In Search of Balanced Metrics: Understanding the Role of Consumer Mindset Metrics in Online Interactions

Kate Gunby

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Statement of Originality

This is to certify that, to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

Kate Gunby

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Abstract

The rise of both digital advertising and eCommerce platforms has provided marketers with more ways to communicate with consumers than ever before. Yet this increased choice has created additional complexity in measuring the performance of advertising communications. A key reason for this complexity is the active role that consumers now take in their own advertising exposure through communication channels, such as search, which are classified as consumer-initiated contacts (CICs). Commonly used metrics and approaches to measuring advertising performance have not been adapted to account for this and consequently can overestimate the role of advertising that is consumer initiated (Blake et al., 2015). One major challenge in improving the way we measure CICs, including search, is the limited knowledge we possess about what leads consumers to engage with a brand on the internet.

Prior research has shown a weak correlation between customer mindset metrics (CMMs) and online behaviours (CICs) at an aggregate level (Pauwels & van Ewijk, 2020), however, this does not allow us to understand the differences across consumers. While customer mindset metrics (CMMs), such as awareness and consideration, play a role in determining online behaviours, these attitudinal and behavioural approaches to performance measurement largely exist in silos, and there is limited understanding of how these two important streams of measurement can be linked.

Using an innovative approach to data collection with passive metering technology which is able to capture data at the individual level, this research demonstrates how consumer attitudes influence interactions with brands online at an individual level for 27 brands across three categories. The application of hurdle model analysis enables us to comprehend not only the effect of CMMs on the probability of a brand website visit, but also the frequency of such visits.

Results show that 85% of all visits come from consumers with at least one positive mindset metric (a top 2 rating for either liking or familiarity), and those with the most

positive mindsets are up to 24 times more likely to visit a brand website. Furthermore, the optimal manner of representing CMMs is not via the traditional measures from a hierarchy of effect models (awareness, consideration and preference) nor, as prior research has suggested, purely using cognitive metrics (Cain, 2022; Dotson et al., 2017), but rather via separate measures of familiarity and liking which allows the strongest CMMs to be revealed as increasing website visit likelihood.

Neglecting to consider the relationship between CMMs and website visits in metrics and performance models could result in an excessive allocation of resources to media channels in which consumers initiate their own advertising exposure. As a result, media investments may be biased towards those who are already predisposed to a brand. This can result in the diversion of funds away from advertising focused upon building positive brand attitudes. Since failure to build positive attitudes could risk the long-term sales potential of a brand, managers need to keep measuring CMMs even if advertising expenditure shifts online if the objective is to build the brand.

Keywords: **Advertising performance measurement, Brand building**

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Table of Definitions

Acronym	Description	Explanation
CBBE	**Consumer Based Brand Equity**	Construct proposed by Keller (1993) that is key to putting individual at the centre of brand equity
CDJ	**Customer Decision Journey**	The journey that potential customers take when making a purchase, could include stages such as awareness, consideration, purchase and post purchase.
CICs	**Consumer initiated contacts**	Advertising where the consumer initiates the exposure such as search.
CMM	**Customer Mindset Metrics**	Survey metrics that capture consumer attitudes towards a brand including key measures such as awareness, familiarity, liking
CPA	**Cost Per Action (Often an Acquisition or Sale)**	The cost for each action that takes place, often a sale where it is possible to track this online. When collected at a highly granular level it is possible to compare these across different attributes (e.g. by day part, by website, etc) CPA = Total Spend/Total actions
CPC	**Cost per Click**	A key reporting metric for digital advertising where the cost for each click is shown and compared across media channels, websites or creative executions. CPC = Total spend/Total clicks
CPM	**Cost Per Mille (Cost per thousand)**	Traditional metric for buying, shows the cost to reach 1000 viewers or for digital channels cost for 1000 impressions.
CTR	**Click Through Rate**	The rate at which people who are exposed to an advertisement online click through to make a website visit CTR = (Clicks/impressions) x100
FICs	**Firm initiated contacts**	Advertising where the firm initiates the exposure such as television
FMCG	**Fast Moving Consumer Goods**	Also called consumer packaged goods, items such as food, toiletries and everyday household items commonly sold in supermarkets or convenience stores. They are generally purchased regularly and considered a low involvement purchase.
HOE	**Hierarchy of Effects**	Brand funnel models starting with AIDA (Awareness, Interest, Desire, Action)
KPI	**Key Performance Indicator**	Critical indicators that evaluate how well an organization is doing at achieving its

