunity to discover patterns or generalisability across populations or samples (Bottomley & Holden 2001; Bound & Ehrenberg 1989; Ehrenberg 1990; Ehrenberg & Bound 2000). By extension, creating an opportunity for emp gens to be discovered. However, not all emp gens are made equal. Barwise (1995) suggests that while emp gens are considered robust and well-established, it does little to help define what a 'good' emp gen is.

The five criteria suggested for 'good' emp gens are: scope, precision, parsimony, usefulness, and link with theory (Barwise 1995):

- *Scope:* Being the emp gen holds under a wide variety of different contexts or conditions.
- *Precision:* An emp gen should be precise in both the description of the findings, and in the findings themselves.
- *Parsimony:* Without omitting necessary information, an emp gen should be simple and easy to replicate.
- *Usefulness:* In reference to marketing science, a useful emp gen is one that is useful and relevant to marketing theory and practice.
- *Link with theory:* Wherein the emp gen can be explained by existing theory/theories.

The search for emp gens is intrinsically tied to study replications (and extensions) of prior knowledge (Holden & Barwise 1995), in that emp gens arise from robust testing, re-testing/replications, and extensions (Holden & Barwise 1995). Within marketing science three pillars of importance were suggested by Uncles (2011) in relation to study replications and extensions:

1. to help to establish the pattern or phenomena holding at least one more time;
2. an additional replication can help to determine whether the findings will hold again; and
3. a replication or extension can identify situations in which the pattern does not hold.

The inherent value of replication and extensions is not necessarily in supporting the results of the original study - though it could be argued if they always did, there would be little need for them. The value then of a replication and extension, is in building the generalisability and predictability of results (Ehrenberg 1990). If the original study is

supported, it helps to contribute to marketing science through true, empirical generalisations. If the results of the replication differ from that of the original study, this can offer valuable insights into the boundary conditions in which the pattern does not hold (Hubbard & Armstrong 1994).

Historically within the social sciences there has been an absence of replications. Some argue it is due to the perceived lack of importance compared to the quest for new findings, others (Hubbard et al. 1992) suggest it is replications' difficulty or lack of popularity to conduct. There has, however, been a progressive shift aimed toward including replicated and extended works in marketing journals, through including through special editions requesting replication research (Sharp & Wright 1999; Sharp & Wind 2009; Sharp et al. 2017; Wind & Sharp 2009; Wind et al. 2013).

The design of replications usually fall under three main categories:

> **Exact replication** (Uncles & Kwok 2013)
> An exact replication requires all variables, method, and sample to be the same as that of the original study. These replications are considered 'impossible', with many factors unable to be fully controlled to replicate the exact circumstances of the original study, such having respondents with the same psychographics or demographics.

> **Close replication** (Lindsay & Ehrenberg 1993; Uncles & Kwok 2013)
> Close replications are characterised by their similarity to the original study. These studies aim to keep as many variables the same as the study being replicated, such as using the same sampling method or population, and utilising the same methodology. With many study elements remaining similar, this type of replication can usually be conducted more efficiently than an exact replication.

Differentiated replication (Lindsay & Ehrenberg 1993; Uncles & Kwok 2013) This involves making deliberate differences to the study being replicated, with the aim of extending or building generalisability of the results of the original study. The differences between the original study and the differentiated replication allows for researchers to seek out emerging patterns and empirical generalisations.

While more replications are slowly being submitted to marketing journals (Evanschitzky et al. 2007) some of these replication works are by definition, not a replication (Easley & Madden 2000; Toncar 2010). Toncar (2010) considers these study replications to be more of a 'spin-off' study than a true replication, with a large proportion (if not all) of the original study being largely ignored. This has led to the results of replicated studies differing sometimes greatly from the results of the original works (Darley 2000).

It is the purpose of this thesis to contribute to marketing literature by building on the work of Vaughan et al., (2021) and Vaughan (2016), with a differentiated replication (Lindsay & Ehrenberg 1993; Uncles & Kwok 2013). This research aims to contribute to the wider literature on advertising, its effect on human memory, and mental availability. This study will further examine the usability and robustness of Romaniuk's (2013) Mental Availability (MA) Metrics for both academics and industry marketers alike, as well as examining how the MA Metrics can be used across an improved methodology.

4.2 PART B: The Original Study by Vaughan et al. (2021, 2016)

Vaughan's (2016) Masters thesis and subsequently published article in the International Journal of Market Research (Vaughan et al. 2021), examined how a brand's advertising effects a brand's mental availability. The four MA Metrics (Romaniuk 2013) (see: Chapter 2, Part C, section 2.3.2 for further detail) were used to measure whether there was any change in consumers' mental availability, from a brand's advertising. This section outlines the limitations of the original study and how this research design will address these in this study.

4.2.1 Refinements to the Original Studies

4.2.1.1 Limitations of the Prior Studies

Vaughan et al. (2021) and Vaughan's (2016) work had two major methodological weaknesses that will be addressed by this research.

Firstly, Vaughan (2016) utilised a cross-sectional study design, examining two different groups of respondents at different points in time (pre- and post-advertising). This methodology was insufficient for examining change in the MA Metrics due to advertising. Using two different groups of respondents, although representations of the same population (category users), does not allow for an accurate baseline measure to examine the differences in MA Metrics for a brand pre and post their advertising activity. This approach also limits the results to an aggregate, rather than providing the ability to explore results at an individual level.

Rather, the work of Vaughan (2016) examines differences in groups and their MA Metrics over time, as opposed to measuring the change in the MA Metrics for the

same individuals over time. While this is not dissimilar to most brand tracking studies, where cross-section samples are compared over time, for robust academic research a longitudinal measure of the same individuals is needed to truly capture change in a brand's mental availability using the MA metrics following advertising. Addressing this limitation, means this study has the ability to investigate how changes in the MA Metrics at the aggregate level happen for individuals.

The second methodological weaknesses of the original studies were the inference of advertising exposure (Vaughan et al. 2021;Vaughan 2016). Due to the use of secondary brand tracking data, the design of the study relied on a self-reported recognition measure as a proxy for validated advertising exposure (Vaughan et al. 2021; Vaughan 2016). With an opportunity to see (OTS) the advertisement not validated, it does not guarantee that individuals were exposed to the brand's advertising of interest. For example, brands may run similar campaigns over a year making it difficult to confirm if respondents had seen the relevant executions being tested. A recognition measure, while an advertising awareness approach validated as being more suitable to determine traces of advertising in consumer memory than recall approaches, relies on respondents self-reporting which can bring with it inaccuracies and errors (Ludwichowska et al. 2017). As the original study has no validation of advertising exposure or confirmed OTS, then there is a possibility of respondents with higher mental availability or greater brand associations being able to correctly identify the brand being advertised, even without being exposed to the particular execution being tested.

Vaughan et al. (2021) also addressed the probability that some respondents who were 'not aware' of the advertising, as categorised using recognition and correct brand recall, may have actually processed the advertisement at a low involvement level. This may have affected their mental availability (or ability for the brand to be noticed) even though they failed to recognise the ad (Heath 1999, 2000; Vaughan 2016; Vaughan et al. 2021). This means the 'Aware' sub-group of the original study may under-represent the true impact of advertising on the target brand's mental availability for the 'Aware'

sub-group, as not all those impacted are categorised into this sub-group. Since the data was based on real-world brands there is a myriad of other factors such as the physical availability of a brand, price, or promotions that may have also impacted the response of the MA Metrics, as well as the number of times a respondent was exposed to the campaign, or length of time since they saw the advertisement and were surveyed. Therefore, it is vital to reduce the noise in the data by addressing this methodological flaw to ensure a direct measure of advertising exposure on the MA Metrics can be obtained.

4.2.1.2 Overall Research Design

To address the first methodological limitation (cross-sectional design with different respondents), this research will employ a longitudinal experimental study design. This will use the same individuals in the first (pre-advertising exposure or Wave 1) and second (post advertising exposure or Wave 2) wave of data collection, using online surveys.

The first survey was used to obtain a benchmark of brand associations to calculate the initial MA Metrics for the target brand (the brand advertising), as well as demographic and brand usage information.

The second survey surveyed the same respondents from Wave 1 and exposed them to the target brand's advertisement, a distractor task and remeasured the brand associations to re-calculate the MA Metrics post-advertising. The control group surveys were conducted in the same manner; however, respondents were not exposed to the target brand advertising in Wave 2. Rather they saw a brand advertisement for an un-related category. This longitudinal design provided a baseline of MA Metrics to measure and investigate aggregate and individual level change over time, following exposure to advertising (for the main sample). It also provides for a point of comparison, between the main sample and the control group.

To address the second limitation in the lack of validated OTS in Vaughan et al. (2021) and Vaughan (2016), advertising exposure for this research will be controlled. This is where the replication differs from the original study - OTS was verified, rather than relying on self-reports using an advertising recognition measure. Doing so, provided the ability to control the time between the advertising exposure and when the brand associations measured post-exposure creating consistency across all respondents. Additionally, the advertisement being used within the controlled exposure is more standardised to one media than the study being replicated, which tested advertising across four media. This research used a 30 second video advertisement for all four categories, limiting the amount of variation within the MSoD and reduced some of the noise (such as movement generated by frequency of exposures, type of media, length of exposure) around predicted changes with the MA Metrics following advertising exposure.

An illustrated overview of the research design across all five primary research questions is provided in Figures 2 and 3 on the following pages. While following a similar structure, the purpose of RQ1a ,RQ1b, and RQ1c is to explore the MA Metrics at the aggregate level, for the main sample and among different consumer groups (brand users and non-users). RQ2 and RQ3 however, seek to examine the MA Metrics at the individual level. The control group (discussed in further detail in section 4.4.5.1) are tested across Wave 1 and 2 and split by categories for RQ1a, RQ1b, and RQ1c. To test RQ2 and RQ3, the control group is combined.

Figure 2: Overview of research design for RQ1a, RQ1b, & RQ1c.

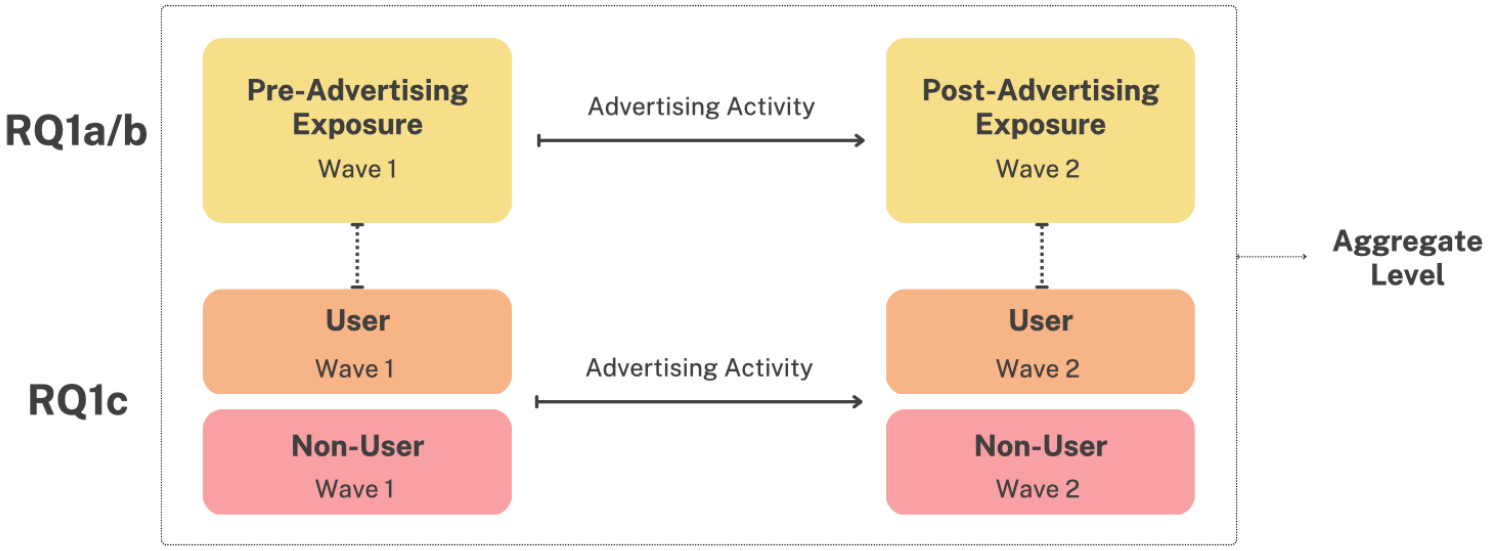
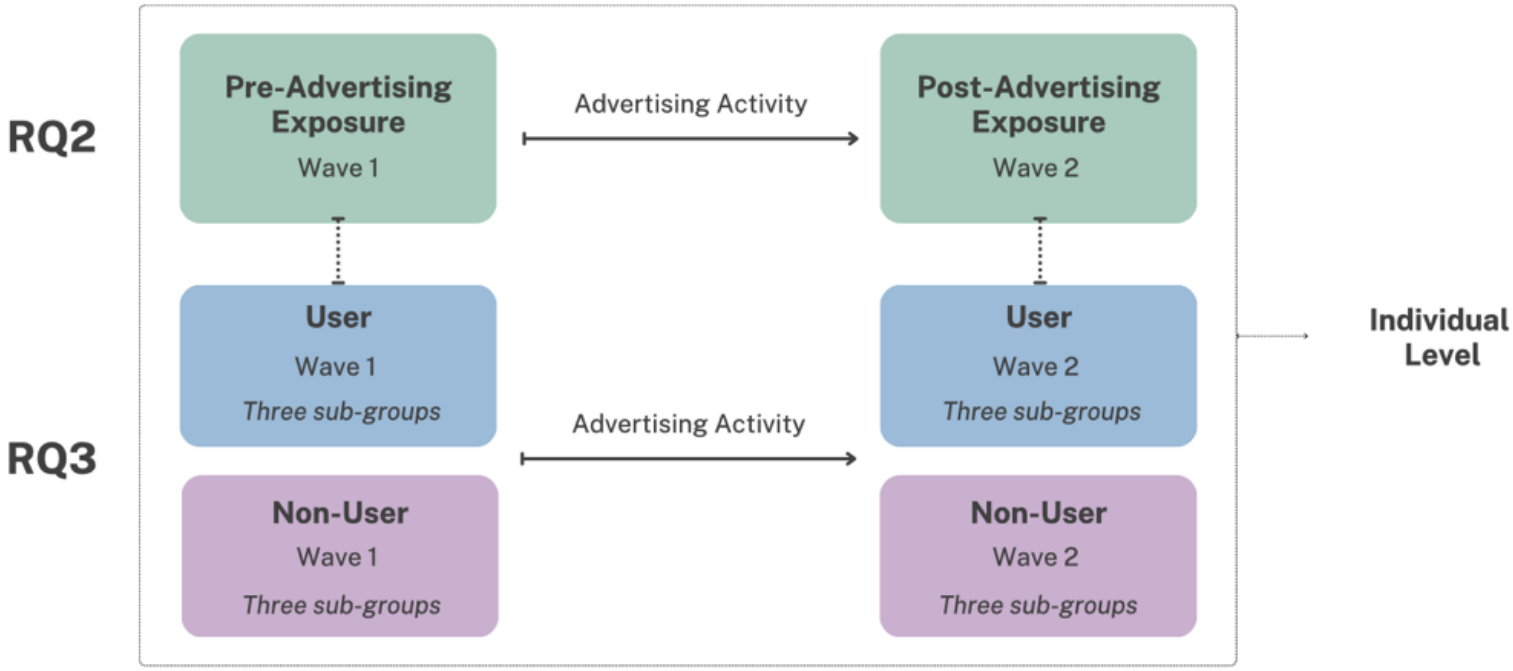


Figure 3: Overview of research design for RQ2 & RQ3.



4.3 PART C: Operationalisation of Variables

4.3.1 Operationalisation of the dependent variable – Mental Availability

4.3.1.1 Mental Availability Metrics

The MA Metrics (Romaniuk 2013) will be used to measure the effect of advertising on mental availability, replicating the original studies. The four MA Metrics were developed by Romaniuk (2013) who drew inspiration from the brand performance measures market share, penetration, buy rate, and share of category requirements. In essence, the four MA Metrics are calculated in a similar way but use brand associations rather than brand purchases. The MA Metrics provide insight into the size of the brand's associative network relative to category competitors – it helps to quantify and contextualise the size and number of associations or links in memory to a given brand (Romaniuk 2013; Vaughan et al. 2021).

To calculate the MA Metrics, brand associations are needed for the entire category. That is for each respondent, do they have any brand associations for each attribute tested in the study. To do this, a 'free choice pick-any' approach was employed, in line with the original study (see next section for further detail). Each respondent was prompted with a single attribute, or in this study referred to as CEPs (see Chapter 2, section 2.1.3.2 for more detail), which were supplied from commercial research (this is discussed in the subsequent section).

Following data collection, the MA Metrics were then be calculated for every brand in the category using this brand perception data. Table 1 below briefly describes each of the four MA Metrics.

Table 1: Mental Availability Metrics (Romaniuk 2013).

Metric	Description
Mental Market Share (MMS)	The brand's share of associations from all category associations.
Associative Penetration (Ab)	The percentage of consumers who have at least one association linked to the brand, of all respondents.
Association Rate (Aw)	The average number of associations, given by those who have at least one association with the brand
Share of Mind (SoM)	The share of associations for the brand, from consumers who have at least one association with the brand.

4.3.1.2 Free Choice, Pick Any Approach

To measure mental availability, the literature recommends the free choice 'pick-any' approach via an online survey (Romaniuk 2013, Vaughan et al. 2021). The 'pick any' method allows respondents to select as many brands that they link to a CEP as they want to. For all questions, a "None of these" option is also provided, to discourage respondents from guessing and not force respondents to provide associations they may not have in memory, which could impact the results (Romaniuk & Nenycz-Thiel 2014). It is the freedom of this method that allows researchers to know if an association with a brand exists, rather than measuring the degree of that association (Driesener & Romaniuk 2006). Compared to the widely used ranking or rating scales, the 'pick any' method is quicker and easier for researchers and respondents (Driesener & Romaniuk 2006). Both Barnard (1990) and Romaniuk (2006) have noted that the free choice method does pose the risk of under-reporting findings in relation to small brands. However, all brands selected for this research were medium-sized within their respective categories.

In the surveys used in this study, the question asked to measure brand associations using the free choice, 'pick-any' approach was as follows:

> *"Which of these <relevant category> brands do you link with the following statement? You can select as many or as few as you like, or none of these, if none are relevant to the statement."*

A single attribute (CEP), such as '*When I need an afternoon pick-me-up'* in the coffee category, appeared on the screen, with a randomised brand list shown underneath. Once brands are selected for an attribute, the next attribute would appear. The order of attributes was randomised for each respondent, as was the list of brands. All brands had the name written, accompanied by a picture of the brand's logo. This was done as processing visual stimuli is a far quicker and an easier cognitive task to recognising brand names – subsequently some respondents may recognise the logo and not the brand name (and vis a vis) (Cohen et al. 2009). The brand list while randomised per respondent, then remained the same for the duration of the brand associations section of the survey. The structure of the survey as well as the questions can be found in Appendix C. See Part D for further detail on the CEPs used within this research.

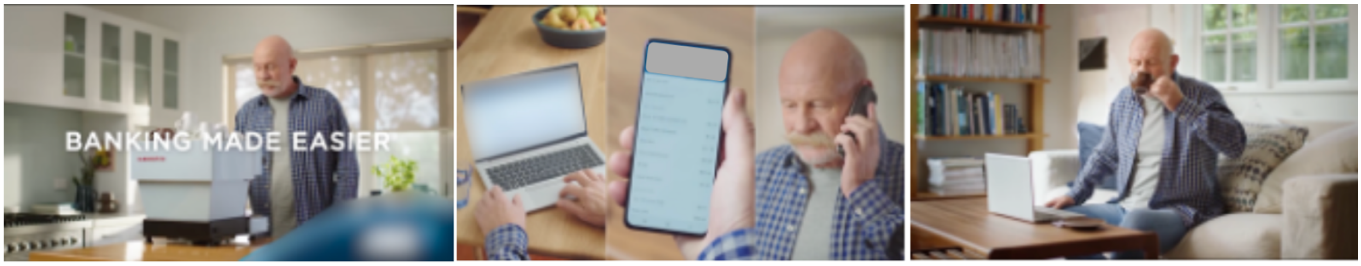
4.3.2 Operationalisation of the independent variable – Advertising exposure

4.3.2.1 Forced Exposure

In the original study, Vaughan et al. (2021) Vaughan (2016) used a self-reported recognition measure as proxy for advertising exposure, which does not validate OTS the advertisement was experienced. To remedy the lack of validated OTS, this research employed forced exposure to advertising as part of the online survey, with all respondents exposed to the target brand's advertisement.

While each respondent in this study is known to have an OTS, advertising recognition questions were still included in the survey. This was to allow comparison with the results in Vaughan et al. (2021) and Vaughan (2016), and to answer RQ3. Implementing the recognition measure within this research required asking respondents whether they remembered seeing an advertisement within the last ten minutes. Three stills from the advertising execution were provided, with branding masked as to not prime respondents, in line with the prior studies (Vaughan et al. 2021; Vaughan 2016). The branding elements that were masked were any visual mentions of the brand name, as well as logos. Below (Figure 4) is an example of the masked advertising stills for the advertisement tested in the financial services category. Respondents were provided with three options when asked if they remembered seeing the specific advertisement: Yes, no, or unsure.

Figure 4: Masked advertising stills example.



4.3.3 Operationalisation of the behavioural variable – Brand usage

To operationalise brand usage, it is necessary to determine the classification of brand users and non-users, and the impact of timeframe on this classification. Time frame differs between categories and their usage, which must be considered when collecting self-usage data in both the structuring of questions, and how the category itself operates.

Within a FMCG category like chocolate, it would be appropriate to ask consumers '*What chocolate brands have you purchased in the last three months?*' and prompting them with a list of brands from the category to choose from. Where questions relating to service categories would be structured differently, such as '*Do you currently hold an account with any of these financial service providers?*' due to the nature of the category, as timeframe is not as relevant a factor. As with much of the testing within the field of brand associations and the like, it relies on the respondents' memory of purchasing within that category (Bird et al. 1970). Due to differences between categories, users are those who have purchased from that brand of chocolate within the specified window, such as Cadbury, within the last three months. Any respondents who have purchased outside of that time frame, are classified non-users.
For service categories, those who are current customers are considered brand users. For repertoire categories, like chocolate, it is known that many buyers continue to be classified as light buyers across various time frames (Graham & Kennedy 2021). Vaughan et al. (2021) acknowledged this as a limitation of the research, thus their study became a comparison between non/light users and heavy users.

To measure usage within this research, the bounded recall approach was be used when asking respondents about their brand buying (Ludwichowska 2013). The bounded recall approach involves asking respondents which brands they have ever bought from/or held a product with. From the reduced brand list, they were asked which of the brands they have purchased from more recently, for example, within the last 3 months or if they are a current user (for service brands. The justification for use of this measures comes from research conducted by Ludwichowska (2013) which found that a bounded recall approach is best to reduce over-reporting of purchase incidences by light buyers, which is done usually through forward-telescoping. Light buyers were said to infer their purchasing behaviour based on previous purchasing habits, rather than remembering when they had purchased. Over-reporting could skew the data to the light-buyer group, while noted under-reporting by heavy users could skew the data even more, demonstrating the need to mitigate these potential self-reporting differences (Ludwichowska 2013).

Table 2 below shows the second brand usage question for the financial services category. This was used to classify respondents as either brand users or brand non-users, of the target brand. The second usage question of the bounded recall approach was used to determine two groups, users and non-users - in line with the prior study (Vaughan et al. 2021; Vaughan 2016).

Table 2: Example brand usage question for the financial services category.

Question	Brand Name & Logo
Which of these financial service providers do you currently hold an account or product with? *Select all that apply*	ANZ
	Aussie Home Loans
	Bank of Melbourne
	BankSA
	Bankwest
	Bendigo Bank
	BT
	Commonwealth Bank of Australia
	Macquarie Bank
	National Australia Bank
	RAMS
	St. George Bank
	Suncorp Bank
	Ubank
	Westpac
	None of these

4.4 PART D: Survey Design & Data Collection

4.4.1 Target Brands & Collection of Advertisements

To identify suitable advertisements to be used within this study was a threefold process; gathering CEPs, identifying the target brands, and finding advertisements used within the experiment. The Ehrenberg-Bass Institute regularly conducts CEP research, across a broad variety of categories and countries. This allowed the author to obtain CEPs that have been elicited by real-world category users, with access only provided to the elicitation analysis of prior CEP studies, where it was brand agnostic. For each category, the commercial study was drawn from a different market, not Australia.

A wide variety of categories have been studied by the Ehrenberg-Bass Institute, so to narrow the choice to cost-effective categories where incidence of category use is high, the Australian Household Expenditure Survey from the Australian Bureau of Statistics was used to select higher-incidence categories based on annual household spend from the 2015-2016 financial year (Australian Bureau of Statistcs 2017). The four categories selected were: Financial services, on-demand streaming, chocolate, and coffee as incidence rates in Australia were 80% or greater.

Secondly, to guarantee the advertising execution tested within the experiment had not aired within Australia and to ensure the campaign was unfamiliar to consumers, research into brands that were present in both the Australian market and at least one other international market was undertaken. Given the data collection was taking place in Australia, English speaking advertisements were needed which limited to markets to the US, UK, and New Zealand. IBISWorld industry reports were used to create the

brand lists for each category, ensuring that the brands had a presence in the Australian market. Selecting a target brand that was present within the Australian market was to ensure that consumers were likely aware of the brand and had the opportunity to build some prior knowledge of the brand in memory. This study is focussed on testing mental availability for established brands, not new brands where little to no memories would exist.

From the brand lists found within the industry reports, the target brands were selected based on market size and availability of 30 second ads from another market. Large brands, with market shares over the category average, were not chosen to be the target brand. Larger brands are likely to be linked to more CEPs, that is, the memory structures for larger brands are typically fresher and wider (Romaniuk & Sharp 2000; Sharp & Romaniuk 2016). As this research examines how advertising effects a brand's memory structures, there would be little room for movement in the MA Metrics if testing a larger brand due to ceiling effects. As such, a medium sized brands from their respective categories were selected as the target brands (see: Table 3 below).

Once the target brands for each category were selected, Facebook and YouTube were used to find advertisements for the brand that had aired within the UK and US markets but were not familiar to the author as being aired in Australia.

Table 3: Size of target brands, relative to category.

Category	Brand	Market Share % (relative to category, as of 2022)
Financial Services	ANZ	14%
Coffee	Nespresso	14%
Chocolate	Ferrero Rocher	5%
On-Demand Streaming	Disney+	3%

4.4.1.1 Coding of Advertisements

Following the selection of advertisements, the author provided an internal panel of academics who specialise in advertising a short-list of potential advertisements for each of the target brands. Discussion was used to identify those which may be suitable for testing in this study, based on aspects such as branding, length of ad, and whether brand attributes are present in the ad copy/creative.

Following the internal discussion, a coding spreadsheet was created and provided to two independent coders, as well as an advertising academic and the researcher (an example coding spreadsheet can be found in Appendix A). Coding was to determine if any of the two short-listed advertisements had attributes/CEPs present either explicitly or implicitly. The coders were asked to select from the list of CEPs (numbering 24, on average per category) which they thought were present or not within the two advertisements per category. The coders were able to watch the advertisements as many times as needed to determine whether a CEP was present.

The Percentage Agreement was used to assess the commonality of responses among the four coders. This was calculated through summing the number of times that the coders agreed, then dividing the number by the components (in this case, CEPs) coded (Lombard et al. 2004; O'Connor & Joffe 2020). A Percentage Agreement of >80% is considered acceptable within most fields of research (Miles & Huberman 1994). The Percentage Agreement among the coders for each of the categories is detailed in Table 4.

Table 4: Percentage Agreement for all categories.

Category	Ad 1: Percentage Agreement	Ad 2: Percentage Agreement
Financial Services	77	72
On-Demand Streaming	63	84
Chocolate	61	74
Coffee	40	40

The only category to receive a Percentage Agreement of >80% among all coders was Ad 2 for on-demand streaming. While out of the scope for this research, it is possible that the advertisements chosen were indicative of the advertising styles of these categories – the subscription category advertisements (financial services and on-demand streaming) had higher percentage agreements than that of the repertoire categories (chocolate and coffee). While lower than the suggested Percentage Agreement, the advertisements (after internal discussion) were still deemed appropriate for this research.

The final advertisement chosen for use within the research were the advertisements that all coders agreed the same CEP was present and was chosen after a final discussion with the internal panel of academics. The advertisements chosen were Ad 2 for financial services, Ad 1 for on-demand streaming, Ad 1 for chocolate, and Ad 2 for coffee. The list of CEPs, as well as the CEP that was deemed to be present in the advertising for all four categories can be found in Appendix D.

4.4.2 Distractor Task

To test the target brand advertising, steps were taken to make the exposure as natural as possible, and to disguise the purpose of the research. Two advertisements (a distractor ad, and the target brand advertisement) were embedded within a video which formed a distractor task within the survey. The purpose of distractor tasks in

research such as this, where advertising recognition measures are used, is to reduce the potential ceiling effects on scores (Singh et al. 1988).

Corkindale (2021) noted that within certain types of media, there is an expected level of product placement. When there are persuasion attempts in media, reactance (or how consumers react to 'perceived threats on their personal freedom of choice') differs based on the media vehicle. Within an informational program, such as a travel show, there is lower reactance due to an expected level of product placement. The level of reactance is higher for media such as drama shows, as the expected amount of more overt product placement is far lower. Reactance for advertisements also tends to be lower, which Corkindale (2021) suggests is due to their lack of relevance to the program being watched, when compared with billboards.

As such, the video selected as part of the distractor task was an informational video on passengers in cars, and the impact on driving safety. The video was created and distributed by the Royal Automobile Association of South Australia (RAA), on their public YouTube channel. Permission was granted by RAA to use the video in the survey. The video's total runtime, without the distractor and target brand ads, was 2 minutes 35 seconds. To safeguard against respondents having technical audio or visual issues, impacting their ability to watch the video in full with sound on, the external panel provider issued respondents with an audio and visual test prior to commencing the survey. The video provided was not able to be skipped in any way, respondents could only progress once the video had been watched in full. The video was shown at the beginning of the Wave 2 survey, prior to respondents being asked about their brand associations.

Distractors reduce respondents' guessing, by making the recognition tasks slightly more difficult (Singh et al. 1988). Within the distractor video, the distractor ad was shown before the target brand ad, to reflect a real-world 'ad-break'. Both ads were similar in length (~30 seconds), to not prime respondents to examine one ad more

closely than the other (Loginova 2009; Singh et al. 1988). The same distractor ad was used for all four categories and was for a brand in an unrelated category. Following the video, respondents were asked a series of eight questions related to the content of the RAA distractor video. Respondents were asked questions including whether they hold a current Australian driver's license, the impact of playing loud music on driving safety, and how often they are a passenger in a car – all topics covered in the video (the distractor questions can be found in the example Wave 2 survey, in Appendix C).

4.4.3 Ethics Approval

In accordance with the University of South Australia's Human Research Ethics Policy, a proposal of the research for primary data collection was sent to the Human Research Ethics Committee for review and approval. The application provided a detailed overview on the study, with information and consent details in a participant information sheet that was given to the panel provider. The participant information sheet explained the purpose and nature of the study, the method of research, the rights of the participants (including confidentiality, anonymity, and right to withdraw), and how the data would be used and stored. The University of South Australia Human Research Ethics Committee approved the proposal and supporting documentation in September 2021 (Ethics approval no. 052-2021), before the survey was distributed for the soft launch in April 2022, and full data collection in November/December 2022.

4.4.4 Pilot Study

Prior to the main study, a pilot study of a single category (financial services) was conducted to test the survey design and gain initial insight into the data being collected. The pilot study recruited n=806 respondents to complete the first and second survey, with approximately one week between the surveys. Respondents were selected by Australian external panel provider, Humaniti, for the online surveys. Those selected were a nationally representative sample of the Australian population and

category users. Data for the pilot study was cleaned in line with data collection for the main study, which is detailed further in section 4.4.5.2.

The MA Metrics were calculated to ensure data of pilot study were suitable to answer the RQs prior to the main data collection – the results of the pilot study can be found in Appendix B. Minor changes to the survey were adapted prior to full launch of data collection across all four categories. Changes included implementing time stamps into the surveys to track respondents re-entering the survey, as well as only allowing respondents to complete the Wave 2 survey up to 48 hours after starting.

4.4.5 Main Study Data Collection

This research utilised online surveys for Wave 1 and Wave 2 data collection. The primary benefit of this online survey method is accessibility and ease for the respondents as well as cost. Online surveys are not bound by geographical location, allowing for more representative samples that are not restricted by physical location (Wydra 1999). An online methodology can reduce the effects of social desirability bias in respondent answers that may occur with the likes of face-to-face interviewing and are in line with the method of the prior studies being replicated (Nancarrow et al. 2001; Vaughan et al. 2021).

The respondents were recruited from Australian external panel provider Humaniti's database and recruited based on a nationally representative of the Australian population, with non-category users being screened out (see Tables 5, 6, 7, and 8). Humaniti is an Australian-based personal finance and budgeting app, powered by Fonto. Using a permission-based service, they have over 125,000 members, with more than 40,000 linked bank accounts – these linked accounts allow for access to non-identifiable transactional data. No respondents were able to be identified in the data and all were compensated for their time by Humaniti.
Survey programming took approximately two weeks to complete for all categories,

with data collection taking place in November and December 2022. The tables below (Tables 5, 6, 7, and 8) show the category screeners, which were randomised for each respondent (not shown here for demonstration purposes). Respondents were terminated if the category screener was not selected.

Table 5: Category screener for financial services category.

Question	Responses	Programming Instructions
Which, if any, of the following financial products do you currently hold? *Select as many responses as relevant*	Savings account	Continue
	Debit card	
	Personal loan	Terminate respondent
	Refinanced a personal loan	
	Credit card	
	Home loan/mortgage	
	Business account	
	None of these	

Table 6: Category screener for on-demand streaming category.

Question	Responses	Programming Instructions
Which, if any, of the following subscription-based services do you currently have? *Select as many responses as relevant*	On-demand streaming services (i.e., Netflix, Disney+)	Continue
	Food delivery (i.e., Uber Pass)	Terminate respondent
	Magazine or newspaper subscription	
	Music streaming service (i.e., Spotify, Apple Music)	
	Cloud-based storage (i.e., iCloud, Google)	
	None of these	

Table 7: Category screener for chocolate category.

Question	Responses	Programming Instructions
Which, if any, of the following have you bought in the last 3 months? *Select as many responses as relevant*	Chocolate	Continue
	Lollies/sweets	Terminate respondent
	Potato chips	
	Sweet biscuits	
	None of these	

Table 8: Category screener for coffee category.

Question	Responses	Programming Instructions
Which, if any, of the following have you bought in the last 3 months? *Select as many responses as relevant*	Coffee	Continue
	Tea	Terminate respondent
	Soft drinks	
	Juice	
	Energy drinks	
	Water (Still or sparkling)	
	None of these	

A total of 3,232 respondents were recruited as part of the main sample (806 for the financial services category, 800 for the on-demand streaming category, 822 for the chocolate category, and 804 for the coffee category), with respondents exclusive to each category. For further information on the consumer dataset, please see section 4.4.5.2. The total number of respondents collected for the control group was 221 (56 for financial services, on-demand streaming, and chocolate, with 53 recruited for coffee).

4.4.5.1 Control Group

The purpose of the control group was to collect responses for a group of respondents who did not see the target brand's advertisement. For example, if in the financial services category – they would not see a banking advertisement. Rather, in Wave 2 these respondents were exposed to an advertisement for another unrelated category, with the distractor video, distractor ad, and content of the survey remaining the same as that of the main sample of ~800 respondents. In Wave 1, the survey provided to the control group was the same as for the main sample. The advertisements shown to the control group for each category are detailed in Table 9. The analysis of the data (detailed in Chapter 5) for the control group was conducted in the same way as that of the main sample.

Table 9: Advertisements shown to control groups for each category.

Category	Category Advertisement Shown
Financial Services	Chocolate
On-Demand Streaming	Coffee
Chocolate	Financial Services
Coffee	On-Demand Streaming

4.4.5.2 Data Cleaning

Prior to conducting the analysis, the datasets were cleaned for respondents that may affect the quality of data. All four categories across both the main sample and control groups were cleaned using the same criteria. The following outlines the data cleaning considerations:

- Firstly, the completion time for both Waves 1 and 2 were checked. Those who took ~1 minute or more than 5 days to complete Wave 1, or ~4 minutes to complete Wave 2 (based on the runtime of the distractor video) were flagged. Those who had a completion time of 0 minutes in either wave was automatically removed.
- Next, the total number of 'Don't know' responses for Wave 1 and Wave 2 were checked for the question relating to brand associations. That is, those who said they did not link any brands to a CEP, were flagged where 'Don't know' was selected for all CEPs, or the vast majority of CEPs. The difference in the number of "Don't know" from Wave 1 to Wave 2 was also examined to identify potential respondent fatigue. For example, if someone only selected 'Don't Know' once or twice in Wave 1, but then selected it 12 times in Wave 2, it suggests possible fatigue and familiarity with the survey. Across the four categories there were between 16 and 24 CEPs, and the decision was made to flag respondents for removal where the difference between the two waves of data collection was more than -10 CEPs (Wave 1 less Wave 2).

- The brand usage variable was the next data quality check and was used in combination with the prior data quality checks. This step looked for respondents who claimed to not be currently using any brand from the category, who also had questionable completion times and/or number of 'Don't Know' responses.
- The final data check was among the verbatim responses. All written, verbatim responses were also checked with the other criteria – those who did not answer the question appropriately (i.e., answering with a jumble of letters or repeating the same response for all questions) were automatically removed.

As an additional check for the on-demand streaming category, a fake brand was added. The purpose was to check the number of respondents who said they have a current account with this brand, and/or associations with the fake brand. Of the total respondents, three reported that they were current users of the fake brand. As their interview times, CEP responses, and verbatim responses were not flagged by the author or other researchers, these respondents were kept in the final data set. The fake brand was also kept in the analysis, as the proportion of responses was very small, and did not appear to pose any risks to overall data quality.

The researcher was assisted by a research supervisor to review the flagged respondents before removal from the final datasets. Working on a case-by-case basis for each respondent within each category, the criteria were applied to narrow down which respondents to remove. The total number of respondents before and after removal, along with a description of the consumer dataset, can be found in Table 10.

Table 10: Description of the consumer dataset.

Category	Recruitment Criteria	N of respondents before removal (Main sample W1 & W2)	N of respondents after removal (Main sample W1 & W2)	N of respondents before removal (Control)	N of respondents after removal (Control)	N of attributes	N of brands	Date of collection
Financial Services	Current savings account or debit card	806	792	56	55	18	15	November/ December 2022
On-Demand Streaming	Current on-demand streaming subscription	800	791	56	55	21	11	
Chocolate	Purchased from the category in the past 3 months	822	813	56	55	23	12	
Coffee	Purchased from the category in the past 3 months	804	798	53	52	16	9	
	Total	**3, 232**	**3, 193**	**221**	**217**	**79**	**44**	

4.5 Chapter Summary

This chapter discussed the need for replications and extensions in marketing science, critiques the methodological limitations of the study being replicated and extended, and the addresses how the prior methodological limitations will be addressed in this research.

The research design was outlined, and how the independent and dependent variables will be operationalised to answer the five RQs was explained, in addition to how the survey was compiled and data collected. The process of data cleaning, to prepare for data analysis was also covered.

CHAPTER FIVE

Data Analysis

This chapter details the overall data preparation process prior to data analysis, and the preparation of the data prior to calculating the MA Metrics to answer the five RQs. A hypothetical example is provided to illustrate how the calculations of the MA Metrics are made.

5.1 Purpose

In order to answer the research questions, the data collected had to be prepared in order to analyse and calculate the MA Metrics. This process included selecting brand attributes that represented distinctly different concepts within consumer memory, and classifying brand users/non-users, as well as those aware/not aware of the brand advertising.

5.2 Selection of Brand Attributes

Prior to running analysis, the brand attribute lists for each category needed to be examined for duplication of concepts, and to identify any attributes to be removed that represent similar ideas or concepts as another (Romaniuk 2013). For example, attributes that represented similar concepts in the chocolate category were "*To say thank you*" and "*A fail-safe gift."* As these attributes represent the same idea in consumer memory, they were removed from the final set of CEPs analysed.

As recommended by Romaniuk (2013), and following the same analysis conducted by Vaughan et al. (2021) and Vaughan (2016), non-parametric correlations on the binary brand attributes was run. Removing correlated attributes reduces the cognitive load for brand non-users, as well as more accurately capturing evaluations than links between the brand and attributes (Romaniuk 2013). Only one correlation with a value of <0.2 was found in the Chocolate dataset. Upon discussion with all research supervisors, this attribute was kept in the competitive set as it was not deemed a risk to data quality or further analysis given the small correlation.

5.3 Classifying Brand Users and Non-Users

To classify respondents as brand users or non-users to answer RQ1c and RQ3, a self-reported usage measure was used. Two time periods were used, to prevent telescoping (further detail on telescoping in Chapter 4, section 4.2.1.1).

For the two service categories, respondents were asked which brands '*ever held an account with/ever held a subscription with*', which was followed by asking which of the brand they currently have an account or subscription with. Respondents surveyed for the repertoire categories were asked which of the following brands they had purchased in the last three months, followed by which they had bought in the last month. The respondents were coded as either users or non-users of the target brand based on the most recent time frame. Table 11 below shows the number of brand users and non-users for each of the four categories.

Table 11: Number of brand users and non-users per category.

Brand Users		Brand Non-Users	
Financial services category	n= 149	Financial services category	n= 643
On-demand streaming category	n= 265	On-demand streaming category	n= 526
Chocolate category	n= 128	Chocolate category	n= 685
Coffee category	n= 127	Coffee category	n= 671

5.4 Classifying Sub-Groups

5.4.1 RQ2: Increase, Stable, Decline

As a component of RQ2, the Mental Market Share (MMS) and the Number of Associations (NOA) for individuals were examined, in addition to determining the proportion of individuals who increase, decrease, or have stable metrics across these two measures.

Mental Market Share (MMS)

For MMS, which is the share of associations for a brand as a percentage of total associations for the category, the difference in MMS for Wave 2 was subtracted from the Wave 1 scores for all individuals. To the best of the author's knowledge, there is no existing evidence that compares the MA Metrics over time at the individual level. As such, the cut-offs listed below provide the best possible benchmark of what to expect post-advertising. Drawn data from Vaughan et al. (2021) and Vaughan (2016) where MMS was found to increase (on average) by +5 percentage points after advertising exposure, the following classifications were used to categorise each individual respondent into one of the three sub-groups.

- *Increase*: Change in MMS (W2-W1) by +5 percentage points.
- *Stable:* MMS difference (W2-W1) of +/-5 percentage points.
- *Decrease:* Change in MMS (W2-W1) of -5 percentage points.