		goals and where improvements need to be made.
MMM	**Marketing Mix Modelling**	Econometric modelling applied to marketing variables to show the ROI different marketing mix variables provide to the business.
MPA	**Marketing performance assessment**	Framework or tool to help marketers understand which metrics to capture to measure success and how different metrics may influence each other. By regularly assessing performance marketers aim to achieve a higher ROI
OOH	**Out of Home**	Outdoor, poster advertising
OTS	**Opportunity to see**	Traditional media is measured by the opportunity to see rather than confirmed viewing
PPC	**Pay per Click**	The investment model used where advertisers pay for each click. This price often changes dynamically depending on demand.
ROI	**Return on Investment**	A ration of financial returns and in investment. Anything over 1 considered a positive return This is often not reflective of how it is used in industry so when claims are made of how many business are using an ROI metric, we need to express caution
ROMI	**Return on marketing investment**	The incremental revenue achieved from marketing spend Most often presented as a ratio 1:1.2 showing that there is a $1.20 return for every $1 invested. In some contexts, ROMI has been used to mean return on marginal investment responding to the need to understand where the next dollar is best investment. In this research I specify this separately and without acronym in discussion
RTB	**Real Time Bidding**	An automated approach to buying and selling media impressions using automated algorithms. Bids are placed as to how much advertisers are willing to pays and the highest bid wins.
SEO	**Search Engine Optimisation**	Approach to optimising website content to improve visibility and ranking in search engine results.
TVC	**Television Commercial**	An advertisement shown on television, there are now subcategories such as subscription TV (STV) but this detail does not impact this research
VIF	**Variance Inflation Factor**	A measure for multicollinearity used in regression modelling.

Chapter 1: Introduction

The estimated value of the global advertising industry has grown to USD 881 billion, representing an 8.3% increase from 2001 (McDonald, 2022), and it has risen from USD 336 billion at the beginning of the 21st century (Zenith, 2022a). Owing to the high value of the industry and the fact that advertising spend is typically the largest discretionary item that marketers have control over (Ambler, 2003), there has been an ongoing push for accountability in advertising. Thus, one of the crucial responsibilities of managing advertising budgets is demonstrating the value of their investments (Katsikeas et al., 2016; Verhoef & Leeflang, 2011). If accountability is not present in marketing, marketing executives may lose power within the organisation (Rust et al., 2004). However, metrics are important not only for accountability but also for decision-making. Choosing incorrect metrics can result in poor decisions (Mintz, Gilbride et al., 2021). Despite recognition that metrics are essential for control, communication and improvement (Melnyk et al., 2004), selecting the right metrics to track, communicate and act upon remains a significant challenge (Katsikeas et al., 2016; Mintz, Gilbride et al., 2021). The consequences of choosing incorrect metrics could include investing in unprofitable media channels (Blake et al., 2015; Kehrer, 2013), focusing on ineffective advertising messages (Heath & Feldwick, 2008; Sharp, 2010), or targeting suboptimal audiences (Romaniuk, 2012).

The requirement of accountability and risk of poor decision making has made selecting metrics a focus for marketers for many years. Recommendations include using multiple metrics through a balanced scorecard approach (Ambler, 2003) that tracks financial and operational performance or a performance measurement outcome chain that maps the relationships between metrics (Ambler & Roberts, 2008; Islam et al., 2013; Katsikeas et al., 2016). Dashboard reports are commonly used to provide managers with metrics. However, interpreting metrics that often have low correlations and do not move in tandem remains difficult (Hanssens & Pauwels, 2016; Pauwels & van Ewijk, 2020).