Number of Associations (NOA)

For the number of associations (NOA), this measure was the number of associations held an individual for the target brand in Wave 1 or Wave 2. The same, difference variable was created where the NOA for Wave 2 was subtracted from Wave 1.

As this was not a share metric, and simply a count of associations, the classifications of these sub-groups differed from that of MMS. It was deemed appropriate that the cut-offs were based on the actual number of associations growing or declining, rather than using another measure such as standard deviations. This was due to the advertisement respondents were exposed to having at least one CEP present – which could then be inferred that if this attribute was new to the respondent and processed in memory, that their NOA would increase by one. Therefore, the following classifications were used to classify each individual into a sub-group for the NOA measure:

- *Increase*: Change in NOA (W2-W1) by +1 association.
- *Stable:* NOA difference (W2-W1) of 0 associations.
- *Decrease:* Change in NOA (W2-W1) of -1 associations.

5.4.2 RQ3: Advertising Recognition

To answer RQ3, where the purpose is to understand the suitability of using a recognition measure to capture advertising exposure, the brand user and non-user consumer groups were further divided into three sub-groups:

- Recognised And Correct Brand – Respondents who recognised and correctly identified the target brand from the advertisement,
- Recognised Not Correct Brand – Respondents who recognised but did not correctly identify the target brand in the advertisement,
- Not Recognised – Respondents who did not recognise the target brand's advertisement.

Firstly, respondents who, when asked the open-ended question "*Below are some images from a video advertisement. Do you recall seeing this video ad recently?*", were provided with three options of: Yes, no, or unsure, and provided with three masked stills from the advertisement (see: Appendix C). This variable was manually coded

(using '1' for answered 'yes' or 'unsure,' and '0' for those who answered 'no'), to place respondents into the 'Not Recog' sub-group (if given a '0').

Secondly, for those who answered 'yes' or 'unsure' on the advertising recognition question, their verbatim responses for the open-ended question "*Which brand was the advertisement for?*" was manually coded into a new variable. Correct brand identification was given a '1', and incorrect branding was coded as '0'. Misspellings of the brand name, such as (hypothetically) "disbney" for "Disney+", as well as long verbatim responses like "I think this ad is for Disney" were all coded as correctly branded. Those who received a '1' value for correct branding, and a '1' value for recognition were placed into the sub-group 'Recognised And Correct Brand'.

Finally, those who received a '1' value for advertising recognition, but a '0' for correctly identifying the brand the advertisement was for, were placed in the final sub-group of 'Recognised Not Correct Brand.'

5.5 Calculating the MA Metrics

All four MA Metrics were calculated for all brands in each category of this research, so that the share metrics (Mental Market Share and Share of Mind) could be calculated as the total number of category associations is needed. The following section details how the MA Metrics were calculated, and how the results are to be interpreted.

Mental Market Share

Mental Market Share (MMS) captures how competitive a brand is in the context of the whole retrieval network. It's the brand's share of associations, of all associations from the category (Romaniuk 2013). To calculate MMS, the total number of associations for a brand is divided by the total number of category associations, and then multiplied by 100 to convert the number into a percentage.

How MMS is calculated can be illustrated with a hypothetical data set with 15 attributes and 20 brands, with a sample of 500 buyers. If Brand X received 1000 associations, of a total of 5000 associations for the category., Brand X's MMS would be 20% ((1000 / 5000) * 100 = 20%).

Associative Penetration

Associative Penetration (Ab) provides the proportion of buyers in the category who have a chance of retrieving a given brand from memory (Romaniuk 2013). The calculation of Ab draws on the sample of buyers who have at least one association in memory with the brand – the number of consumers with an association is divided by the total sample and multiplied by 100 to convert the Ab score to a percentage.

Building on the previous example, of the total sample of 500 respondents, 250 could have an association with Brand X, making Ab 50% ((250 / 500) * 100) = 50%). This means that 50% of buyers have a chance of Brand X coming to mind in a buying situation.

Association Rate

Association Rate (Aw) uses the proportion of buyers who have an association with a brand (Associative Penetration), to understand the average number of retrieval paths in memory (Romaniuk 2013).

To continue with the example, this is calculated using the 50% of buyers who have a chance of Brand X coming to mind (n=250). The total number of associations for Brand X is divided by the 250 consumers to provide Aw score. Therefore, 1000 associations for Brand X are divided by 250, to provide an Aw score of 4 (1000 / 250 = 4). So, of the 50% of buyers with a chance for Brand X to come to mind, there are an average of 4 opportunities for the brand attributes to be retrieved.

Share of Mind

Share of Mind (SoM) is the brand's share of associations within the category, from those who have at least one association with the brand (Romaniuk 2013). Where SoM differs from MMS is the base it is calculated from – MMS uses the total sample, while SoM uses only those who have at least one association (Associative penetration).

To calculate SoM for Brand X, 1000 brand associations is divided by the total of category associations held by the 250 buyers. If there are 3000 associations for 250 buyers, the SoM for Brand X would be 33.3% ((1000 / 3000) *100 = 33.3%).

5.6 Goodness of Fit: NBD-Dirichlet

Following from the calculations of the MA Metrics, it was necessary to ensure that the brand attributes used within the research were appropriate and could give sound insight into the expected MA Metrics of each of the brands within the four competitive sets. To calculate these expected values, the NBD-Dirichlet model was used in line with the original study being replicated (Vaughan et al. 2021) and the use of MA Metrics by Romaniuk (2013).

The NBD-Dirichlet (Goodhardt et al. 1984) is a stochastic mathematical model, typically used to benchmark brand sales metrics, with wide use across varying markets around the world (Driesener et al. 2017; Ehrenberg et al. 2004). Romaniuk (2013) and Vaughan et al. (2021) established the use of the NBD-Dirichlet model for providing predictive benchmarks for a brand's Associative Penetration (Ab) and Association Rate (Aw), relative to that of the category through using the rest of the generated MA Metrics. Table 12 highlights the similarities of the MA Metrics to the widely used brand sales metrics. The MA Metrics work similarly to that of the brand sales metrics, due to their binary nature – a consumer can buy a brand or not within a given time

period, much as they can have an association with a brand or not (Romaniuk 2013; Vaughan et al. 2021).

Table 12: Comparison of Mental Availability Metrics with brand sales metrics.

MA Metrics		Brand Sales Metrics	
MMS	The brand's share of associations from all category associations.	Market Share	The brand's share of sales from total category sales.
Ab	The percentage of consumers who have at least one association linked to the brand, of all respondents.	Buyer Penetration	The percentage of consumers who bought the brand at least once.
Aw	The average number of associations, given by those who have at least one association with the brand.	Buy Rate	The average number of times the brand is bought buy the customer base.
SoM	The share of associations for the brand, from consumers who have at least one association with the brand.	Share of Category Requirements	The brand's share of purchases from the customer base.

To use the model, the Ab and Aw metrics are used, and theoretical model estimates generated through the NBD-Dirichlet separately for Wave 1 and Wave 2 (for each category). To assess the fit of the model, as suggested by Ehrenberg et al. (2004) and demonstrated by Romaniuk (2013) and Vaughan et al. (2021), the correlations between the theoretical and observed metrics is examined, in addition to the mean absolute deviations (MAD). Without a single goodness-of-fit statistic provided by the NBD-Dirichlet, correlations greater than 0.70 and low MADs (<0.1~) suggest a good fit (Romaniuk 2013; Vaughan et al. 2021).

Shown in Table 13 are the NBD-Dirichlet goodness-of-fit indicators of for all categories, across both waves of data collection. All correlations for the Ab and Aw metrics fit the model. The MADs for the on-demand streaming category for the Ab metric are the only two that are higher than expected. However, the NBD-Dirichlet

assumes market stationarity, which does not apply for this category where there is consistent growth. As such, all brands for this category were included in analysis.

Table 13: NBD-Dirichlet goodness-of-fit for all categories in Waves 1 and 2.

Category	Wave	Correlations		MADs	
		Ab	Aw	Ab	Aw
Financial Services	1	0.98	0.97	0.05	0.05
	2	0.99	0.97	0.04	0.05
On-Demand Streaming	1	0.97	0.97	0.14	0.11
	2	0.96	0.96	0.12	0.10
Chocolate	1	0.82	0.97	0.04	0.04
	2	0.75	0.96	0.05	0.05
Coffee	1	1.0	1.0	0.02	0.02
	2	1.0	0.98	0.03	0.04

5.7 Chapter Summary

This chapter outlines the process of data analysis uses to generate different consumer groups and ad awareness sub-groups, how the four MA Metrics are calculated, as well as explaining the use of the NBD-Dirichlet model for assessing goodness-of-fit.

CHAPTER SIX

Results

Chapter Six reports the results for the five research questions.

To answer RQ1a and RQ1b, the tables detail the four MA Metrics for the target brands of all categories, with differences documented across both waves. Summary tables of the results for this study, as well as for Vaughan (2016) are provided for comparison. The results for the target brand in the control groups for each category are also discussed, with the tables available in Appendix E.

The results for RQ1c are presented in four tables, comparing brand user and non-user consumer groups of the target brands. A summary of results for Vaughan (2016) are again shown for comparison.

RQ2's results are presented separately for MMS and NOA at the individual level for the target brands, displayed in two tables each. For both measures, the tables detail the proportion of category users in each sub-group (Increase, Stable, and Decline) and the average difference for these measures.

Three tables of results are presented for RQ3. These show the proportion of brand users and non-users that were classified for each sub-group (Recognised And Correct Brand, Recognised Not Correct Brand, and Not Recognised). This is followed by a table with the average difference in MMS and then NOA for individuals within these sub-groups.

6.1 RQ1a Results

RQ1a: *Are Mental Availability Metrics responsive to brand advertising?*

To test RQ1a, all four MA Metrics were calculated at the aggregate level for each target brand. This was done across both Wave 1 (pre-advertising exposure) and Wave 2 (post-advertising exposure), with the difference between the two waves calculated (see Table 14 for main sample results). The figures are ordered by size from largest MMS (%) score in Wave 2 to the lowest.

The MA Metrics for all brands across the main sample can be viewed in Appendix E and the results for the control group can be found in Appendix F.

Table 14: Brand level MA Metrics in Wave 1 and Wave 2 for the main sample.

	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Coffee brand (n= 798)	15.9	20.0	*4.1*	69.4	77.6	*8.1**	4.0	4.5	*0.5*	22.5	26.8	*4.3*
On-demand streaming brand (n= 791)	13.7	14.4	*0.7*	75.0	79.4	*4.4**	8.5	8.4	*-0.1*	17.1	17.7	*0.6*
Financial services brand (n= 792)	10.6	12.0	*1.3*	66.9	72.1	*5.2**	6.4	6.9	*0.5*	16.1	19.8	*3.7*
Chocolate brand (n= 813)	10.0	11.5	*1.4*	88.2	86.6	*-0.9*	6.8	7.5	*0.6*	11.8	14.0	*2.1*
Average	12.6	14.5	*1.9*	74.9	78.9	*4.2*	6.4	6.9	*0.4*	16.9	19.6	*2.7*

**p<0.05*

Examining the results in Table 14 there is largely positive movement (i.e., the MA Metrics increase) for all metrics at the average category level. For Mental Market Share (MMS), all four target brands see positive change, with average MMS increasing after exposure to advertising. For Associative Penetration (Ab), three of four target brands saw the percentage of respondents who gave one association have a positive increase. The Association Rate (Aw) metric also increased for three of four target brands, post-advertising exposure, with the remaining target brand essentially stable. Finally, the Share of Mind (SoM) metric saw an increase across all four target brands, after exposure to brand advertising.

This shows that the four MA Metrics are responsive to advertising, with 14 out of 16 observations increasing for the four target brands post-advertising exposure. With some changes being close to zero (i.e., -0.1 pp change on average in Aw), it does suggest the presence of ceiling effects – with target brands that have a higher metrics in Wave 1, there is little movement in their metrics in Wave 2. Such as for the Chocolate brand, where the Ab metric in Wave 1 is 88.2% and sees a decline of -0.9 percentage points, however it is the target brand with the largest Ab prior to advertising exposure. Noting that the Ab metric does appear to be (at the aggregate level) the most responsive, the largest movement from Wave 1 to Wave 2 post-advertising (average category increase of 4.2pp) is seen here.

6.2 RQ1b Results

> **RQ1b:** *How do Mental Availability Metrics move in response to brand advertising at the aggregate level?*

To answer RQ1b, the results presented in Table 14 are again drawn upon, with the focus here on the average actual and percentage difference scores for the main sample in Table 15, and summary of results from Vaughan (2016) in Table 16.

As outlined in Chapter 3, section 3.1, RQ1b is divided into four sub-questions to further examine the effect of the target brand's advertising on each of the four MA Metrics:

> **RQ1b.1:** *How does a brand's Mental Market Share (MMS) metric change with a recent advertising exposure?*
> **RQ1b.2:** *How does a brand's Associative Penetration (Ab) metric change with a recent advertising exposure?*
> **RQ1b.3:** *How does a brand's Association Rate (Aw) metric change with a recent advertising exposure?*
> **RQ1b.4:** *How does a brand's Share of Mind (SoM) metric change with a recent advertising exposure?*

6.2.1 Brand Level Change

On average, the MA Metrics move in a positive direction from Wave 1 to Wave 2 for the main sample (see Table 14). Examining the average scores for the target brands, all four MA Metrics increased after exposure to advertising – MMS (1.9pp increase), Ab (4.2pp increase, three of four observations were statistically significant $p<0.05$), Aw (0.4 increase), and SoM (2.7pp increase).

Specifically, 14 of the 16 individual metrics across the four target brands, moved in a positive direction following exposure to advertising. The two observations that did not follow this trend were the Ab metric for the advertised chocolate brand and the Aw metric for the on-demand streaming brand, however, the size of the negative change was small for this metric (less than 1pp). In both instances, the scores in Wave 1 were notably higher than for the other target brands, suggesting a ceiling effect may be present for these two observations.

6.2.1.1 Control Group

Comparing to the control group (Appendix F), which was not exposed to the target brand's advertising, on average, two of the four MA Metrics (MMS and Ab) moved in a negative direction – MMS (-1.2pp decrease), Ab (-3.6pp decrease). While the other two metrics remained largely stable - Aw (0.1 increase) and SoM (0.1pp increase) (see Appendix F).

For the control group: only 4 of the 16 target brand observations moved in a positive direction; all target brands' MMS decreased in Wave 2, with the magnitude of change in this metric being between -0.1 to -3.2 percentage points; and the Ab, Aw, and SoM metrics had only two of the four target brands tested move in a positive direction. It suggests that there is no clear patterns or direction of change without the intervention of advertising, as seen when comparing with the main sample.

6.2.2 Average Differences in Scores

To further examine the changes in the MA Metrics (for the main sample), as well as to answer the sub-questions for RQ1b, Table 15 below provides the average actual difference of the four target brand-level observations as well as the percentage difference, between Wave 1 and Wave 2. Following this, Table 16 details the results from Vaughan (2016) for comparison. Table 53 in Appendix F displays these same results for the control group.

The results in Table 15 show advertising exposure in Wave 2 has affected all MA Metrics at the aggregate level for the target brands - all four metrics moved in a positive direction (on average). The results of this study show a similar pattern to Vaughan (2016). However, this study has greater average increases (actual and percentage difference), and more consistent positive change across the observations (14 out of 16 (88%) versus 25 out of 40 (63%)).

Table 15: Average actual and percentage difference in MA Metrics across brand level results for the main sample.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
# of observations with positive change	4 of 4	3 of 4	3 of 4	4 of 4
Average actual difference	1.9	4.2	0.4	2.7
Average percentage difference (%)	13.1	5.4	5.8	13.6

Table 16: Average actual and percentage difference in MA Metrics for Vaughan (2016).

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
# of observations with positive change	8 of 10	4 of 10	5 of 10	8 of 10
Average actual difference	0.6	-0.4	0.1	0.8
Average percentage difference (%)	4.5	-1.2	2.0	4.9

The following section examines the changes in the four MA metrics in more detail across the four sub-questions (RQ1b.1, RQ1b.2, RQ1b.3, and RQ1b.4), for both the main sample, Vaughan's (2016) study, as well as the control group[1].

RQ1b.1 Mental Market Share (MMS)

- This study finds an increase in MMS for the target brands following advertising exposure is 1.9 percentage points on average.
- MMS for the target brands in Vaughan (2016) increased by 0.6 percentage points post-advertising exposure (on average).
- While examining the actual percentage point difference, the magnitude of change ranges from 0.7 to 4.1 percentage points across the four target brands (as show in Table 14). All changes in MMS are in a positive direction, whereas for Vaughan (2016), eight of the ten observations of the MMS metric moved in a positive direction.
- On average, advertised brands experienced a 13.1% increase in the share of brand associations following advertising exposure. This compares to an average increase of 4.5% for Vaughan (2016).

Control group:

- The average change is -1.2 percentage points for the target brands, with the range of actual difference in scores for MMS between -0.1 to -3.2 percentage points with all observations moving in a negative direction (see Appendix F).
- The share of brand associations decreases by -9.6% on average.

The following three metrics, Associative Penetration, Association Rate, and Share of Mind are all based on the smaller base of respondents who gave at least one association with the target brand. This is taken from the Associative Penetration metric.

[1] Noting comparison to Vaughan (2016) is only available for the main sample of this study, as Vaughan (2016) did not include a control group.

RQ1b.2 Associative Penetration (Ab)

- The average actual difference is 4.2 percentage points for the target brands post-advertising, with Ab in Vaughan's (2016) study decreasing at the aggregate level by -0.4 percentage points (on average).
- There is some variation in the actual difference in the scores across Wave 1 and Wave 2 for Ab. The differences range from -0.9 to 8.1 percentage points. Three of the four observations are in the positive direction. For Vaughan (2016), four of the ten observations had positive change in the Ab metric.
- On average, 5.4% more consumers gave at least one association for the target brands following advertising exposure, this compares to Vaughan (2016) who saw Ab decrease, on average, by -1.2%.

Control group:

- The Ab metric decreased by -3.6 percentage points, or -4.9% for the target brands (see Appendix F).
- Two of the four observations for the control group moved in the positive direction, with actual differences between -10.9 to 1.8 percentage points.

RQ1b.3 Association Rate (Aw)

- The average actual difference in the Aw metric for the target brands shows that there is a 0.4 increase in associations, which compares to Vaughan's (2016) increase on average of 0.1 for the Aw metric.
- Three of the four observations are in the positive direction, with the range of observation within the range of -0.1 to 0.6. For Vaughan (2016), of the ten observations, half moved in a positive direction for the Aw metric.
- There was a 5.8% increase in the average number of associations made for the target brand (by those who have at least one association) following advertising exposure. While Vaughan (2016) found the Aw metric to increase by 2.0%.

Control group:

- Two of the four target brand level observations moved in the positive direction, the range of actual difference being -0.6 through to 0.8.
- The Aw metric increased by 2.1% or 0.1 associations for the target brands in Wave 2 (see Appendix F).

RQ1b.4 Share of Mind (SoM)

- SoM across all four observations for the target brands had an average actual difference of 2.7 percentage points. For Vaughan (2016), SoM increased by 0.8 percentage points.
- Of the four observations for the target brands, which ranged from 0.6 to 4.3 percentage points, all moved in a positive direction. Eight of the ten observations made for the target brands in Vaughan (2016) moved in a positive direction for SoM.
- Advertised brands experienced a 13.6% increase in the share of associations (on average) among those who gave at least one association. Vaughan's (2016) study reported a SoM increase of 4.9% on average.

Control group:

- The average actual difference for the target brands SoM was 0.1 percentage points (see Appendix F).
- Two of the four observations for the control group moved in a positive direction – actual difference in scores was between -1.6 to 2.4 percentage points.
- While among the target brands in the control group, there was an average increase in the SoM metric of 0.3%.

6.2.3 Brand level results summary

At the aggregate level for the main sample, the results for RQ1a and RQ1b show mental availability increases following exposure to advertising. On average, all four MA Metrics (MMS, Ab, Aw, and SoM) moved in a positive direction for the target advertised brands across the four categories, with 14 of the 16 brand level observations increasing.

This study showed a broadly consistent pattern of results to Vaughan (2016), which reported a positive change in three of the four metrics – MMS, Aw, and SoM. The Ab metric did not show positive change on average, which Vaughan (2016) suggests is brands not building new associations among the base of consumers who already had an association.

When exploring the brand level results for the control group, who did not see advertising for target brand, on average only the Aw and SoM metrics moved in a positive direction in Wave 2. The magnitude of change was also less than that of the main sample for both Aw (0.4 pp change for the main sample vs 0.1 pp change for the control) and SoM (2.7 pp change for the main sample vs 0.1 pp change for the control).

6.3 RQ1c Results

> **RQ1c:** *How do Mental Availability Metrics move in response to advertising for different consumer groups?*

RQ1c sought to examine the differences in MA Metrics for the target brands' users and non-users from Wave 1 (pre-advertising exposure) to Wave 2 (post-advertising exposure). Here the results are reported separately for users and non-users, with the tables showing actual scores for Wave 1 and 2, ordered by the largest to smallest MMS (%) score in Wave 2. The results are first presented at brand level for users, and then non-users. Following this, the average actual and percentage differences are examined across the two consumer groups and compared to Vaughan (2016).