While CFOs and CEOs are frequently judged on financial metrics (Lehmann, 2006), advertising agencies are often judged on intermediate metrics (Bruce et al., 2012), these are metrics that are known to be responsive to advertising communications and help demonstrate that advertising is influencing consumers and therefore a financial return could be expected. Intermediate metrics historically meant consumer mindset metrics (CMMs), such as brand and advertising awareness, consideration and liking. New forms of intermediate metrics are now available due to the trackability of digital media channels; every click, search and website visit is now available to marketers to use as indicators of marketing performance or consumer preference. However, these two streams of metrics, showing attitudes and online behaviours, largely exist in isolation, with a limited understanding of the link between them. Rather than focusing on how to combine them, the trend is that the metrics used to report digital advertising activities begin to dominate (Dotson et al., 2017). However, doing this without first understanding how digital metrics relate to existing knowledge of how advertising works risks using inappropriate models or metrics (Morgan et al., 2022).

The rapid growth of digital advertising is partly attributed to its ability to provide direct accountability, as clickstream data allow advertisers to track the relationship between advertising exposure and product or service sales (Telang & Bhatt, 2011). Digital marketing offers new opportunities for companies to engage with customers, gather data and insights, and reach new market segments (Leeflang et al., 2014), while also enabling a more personalised approach to customer engagement (Lemon & Verhoef, 2016). However, the rise of digital advertising brings new challenges because there is no comprehensive guide of how to measure and interpret these new advertising performance metrics (Smallwood, 2016). Despite 20 years of increasing investment in digital channels, much remains to be learnt about online performance metrics. First, metrics have evolved from surveying brand attitudes to capturing behaviour-based metrics digitally (Dotson et al., 2017). Second, in the digital age, a significant portion of marketing budgets have moved towards consumer-initiated advertising exposures, such as search engine advertising, causing changes in both the conceptual and empirical understanding of the role of advertising (Pauwels & van Ewijk, 2020).

> *Although marketing metrics aren't perfect, they might be more useful if people understood what the different measures actually mean. (Bendle & Bagga, 2016, p. 73)*

This thesis focuses on key metrics used by marketers to measure the impact of advertising. The risks and implications of the shift away from CMMs, such as brand awareness and brand liking, in favour of digital performance metrics, such as clicks and website visits, are highlighted. It draws upon the perspective that CMMs better represent the brand-building component of advertising (Cain, 2022; Pauwels & van Ewijk, 2020) and that online behaviours are generally used to show an immediate response to advertising (H. Li & Kannan, 2014) By understanding which CMMs better help explain online behaviours, we can be better informed about our selection of metrics and how to interpret them. This is the first step in improving marketing performance measurement models to better reflect what is known about how advertising works

1.1 Motivation

> *Marketing is at a crossroads. Managers are frustrated by the gap between the promise and the practice of effect measurement, big data an online/offline integration (Hanssens & Pauwels, 2016, p. 173)*

This research is motivated by the desire to evolve approaches to online media performance measurement that are not bound by the constraints of day-to-day projects. After years spent building and leading marketing analytics teams, I have witnessed firsthand the confusion caused by current approaches to digital media measurement, 'analysis paralysis', 'death by data', and 'all data no insight' are common sentiments among those attempting to use data to make advertising investment decisions. There is endless reporting of different metrics and difficulties in using them to drive the strategic or tactical decisions required. Brand tracking of CMMs was becoming ‘old school’ in favour of behavioural data. Investments are being made in large technology systems that can help with targeting and automated reporting. Despite all the technologies, I saw little evidence of significant sales growth from brands reporting strong returns from digital advertising.

Numerous practitioners have made similar observations, and in the quest for accountability, it has been claimed that reporting is the most ‘carried out’ function across the industry (Holden, 2021). Despite a plethora of data and reports, a decline in return on investment (ROI) has been observed alongside increased investment in digital channels (Binet & Field, 2017; Kite, 2022), contrary to the expectations of improved ROI. There is a genuine concern that ‘big data’ fuelled by the digital ecosystem will ‘cultivate a short-term decision-making mindset’ (Fulgoni, 2013), and evidence suggests that the result will be less enjoyable and less effective at building brands (Levine, 2019). Measuring advertising performance remains challenging despite advances in data, automation and technology. Indeed, some argue that current tools, such as Google Analytics, the dominant tool for reporting digital advertising metrics, do not lead to better decision-making (Scott, 2016). Because of the apparent success of digital advertising, there has been a shift towards ‘conversion’ channels, primarily search marketing, and a decrease in traditional brand-building efforts. (Chapter 2, Figures 2.1 and 2.3).

> *We’ve seen some pretty dramatic changes that are making advertising less enjoyable, less watchable, frankly, and not the sort of advertising by and large, that puts your brand into long-term memory. (Orlando Wood, Chief Innovation Officer of System1)*

Consequently, one of the primary goals of this research is to emphasise the significance of a favourable consumer mindset before visiting a website. In other words, clicks, shares and purchases are not solely driven by the immediate impact of advertising but rather by a strong brand foundation. An overemphasis on advertising solely to drive sales from ready-to-buy customers risks neglecting brand building, resulting in being ignored by consumers who have not developed a pre-disposition towards the brand. The Marketing Science Institute (MSI) has acknowledged these challenges and has long been interested in the relationship between “soft” and “hard” metrics and their appropriate use. For nearly a decade, MSI has advocated for a better understanding of the interplay between soft and hard metrics (Marketing Science Institute, 2014, 2018, 2020). There are three key reasons why the link between ‘soft’ mindset metrics and ‘hard’ behavioural metrics is growing in importance to managers.

First, the diversification of media channels and associated metrics make it difficult to report impacts consistently.

> *Industry has been obsessed with the wrong metrics for a decade or more, with serious brand health consequences. (Peter Field, Orlando Wood and Karen Nelson-Field, interviewed for Cannes festival of media 2022)*

The digitisation within the advertising industry has created the opportunity to become more personalised with media, both in terms of who is targeted, and the message sent. This means that different media channels are evaluated based on their roles, such as brand-building versus sales generation (performance measurement). Although some agreement exists on which metrics should be used for which roles, their interaction remains poorly understood. Soft metrics are more closely associated with brand-building activities, whereas behavioural metrics are more closely associated with immediate responses (Bruce et al., 2012; Cain, 2022). Therefore, understanding the relationship between these metrics is critical to better understanding the true impact of advertising.

Second, both the consumer and the firm can now influence media exposure:

While traditionally firms initiated media contacts to find the most suitable consumers, a significant portion of media budgets are now initiated by customers through channels such as search marketing. Consequently, marketers must not only understand what actions they can take to increase the likelihood of a consumer initiating contact but also how much they should invest in these actions. Behavioural response is no longer just a measure of sales; it is also an important measure of consumer-initiated advertising exposure.

Third, Limited knowledge of how to connect various measurement streams.

The simplicity of digital reporting and the ability to use the resulting data in real-time for targeting and measurement have made it a popular choice for budget allocation (Danaher & van Heerde, 2018). If the concept of brand building and sales activation is correct, this could cause a problem if budgeting decisions are heavily influenced solely by sales activation. Therefore, understanding the relationship between the metrics is critical to adopting a more balanced approach to budget allocation.

1.2 Research Questions and Objectives

CMMs and website metrics are two of the most widely used types of metrics by marketers (ANA, 2021; Mintz, Currim et al., 2021); yet our understanding of how they interact is limited. This raises two potential issues. First, our understanding of the most appropriate CMMs to capture has not evolved for digital ecosystems. Second, our interpretation of website visitation data does not provide enough credit for offline advertising overall or online advertising in situations where there is no immediate behavioural response.