As with RQ1b, RQ1c is split into four sub-questions to better explore the changes across all four metrics for the target brands' user and non-user groups:

> **RQ1c.1:** *How does a brand's Mental Market Share (MMS) metric change with a recent advertising exposure for different consumer groups?*
> **RQ1c.2:** *How does a brand's Associative Penetration (Ab) metric change with a recent advertising exposure for different consumer groups?*
> **RQ1c.3:** *How does a brand's Association Rate (Aw) metric change with a recent advertising exposure for different consumer groups?*
> **RQ1c.4:** *How does a brand's Share of Mind (SoM) metric change with a recent advertising exposure for different consumer groups?*

6.3.1 Brand Level Change Across Brand Users

The results for the brand users (of the target brands) are presented in Table 17 across all four categories for this study, where there is minimal movement across the MA Metrics. Looking at the averages across the four MA Metrics for brand users, SoM had the biggest increase of 1.7 percentage points while the next biggest increase for MMS was only 0.5 percentage points. The Ab and Aw metrics both decreased slightly after exposure to advertising (-0.6 and -0.1 respectively).

The actual difference in the MA Metrics for the target brands' user showed some consistency in the direction of change, with 10 of 16 observations moving in a positive direction. For the Associative Penetration metric, all four observations moved in a negative direction – suggesting that there may be a ceiling effect among brand users.

Table 17: Brand level MA Metrics in Wave 1 and Wave 2 for brand users.

	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Coffee brand: Users (n= 127)	27.2	27.8	*0.6*	95.3	94.5	*-0.8*	5.7	5.8	*0.2*	34.8	36.2	*1.4*
On-demand streaming brand: Users (n= 265)	19.7	19.8	*0.1*	97.4	96.2	*-1.1*	11.5	10.7	*-0.8*	22.3	22.5	*0.2*
Financial services brand: Users (n= 149)	19.4	19.1	*-0.4*	89.9	91.9	*2.0*	9.7	9.4	*-0.3*	31.0	33.7	*2.7*
Chocolate brand: Users (n= 128)	13.4	15.0	*1.7*	96.9	94.1	*-2.3*	8.9	9.5	*0.6*	16.0	18.5	*2.6*
Average	20.0	20.4	*0.5*	94.9	94.2	*-0.6*	9.0	8.9	*-0.1*	26.0	27.7	*1.7*

*$p<0.05$

6.3.2 Average Differences in Scores for Brand Users

Looking at Table 18 and Table 19 below, the magnitude of change in the MA Metrics for the target brands' users (at the average actual difference level) is greater for the current study for MMS (0.5pp vs 0.1pp), Aw (-0.1 vs 0.0), and SoM (1.7pp vs 0.4pp). Whereas a greater change in the Ab metric occurred in Vaughan (2016), however, this was in a negative direction. The results for each of the MA Metrics are explored in more detail below.

Table 18: Average actual and percentage difference in MA Metrics for this study, across brand users.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
# of observations with positive change	3 of 4	1 of 4	2 of 4	4 of 4
Average actual difference	0.5	-0.6	-0.1	1.7
Average percentage difference (%)	2.3	-0.7	-1.1	6.1

Table 19: Average actual and percentage difference in MA Metrics for Vaughan (2016) across brand users.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
# of observations with positive change	4 of 10	1 of 10	5 of 10	6 of 10
Average actual difference	0.1	-2.9	0.0	0.4
Average percentage difference (%)	3.8	-3.7	0.9	5.1

RQ1c.1 Mental Market Share (MMS)

- On average across the user group for the advertised target brands, Mental Market Share increased by 0.5 percentage points. The results for Vaughan (2016) showed a 0.1 percentage point change.
- The brand user scores for MMS ranged from -0.4 through to 1.7 percentage points, with three of the four observations moving in a positive direction. For Vaughan (2016) only four of the ten observations for brand users were in a positive direction for MMS.
- For the user group, the target brands (on average) experienced a 2.3% increase in the share of associations for the category after advertising exposure. This compares to a 3.8% for the previous study.

Control group:

- The range of scores for change in MMS was -5.4 to 1.1 percentage points (see Appendix F).
- Of the four observations for brand user control group, two moved in a positive direction from Wave 1 to Wave 2.

This following section discusses and compares the results of the other three metrics, as all calculations came from the same base of respondents generated from the Ab metric (those who gave at least one association).

RQ1c.2 Associative Penetration (Ab)

- The actual and percentage difference for Associative Penetration for the target brands' user group moved in a negative direction. Ab decreased by an average of -0.6 percentage points following advertising exposure. Vaughan's (2016) results show an average -2.9 percentage point decrease for the user group.
- Three of the four observations for the Ab metric were in a negative direction for the target brands' users in this study. For Vaughan (2016), one of the ten observations were in the positive direction.

- The percentage point difference of observed scores ranged from -2.3 to 2.0.
- On average the advertised brands experienced a -0.7% decrease in the amount of brand users who gave at least one association with the brand, after being exposed to the brand's advertising. While there was a larger decrease of -3.7% for Vaughan (2016) for brand users who gave one association.

Control group:

- The magnitude of change for the target brands' users in the control group was between -16.7 and 11.1 percentage points for the Ab metric (see Appendix F).
- Two of the four observations made were in a positive direction among brand users in the control group.

RQ1c.3 Association Rate (Aw)

- The actual difference scores for Association Rate, showed on average a -0.1 decrease among brand users of the target brands.
- The average actual difference for Aw in the previous study by Vaughan (2016) was 0.0 for brand users.
- Half of the observations for Association Rate moved in a positive direction, with the range of scores being at -0.8 at the lowest and 0.6 at the highest.
- On average, the number of associations given (by those who had at least one association) was found to decrease by 1.1% in this research amongst the target brands' users, and increase by 0.9% in Vaughan (2016).

Control group:

- The average difference in the Aw metric from Wave 1 to Wave 2 for the target brands users was between -0.8 and 1.1 for the control group (see Appendix F).
- Only one of the four observations were in a positive direction.

RQ1c.4 Share of Mind (SoM)

- Share of Mind moved in a positive direction on average among brand users of the target brands, with the average actual difference of 1.7 from Wave 1 to Wave 2. In Vaughan's (2016) study users (on average) experienced a 0.4 percentage points increase.
- All four observations moved in a positive direction, the only MA Metric for the target brands' user group to do this in this study. The scores ranged from 0.2 to 2.7 percentage points after advertising exposure. In contrast with Vaughan (2016), where SoM moved in a positive direction across six of the ten observations.
- Of the base of users who gave at least one association to the target brand, the brand received an average increase of 6.1% of the share of associations from the category, while SoM increased by 5.1% in Vaughan et al. (2021) and Vaughan (2016).

Control group:

- The control group saw scores for SoM range from -7.6 through to 4.0 for the brand users of the target brand (see Appendix F).
- One of the four observations for the control group moved in a positive direction for brand users.

6.3.3 Brand Level Change Across Non-Users

The MA Metrics scores for brand non-users across Waves 1 and 2 are shown in Table 20 for the target brands. Data is ordered by MMS scores for Wave 2, from highest to lowest.

For the non-user group, the result show consistency across the metrics, with most observations close to the averages. By examining the averages, all four MA Metrics for the target brands increased following advertising for non-users – MMS (10.1 % for W1 vs 12.5% for W2), Ab (69.1% vs 74.5%, with three of four observations being statistically significant, $p<0.05$), Aw (5.4 vs 6.1), and SoM (13.6% vs 16.9%). Of the 16 observations for the brand non-user group (see: Table 20), 15 were in the positive direction. The Ab metric for the chocolate brand was the only metric to move in a negative direction, decreasing by -1.5 percentage points.

The results for brand non-users in the control group are displayed in Appendix F (Table 56). Eight of the 16 observations made across all brands were in the positive direction.

Table 20: Brand level MA Metrics in Wave 1 and Wave 2 for brand non-users.

	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Coffee brand: Non-Users (n= 671)	13.5	18.0	*4.6*	64.5	74.4*	*9.8*	3.6	4.2	*0.6*	19.1	24.6	*5.5*
On-demand streaming brand: Non-Users (n= 526)	9.6	11.2	*1.6*	63.7	70.9*	*7.2*	6.3	6.9	*0.6*	13.2	14.4	*1.3*
Chocolate brand: Non-Users (n= 685)	9.4	10.8	*1.4*	86.6	85.1	*-1.5*	6.3	7.1	*0.8*	10.9	13.0	*2.1*
Financial services brand: Non-Users (n= 643)	8.3	10.1	*1.9*	61.6	67.5*	*5.9*	5.3	6.2	*0.9*	11.1	15.4	*4.3*
Average	10.1	12.5	*2.4*	69.1	74.5	*5.4*	5.4	6.1	*0.7*	13.6	16.9	*3.3*

*p<0.05

6.3.4 Average Difference in Scores for Brand Non-Users

To further explore the change in the non-user group for the target brands, the subsequent section details the average actual difference and average percentage difference (figures for this study in Table 21 below, and Table 22 for Vaughan's (2016) study). Among the brand non-user group, the largest change in average actual difference and average percentage difference was found in the results of this study (Table 21) compared to Vaughan (2016) for the Ab metrics (5.4pp). All four MA Metrics increased (on average) after brand non-users were exposed to advertising for the target brands in this study. In contrast, the results for Vaughan (2016) show three of the four metrics, MMS, Aw, and SoM, had positive change on average, while Ab moved in a negative direction (Table 22).

In the control group, on average, two of the four metrics (Aw and SoM) increased among the target brands' non-users. The table with these results for the control group can be found in Appendix F. The section below examines the changes within the main sample in more detail.

Table 21: Average actual and percentage difference in MA Metrics for this study, across brand non-users.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
# of observations with positive change	4 of 4	3 of 4	4 of 4	4 of 4
Average actual difference	2.4	5.4	0.7	3.3
Average percentage difference (%)	19.2	7.2	11.9	19.4

Table 22: Average actual and percentage difference in MA Metrics for Vaughan (2016) across brand non-users.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
# of observations with positive change	9 of 10	5 of 10	7 of 10	9 of 10
Average actual difference	1.1	-0.5	0.1	1.5
Average percentage difference (%)	9.4	-0.7	3.5	11.0

RQ1c.1 Mental Market Share (MMS)

- The average actual difference across the target brands' non-user group for MMS is 2.4 percentage points. This compares to the average actual difference for MMS in Vaughan (2016) was 1.1 percentage points.
- Of the four observations for MMS, all moved in a positive direction, with the difference between the two waves ranging from 1.4 to 4.6 percentage points. Nine of the ten observations for Vaughan (2016) also moved in a positive direction.
- Following advertising exposure, the advertised brands experienced a 19.2% increase (on average) in their share of associations from brand non-users. While there was a 9.4% increase for this group in Vaughan's (2016) study.

Control group:

- For the target brands' non-users, scores ranged from -1.2 to 1.2 percentage points for MMS for the control group (see Appendix F).
- Three of the four observations made for this group moved in a positive direction.

The subsequent section below details the difference in Ab, Aw, and SoM for the target brands' non-users. These are discussed separately as they are calculated from the proportion of the sample who gave at least one association.

RQ1c.2 Associative Penetration (Ab)

- The average actual difference in the Ab metric is 5.4 percentage points. Compared to Vaughan (2016) who found among brand non-users, the Ab metric decreased by -0.5 percentage points on average.
- Of the four observations for all target brands, three moved in a positive direction. The magnitude of change for actual differences ranged from -1.5 to 9.8 percentage points. While Vaughan (2016) saw five of the ten observations move in a positive direction.
- After advertising exposure, there is a 7.2 % increase (on average) in the proportion of brand non-users able to make at least one association to the advertised brand in this study. Whereas the average difference was -0.7% for non-users in and Vaughan (2016).

Control group:

- Scores for the Aw metric were between -9.3 and 2.5 percentage points for the target brand's non-users, with one of the four observations moving a positive direction (see Appendix F).

RQ1c.3 Association Rate (Aw)

- The average actual difference for the Aw metric for target brands' non-users was 0.7 percentage points in this study.
- The actual differences for Aw ranged from 0.6 to 0.9 points, and all four observations moved in a positive direction. For Vaughan (2016), the average actual difference was 0.1, with seven of ten observations moving in the positive direction for brand non-users.
- On average, the number of associations given by those who had at least one association with a brand increased by 11.9% in this study for non-users. The average percentage difference for non-users in Vaughan's (2016) work was 3.5%.

Control group:

- The scores for Aw ranged between -1.2 and 1.5 for the target brands' non-users in the control group.
- Two of the four observations made were in a positive direction for the target brands' non-user group.

RQ1c.4 Share of Mind (SoM)

- The SoM metric had an average actual increase of 3.3. percentage points after brand non-users were exposed to advertising. The average actual difference for the SoM in Vaughan's (2016) work was 1.5 percentage points.
- With differences in scores ranging from 1.3 to 5.5 percentage points, the SoM metric moved in a positive direction for all brands non-users after advertising exposure. Nine of ten observations for non-users made by Vaughan (2016) were in the positive direction for the SoM metric.
- Of the brand non-users who had at least one association, the share of associations increased by 19.4% on average after this consumer group was exposed to advertising. The SoM metric also increased (on average) in Vaughan's (2016) work, by 11.0%.

Control group:

- SoM among the target brands' non-users ranged from -0.4 through to 3.4 percentage points in the control group.
- Two of the four observations made across the brands were in a positive direction.

6.3.5 User/non-user results summary

Summarising the results for the target brands' users, two of the four MA Metrics (MMS and SoM) increased (on average) after exposure to advertising. However, as Ab and Aw did not move in a positive direction, it suggests that on average, there is no increase in the proportion of brand users who could give an association with the target

advertised brand, nor an increase in the average number of associations held by this group.

In contrast, all four metrics for the target brands' non-users increased, on average, after exposure to advertising. The Ab metric (those who gave at least one association) had the greatest average increase among this group of 5.4 percentage points after exposure to advertising.

Comparing across the two consumer groups, the greater change is among the target brands' non-user group. MMS change from Wave 1 to Wave 2 was larger for non-users, increasing by 19.2% compared to 2.3% for brand users. This pattern of change across the average percent difference continues across the other three metrics – Ab (7.2% for non-users vs -0.7% for users), Aw (11.9% vs -1.1%), and SoM (19.4% vs 6.1%).

Comparing with Vaughan (2016), the patterns in results across the two consumer groups for the advertised brands are very similar. As with this study, the Ab metric in Vaughan (2016) saw an average decrease from Wave 1 to Wave 2 among brand users. For brand non-users, the magnitude of change in this study was greater across all metrics compared to the change of brand users, which is consistent with Vaughan (2016). At least three of four observations for the target brands' non-users were in a positive direction in this study, and at least 50% or more observations moving in a positive direction in Vaughan (2016).

Results for the control group show that across all observations for all four metrics, there was minimal change among the target brands' users in this study. Three of the four observations for MMS among the non-user group moved in a positive direction, however across the other three metrics, there was consistently little positive change.

6.4 RQ2 Results

RQ2: *How does mental availability move in response to advertising, at the individual-respondent level?*

The examination of RQ2 is an exploration of two new measures created for the purpose of this study: individual level Mental Market Share (MMS) and number of associations (NOA) for the target brands. This section examines the proportion of respondents who were classified into one of three sub-groups, for both MMS and NOA. The descriptive results provided gives context to the results across the two metrics. The results for MMS are detailed first, followed by the results for NOA.

To answer RQ2, MMS from the suite of MA Metrics and the number of associations (NOA) were calculated for the target brands at the individual respondent level in each category. As outlined in Chapter 5, section 5.4.1, this means MMS in this section refers to an individual's share of associations for the target brand, amongst all their category associations. NOA refers to the number of associations each individual has for the target brand. Using the change in MMS and NOA at the individual level, the respondents were divided into three sub-groups of Increase, Stable, and Decline (further information on the cut-offs for these sub-groups are detailed in Chapter 5, section 5.4.1).

The proportion of each of these sub-groups was calculated by dividing the number of respondents in each sub-group, by the number of total respondents from the main sample for each category. For the control group, all respondents were combined across the four categories, and the MMS and NOA difference results are the average of all 217 individuals in this group.

As detailed in Chapter 3, section 3.3, RQ2 is split into two sub-questions, aimed at understanding how these two measures change across all individuals within the main sample and the control group:

> **RQ2a.1:** *How does a brand's Mental Market Share (MMS) metric change with a recent advertising exposure within individuals?*
>
> **RQ2a.2:** *Does the number of associations a brand receives change with a recent advertising exposure within individuals?*

6.4.1 MMS Change at the Individual respondent level

6.4.1.1 MMS Sub-Group Proportions

The results in Table 23 detail the proportion of respondents who were classified into the three sub-groups of Increase, Stable, and Decline for the MMS metric at the individua level. Examining the average of individuals within the Increase sub-group, 28% of all respondents on average saw their individual MMS increase for the target brand after exposure to advertising. There was a larger proportion of individuals in this sub-group for the coffee category, with 38% of these respondents seeing their MMS increase.

The Stable sub-group was the largest of the three on average. Over half of respondents in the main sample (on average 56%.) were considered to have Stable MMS after exposure to brand advertising. The smallest sub-group was those whose MMS decreased after advertising exposure, on average, 16% of the main sample.

Looking to the final row of Table 23, which shows the proportion of the control group classified into each of the three sub-groups for MMS at the individua level – the largest of these is again the stable sub-group, with 55% of respondents on average. The increase sub-group however only made up 18% of the control group individuals, with the remaining 27% of individuals seeing their MMS decline from Wave 1 to 2 following exposure to the target brand's advertising. The individual-level actual difference in MMS for each category, and the control group, is shown in Table 24. All changes were in the positive direction on average, from Wave 1 to Wave 2 for all categories and the control group and were statistically significant ($p<0.05$).

Table 23: Proportion of all individual sub-groups across MMS.

	MMS All Individuals %	MMS Increase % (>5pp)	MMS Stable %	MMS Decline % (<-5pp)
Coffee brand (n= 798)	100	38	42	20
Financial services brand (n= 792)	100	28	56	16
Chocolate brand (n= 813)	100	24	65	11
On-demand streaming brand (n= 791)	100	23	62	15
Average	100	28	56	16
Control group (n= 217)	100	18	55	27

Table 24: MMS individual-level actual difference across each category and control group.

	Coffee All individuals (n= 798)	Financial Services All individuals (n= 792)	Chocolate All individuals (n= 813)	On-Demand Streaming All individuals (n= 791)	Control group (n= 217)
MMS W1 Average	15.6	10.6	10.4	12.8	16.5
MMS W2 Average	20.8	14.2	12.1	14.0	14.1
Average Actual Difference (W1-W2)	5.2*	3.6*	1.7*	1.2*	-1.1*
Stand Dev	20.3	15.4	10.5	10.7	15.0
Min	-100.0	-46.4	-100.0	-100.0	-66.7
Max	100.0	100.0	95.0	100.0	72.7

*$p<0.05$

The average actual difference for the three sub-groups is detailed in the following section for the main sample.

6.4.1.2 MMS Change Across All Sub-Groups

The average actual difference in individual level MMS for all sub-groups, from Wave 1 to Wave 2 is shown in Table 25, for the target brands. The results are discussed first across all individuals, then for each of the three sub-groups, and finally across the control group. The table is ordered from smallest to largest MMS, from the Increase sub-group.

Table 25: Average actual difference in individual MMS across all categories and sub-groups.

	MMS All Individuals (W2-W1)	MMS Increase (W2-W1)	MMS Stable (W2-W1)	MMS Decline (W2-W1)
Coffee brand (n= 798)	5.2*	22.0*	0.1	-15.7*
Financial services brand (n= 792)	3.6*	19.5*	0.1	-11.5*
Chocolate brand (n= 813)	1.7*	12.7*	0.2	-12.8*
On-demand streaming brand (n= 791)	1.2*	13.3*	0.0	-11.8*
Average Actual Difference (W2-W1)	2.9	17.6	0.1	-13.2
Control group (n= 217)	-1.1*	14.4*	0	-18.2

*$p<0.05$

All Individuals

- Across all categories, individual level MMS saw an increase (on average) after exposure to the target brand's advertising of 2.9 percentage points.
- For the four categories tested, the change in individual level MMS was statistically significant ($p<0.05$) across all target brands, with the largest change being for the coffee brand with a 5.2 percentage point increase.

Increase Sub-Group

- For the Increase sub-group, where individuals had MMS that increased more than 5 percentage point after advertising exposure, the average percentage point increase was 17.6 for the target brands.

- The coffee brand again had the largest actual difference, with a 22 percentage point increase from Wave 1 to Wave 2. All differences in individual MMS across each of the categories was statistically significant at the $p<0.05$ level.

Stable Sub-Group

- Individuals with Stable MMS pre- to post-advertising exposure did not have any statistically significant change as expected for this sub-group.
- The average MMS change for this sub-group, was 0.1 percentage point.

Decline Sub-Group

- The individuals with MMS that declined by -5 percentage points or more for the target brand had (on average), a -13.2 percentage points decrease in this metric. All changes in MMS for this sub-group were statistically significant, at the $p<0.05$ level.

Control Group

- The control group saw MMS decrease by -1.1 percentage points on average, from Wave 1 to Wave 2, this change was significant at $p<0.05$.
- For the Increase sub-group, the average change in individual level MMS for the target brands was 14.4 percentage points, and this was statistically significant ($p<0.05$).
- There was no change within the individuals in the Stable sub-group, as expected for the target brands.
- The Decline sub-group saw MMS calculated at the individual respondent level decrease for the target brands on average of -18.2 percentage points between Wave 1 to Wave 2.

The individual level results for NOA are now presented.

6.4.2 NOA Change at the Individual level

6.4.2.1 NOA Sub-Group Proportions

For Number of Associations (NOA), the proportion of individuals in each sub-group (Increase, Stable, and Decline) is detailed in Table 26 below. On average 43% of the respondents increased their associations (by one or more) with target brand. While 32% had no change in their NOA for the target brand on average. Finally, 28% decreased their association by one or more from Wave 1 to Wave 2 for the target brand.