Research in this area has focused on whether and when CMMs should be used, for example (Colicev et al., 2018; Dotson et al., 2017; Pauwels & van Ewijk, 2020), rather than which ones are useful and how they should be represented. Although CMMs have been said to represent enduring attitudes (Pauwels & van Ewijk, 2020) or brand equity, they have largely been captured using a classic **marketing funnel**, showing a sequence of stages a consumer must progress through with the key mindset metrics being awareness, consideration and preference. Without first testing alternative conceptually grounded options it is not clear that this is the best approach.

Understanding the behavioural and attitudinal antecedents of online website interactions is the primary problem in this research. This research seeks to better understand the relationship between the key metrics for various measurement streams by employing constructs based on CMMs to capture **brand-building or long-term activity** and website visits to capture **performance or short-term activity**. Individual-level data can be used to determine whether there is evidence of a sequence of stages that consumers go through as represented in the classical HOE approach versus alternative approaches of independent dimensions. That is, not just whether CMMs are important, but how they should best be captured and represented to build our understanding of how mindset metrics can help predict future consumer behaviour at an individual level and how marketers should balance metrics between long- and short-term goals.

First, I conceptually examine how we expect CMMs and website visits to be related and empirically test this. The following three questions are used to test this relationship:

RQ1: Which CMMs best explain website visits, and is a sequence of CMMs supported?

RQ2: Do CMMs combined with a behavioural measure provide a better prediction of who is likely to visit a website than past behaviour alone?

RQ3: If CMMs are important what is the relative importance of CMMs and behaviours?

1.3 Overview of Thesis Structure

The remainder of this chapter explores the research context, demonstrating the importance of website visits and CMMs in underpinning of advertising performance measurement.

The rest of the thesis is organised into seven chapters. In Chapter 2, I examine the market environment surrounding the research problem. First, I review the dramatic shift brought about by digital media channels and their impact on performance measurement, focusing on how the promise of accountability has aided their growth while also raising concerns. This demonstrates the shift towards behavioural metrics and the silos that are growing in how the impact of different communications channels are judged.

Chapter 3 reviews the existing literature on digital performance measurement to demonstrate how digital metrics are used in marketing performance models. I emphasise the lack of integration of consumer-brand metrics in performance measurement and I argue that there is a lack of understanding of how consumers' attitudes and feelings towards a brand relate to their online interactions. To fill this void, I propose a conceptual framework for measuring advertising performance and three research questions to investigate the understudied area of understanding the impact of CMMs on website visits.

Chapter 4 discusses what is known about CMMs and what should be tested to better understand the relationship between CMMs and website visits. The fifth chapter focuses on data collection and how CMMs and website visits can be captured across individuals. Chapter 6 describes the methods used to conduct the research and the selection of brands and categories. The findings of the empirical study are presented in Chapter 7, which analyses each of the three research questions.

Finally, Chapter 8 discusses the significance of the findings and their contributions to the existing literature. In summary, this study assists marketers in selecting the most relevant metrics and interpreting consumer advertising responses more effectively, as well as contributing to theory by better understanding how unobserved attitudes can be used to measure the propensity of individuals to visit a brand website, thus connecting two important streams of literature on advertising performance measurement.

1.4 Research context - What We Know About Advertising Performance Metrics

I draw on several important streams of literature for this research. First and foremost, the objective is to gain a better understanding of how the most commonly used marketing metrics for customer mindsets and online behaviours relate to each other both conceptually and empirically, what this means for the data that should be collected, what role they play in measuring advertising performance and how and when they should be used and how they should be interpreted. Therefore, I examine the different metrics, both attitudinal and behavioural, and the roles they play.

1.4.1 The Increasing Usage of Website Visits as a Form of Behavioural Data

The ecosystems now built around digital marketing give marketers visibility of consumer actions they did not previously have. The richness of this behavioural data has greatly influenced recent research focused on online behavioural data (Wedel & Kannan, 2016), which provides quick campaign feedback (Moral et al., 2014), can be linked directly to sales, and can be used to programmatically buy media inventory (J. Shin et al., 2016, Sieliutina, 2020). Forrester (2016) estimates that 71% of new product or service purchases begin with a search, this highly trackable data linked to sales has been a key driver in the changes in performance measurement.