Looking across the control group, here the largest sub-group was Decline, with 42% of the 217 respondents being categorised into this sub-group. The Increase sub-group was 34% of all individuals in the control, and the remaining 24% saw no change in the NOA.

Table 26: Proportion of all individual sub-groups across NOA.

	NOA All Individuals %	NOA Increase % (+1 association)	NOA Stable %	NOA Decline % (-1 association)
Coffee brand (n= 798)	100	46	37	28
Financial services brand (n= 792)	100	45	28	27
Chocolate brand (n= 813)	100	41	31	28
On-demand streaming brand (n= 791)	100	40	31	28
Average	100	43	32	28
Control group (n= 217)	100	34	24	42

The average actual difference of individual NOA for the target brands across the two waves is detailed in Table 27. For all categories, the actual difference in this measure was in a positive direction and was statically significant ($p<0.05$).

Table 27: NOA individual-level actual difference across each category and control group.

	Coffee brand All individuals (n= 798)	Financial Services brand All individuals (n= 792)	Chocolate brand All individuals (n= 813)	On-Demand Streaming brand All individuals (n= 791)	Control group (n= 217)
NOA W1 Average	4.3	2.8	6.0	6.4	5.1
NOA W2 Average	5.0	3.5	6.5	6.7	4.9
Average Actual Difference (W1-W2)	0.7*	0.7*	0.5*	0.3*	-0.2
Stand Dev	4.0	2.6	3.9	4.3	4.0
Min	-17.0	-9.0	-22.0	-21.0	-18
Max	17.0	9.0	21.0	21.0	17

*$p<0.05$

The average actual scores for these sub-groups is detailed in the following section.

6.4.2.2 NOA Changes Across All Sub-Groups

This section explores the changes in NOA across all individuals surveyed in the main sample, with results presented in Table 28. It is followed by an exploration of the results across the Increase, Stable, and Decline sub-groups, as well as these groups within the control sample.

Table 28: Average actual difference in individual NOA across all categories and sub-groups.

	NOA All Individuals (W2-W1)	NOA Increase (W2-W1)	NOA Stable (W2-W1)	NOA Decline (W2-W1)
Coffee brand (n= 798)	0.5*	3.5*	0.0	-2.8*
Financial services brand (n= 792)	0.7*	2.8*	0.0	-2.0*
Chocolate brand (n= 813)	0.7*	3.9*	0.0	-3.1*
On-demand streaming brand (n= 791)	0.3*	3.7*	0.0	-3.6*
Average Actual Difference (W2-W1)	0.6	3.5	0.0	-2.9
Control group (n= 217)	-0.2*	3.4*	0	-3.2*

*p<0.05

All Individuals

- The average increase in the NOA from pre- to post-advertising exposure was 0.6 associations for individuals.
- All changes in the individual level NOA measure for all target brands in the main sample was statistically significant (p<0.05).

Increase Sub-Group

- Those who had an increase of one association or more saw the average number of associations after exposure to advertising increase by 3.5 associations, for the target brands.
- For this sub-group, all NOA changes were statistically significant (p<0.05).

Stable Sub-Group

- The stable group saw no change, as per the cut offs for this sub-group.

Decline Sub-Group

- After advertising exposure, this sub-group saw the average number of brand associations for the target brand's decrease by -2.9.
- The changes in the average number of associations for the Decline sub-group was significant for all categories ($p<0.05$).

Control Group

- The average NOA score for the control group across all individuals was -0.2 associations for the target brand (significant at $p<0.05$).
- The Increase control sub-group's change was 3.4 associations from Wave 1 to Wave 2 (statistically significant at $p<0.05$).
- There was no change in the Stable sub-group in the control sample.
- For the Decline sub-group, NOA decreased by -3.2 associations, and this change was significant ($p<0.05$).

6.5 RQ3 Results

> **RQ3:** *Is advertising recognition a sufficient measure to capture advertising exposure?*

Answering RQ3 required an examination of individuals in the main sample who were categorised as either: able to recognise the target brand's advertisement and correctly recall the advertised brand, could recognise the advertisement but not correctly recall the advertised brand, and those who did not recognise the target brand's advertisement at all. This created the three sub-groups of Recognised And Correct Brand, Recognised Not Correct Brand, and Not Recognised. These three sub-groups were examined among the target brands' users and non-users (as per Chapter 5, section 5.4.2).

This RQ3 is exploratory in nature, as such, the proportion of the respondents for each of the three sub-groups (across the main sample), and then for the different consumer groups is presented first (Tables 29 and 30). This descriptive information provides context as well as insights into the individual level MMS (Table 31) and NOA (Table 32) differences across the user and non-users groups. A comparison with Vaughan (2016) is not possible for RQ3, as this was not explored in the prior study.

6.5.1 Proportion of Samples

6.5.1.1 Main Sample Proportions

The proportion of individuals who were categorised into one of the three sub-groups, based on their brand usage, are presented in Table 29. These are proportions of the main sample, rather than across consumer groups. For example, coffee brand users, who were able to recognise and correctly brand the advertisement made up 10% of the total sample for this category (i.e., 82 / 798 = 10%). A table with the count of individuals for each sub-group can be found in Appendix G.

Table 29: Users and non-users sub-groups, as a proportion of main sample.

	Users (20% of main sample)			Non-Users (80% of main sample)		
	Recognised And Correct Brand %	Recognised Not Correct Brand %	Not Recognised %	Recognised And Correct Brand %	Recognised Not Correct Brand %	Not Recognised %
Coffee brand (n= 798)	10	3	3	48	22	13
Financial services brand (n= 792)	12	3	3	46	22	13
On-demand streaming brand (n= 791)	18	9	6	29	23	15
Chocolate brand (n= 813)	6	5	5	32	26	29
Average	12	5	4	39	23	18

Observing the proportion of brand users, this consumer group makes up 20% of the overall sample in this research. The largest sub-group among the brand users were those in the Recognised And Correct Brand sub-group, making up an average of 12% across all categories.

Looking to brand non-users, on average, 80% of the consumer sample were in this group. Delving into the sub-groups, the largest was the same as for brand users – those who were in the Recognised And Correct Brand were on average 39% of the sample.

Given the majority of respondents in this research were brand non-users, the proportion of the three sub-groups (Recognised And Correct Brand, Recognised Not Correct Brand, and Not Recognised) were naturally far larger. The next section examines these proportions, but across the base of brand users and non-users, rather than across the overall sample for each category.

6.5.1.2 Consumer Group Proportions

The proportion of brand users and non-users across the three sub-groups are shown in Table 30, drawn from within these separate samples. For example, to calculate the percentage of brand users who were in the Recognised And Correct Brand sub-group for coffee, 82 individuals / 127 brand users = 65%. The table with the count of these sub-groups can be found in Appendix F.

Table 30: User and non-user sub-groups, as a proportion of each consumer group sample.

	Users (20% of main sample)			Non-Users (80% of main sample)		
	Recognised And Correct Brand %	Recognised Not Correct Brand %	Not Recognised %	Recognised And Correct Brand %	Recognised Not Correct Brand %	Not Recognised %
Coffee brand	65	18	17	57	27	16
Financial services brand	65	18	17	57	25	16
On-demand streaming brand	55	28	17	43	35	22
Chocolate brand	40	30	30	37	29	33
Average	56	24	20	49	29	22

Inspecting the proportions of each sub-group, on average the Recognised And Correct Brand sub-group was the largest for brand users (56%). The remaining user sample is split relatively similar across the other classifications, with slightly more users able to recognise but not correctly identify the brand (24% vs 20% not recognised). A very similar pattern was seen for brand non-users, with the largest sub-group (on average) also the Recognised And Correct Brand sub-group (49%).

6.5.2 MMS Change

The change in the individual level MMS across the three sub-groups for brand users and non-users is shown in Table 31 below and reported as the actual difference.

Table 31: Actual difference in individual-level MMS, across the sub-groups.

	All individuals	Users (20% of main sample)			Non-Users (80% of main sample)		
		Recog. And Correct Brand	Recog. Not Correct Brand	Not Recognised	Recog. And Correct Brand	Recog. Not Correct Brand	Not Recognised
Coffee brand	5.2*	2.2	-3.6	1.6	7.9*	3.6*	2.9
Financial services brand	3.6*	4.0*	5.1	0.1	5.4*	1.1	1.9
On-demand streaming brand	1.7*	0.4*	-2.5	2.5	2.6*	1.3*	1.2
Chocolate brand	1.2*	5.0*	2.5	-2.4	2.3*	0.9*	1.4*
Average	2.9	2.9	0.4	0.4	4.6	1.7	1.8

(*p<0.05)

Across all individuals the actual difference for the target brands was positive, and statistically significant (p<0.05). Moving across to the user sub-groups, the largest actual difference in the individual MMS was for the Recognised And Correct Brand sub-group, with 2.9 percentage point increase on average for the target brands, and three of the four observations statistically significant (p<0.05). The two other user sub-groups saw the average MMS increase by 0.4 percentage points from Wave 1 to Wave 2, none of these changes in the MMS metric were statistically significant.

For brand non-users, all changes in the individual level MMS from Wave 1 to 2 for was for those in the Recognised And Correct Brand sub-group, with an increase of 4.6 percentage points post-advertising exposure, all statistically significant (p<0.05). The Recognised Not Correct Brand sub-group saw an average MMS increase of 1.7 percentage points, with this change significant (p<0.05) across three of the four

observations. Finally, the non-users in the Not Recognised sub-group had an increase of 1.8 percentage points (on average), with one change statistically significant ($p<0.05$).

6.5.3 NOA Change

The NOA change across all four categories is detailed in Table 32 and reported as the actual difference in NOA from Wave 1 to Wave 2.

Table 32: Actual difference in individual-level NOA, across the sub-groups.

	All individuals	Users (20% of main sample)			Non-Users (80% of main sample)		
		Recognised And Correct Brand	Recognised Not Correct Brand	Not Recognised	Recognised And Correct Brand	Recognised Not Correct Brand	Not Recognised
Coffee brand	0.5*	0.3	-0.9	0.6	1.1*	0.6*	0.4
Financial services brand	0.7*	0.1	-0.1	-0.4	1.3*	0.1	0.8*
On-demand streaming brand	0.7*	-0.6	-1.4*	-0.8	1.2*	0.8*	0.4
Chocolate brand	0.3*	1.2	0.2	-0.7	1.0*	0.2	0.5
Average	0.6	0.2	-0.6	-0.3	1.1	0.4	0.5

(*p<0.05)

Firstly, looking at the user sub-groups, the largest actual difference in the individual level NOA measure was among those in the Recognised And Correct Brand sub-group. This sub-group saw an average actual difference of 0.2 associations from Wave 1 to 2, showing little change in the individual-level NOA for the target brands. The Recognised Not Correct Brand and Not Recognised user sub-groups saw average actual difference in the negative direction, after exposure to the target brand's advertising. One observation for the Recognised Not Correct Brand user sub-group for on-demand streaming, was statistically significant ($p<0.05$).

The greatest actual difference in the individual-level NOA for non-users is for the Recognised And Correct Brand sub-group, with an average increase of 1.1 associations after exposure to the target brand's advertising. All changes in NOA for this sub-group were statistically significant ($p<0.05$). There were smaller, positive changes in this measure for the other two non-user sub-groups. The Recognised Not Correct Brand sub-group saw an average increase of 0.4 associations, with two of the four observations being statistically significant ($p<0.05$). The Not Recognised sub-group had an average increase of 0.5 associations after exposure to advertising, where one observation for this measure was significant ($p<0.05$).

6.6 Chapter Summary

This chapter detailed the results of the five research questions this research set out to answer. The results of RQ1a showed the MA Metrics are responsive to brand advertising – change was detected across all target brands from Wave 1 to Wave 2. For RQ1b, consistent patterns in how advertising effects brand mental availability were documented (both across categories and compared to Vaughan (2016). At brand level, on average, all four MA Metrics increase after advertising exposure for the target brands. The magnitude of change was greater for the current study (where forced exposure to the advertising occurred), compared to the prior in-market research (Vaughan 2016).

The MA Metrics were calculated for brand users and non-users, pre- and post-advertising exposure, to answer RQ1c. Here, it was found that of the two consumer groups, the non-user group experienced the greatest magnitude of change (on average) once exposed to advertising. On average, all four metrics for the non-user group moved in a positive direction. The patterns between users and non-users seen in this research were consistent with Vaughan's (2016) study, whereby non-users experienced the greater change across all four MA Metrics (on average). In RQ1c the largest change was among the Ab metric for brand non-users from this research.

To answer RQ2, MMS and number of associations (NOA) calculated at the individual respondent level were explored. It was found that MMS and NOA do show instability from Wave 1 to Wave 2 post-advertising when calculated for individuals. The largest proportion of groups for MMS were Stable, while the Increase group was larger for NOA.

Finally, the results for RQ3 show there were a large portion of respondents (particularly non-users) who could recognise, but not correctly identify the brand in the advertisements shown. For both users and non-users, the largest proportions of the total sample were recognised and correct brand It raises questions about the use of recognition measures which are discussed in the next chapter.

CHAPTER SEVEN

Discussion

This chapter discuss the key findings of this research, including reference to prior literature, with examination of why these findings may have occurred and what they mean.

7.1 Key Findings

The purpose of this thesis is to explore whether the MA Metrics produced by Romaniuk (2013) are a robust method for assessing advertising's effect on memory – more specifically, whether the effect of advertising on brand mental availability can be quantified. The research conducted was a differentiated replication of the work of Vaughan et al. (2021) and Vaughan (2016), which provided the first empirical evidence in exploratory research. This study replicates and extends the prior research, incorporating methodological changes (primary data, forced advertising exposure, and longitudinal study design) to address the prior study's limitations and to further contribute to the literature on advertising and how it effects consumer memory. Additionally, this research explored the efficacy of individual-level MMS and a new measure of NOA at the individual respondent level, to see how these measures change following advertising exposure.

The eight key findings of this research will now be discussed.

7.1.1 Key Finding 1: *Mental availability is affected by advertising exposure at the aggregate brand level.*

RQ1a found that across the four target brands, at the aggregate brand level, the four MA Metrics were responsive following advertising exposure. Largely, change was in the positive direction, with the metrics increasing for target brands. While some changes were less than 1 percentage point in either direction, this was still able to be detected in the MA Metrics. It demonstrates the MA Metrics are sensitive to brand advertising, and (on average) positive increases in a brand's mental availability should be expected.

The results of RQ1b show the four MA Metrics are all positively affected by the target brand's advertising. On average, MMS increased for all target brands (1.9pp change), as did Ab (4.2 pp change), Aw (0.4 change), and SoM (2.7 pp change) after exposure to

advertising at the aggregate level. Of the 16 brand level observations, 14 move in a positive direction, noting there may be present ceiling effects for metrics that did not see large movement. The consistency demonstrates across the MSoD in this study, at the aggregate level advertising can have a positive effect on brand mental availability. For Vaughan (2016), across all 40 observations for all four MA Metrics, 25 moved in a positive direction. This differentiated replication demonstrates the same patterns across the MA Metrics as the prior studies by Vaughan (2016, 2021) for the target brands, following advertising exposure. Wherein the change in a brand's mental availability from advertising can still be detected when forced exposure and a longitudinal study design is employed (as in this study), as well as in real-world brand tracking studies with cross-sectional design and unverified advertising exposure (as in Vaughan et al. (2021) and Vaughan (2016)).

It does appear that forced advertising exposure creates greater positive change, with the MA Metrics in this study responding more than the prior studies. Important to note this change being measured could be due to the recent exposure to the advertisement, creating greater change in brand MA and the MA Metrics. In that, the forced advertising exposure took place minutes prior to the brand attribute questions, while in Vaughan et al. (2021) and Vaughan (2016) the time between the OTS and the survey could have been weeks. Contrasting with the results for the control group, who were not exposed to the target brand's advertising, only 6 of 16 observations of the MA Metrics moved in a positive direction from Wave 1 to Wave 2 – this is further support for the ability of the MA Metrics to respond to advertising.

These observed changes in the MA Metrics are supported by literature on advertising and its effect on consumer memory (Romaniuk 2013; Vaughan et al. 2021). Advertising is said to work as creative publicity by building and refreshing memories for the brand, serving as a reminder of the brand's existence (Ehrenberg et al. 2002b; Sharp 2010a). This is evidenced by the increase in all four MA Metrics post-advertising exposure for this study, as well as in the study by Vaughan (2016). This also explains the smaller change in the metrics for the control group – with no exposure to the target brand's

advertising stimuli, the associations for these brands were mostly not built or refreshed. Additionally, all brands used in this research were established brands within the Australian market, demonstrating that even for established brands, advertising can continue to have positive impact on mental availability, and the propensity of the brand coming to mind or being noticed in buying situations (Bullmore 1999; Vaughan 2016).

7.1.2 Key Finding 2: *The biggest change in mental availability is among brand non-users.*

RQ1c set out to understand advertising's effect on the mental availability of brand users and non-users. On average, the biggest change in all four MA Metrics was among the brand non-user group. Where 15 of the 16 brand level observations for the target brands' non-users moved in a positive direction after advertising exposure. Comparably, only 10 of the total 16 observations moved in a positive direction for the target brands' user group.

The results for Vaughan (2016) followed a similar pattern – where 30 of 40 observations for brand non-users were in a positive direction, and only 16 of 40 observations for the brand users moving in a positive direction. Across this and the prior studies, there were more consistent, positive observations for brand non-users than brand users. For the MMS metric, there was an increase of 19.2% in the share of associations for non-users, and only 2.3% change for users. Looking across the other three metrics for the target brands, this pattern continues - Ab (7.2% for non-users vs -0.7% for users), Aw (11.9% vs -1.1%), and SoM (19.4% vs 6.1%).

As mentioned in the literature review, usage bias is a well-documented phenomenon (Bird et al. 1970; Burnkrant & Unnava 1995; Krishnan 1996; Romaniuk et al. 2012; Vaughan 2016). Brand users tend to possess more associations in memory than brand non-users, due to their experience and exposure to the brand (Bird et al. 1970; Krishnan 1996; Romaniuk et al. 2012). Therefore, it is unsurprising this usage bias can

be seen in the results for RQ1b. The brand non-users experienced greater movement in the MA Metrics, likely due to having less existing brand knowledge, and therefore a lower baseline mental availability, prior to advertising exposure (Vaughan 2016; Vaughan et al. 2021). Brand users typically have greater established associations in memory (Vaughan 2016; Vaughan et al. 2021), meaning an increase in the number of associations held, and therefore mental availability, is far less likely to occur due to ceiling effects.

7.1.3 Key Finding 3: *The Share of Mind metric captures the change in mental availability for brand users.*

Examining the average change for brand users across all four MA Metrics, the greatest positive change was for the Share of Mind (SoM) metric. SoM measures the share of associations for the target brand, from the group of consumers who gave at least one association with the brand.

This metric increased, on average, by 1.7 percentage points after exposure to brand advertising for the brand user group. The only other MA metric to see an average increase was Mental Market Share (MMS) with 0.5 percentage point change. Both Associative Penetration (Ab) and Association Rate (Aw) decreased from Wave 1 to Wave 2, by -0.6 percentage points and -0.1 associations, respectively. The smaller movement in the negative direction for both Ab and Aw metrics suggest, in line with literature, brand users already have a high number of associations in memory for brands they use (Krishnan 1996; Zinkhan & Muderrisoglu 1985). As such, they are hitting a ceiling, with no additional associations being able to be built from a singular advertising exposure. Then, it is possible that the greater movement seen in SoM, a share metric, for brand users is the result of strengthening pre-existing associations in memory. In turn, increasing the share of associations among those who already had an association for the target brand. Additionally, this could result in interfering with the ability of competitor brand to be retrieved from consumer memory in buying situations.

7.1.4 Key Finding 4: *The Associative Penetration captures the change in mental availability for brand non-users.*

Among brand non-users, Associative Penetration (Ab) saw the greatest positive change of all the MA Metrics – this metric measuring the percentage of respondents who gave at least one association with the target brand. While all four MA Metrics (on average) increased for the target brands' non-users, the Ab metric had the greatest increase of 5.4 percentage points after advertising exposure. This is followed by SoM with a 3.3 percentage points change and MMS with 2.4 percentage points. Non-users also increased by 0.7 associations on average for Aw. This pattern was similar to Vaughan (2016), whereby three of the four MA Metrics increased on average for the non-user group.

It is likely the greatest movement is in the Ab metric for the non-user group is due to usage bias, that was discussed previously. While all metrics for the non-user group see average positive change across the target brands, the Ab metric shows how exposure brand advertising is nudging (Barnard & Ehrenberg 1997) those that have less established memory networks for the brand (i.e., non-users) to think of the target brand at all. Indicating that brand advertising is helping to increase mental availability and increase the change the brand will come to mind for non-users in buying situations. This makes the retrieval process of the target brand from memory easier for these consumers, as establishing a link to the advertised CEP and brand, it provides the opportunity for it to work as a cue for retrieval from memory.

7.1.5 Key Finding 5: *The MA Metrics should be reported separately for brand users and non-users.*

This research, along with prior works have shown that brand users and non-users not only respond differently to questions regarding brands they use (Hammer & Riebe 2006; Romaniuk et al. 2012; Sharp et al. 2001; Vaughan 2016; Vaughan et al. 2018; Vaughan et al. 2021), but that advertising effects mental availability differently for these two consumer groups.

Across the results from this research, as well as Vaughan et al. (2021) and Vaughan (2016) the same pattern emerges – brand users have greater mental availability than non-users (when measured using the MA Metrics). As discussed in the previous key findings (section 7.1.3 and 7.1.4), the SoM metric has the greatest change for users, while the Ab metric moves the most for non-users. However, when considering results at the aggregate level, (section 7.1.1) where all four MA Metrics for the target brands move in a positive direction after advertising exposure, it is not possible to determine the effect of advertising on brand mental availability across these two different consumer groups. While this overall positive change can be seen, it is difficult to understand whether brand advertising has nudged the share of association among the consumer groups that already have pre-existing associations in memory (i.e., brand users), or whether a given advertising execution is building new associations or connections in memory (i.e., for brand non-users).

7.1.6 Key Finding 6: *There is instability in Mental Market Share (MMS) and Number of Associations (NOA) across individuals after exposure to advertising.*

Exploring MMS at the individual level has, to author's knowledge, not been conducted in any previous studies. Additionally, the Number of Associations (NOA) measure at the individual-level has no presence in prior literature.

The results for RQ2 saw, on average, the individual-level MMS for 56% of respondents remains stable after advertising exposure (change between -4.9pp and 4.9pp). Looking across all four categories from this study, the proportion of respondents in this stable sub-group ranged from 42% to 65% of respondents. For individual-level NOA, only 32% on average were stable post-advertising exposure (no associations gained), with proportions for this sub-group ranging from 28% to 37%.

This is reflective of the literature on instability in brand attribute measures at the individual level. Prior studies have shown that when measures that show stability at the aggregate level, typically this is not reflective of the change among individuals

(Dall'Olmo Riley et al. 1997; Sharp 2002). Approximately half of respondents change their responses in the next time period (Dall'Olmo Riley 2012). This is also consistent with the literature around memory and its probabilistic nature – there is no guarantee that the same thing will be retrieved from memory each time (Mitchell 1982; Romaniuk & Sharp 2002).

Then, the instability in individual MMS and NOA becomes even clearer when comparing with the results of the control group, who were not exposed to target brand advertising. There is still instability across this group, though, a larger proportion of the control sample declined in their MMS from Wave 1 to Wave 2.

7.1.7 Key Finding 7: *There are consistent, positive increases in Mental Market Share (MMS) and Number of Associations (NOA) (on average) after advertising exposure.*

While instability among individuals is evident within the MMS and NOA measures from Wave 1 to Wave 2, when looking across all individuals, there is largely positive change in these measures.

For individual MMS, the average difference after advertising exposure was 2.9 percentage points, and examining this across all four categories, the change in MMS from Wave 1 to Wave 2 was statistically significant ($p<0.05$). Looking at individual NOA, where change for all categories was also statistically significant ($p<0.05$), there was a positive increase of 0.6 associations on average, almost one association. Looking to the results for the control group, there was no average positive change in either individual MMS or NOA from Wave 1 to 2. MMS decreased by -1.1 percentage point on average, and NOA by -0.2 associations for the control. This further builds on previous studies that demonstrate instability at the individual level, but when measures are examined at the aggregate level, stability is more likely to be seen (Dall'Olmo Riley 2012).

7.1.8 Key Finding 8: *Using a combination of advertising recognition and correct branding does not sufficiently capture all who recognise an advertisement.*

The purpose of RQ3 was to examine who traditional advertising recognition measures capture, and whether this measure is sufficient at capturing enough of the sample who are exposed to an advertisement. For this research, traditional recognition measures (as noted in Chapter 2, section 2.3.1.1.) are considered to be those that use advertising recognition and correct brand recall as a combined measure (Crommelin et al. 2014; Vaughan et al. 2021). Typically, respondents are given a visual cue, such as masked stills of a TV advertisement (du Plessis 1994a) and asked if they recognise the advertisement and then unprompted asked which brand the advertisement was for.

With forced exposure employed in this research, the proportion of respondents who were able to: recognise the advertisement and correctly identify the advertised brand (as in typical advertising recognition measures), recognise the advertising but not correctly identify the advertised brand, and those who did not recognise the advertisement were examined. The forced exposure guaranteed all respondents had an OTS the target brands advertising, and yet despite this, the findings from RQ3 demonstrate not all respondents were able to be categorised as recognising the advertisement (based on recognition and correct brand identification only).

On average, among brand users, 56% were classified into the Recognised And Correct Brand sub-group, and 49% of non-users to the same sub-group. While capturing (on average) half of these consumers groups, the remaining half either were able to recognise the advertisement and not correctly identify the brand (24% of users, 29% of non-users). Based on widely used recognition measures, these consumers would not be captured by this measure. Approximately, one in five did not recognise the advertisement at all (20% of users, 22% of non-users). Noting that among brand non-users (who were 80% of the consumer sample in this research), there were still statistically significant ($p<0.05$) increases in both individual-level MMS (target brand's share of associations), and the individual-level NOA for the target brand. Suggesting

that significant change in brand mental availability is not being measured or captured when respondents are excluded on the basis of advertising recognition and correct brand identification.

7.2 Chapter Summary

The key findings from the research were discussed, in conjunction with the existing literature.

This thesis found that at the aggregate level, the MA Metrics across this study and Vaughan (2016) largely follow the same pattern, with positive increases to a brand's advertising. It suggests there is consistency in patterns detected using the MA Metrics across differing methodologies, such as in forced exposure in this research, and in using in-market data as seen in Vaughan et al. (2021) and Vaughan (2016).

Similarly, the patterns found by Vaughan (2016) across the different consumer groups are evident in this research. Brand users see far less consistent change in the metrics after exposure to the target brand's advertising. The brand non-users, across both studies, on the other hand, had consistent, positive increases post-advertising exposure.

The instability of the MMS and NOA measure was examined at the individual level. It was found there is greater instability in these measures than at the aggregate level.

Finally, the results of this thesis found that traditional advertising recognition measures, combined with correct brand recall, were unable to capture all respondents who recognised the advertisement.

CHAPTER EIGHT

Conclusion

This chapter concludes this thesis and explores implications for marketing practitioners and academics alike. The limitations of this study, as well as avenues of future research are also detailed.

8.1 Implications

Firstly, the implications for marketing practice are discussed, with a focus on the applicability of the MA Metrics (Romaniuk 2013) as a simple but effective measure for brands to benchmark and track the effect of advertising on mental availability. Additionally, this thesis' contributions to marketing theory and research are explored.

8.1.1 For Marketing Practice

8.1.1.1 MA Metrics & Brand Tracking

This research, while still exploratory in nature, was a differentiated replication and extension of the work of Vaughan et al. (2021) and Vaughan (2016). RQ1 sought to compare the aggregate level results from this study to the aforementioned works, to understand any differences in methodology (more notably to this point, the data type) and how this may have affected the MA metric's ability to measure or show change following exposure to a brand's advertising.

As noted in Chapter 7, section 7.1.1, the same patterns emerged across the MA Metrics in the current and past research. It suggests that irrespective of how the data is collected (specifically either via in-market brand-tracking studies (i.e., Vaughan et al. (2021) and Vaughan (2016)), or in more controlled, forced exposure conditions, as in this research), the same broad patterns are still clear. This being advertising typically has a positive effect on brand mental availability. The scale of change differs slightly between this research and Vaughan (2016), however the overall patterns across the different approaches and studies are still evident.

Given the consistency of results with Vaughan et al. (2021) and Vaughan (2016) it also suggests that it is not necessary for brands to run their own, likely costly, experiments to generate advertising effects on the four MA Metrics. Rather, as Vaughan (2016)

suggests, so long as brands have tracking studies that include brand perception measures, the MA Metrics can be calculated and are likely to be responsive to advertising – provided a measure of advertising exposure is also captured. It is clear then, the MA Metrics remain an easy, and extremely useful tool with which marketing professionals can track the effect of advertising on their brand's mental availability.

8.1.1.2 Brand Users & Non-Users (most buyers are light buyers)

The results of thesis demonstrate the presence of usage bias within the data, which is expected, given its prevalence in the wider literature (Bird et al. 1970; Burnkrant & Unnava 1995; Krishnan 1996; Romaniuk et al. 2012; Vaughan et al. 2021). As found in Vaughan et al. (2021) and Vaughan (2016), as well as this research, brand advertising has a larger, and more consistent effect (across the metrics) on brand mental availability for brand non-users. It indicates to this author two things that marketing practitioners should be mindful of, if conducting research with the mental availability space or similar:

- The usage bias seen must be controlled for by ensuring recruitment captures both consumer groups, and importantly reporting for these groups is separate. Brand non-users typically do not have as many associations in memory, when compared to the established memory networks of brand users (Craik & Lockhart 1972; du Plessis 2005; Wyer 2008). Having a greater understanding for how these consumer groups differ means that it reduces the possibility of misunderstanding results at the aggregate level and being able to better predict patterns. Such as, brand users' MA Metrics moving less than non-users after advertising is of lower concern, given that it can be assumed that the brand users are simply having their associations strengthened or reinforced, rather than building new associations (as done for non-users).
- Secondly, advertising does increase Mental Availability across users and non-users, but greater change is among non-users – as users typically already have greater mental availability to begin with, so ceiling effects occur. It is crucial for

marketing practitioners to understand the importance of advertising that reaches all consumer groups. On average (from this research) 80% of consumers were brand non-users in their respective category. Missing an opportunity to build new associations and grow Mental Availability among this consumer group would be detrimental to any brand, especially as brands grow by increasing the size of its customer base (Sharp 2010b).

- Finally, practitioners should expect to see change in different metrics for the different consumer groups. Where Share of Mind (SoM) sees greater change for brand users, the greater change is in the Associative Penetration (Ab) metric for brand non-users. Therefore, marketing professionals should be mindful that with brand users already having many pre-existing associations in memory, it is not expected that the number of associations would necessarily increase. Subsequently, the presence of ceiling effects is most likely to be present for this consumer group, where the MA Metrics would not see much positive movement. For non-users however, the greatest movement is likely to be seen in the Ab metric, whereby the exposure to advertising is typically going to see the mental availability for this consumer group increase as it is building familiarity and new memory structures.

8.1.1.3 Ad Recognition Measures as a Proxy

The purpose behind RQ3 was to better understand whether widely used advertising recognition measures are limiting in any way, when used as a proxy for validated OTS (as used in Vaughan et al. (2021) and Vaughan (2016). As this research used forced advertising exposure, the guaranteed exposure provided the author with an opportunity to unpack the traditional recognition measure, and what proportion of respondents this measure captures.

- Looking across the three sub-groups for each of the consumer groups (Recognised And Correct Brand, Recognised Not Correct Brand, Not Recognised), the largest proportion of respondents for both users and non-users are in the Recognised And Correct Brand sub-group. For the 56% of users

and 29% of non-users, these respondents were able to recognise the advertisement, and correctly identify the brand without the use of a prompted list of brands.

The Recognised Not Correct Brand sub-group consisted of 24% of users, and 29% of non-users, who were able to recognise the advertisement, but were not able to correctly identify the brand. Lastly, the remaining 20% of brand users and 22% of brand non-users did not recognise the advertisement, which placed them in the Not Recognised sub-group.

- It appears that the recognition of visual information sees almost 80% (combined) of users and non-users alike being able to recognise the advertisements, when presented with the three masked stills. It suggests the presentation of such visual cues do aid in advertising recognition. Then for 20% of users and non-users, even with forced advertising exposure they are still unable to recognise the brand advertisement when presented with a visual cue. It is evident these advertising recognition measures – where respondents are asked if they recognise an advertisement, with a follow up of which brand the advertisement was for (Aribarg et al. 2010; Crommelin et al. 2014; Mehta & Purvis 2006; Vaughan et al. 2021) do have some shortcomings. Using such a measure would leave (in the case of this research), approximately half of all respondents being considered to have a valid OTS, while missing another quarter of the sample that have seen the advertisement but were simply unable to correctly identify the brand.

It suggests advertising recognition measures are limiting in their scope and assumes that recognition in addition to correct identification of the brand that is present equals advertising recognition, when this is not the case.

When it is known from the literature that advertising is typically processed at the low-involvement level, with little attention, assuming that consumers must be able to accurately identify a brand from an ad is at odds with what is usually seen (Heath &

Nairn 2005). So, classifying these respondents in the Recognised And Correct Brand sub-group as those who had a valid OTS, means only respondents who are included are those who have not only been exposed but also sufficiently processed the advertisement in memory in order to correctly identify the brand.

This has additional implications for branding. The range of brand users who recognised the advertisement and correctly identified the brand was between 40%-65%, and the range for non-users was 37%-57%. This variation in advertising recognition and correct brand recall could be due to the branding used within the advertisements. Even for brand users, an advertisement that is lacking in clear, branding elements like the brand name or the logo could still hinder their ability to correctly identify who the advertisement was for.

For individual-level MMS and NOA, the greatest movement is seen in those in the Recognised And Correct Brand sub-group, across both consumer groups, with this change being statistically significant ($p<0.05$). However, there is also some positive, statistically significant movement for non-users within the Recognised Not Correct Brand sub-group. Hence, the memories of those non-users in this sub-group have been nudged when presented with the CEPs that were present with the advertising.

Then, marketing practitioners using this method of identifying exposure will leave a portion of respondents who have had their mental availability nudged by brand advertising but weren't able to articulate the brand. It suggests presenting a brand list to capture brand response after the free-recall and presentation of the visual cue could be a viable solution to capturing this part of the sample and is something that could be explored in future research.

8.1.2 For Marketing Research

8.1.2.1 Individual level for MA Metrics & stability

This is the first study (to the author's best knowledge) that explores the change in mental availability at the individual respondent level.

The results found in RQ1b, where MMS was examined at the aggregate level, MMS increased on average for the target brand after advertising exposure. Then, exploring the results from RQ2, where MMS was examined at the individual level, we see over half of respondents (average of 56%) maintained a stable MMS (+/-4.9 pp). This leaves the remaining 44% where their MMS increased or declined. For individual-level NOA, 32% of respondents (on average) were stable post-advertising exposure (no associations gained), with proportions for this sub-group ranging from 28% to 37%.

It is supported by the literature that suggests on average, 50% of respondents will change their brand image response within the second interview, when asked the same question/s (Sharp 2002). It further builds on the findings from brand attribute literature that stability is typically seen at the aggregate level, and instability at the individual level (Sharp & Romaniuk 2002a, 2002b).

However, it must be acknowledged that previous instability is largely seen when there are no interventions from one time period to another. This research did employ an advertising intervention, between Wave 1 and Wave 2 measurements of brand associations, as such, it can be expected that this instability is even greater due to this.

This research demonstrates while the MA Metrics can be examined across individual-level data, it is not wholly necessary to understand any variations in movement for practitioners. However, for academics and marketing researchers, the ability to explore at the individual level provides an opportunity to develop a deeper

understanding of how the metrics at the aggregate level are composed from individual level change. For the exploration at the individual level, examining how individuals change in both MMS and NOA provides insight into how these measures are capturing what happens in consumers memories. Such as, whether advertising exposure means respondents will link more CEPs to a given brand (though moving NOA). Or does this create interference for competitor brands by refreshing the advertised brands memory networks, and limiting the chance a competitor brand will come to mind in buying situations.

8.1.2.2 Methodological impact on MA Metrics

RQ1a and RQ1b explored the effect of advertising on the MA Metrics at the aggregate level, across this study and the work of Vaughan (2016). Patterns of change (across the observations) were greater for this study than for Vaughan (2016), however, the patterns were largely the same.

For RQ1a, there was positive change across the four MA Metrics, which showed after advertising exposure at the aggregate level, the mental availability of a brand is positively affected. This was also seen in Vaughan (2016).

Across RQ1b, which explored the difference across consumer groups, again, the patterns were much the same as prior studies. The greatest positive change after advertising exposure occurred for the target brands' non-users for both this study, and for Vaughan (2016). The target brands' users, while showing some positive change, it was not of the same magnitude as the change seen for the target brands' non-users.

What can largely be seen then, across the MSoD employed in this research and in Vaughan (2016), is that the methodological differences between this research and the previous works did not have a large effect on the results. While mentioned previously as an implication for marketing managers, it suggests that the MA Metrics across both

primary, experimental data as well as secondary, in-market brand-tracking data will detect similar patterns. Such as, the MA Metrics move at the aggregate level for the target brand after to the brand's advertising, and brand users experience less positive change in the MA Metrics compared to non-users.

8.2 Limitations & Future Research

The results of this thesis provide further insight into the use of the MA Metrics to measure the effect of advertising, with methodological changes implemented in this research to address the limitations of the study being replicated. However, this study is still subject to limitations, from which several interesting avenues for future research have emerged. They are now discussed in more detail.

8.2.1 Choice of Advertisements

8.2.1.1 Percentage Agreement in Real World Ads

As noted in Chapter 4, section 4.4.1.1, some of the advertisements selected for this research did not have a high Percentage Agreement across the coders (i.e., where there was a large difference in the CEPs that were considered evident in the advertisements). It suggests that the advertisements chosen may have had multiple messages or CEPs present. While potentially limiting in building one specific CEP, it does better replicate the real-world media environment, given the advertisements chosen were for real brands, that had been on-air (albeit in different markets).

An avenue of future research could be to examine the number of associations built after advertising exposure, across advertisements that have one, two, or multiple CEPs/attributes present. This could help industry professionals to better understand how their advertising is processed, and whether leveraging multiple CEPs, or a single CEP result in greater mental availability over time.

8.2.1.2 On-Demand Streaming Category & Co-Branding

For the on-demand streaming category, the advertisement chosen for the target brand had multiple brands present. While care was taken to remove the logos of the secondary brands in the final still, there were audio mentions of these brands throughout the advertisement. At the aggregate level (RQ1b, see Appendix E for more detail), these two brands had a small increase in their MMS and Ab from Wave 1 to Wave 2. It is possible due to the interference effect, the target brand's MA Metrics did not experience a higher degree of change, with the information learned in the advertisement becoming associated with those additional brands (Anderson & Neely 1996; Rossiter & Percy 1980). This leads to an interesting area of possible future research, to consider co-branded advertisements.

An exploration of this interference effect across multiple brands in multiple categories could explore any potential effects (beneficial or detrimental) to the primary brand's mental availability. Prior research has been conducted on advertising and brand awareness in various co-advertised contexts (Atkin & Block, 1983; Dickinson & Barker, 2007; Erdogan & Baker, 2000; Erfgen et al., 2015; Huang & Li, 2001; Lafferty & Goldsmith, 2005; Nguyen et al., 2018), the research has not been extended to the effect on mental availability. Better understanding of sub-brand/variant, or co-branding advertising executions and the effect on a brand's ability to continue to build and refresh memory structures, even with interference, could be beneficial not only to academics, but advertising practitioners.

8.2.1.3 Chocolate Category & Seasonality

The choice of the advertisement for the chocolate category, in conjunction with the timing of data collection (November to December of 2022) could have impacted the results for this target brand. The content of the advertisement was a stereotypical Christmas scene – snow, families gift giving, and Christmas-themed music in the

background. As White (2007) notes, chocolate (along with similar categories) tends to use more holiday-themed packaging and advertising.

Due to this, it is possible the recognition and correct branding of the advertisements was affected by the generic nature of advertising style – respondents could have assumed this advertisement was for a competitor brand. While a potential limitation of this research, it raises some interesting points about clear and consistent branding that could be used throughout the year, irrespective of the holiday season. Future exploration into this could examine the effect of such seasonal advertisements on a brand's mental availability throughout the year.

8.2.2 Increase, Stable, & Decline Group Cut Offs

The group cut-offs used within RQ2 to establish those who were classified as stable, increase, or decline in individual-level MMS and NOA from Wave 1 to Wave 2, were created with limited backing from literature, due to the measures not previously being used in prior research.

For MMS, the grouping classifications were decided based on the results of Vaughan et al. (2021) and Vaughan (2016). This was deemed most appropriate given the lack of literature in this space, and secondly, that this research is a replication and extension of the previously mentioned works. Therefore, some similar patterns in the data were expected to emerge, even though the prior studies focussed on MMS at the aggregate level and not individual-level. For NOA, this was based on the how many CEPs the independent coders and this author believed to be present in any of the four advertisements. With at least one CEP present in all advertisements, this was considered to be a suitable cut off for these groups (where the increase group gain at least one association in Wave 2, for example).

While this could be limiting, the lack of research in this space (i.e., how many associations could be built after one advertising campaign) suggests that there is an opportunity for this to be explored further. Using this current research as a benchmark, future researchers could deep-dive into these increase, stable, and decline cut offs and unpack whether these groupings are still indicative of change after advertising exposure.

8.2.3 Individual-Level Replication or Extension

This research replicated and extended the work of Vaughan et al. (2021) and Vaughan (2016) and explored how the MA Metrics change at the aggregate level following brand advertising, with a focus on the publicity model of advertising (Chapter 2, section 2.2.1.2). The new contribution to MMS and NOA at the individual level, was exploratory in nature, and thus further investigation and replication would give better insight into some of the findings and classifications made by the author.

Firstly, understanding the variability in the Increase, Stable, and Decline groups (Chapter 5, section 5.4.1) that the author used across different categories could help to further research in the repeat-rate of individual level measures. For example, is the 'Stable' group typically the largest across other diverse conditions, such as other categories, or countries. Secondly, further exploration of the three sub-groups for a brands users and non-users (from Chapter 5, section 5.4.2: Recognised And Correct Brand, Recognised Not Correct brand, Not Recog) could provide similar evidence for the repeat-rate area of research – such as where the largest change in MMS and NOA is found, whether this differs when sample sizes for any of these groups is larger or smaller.

Finally, replications and extensions in future should more directly test competing schools of thought around how advertising works (see: Chapter 2, section 2.2.1 for

more detail). As the focus of this research a direct test of mental availability measures consistent with the publicity model of advertising (Chapter 2, section 2.2.1.2), there was no further exploration of differing theories. Future research could explore and directly test these competing hypotheses around how brand advertising works, to see if and how they can predict or describe differences between brand users and non-users. To test such scenarios, additional variables or measures could be introduced. For example, measuring the changes in attitude pre- and post-advertising, or using new information to persuade respondents and comparing this with advertising that provides less information. Then, it would offer an opportunity to examine the differences between these two competing models and see which of the two offered better or more accurate predictions of advertising performance.