Behavioural data are thought to be more accurate in predicting future sales than attitudinal CMMs (Kumar et al., 2013; Pauwels & van Ewijk, 2020, Tanusondjaja, 2016) and more objective (Mirzaei et al., 2015). Consequently, marketing performance models, such as marketing mix models (MMM) and digital attribution models, have primarily focused on demonstrating the financial return from marketing. According to the Association of National Advertisers (ANA, 2021), this focus on financial returns has meant that the ability to directly link digital metrics, such as clicks or website visits to a sale, has made these metrics highly sought-after measures of advertising performance,

Automation is a major driver of the shift in emphasis towards behavioural data (Hanssens & Pauwels, 2016). This necessitates a large amount of data; sales are frequently unavailable, and thus automation is driven by clicks and website visits. Driving consumers to websites has become a key function of advertising (Goić et al., 2022) and website visits are regarded as a strong indicator of a consumer being in the market and are thus used by advertisers to retarget consumers (Shin & Kim, 2017). Finally, many brands can now sell products through their websites, and eCommerce is becoming increasingly valuable, and is predicted to be worth over USD 7 trillion by 2025 (*Phaneuf, 2022*). In this way, website visits are the central element of performance metrics, captured either as overall visits or as clicks on advertisements that direct users to the website.

Much research has been conducted to determine which online behaviours precede a website visit before a sale (Danaher & van Heerde, 2018; H. Li & Kannan, 2014; Y. Li et al., 2019; Shao & Li, 2011; Zhao et al., 2019). Although clicks and views are widely used metrics, the understanding of how they relate to traditional intermediate attitudinal metrics, such as liking and preference, is limited. The limited work of Cain (2022), Pauwels and van Ewijk (2020) shows that this is an important link for better understanding the direct and indirect impacts of advertising.

1.4.2 Our Evolved Understanding of Consumer Search Processes

A rich literature exists to understand how consumers now search for information in this new world. Bucklin & Sismerio (2009) provided a comprehensive research agenda grounded in the behavioural data available from website visits. Many of these areas have been explored in recent years and much of this has blended with a rich literature in consumer search (Moe et al., 2009). Search is now more than a process that consumers undertake to find information about a brand or product, it is also a major source of spend in the advertising industry. For this reason, search behaviours leading to website visits has become a major focus of marketing performance metrics and the rich consumer data in this area has redefined interactive marketing (Moe & Ratchford, 2018)

Two important streams exist in this area, one where researchers look to identify motivations for search and website visits, for example differentiating buying, searching and browsing website visits (Moe, 2003; Pallant et al., 2017), Motivations for browsing on mobile devices (Ono et al., 2012) or differences between product categories (Tangmanee, 2017). Another area looks to improve website design for example showing the importance of key attributes in driving basket value (Mallapragada et al., 2016). Yet one of the biggest implications for this data is not how we have been able to deepen our consumer understanding but rather the domination of these metrics in advertising performance measurement, with search engine marketing now considered a major advertising channel and website visits considered a key performance indicator from digital advertising (ANA, 2021).

1.4.3 The Role of Performance Metrics for Measuring Advertising Response

Good metrics are those that can be measured today but which impact future outcomes (Hauser & Katz, 1998). These metrics are the critical link between strategy, tactics and profits (Melnyk et al., 2004), allowing managers to demonstrate the role of advertising in building brand value and justifying the investment to shareholders (Ambler, 2003), as well as assisting decisions on marketing budget setting and allocation (Berry, 2014; Hutchinson et al., 2010), and different creative messages (Aaker, 1975; Ambler, 2003; Hanssens & Pauwels, 2016). How we measure marketing success significantly impacts decision-making (Berg et al., 2007). Despite the abundance of measurement options, there has been a growing emphasis on financial return and ROI due to the increased financial scrutiny of marketing investments (Ambler, 2003; Hanssens et al., 2014). However, linking campaigns to a single objective in a system can be difficult, especially when managers have large marketing budgets (Berry, 2014). As a result, intermediate metrics more closely related to media activities are frequently used instead of ROI, which is more difficult to link to marketing activities (Katsikeas et al., 2016).