8.2.4 Repeated Advertising Exposures

As it was out of the scope of this Masters-level research, only one advertising exposure per category was used. The results showed that even with a single exposure to a brand's advertising, that mental availability can be affected. However, it does not replicate the real-world advertising environment, whereby consumers are exposed to advertising daily and may have multiple OTS to the same brand advertisement. This does lead to an exciting avenue of potential research. Both this research and Vaughan et al. (2021) and Vaughan (2016) have found that the MA Metrics (on average) increase after advertising exposure. While Vaughan et al. (2021) and Vaughan (2016) did look at real-world data, as with this study, the MA Metrics were measured at two different points in time.

Measuring across multiple points in time would allow for any future researchers to explore how the metrics may change for brands when consumers have been exposed to multiple advertising executions from competitors during periods where they are off-air. It would also greatly benefit advertising or marketing practitioners, to show the level of change that is expected in their MA Metrics over a longer time period where the MA Metrics can be measured across multiple points in time. Such insight would also have implications for scheduling and effective media planning.

8.2.5 Transactional Data

To bolster results in any future replications or extension of this work (or similar), obtaining real world spend or transactional data for the advertised brands could prove to be useful in a number of ways.

Firstly, the use of transactional data across multiple time periods provided actual brand usage data, rather than solely relying on self-reported measures. It would allow for tracking over time, and a better examination of any potential changes in buying

behaviour following advertising interventions and changes to a brand's mental availability.

Using the transactional data, in conjunction with measuring the MA Metrics across time periods would allow for better tracking of changes in these metrics, and which metric sees the greatest changes when behaviour or spend also changes.

8.2.6 Control Group

The control group used within this research was limited by sample size. For each category, the number of respondents in each control group was approximately n=55. When exploring the results for the control group in more detail for RQ2 and RQ3, there were some statistically significant differences from Wave 1 to Wave 2. It is possible, that due to the far smaller sample size (n=217 combined, compared to approximately n=~790 for combined main sample groups), these are over-inflated results. It does call in to question where changes in the MA Metrics, individual-level MMS and NOA are coming from. Because of this, it would be pertinent for future researchers to consider the size of the control groups that are not exposed to the target brand's advertising, to offer a cleaner comparison with the results of the total sample being tested.

8.3 Chapter Summary

This chapter concludes this thesis.

Implications and contributions to both marketing practice were explored, with use of the MA Metrics across brand tracking studies one of the key areas for marketing practitioners to consider.

For market research, methodology and its impact of advertising on the MA Metrics was one of the contributions this thesis provided. While this thesis was limited by the choices of advertisements, and lack of transactional data among other factors, it led to some interesting areas of potential future research. Some of these rich areas of future research were in the co-branding space, replication across individual level MMS and NOA, and even examining seasonality of advertising in a similar research space.

APPENDICIES

APPENDIX A: Coding Spreadsheet

Appendix A provides the coding spreadsheet used by the independent coders, to identify the presence of CEPs in the target brand advertisements (Table 33). The key that was provided to coders, is in Table 34.

Table 33: Example of coding spreadsheet for financial services category.

CEP	Ad 1	Ad 2
When someone needs a quick response		
Would not waste someone's time		
To help someone who wants to quickly improve their financial situation		
Would have the technology to help someone easily access and manage their finances from anywhere		
Would protect someone's money, even when the economic conditions are uncertain		
Would be there to help with financial decisions when there are big changes in someone's life (e.g., changing jobs, having a baby, getting married, death of a loved one)		
To help someone have enough extra money to give my loved ones the occasional gifts		
When making a big financial decision that will involve other people you care about/respect		
Has good relationships with retailers that will help me easily finance my purchases		
Has staff with the expertise I need to help me make good decisions		
Has the tools for when someone wants to keep close track of their expenses		
Help someone be financially secure so they can help their loved ones if needed		
Would help someone get out of the cycle of feeling constantly like they just do not have enough money		
Help someone achieve a more stable and secure financial future		
Could help when emerging financial worries are making someone stressed and unhappy		
To buy furniture, household appliances or generally renovate to improve a home		
Need money for a big emergency such as a medical issue or something important broken down		
Get the money to buy something big/expensive like an apartment or a car		

For refinancing an existing loan/credit card to get better conditions		
When someone wants to make a business-related investment		
Good to talk to when financing is a bit of a challenge/more complicated		
Good to approach when someone wants to have a wide variety of options		
Would help someone make smart use of any cash bonuses or prizes		
Would be understanding if someone had financial difficulties due to unfortunate circumstances such as losing their job or an illness		

Table 34: Key for coding spreadsheet.

Code	Meaning
0	No, CEP is not present
1	Yes, CEP is present, explicitly mentioned/shown
2	Not directly in the ad, implicitly mentioned/shown
99	Unsure

APPENDIX B: Pilot Study Results

Appendix B offers the results for one target brand, from the pilot study which was conducted prior to main data collection. The results for RQ1a at the aggregate level are detailed in Tables 35 and 36 in section 1, with the results for RQ1b shown in Tables 37 and 38 in section 2.

Section 1: RQ1a

Table 35: Brand level MA Metrics in Wave 1 and Wave 2.

	MMS %		Assoc Pen (Ab) %		Assoc Rate (Aw) #		SoM %	
	W1	W2	W1	W2	W1	W2	W1	W2
Financial Services (n= 806)	10.3	11.2	63.9	67.5	6.3	6.8	16.8	16.9

Table 36: Actual difference in MA Metrics between Wave 1 and Wave 2.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
	W2 – W1	W2 – W1	W2 – W1	W2 – W1
Financial Services (n= 806)	0.9	3.6	0.5	0.1

Section 2: RQ1b

Table 37: MA Metrics for users and non-users across Wave 1 and Wave 2.

Total Sample (n= 806)	MMS %		Assoc Pen (Ab) %		Assoc Rate (Aw) #		SoM %	
	W1	W2	W1	W2	W1	W2	W1	W2
Financial Services: Users (n= 133)	18.2	17.9	94.7	94.7	8.4	8.5	31.6	30.4
Financial Services: Non-Users (n= 673)	8.4	9.7	57.8	62.1	5.5	6.2	12.0	12.9

Table 38: Actual difference in MA Metrics between Wave 1 and Wave 2, for users and non-users.

Total Sample (n=806)	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
	W2 – W1	W2 – W1	W2 – W1	W2 – W1
Financial Services: Users (n= 133)	-0.4	0.0	0.0	-1.3
Financial Services: Non-Users (n= 673)	1.2	4.3	0.7	0.9

APPENDIX C: Example Surveys

Appendix C shows the survey used in the main data collection, for the financial services category. Section 1 provides the Wave 1 survey, and section 2 the Wave 2 survey. The surveys are in the format provided to the panel provider, to show programming and screening information.

Section 1: Wave 1 Survey

Financial Services Category in Australia

Thank you for agreeing to participate in this survey. It should take about 15 minutes to complete. All of your responses will be kept confidential. *The survey is about your awareness, knowledge, and experiences. There are no right or wrong answers; we are just interested in your experiences and opinions.* *The first set of questions are about you, so we can make sure we are speaking to a broad cross section of the community.*

SCRepeatSurvey: This study includes a follow-up survey to be completed within seven days from the completion of this survey. Would you be willing to complete a second survey? *Please select one response*
Yes
No
Maybe

SQ1Gender: Are you… *Please select one response*
Male
Female
Non-binary
Non-gendered identity
Prefer not to say

SQ2Age: Which of these age categories do you fall into *Please select one response*
Under 18 years
18-29 years
30-39 years
40-49 years
50-59 years
60-69 years
70-79 years
80+ years
Prefer not to say

SQ3Location: Where do you live? *Please select one response*
Australian Capital Territory
New South Wales
Northern Territory
Queensland
South Australia
Western Australia

Victoria
Tasmania
None of the above

SQ5Category: Which, if any, of the following financial products do you currently hold? *Select as many responses as relevant*
Savings account
Debit card
Personal loan
Refinanced a personal loan
Credit card
Home loan/mortgage
Business account
None of these

Brand Awareness

Q1Awareness: Which of these financial service providers had you heard of before today?

Please select all brands you are aware of

ANZ	Macquarie Bank
Aussie Home Loans	National Australia Bank
Bank of Melbourne	RAMS
BankSA	St. George Bank
Bankwest	Suncorp Bank
Bendigo Bank	Ubank
BT	Westpac

Commonwealth Bank of Australia	None of these

Brand Image Attributes

You will now be shown some statements that may be associated with financial service providers.

Please look at each statement and indicate which, if any, of the listed brands, you associate with that statement. You can select as many or as few brands as you like.

It does not matter if you have bought or used the brand or not, it is your opinion we seek to collect.

Q2Attributes: Which of these financial service providers do you link with the following statement? You can select as many or as few as you like, or none of these, if none are relevant to the statement.

[INSERT CEP]

Please select as many as apply

ANZ	Macquarie Bank
Aussie Home Loans	National Australia Bank

Bank of Melbourne	RAMS
BankSA	St. George Bank
Bankwest	Suncorp Bank
Bendigo Bank	Ubank
BT	Westpac
Commonwealth Bank of Australia	None of these

Brand Usage

Brand	*Q3aUsage* *Which of these financial service providers have you ever held an account or product with?* *Select all that apply*	*Q3bUsage* *Which of these financial service providers do you currently have an account or product with?* *Select all that apply*
ANZ		
Aussie Home Loans		
Bank of Melbourne		
BankSA		
Bankwest		
Bendigo Bank		
BT		
Commonwealth Bank of Australia		

 Macquarie Bank		
 National Australia Bank		
 RAMS		
 St. George Bank		
 Suncorp Bank		
 Ubank		
 Westpac		
None of these		

Demographics

We are almost at the end of the survey. All of your answers will remain anonymous.

You can be confident that no one associated with this research project can personally identify you from your answers to the questions.

The following questions are about yourself and are for classification purposes only.

DEMO1: Which of the following best describes your work status? *Please select one response*
Work full time (30+ hours per week)
Work part time (Less than 30 hours per week)
Work casual hours (No set hours per week)
Student
Full time parent homemaker
Unemployed
Retired
Other

DEMO2: How many people, including yourself, live in your household? *Please select one response*
One
Two
Three
Four
Five
More than five people

DEMO3: And finally, which of the following categories best represents your total annual household income? Please select one response
Under $35,000
$35k to $59,990
$60k to $79,999
$80k to $99,999
$100k to $149,999
$150k to $199,999
$200k or more
Don't know
Prefer not to say

THANK YOU FOR TAKING THIS SURVEY

Section 2: Wave 2 Survey

Financial Services Category in Australia

Thank you for agreeing to participate in this survey. It should take about 15 minutes *to complete. All of your responses will be kept confidential.*

The survey is about your awareness, knowledge, and experiences. There are no right or wrong answers; we are just interested in your experiences and opinions.

Please complete the survey within 24-48 hours of starting.

Advertising Exposure

You will now be shown a video.

After watching, you will be asked a series of questions related to the video.

Distractor Task

We are now going to ask you some questions related to the video you just watched.

Q1Distractor: Do you hold any Australian driver's licenses? This includes motorbike and heavy vehicle licenses, as well as L or P licenses. *Please select one response*
Yes
No

Q1bDistractor: What is the main reason you do not have an Australian driver's license? *Please type your response below.*

Q2Distractor: At what age did you get your Australian driver's license? *Please select one response*
16-24 years old
25-39 years old
40-54 years old
55+ years old

Q3Distractor: How often do you drive with passengers in your vehicle? *Please select one response*
Every day
Most days i.e., 4 or more times a week
Once a week
Rarely

Never
Does not apply to me

Q4Distractor: How often are you a passenger in a private vehicle? This includes Uber or taxis. *Please select one response*
Every day
Most days i.e., 4 or more times a week
Once a week
Rarely
Never

Q5Distractor: If you spend two seconds looking at your phone how many times more likely are you to have an accident? *Please select one response*
Not more likely to have an accident
Two times more likely to have an accident
Three times more likely to have an accident
Four times more likely to have an accident
Five or more times more likely to have an accident

Q6Distractor: Does playing loud music have an impact on driving safety? *Please select one response*
Yes
No
Not sure

Q7Distractor: Which of these is more likely to be distracting to a driver?

Please select one response
Using a mobile phone
Talking to a passenger
Playing loud music
Having children in the car
Using GPS or a navigation system
Don't know

Q8Distractor: Do you recall which company/brand made the video you just watched? *Please type your response below.*

Q9Distractor: What was your key takeaway from the video? *Please type your response below.*

Q1Awareness: Which of these financial service providers had you heard of before today? Please select all brands you are aware of	
ANZ	Macquarie Bank
Aussie Home Loans	National Australia Bank
Bank of Melbourne	RAMS
BankSA	St. George Bank
Bankwest	Suncorp Bank
Bendigo Bank	Ubank
BT	Westpac
Commonwealth Bank of Australia	None of these

Brand Image Attributes

You will now be shown some statements that may be associated with financial *service providers.*

Please look at each statement and indicate which, if any, of the listed brands, you associate with that statement. You can select as many or as few brands as you like.

It does not matter if you have bought or used the brand or not, it is your opinion we seek to collect.

Q2Attributes: Which of these financial service providers do you link with the following statement? You can select as many or as few as you like, or none of these, if none are relevant to the statement.

[INSERT CEP]

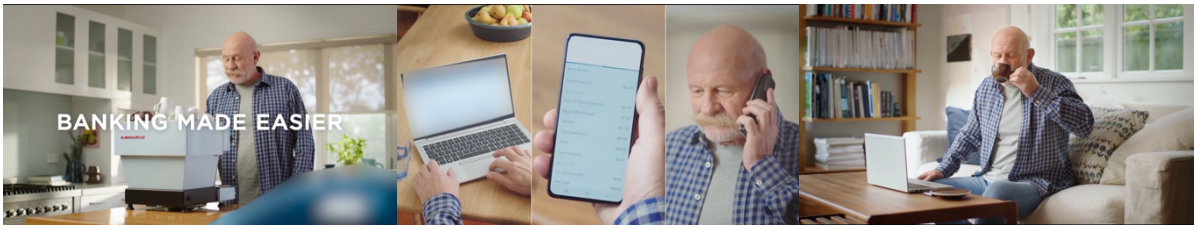
Please select as many as apply

ANZ	Macquarie Bank
Aussie Home Loans	National Australia Bank
Bank of Melbourne	RAMS

BankSA	St. George Bank
Bankwest	Suncorp Bank
Bendigo Bank	Ubank
BT	Westpac
Commonwealth Bank of Australia	None of these

Advertising Awareness

Q1AdAwareness: Do you recall seeing any advertising during the video you just watched? If so, for which brands? *Please type your response below.*
Saw no advertising in video



Q1AdRecog: Below are some images from a video advertisement. Do you recall seeing this video ad recently? *Please select one response*
Yes
No
Unsure

Q2aDebranded: Which brand was the advertisement for? *Please type your response below*
Unsure

Q2bBranded: Which brand was the advertisement for? *Please type your response below*
Unsure

Q3Likability: Thinking about the ad you just saw, which of these best describes your feelings about the ad? *Please select one response*
I liked it very much
I liked it
I neither liked or disliked it
I disliked it
I disliked it very much

Q4Message: What message do you believe the advertisement was trying to convey? *Please type your response below*

Q5Emotion: Do you feel emotionally close to any of these brands? *Please select all brands that apply*	
ANZ	Macquarie Bank
Aussie Home Loans	National Australia Bank
Bank of Melbourne	RAMS
BankSA	St. George Bank

Bankwest	Suncorp Bank
Bendigo Bank	Ubank
BT	Westpac
Commonwealth Bank of Australia	None of these

Q6Purpose: And lastly, what do you think was the intent of this study?

Please type your response below.

THANK YOU FOR TAKING THIS SURVEY

APPENDIX D: Category Entry Points Per Category

In Appendix D, the CEPs used in each category are provided. The categories are in the following order: Financial services, on-demand streaming, chocolate, and coffee. The CEP that was agreed to be present by all four coders in the given advertising for each category is highlighted in blue.

Table 39: Category Entry Points for the financial services category.

(n= 18)
To help someone who wants to quickly improve their financial situation
Would have the technology to help someone easily access and manage their finances from anywhere
Would protect someone's money, even when the economic conditions are uncertain
Would be there to help with financial decisions when there are big changes in someone's life (e.g., changing jobs, having a baby, getting married, death of a loved one)
When making a big financial decision that will involve other people you care about/respect
Has good relationships with retailers that will help me easily finance my purchases
Has staff with the expertise I need to help me make good decisions
Has the tools for when someone wants to keep close track of their expenses
Help someone be financially secure so they can help their loved ones if needed
Would help someone get out of the cycle of feeling constantly like they just do not have enough money
Help someone achieve a more stable and secure financial future
Could help when emerging financial worries are making someone stressed and unhappy
Need money for a big emergency such as a medical issue or something important broken down
Get the money to buy something big/expensive like an apartment or a car
For refinancing an existing loan/credit card to get better conditions
Good to talk to when financing is a bit of a challenge/more complicated
Would help someone make smart use of any cash bonuses or prizes
Would be understanding if someone had financial difficulties due to unfortunate circumstances such as losing their job or an illness

Table 40: Category Entry Points for the on-demand streaming category.

(n= 21)
To binge an entire series
To have a wide variety of genres to choose from
When I want to watch my favourite sports
To rewatch old favourites
To learn things
For someone who wants to avoid advertising
To watch new releases people are talking about
Good to watch before bed
When I've got some time to watch something just for me
For a movie night in
To have a treat after a busy week
I can conveniently watch when I'm out and about
For a cosy night in
Good to have on while I do something else like scroll social media
To have on while I get housework done
Something to do while eating a meal
For the whole family to enjoy
To connect with my partner
To watch and socialise with friends
Can cheer me up if I'm feeling down
Helps to take my mind off life's stresses

Table 41: Category Entry Points for the chocolate category.

(n= 24)
To give me a boost of energy
Something to tide me over between meals
For the pleasure of its texture and taste
For special events and holidays - e.g., Christmas, Easter, Halloween, Father's Day, Mother's Day, Valentine's Day
Part of my everyday routine
For after/to finish a meal
Good to eat while watching TV, sports or movies
Good for social occasions
Something children will like
To have with a drink e.g. tea, coffee, wine, spirits
When outdoors - picnic, BBQ, Beach
At work or school
For me, to spoil or treat myself
Something that is always good to have in the pantry at home
A fail-safe gift
When someone wants something healthier or more natural
To say thank you
To use in cooking or baking
To share with my family
A little treat for someone close to you
When I want something fresh, new, and different
While I relax and unwind
When I want something to savour and eat slowly
When I just want something to relieve boredom

Table 42: Category Entry Points for the coffee category.

(n= 16)
Need something that is easy to prepare
When someone has more time to prepare coffee
Helps someone to achieve and perform/be at their best
To have first thing in the morning, after getting up
To have at the end of a long day, after getting home
Something to have every day, as part of the daily routine
When doing work around the house (e.g., cleaning, gardening)
When relaxing at home
When at work or school
For when people visit
When taking a moment for myself/doing something good for myself
Something that is good on its own, with nothing else added
To have when eating something sweet (e.g., biscuits, cake)
Helps to wake up someone who is tired
Can put someone in a good mood
Helps someone to rest and recharge when taking a break

APPENDIX E: RQ1b Results for All Brands

Appendix E shows the MA Metrics across all brands within the competitive set. The target brand in each of the categories is highlighted within the table. This appendix is divided up as follows:

Section 1: Main sample – RQ1b results for financial services, on-demand streaming, chocolate, and coffee categories (Tables 43 to 46).

Section 2: Control – RQ1b results for financial services, on-demand streaming, chocolate, and coffee categories (Tables 47 to 50).

Section 1: Main Sample

Financial Services Category

Table 43: MA Metrics measured in Wave 1 and Wave 2 for all brands in the financial services category, for the main sample.

Total Sample (n= 792)	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
ANZ	10.6	12.0	*1.3*	66.9*	72.1*	*5.2*	6.4	6.9	*0.5*	16.1	19.8	*3.7*
Aussie Home Loans	4.4	4.6	*0.2*	47.6	47.7	*0.1*	3.8	4.1	*0.3*	7.7	8.0	*0.3*
Bank of Melbourne	4.3	4.2	*0.0*	36.5	34.2	*-2.3*	4.7	5.2	*0.5*	7.7	7.8	*0.1*
BankSA	3.4	3.3	*-0.1*	31.4	29.0	*-2.4*	4.4	4.8	*0.4*	7.5	7.4	*-0.1*
Bankwest	4.2	4.4	*0.2*	38.3	36.9	*-1.4*	4.4	5.0	*0.5*	8.6	8.9	*0.3*
Bendigo Bank	7.0	6.5	*-0.5*	51.0	49.6	*-1.4*	5.5	5.5	*0.0*	12.6	12.1	*-0.5*
BT	2.2	2.3	*0.1*	25.0	22.9	*-2.1*	3.5	4.2	*0.7*	5.1	5.8	*0.6*

Commbank	16.1	15.4	-0.7	79.7	77.9	-1.8	8.2	8.3	0.1	27.3	27.7	0.4
Macquarie	4.3	4.3	0.0	40.2	39.8	-0.4	4.3	4.5	0.2	7.7	7.9	0.2
NAB	12.0	11.3	-0.7	70.5	70.6	0.1	6.9	6.7	-0.2	19.2	18.5	-0.7
RAMS	3.8	4.0	0.2	41.3	40.0	-1.3	3.7	4.2	0.5	7.0	7.4	0.4
St George	7.5	7.3	-0.2	55.1	51.8	-3.3	5.5	5.9	0.4	12.4	12.2	-0.2
Suncorp	6.1	6.0	-0.1	48.4	46.3	-2.0	5.1	5.5	0.3	10.4	10.1	-0.4
Ubank	3.5	3.6	0.1	37.6	34.3	-3.3	3.8	4.4	0.6	8.4	8.4	0.0
Westpac	10.7	10.8	0.1	70.5	68.4	-2.0	6.2	6.6	0.5	16.7	17.4	0.7
Average	6.7	6.7	0.0	49.3	48.1	-1.2	5.1	5.4	0.4	11.6	12.0	0.3

*$p<0.05$

On-Demand Streaming Category

Table 44: MA Metrics measured in Wave 1 and Wave 2 for all brands in the on-demand streaming category, for the main sample.

Total Sample (n= 791)	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Amazon Prime	11.3	10.4	*-0.9*	62.5	62.1	*-0.4*	8.4	7.8	*-0.7*	16.3	15.6	*-0.7*
Apple TV+	4.8	4.6	*-0.2*	39.7	38.9	*-0.8*	5.6	5.5	*-0.1*	9.0	8.6	*-0.4*
Binge	8.2	8.1	*-0.1*	54.6	56.0	*1.4*	7.0	6.7	*-0.3*	12.8	11.7	*-1.1*
Cotto (Fake Brand)	0.7	0.8	*0.1*	8.5	10.1	*1.6*	3.7	3.5	*-0.2*	6.4	5.2	*-1.2*
Disney+	13.7	14.4	*0.7*	75.0	79.4*	*4.4*	8.5	8.4	*-0.1*	17.1	17.7	*0.6*
ESPN	2.3	2.5	*0.3*	36.5	46.0*	*9.5*	2.9	2.5	*-0.3*	5.1	4.7	*-0.5*
Foxtel	9.8	10.3	*0.5*	61.9	64.1	*2.1*	7.4	7.5	*0.1*	15.7	16.1	*0.4*
Hulu	1.6	2.1	*0.5*	19.6	24.4*	*4.8*	3.9	4.1	*0.2*	5.6	6.1	*0.5*
Netflix	29.2	28.6	*-0.5*	97.6	96.6	*-1.0*	14.0	13.8	*-0.2*	38.7	38.3	*-0.4*
Paramount+	7.2	7.2	*0.0*	51.3	51.5	*0.1*	6.6	6.5	*-0.1*	10.6	10.2	*-0.4*
Stan	11.2	10.9	*-0.3*	65.6	65.6	*0.0*	8.0	7.7	*-0.3*	15.2	14.4	*-0.8*
Average	9.1	9.1	*0.0*	52.1	54.1	*2.0*	6.9	6.7	*-0.2*	13.9	13.5	*-0.4*

*$p<0.05$

Note: ESPN and Hulu both had audio mentions in the advertisement shown. This is explored in Chapter 8, section 8.2.1.2 as a limitation of this research.

Chocolate Category

Table 45: MA Metrics measured in Wave 1 and Wave 2 for all brands in the chocolate category, for the main sample.

Total Sample (n= 813)	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Cadbury Favourites	13.4	13.2	*-0.2*	94.8	93.2	*-1.6*	8.4	8.0	*-0.4*	15.7	15.8	*0.1*
Cadbury Roses	9.5	9.4	*-0.1*	87.7	85.2*	*-2.5*	6.4	6.2	*-0.2*	10.9	10.9	*0.0*
Celebrations	9.3	9.2	*-0.1*	85.2	85.5	*0.2*	6.5	6.1	*-0.4*	10.5	10.4	*-0.1*
Darrell Lea	6.0	5.9	*-0.1*	69.5	68.6	*-0.9*	5.1	4.9	*-0.3*	7.5	7.3	*-0.1*
Ferrero Rocher	10.0	11.5	*1.4*	88.2	86.6	*-1.6*	6.8	7.5	*0.7*	11.8	14.0	*2.2*
Kinder Bueno	4.8	4.6	*-0.2*	79.6	78.7	*-0.9*	3.6	3.3	*-0.3*	5.6	5.5	*-0.1*
KitKat	9.4	9.1	*-0.3*	91.1	87.3*	*-3.8*	6.1	5.9	*-0.2*	11.1	10.8	*-0.3*
Lindt Lindor	10.0	9.9	*0.0*	85.6	82.8*	*-2.8*	6.9	6.8	*-0.1*	12.1	12.5	*0.4*
M&M's	8.0	7.7	*-0.3*	88.9	85.6*	*-3.3*	5.3	5.1	*-0.2*	8.9	9.0	*0.2*
Mars	7.3	7.1	*-0.2*	80.7	80.2	*-0.5*	5.4	5.0	*-0.4*	8.8	8.6	*-0.2*
Raffaello	5.6	6.0	*0.4*	66.4	63.5	*-3.0*	5.0	5.3	*0.3*	7.2	7.9	*0.7*
Snickers	6.6	6.4	*-0.2*	77.2	75.6	*-1.6*	5.1	4.8	*-0.3*	8.1	8.0	*-0.1*
Average	8.3	8.3	*0.0*	82.9	81.1	*-1.8*	5.9	5.7	*-0.1*	9.8	10.1	*0.2*

*$p<0.05$

Coffee Category

Table 46: MA Metrics measured in Wave 1 and Wave 2 for all brands in the coffee category, for the main sample.

Total Sample (n= 798)	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Caffe Aurora	3.8	3.8	*0.0*	26.8	25.8	*-1.0*	2.5	2.6	*0.1*	10.4	10.6	*0.2*
Delta	2.2	2.0	*-0.2*	15.2	15.0	*-0.1*	2.6	2.4	*-0.2*	9.3	8.5	*-0.9*
Harris	4.3	4.1	*-0.2*	26.8	23.1*	*-3.8*	2.8	3.2	*0.3*	12.7	13.5	*0.8*
L'OR	7.4	6.9	*-0.5*	43.4	37.2*	*-6.1*	3.0	3.3	*0.3*	13.8	13.8	*0.1*
Moccona	23.1	22.7	*-0.4*	80.7	79.2	*-1.5*	5.1	5.1	*0.0*	32.9	31.8	*-1.0*
Nescafé	23.0	22.7	*-0.3*	80.7	81.7	*1.0*	5.1	4.9	*-0.1*	32.6	30.5	*-2.1*
Nespresso	15.7	19.8	*4.1*	69.4	77.6*	*8.1*	4.0	4.5	*0.5*	22.5	26.8	*4.3*
Starbucks	8.5	8.6	*0.2*	48.9	49.7	*0.9*	3.1	3.1	*0.0*	15.3	15.2	*-0.1*
Vittoria	10.7	9.3	*-1.4*	54.9	50.0*	*-4.9*	3.4	3.3	*-0.1*	17.9	16.6	*-1.3*
Average	11.0	11.1	*0.2*	49.6	48.8	*-0.8*	3.5	3.6	*0.1*	18.6	18.6	*0.0*

*$p<0.05$

Section 2: Control

Financial Services Category

Table 47: MA Metrics measured in Wave 1 and Wave 2 for all brands in the financial services category, for the control group.

Total Sample (n= 55)	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
ANZ	11.6	11.4	*-0.1*	65.5	54.5	*-10.9*	6.1	6.9	*0.8*	23.0	23.1	*0.1*
Aussie Home Loans	3.4	3.6	*0.3*	41.8	38.2	*-3.6*	2.8	3.1	*0.4*	5.7	6.2	*0.5*
Bank of Melbourne	2.9	2.8	*-0.1*	29.1	23.6	*-5.5*	3.5	3.9	*0.4*	5.5	7.1	*1.6*
BankSA	4.1	3.4	*-0.7*	29.1	25.5	*-3.6*	4.9	4.4	*-0.5*	10.5	13.2	*2.7*
Bankwest	4.3	3.5	*-0.8*	25.5	29.1	*3.6*	5.8	3.9	*-1.8*	12.9	11.5	*-1.4*
Bendigo Bank	7.3	6.7	*-0.6*	38.2	32.7	*-5.5*	6.6	6.8	*0.2*	12.8	13.5	*0.7*
BT	1.3	1.2	*-0.2*	20.0	14.5	*-5.5*	2.3	2.6	*0.4*	3.0	4.0	*1.0*
Commbank	14.6	16.8	*2.2*	69.1	69.1	*0.0*	7.3	8.1	*0.7*	25.2	29.0	*3.8*
Macquarie	3.9	3.3	*-0.6*	30.9	34.5	*3.6*	4.4	3.2	*-1.2*	5.6	5.6	*0.0*
NAB	13.2	14.0	*0.9*	65.5	63.6	*-1.8*	7.0	7.3	*0.3*	22.6	25.7	*3.1*
RAMS	3.1	4.4	*1.3*	34.5	41.8	*7.3*	3.1	3.5	*0.4*	5.3	7.3	*2.0*
St George	8.5	6.4	*-2.1*	50.9	45.5	*-5.5*	5.8	4.6	*-1.1*	15.3	10.0	*-5.3*
Suncorp	6.0	6.0	*-0.1*	40.0	40.0	*0.0*	5.2	5.0	*-0.3*	11.5	11.2	*-0.3*
Ubank	3.3	2.6	*-0.6*	34.5	30.9	*-3.6*	3.3	2.8	*-0.4*	7.5	5.6	*-1.9*

Westpac	12.6	13.9	*1.3*	67.3	69.1	*1.8*	6.5	6.7	*0.2*	24.7	28.3	*3.6*
Average	6.7	6.7	*0.0*	42.8	40.8	*-1.9*	5.0	4.9	*-0.1*	12.7	13.4	*0.7*

*$p<0.05$

On-Demand Streaming Category

Table 48: MA Metrics measured in Wave 1 and Wave 2 for all brands in the on-demand streaming category, for the control group.

Total Sample (n= 55)	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Amazon Prime	10.0	9.9	*-0.1*	65.5	63.6	*-1.8*	7.7	6.9	*-0.8*	12.6	11.9	*-0.8*
Apple TV+	5.1	5.0	*-0.1*	47.3	43.6	*-3.6*	5.5	5.1	*-0.4*	8.4	11.5	*3.1*
Binge	8.0	8.0	*0.0*	63.6	65.5	*1.8*	6.3	5.4	*-0.9*	12.4	11.9	*-0.5*
Cotto (Fake Brand)	1.3	1.1	*-0.3*	14.5	10.9	*-3.6*	4.6	4.3	*-0.3*	6.0	12.1	*6.0*
Disney+	13.3	13.1	*-0.2*	81.8	76.4	*-5.5*	8.2	7.6	*-0.6*	15.2	14.5	*-0.7*
ESPN	2.2	2.3	*0.1*	50.9	50.9	*0.0*	2.2	2.0	*-0.2*	4.4	4.6	*0.2*
Foxtel	9.0	9.0	*0.0*	67.3	69.1	*1.8*	6.8	5.8	*-1.0*	13.6	14.1	*0.4*
Hulu	2.7	1.4	*-1.3*	29.1	21.8	*-7.3*	4.7	2.8	*-1.9*	6.8	4.6	*-2.1*
Netflix	26.4	27.8	*1.4*	96.4	94.5	*-1.8*	13.9	13.0	*-0.9*	35.7	37.3	*1.6*
Paramount+	9.0	9.0	*0.0*	61.8	63.6	*1.8*	7.4	6.3	*-1.1*	11.3	11.6	*0.3*
Stan	13.0	13.5	*0.4*	80.0	83.6	*3.6*	8.3	7.1	*-1.1*	14.7	13.8	*-0.9*
Average	9.1	9.1	*0.0*	59.8	58.5	*-1.3*	6.9	6.0	*-0.8*	12.8	13.4	*0.6*

*$p<0.05$

Chocolate Category

Table 49: MA Metrics measured in Wave 1 and Wave 2 for all brands in the chocolate category, for the control group.

Total Sample (n= 55)	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Cadbury Favourites	12.6	12.0	*-0.6*	94.5	89.1	*-5.5*	7.9	7.9	*0.0*	14.1	14.9	*0.9*
Cadbury Roses	8.6	9.5	*0.9*	81.8	87.3	*5.5*	6.2	6.3	*0.2*	10.3	11.7	*1.4*
Celebrations	8.6	8.3	*-0.4*	78.2	80.0	*1.8*	6.5	6.0	*-0.5*	10.4	10.3	*-0.1*
Darrell Lea	6.1	6.5	*0.3*	72.7	65.5	*-7.3*	5.0	5.8	*0.8*	8.3	9.3	*1.0*
Ferrero Rocher	9.6	10.8	*1.2*	87.3	87.3	*0.0*	6.5	7.2	*0.7*	11.3	13.9	*2.5*
Kinder Bueno	4.4	5.5	*1.0*	70.9	83.6*	*12.7*	3.7	3.8	*0.1*	5.1	5.2	*0.1*
KitKat	11.7	9.8	*-1.9*	94.5	83.6*	*-10.9*	7.3	6.8	*-0.5*	14.7	13.1	*-1.6*
Lindt Lindor	8.3	8.0	*-0.4*	83.6	74.5	*-9.1*	5.8	6.2	*0.4*	10.6	11.2	*0.6*
M&M's	9.0	8.3	*-0.7*	81.8	85.5	*3.6*	6.5	5.7	*-0.8*	11.3	10.1	*-1.2*
Mars	8.1	8.6	*0.5*	76.4	76.4	*0.0*	6.2	6.5	*0.3*	9.5	9.8	*0.4*
Raffaello	5.3	5.7	*0.5*	54.5	56.4	*1.8*	5.7	5.9	*0.3*	8.3	7.3	*-0.9*
Snickers	7.6	7.0	*-0.6*	80.0	72.7	*-7.3*	5.6	5.7	*0.0*	8.6	8.5	*-0.2*
Average	8.3	8.3	*0.0*	79.7	78.5	*-1.2*	6.1	6.2	*0.1*	10.2	10.4	*0.2*

*$p<0.05$

Coffee Category

Table 50: MA Metrics measured in Wave 1and Wave 2 for all brands in the coffee category, for the control group.

Total Sample (n= 52)	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Caffe Aurora	4.8	4.0	*-0.9*	28.8	21.2	*-7.7*	3.0	3.4	*0.4*	9.7	11.9	*2.2*
Delta	1.8	2.2	*0.3*	11.5	19.2	*7.7*	2.8	2.0	*-0.8*	8.2	6.6	*-1.5*
Harris	3.3	4.6	*1.3*	21.2	21.2	*0.0*	2.8	3.9	*1.1*	9.7	13.7	*4.0*
L'OR	6.8	6.4	*-0.4*	42.3	44.2	*1.9*	2.9	2.6	*-0.3*	13.8	12.5	*-1.3*
Moccona	21.2	21.6	*0.3*	84.6	78.8	*-5.8*	4.5	4.9	*0.4*	32.2	32.0	*-0.1*
Nescafé	19.1	21.9	*2.8*	80.8	78.8	*-1.9*	4.2	5.0	*0.7*	25.6	30.8	*5.1*
Nespresso	20.9	19.6	*-1.3*	80.8	80.8	*0.0*	4.6	4.3	*-0.3*	27.6	26.0	*-1.6*
Starbucks	9.9	8.6	*-1.3*	50.0	57.7	*7.7*	3.5	2.7	*-0.9*	16.8	14.0	*-2.8*
Vittoria	11.0	11.2	*0.2*	53.8	50.0	*-3.8*	3.6	4.0	*0.4*	18.1	18.2	*0.2*
Average	11.0	11.1	*0.1*	50.4	50.2	*-0.2*	3.6	3.6	*0.1*	18.0	18.4	*0.5*

*$p<0.05$

APPENDIX F: Control Group Results

Appendix F details the results for the control group, across all four metrics. It follows the same structure as Chapter 6, section 6.1 and 6.2 which shows the results for the main sample.

This appendix is divided into two sections:

Section 1: RQ1b Results (Table 51 and 52)

Section 2: RQ1c Results, with users (Table 53 and 54) followed by non-users (Table 55 and 56).

Section 1: RQ1b Results

Table 51: Brand level MA Metrics in Wave 1 and Wave 2 for the control group.

	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	Diff (W2-W1)	W1	W2	Diff (W2-W1)	W1	W2	Diff (W2-W1)	W1	W2	Diff (W2-W1)
Coffee brand (n= 52)	20.9	19.6	-1.3	80.8	80.8	0.0	4.6	4.3	-0.3	27.6	26.0	-1.6
On-demand streaming brand (n= 55)	13.3	13.1	-0.2	81.8	76.4	-5.5	8.2	7.6	-0.6	15.2	14.5	-0.7
Financial services brand (n= 55)	11.6	11.4	-0.1	65.5	54.5	-10.9	6.1	6.9	0.8	23.0	23.1	0.1
Chocolate brand (n= 55)	9.3	6.2	-3.2	85.5	87.3	1.8	6.1	6.7	0.6	11.2	13.6	2.4
Average	13.8	12.6	-1.2	78.4	74.7	-3.6	6.3	6.4	0.1	19.3	19.3	0.1

*$p<0.05$

Table 52: Average actual and percentage difference in MA Metrics across brand level results for the control group.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
Positive direction of change (over four observations)	0 of 4 positive change	2 of 4 positive change	2 of 4 positive change	2 of 4 positive change
Average actual difference	-1.2	-3.6	0.1	0.1
Average percentage difference (%)	-9.6	-4.9	2.1	0.3

Section 2: RQ1c Results (Users and Non-Users)

Table 53: Brand level MA Metrics in Wave 1 and Wave 2 for brand users in the control group.

	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Coffee brand: Users (n= 12)	33.1	27.7	*-5.4*	100	91.7	*-8.3*	6.5	5.9	*-0.6*	42.0	39.0	*-3.1*
Financial services brand: Users (n= 12)	22.4	19.2	*-3.2*	83.3	66.7	*-16.7*	8.3	7.5	*-0.8*	44.7	37.1	*-7.6*
On-demand streaming brand: Users (n= 22)	16.0	16.3	*0.3*	95.5	95.5	*0.0*	10.2	9.9	*-0.3*	18.3	16.8	*-1.4*
Chocolate brand: Users (n= 9)	10.2	11.3	*1.1*	88.9	100	*11.1*	7.9	9.0	*1.1*	10.6	14.6	*4.0*
Average	20.4	18.6	*-1.8*	91.9	88.4	-3.5	8.2	8.1	*-0.1*	28.9	26.9	-2.0

*$p<0.05$

Table 54: Average actual and percentage difference in MA Metrics across brand users for the control group.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
Positive direction of change (over four observations)	2 of 4 positive change	2 of 4 positive change	1 of 4 positive change	1 of 4 positive change
Average actual difference	-1.2	-3.6	0.1	0.1
Average percentage difference (%)	-9.6	-4.9	2.1	0.3

Table 55: Brand level MA Metrics in Wave 1 and Wave 2 for brand non- users in the control group.

	MMS %			Assoc Pen (Ab) %			Assoc Rate (Aw) #			SoM %		
	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*	W1	W2	*Diff (W2-W1)*
Coffee brand: Non-Users (n= 40)	17.0	16.9	0.1	75.0	77.5	*2.5*	3.9	3.8	*-0.1*	21.8	21.5	*-0.4*
Chocolate brand: Non-Users (n= 46)	9.5	10.6	1.2	87.0	84.8	*-2.2*	6.2	6.8	*0.6*	11.4	13.7	*2.2*
Financial services brand: Non-Users (n= 43)	8.9	9.8	0.9	60.5	51.2	*-9.3*	5.3	6.7	*1.5*	14.6	18.0	*3.4*
On-demand streaming brand: Non-Users (n= 33)	10.8	9.6	-1.2	72.7	63.6	*-9.1*	6.5	5.3	*-1.2*	12.5	12.2	*-0.3*
Average	11.6	11.7	0.2	73.8	69.3	*-4.5*	5.5	5.6	*0.2*	15.1	16.3	*1.2*

**p<0.05*

Table 56: Average actual and percentage difference in MA Metrics across brand non-users for the control group.

	MMS %	Assoc Pen (Ab) %	Assoc Rate (Aw) #	SoM %
Positive direction of change (over four observations)	3 of 4 positive change	1 of 4 positive change	2 of 4 positive change	2 of 4 positive change
Average actual difference	-1.2	-3.6	0.1	0.1
Average percentage difference (%)	-9.6	-4.9	2.1	0.3

APPENDIX G: RQ3 Additional Results

This appendix details the actual number of respondents for each of the sub-groups (Recognised And Correct Brand, Recognised Not Correct Brand, Not Recognised) that were used to calculate the proportions in answer to RQ3. The count across the main sample is detailed in Table 57. Table 58 shows the number of all individuals per category, as well as the number of brand users and non-users for each category.

Table 57: Actual number of respondents per category, across the sub-groups.

	Users (n)			Non-Users (n)		
	Recog. And Correct Brand	Recog. Not Correct Brand	Not Recognised	Recog. And Correct Brand	Recog. Not Correct Brand	Not Recognised
Coffee brand	82	23	22	385	179	107
Financial services brand	97	27	25	367	170	106
On-demand streaming brand	146	74	45	226	183	117
Chocolate brand	51	39	38	256	202	227
Average	94	41	33	309	184	139

Table 58: Number of all individuals, and across different consumer groups.

	All Individuals (n)	Users (n)	Non-Users (n)
Coffee	798	127	671
Financial services	792	149	643
On-demand streaming	791	265	526
Chocolate	813	128	685

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