The role of marketing is to first create a predisposition towards a brand, and then, when a consumer wants to make a purchase, we need to maximise the likelihood of being selected. To capture these complex dynamics, it has long been recognised that having a variety of metrics is important (Ambler & Roberts, 2008; Vakratsas & Ambler, 1999), as is understanding the role of these metrics and how they should inform decisions (Mintz, Gilbride et al., 2021). Selecting and interpreting the metrics that will be most useful for decision-making has become a major challenge for managers (Mintz, Gilbride et al., 2021; Morgan et al., 2022). To answer this question, we must first understand the goals of our activity while acknowledging that metrics are most useful when they are aligned with the goals of a company (O'Sullivan & Butler, 2010). Increasingly those objectives are being divided into two camps, longer term, **brand building activity**, or **performance** through an immediate sale or other observable behaviour such as a click or website visit (Anderson et al., 2022; Binet & Field, 2013, 2017)

The traditional role of advertising is to capture the hearts and minds of consumers (Srinivasan et al., 2010). Therefore, CMMs, such as advertising awareness, brand awareness, brand consideration, and preference, were regarded as critical intermediate metrics for determining the effectiveness of advertising campaigns. While this method is still used for traditional advertising in channels such as television and out-of-home (OOH) posters, CMMs for digital advertising are no longer the dominant method for measuring advertising performance (The CMO Survey, 2021).

The proliferation of widely available and low-cost behavioural measures through the digital ecosystem has resulted in a significant shift in how advertising performance is measured (Dotson et al., 2017; Wedel & Kannan, 2016; Zhang & Moe, 2021). Customer visits to a website, particularly for eCommerce brands, are an important stage on the path to purchase, providing the opportunity not only to research or browse but also to make a purchase. When data recording these actions are linked, they provide numerous benefits in terms of availability, granularity and cost (Dotson et al., 2017; Wedel & Kannan, 2016). One of the most appealing features is that advertising exposure in digital channels can be directly linked to a sale, and there is a perception that digital channels are more accountable because of this direct link to sales (Leeflang et al., 2014). However, there is a growing concern that the emphasis on online behavioural metrics has led to a short-term view of marketing (Binet & Field, 2013; Cain, 2022; Shotton, 2017), that non-digital channels are being overlooked, resulting in lower advertising returns (Binet & Field, 2017)

It has been difficult to demonstrate the link between the impacts of digital and traditional advertising; rather, these two measurement streams have created silos when assessing marketing performance (Nichols, 2013; Rappaport, 2014). The understanding of how these metrics relate to our existing knowledge of how advertising works and how advertisers use other key metrics is limited. This is especially true for research combining behavioural and attitudinal streams, which are thought to represent the short- and long-term impacts of advertising. The lack of understanding has been recognised, the MSI is asking how 'hard' behavioural measures can be combined with 'soft' attitudinal measures to guide marketing decisions (Marketing Science Institute, 2020), 'Which KPIs best capture behaviour, attitudes and values?' to guide marketing decisions (Marketing Science Institute, 2020), and how can new data sources and types help improve these measures? (Marketing Science Institute, 2018). This is driven by a need to identify the optimal balance between digital and traditional media spending which is a top priority for improving media strategies and an important area for development because of growing concerns about the inefficiency of current digital investments (Binet & Field, 2017).

Rather than providing an immediate answer to this complex and potentially tailored question, this research argues that utilising key performance indicators (KPIs) in media optimisation must first be reconsidered. The MSI research priorities recognise the importance of KPIs in driving growth; however, despite the influx of metrics due to big data, much work remains to be done to understand their proper usage and timing. Because the metrics used by marketers to measure performance are not independent but rather fit together in a chain (Lehmann, 2006), it is critical to understand interrelationships and linkages (Hauser & Katz, 1998), meaning that it is not only important to select independent metrics, but also to understand how these metrics fit together.

1.4.4 Our Empirical Understanding of the Relationship Between Consumer Mindset Metrics and Behavioural Metrics

Several important studies have resulted from the call for a better understanding of attitudes and behaviours. For example, some studies have investigated the relationship between consumer attitudes and sales data (Hanssens et al., 2014; Petersen et al., 2009; Srinivasan et al., 2010). Key marketing performance measurement approaches demonstrate how advertising exposure can change consumer attitudes or mindset metrics, increasing the likelihood of sales and driving shareholder value (Katsikeas et al., 2016; Vakratsas & Ambler, 1999).

CMMs are thought to be more responsive to advertising than behavioural metrics, such as sales or market share, and are thus easier to link to spending (Katsikeas et al., 2016). They have recently been shown to be more useful for guiding marketing actions than common financial metrics, such as return on marketing investment (ROMI) (Mintz, Gilbride et al., 2021). However, they lack the influence and clout of financial metrics, which are more highly regarded by CEOs and CFOs (Dotson et al., 2017). Studies that can connect these two streams are critical for marketers to demonstrate the value of their activities (Bruce et al., 2012).

Research linking attitudes to online behaviour is limited. While digital metrics have received much attention because of their prevalence, the new digital context means we cannot assume the same relationships with CMMs as we can with purchases. Even when CMMs are linked to sales, Pauwels and van Ewijk (2020) demonstrate various relationships between categories. One reason for this is the lower search volume for fast-moving consumer goods (FMCG) products (Beckman, 2016), which means that the search-to-sales ratios for FMCG goods will be different than those for higher involvement categories. Another difference is that there are few barriers to repeat levels of search (I may not need multiple cars, but I can visit a website multiple times); in fact, the density of visits is a good predictor of purchase behaviour (C. H. Park & Park, 2016), implying that frequency may be an important factor.

Some studies have examined how people respond to advertising in terms of both CMMs and online behaviours. For example, Chan et al. (2015) and Maddox (2004) show that online advertising can influence CMMs, even when no action is taken. Colicev et al. (2018) demonstrate how earned and owned social media can impact CMMs which in turn drive shareholder value. These studies consider advertising as an input and CMMs as the output. CMMs are considered an antecedent to online behaviour in the alternative approach, which is the focus of this study. Dotson et al. (2017) investigate whether brand search can replace CMMs and discover that people with a more positive mindset are up to seven times more likely to search for a brand by name. However, focusing solely on brand searches limits their research to a small percentage of website visits. To address this, my research examines overall website visits to first understand the drivers of if a consumer is going to interact with a brand online at all.

Pauwels and van Ewijk (2020) investigate the relationship between brand attitudes and online behavioural indicators showing the temporal causality between aggregate consumer attitudes and online behaviour. This dual relationship is crucial to our understanding of the role of both CMMs and online behaviours. They define the relationship between attitudes and online behaviours as a 'when' and 'why' distinction, with online metrics useful for understanding when consumers interact and attitudes useful for understanding why, but it tells us nothing about the relationship at an individual level or the 'who' element. These questions are not well suited to aggregate data, which has been used in much of the prior research, but rather to more individual-level data commonly associated with digital metrics and analysis. The 'Who' questions are especially important in the context of digital advertising, which has a greater ability to target different individual customers with different messages. Online advertising has increased the ability to personalise communication, with the mantra ‘the right message, to the right audience, at the right time’. Consequently, brand attitudes can provide insight into why customers interact with brands online. Thus, it is beneficial to learn which brand attitudes are important and how individuals’ attitudes influence their likelihood of visiting a brand website.

Cain (2022) expands on the approach Pauwels and van Ewijk (2020) use to demonstrate the value of CMMs in measuring the long-term brand-building component of advertising impact. While online behaviours were considered, only two CMMs measuring cognitive responses were included. Due to data collection barriers, key differences in observed (behavioural) and unobserved (survey) data create challenges in accessing data for both attitudes and behaviours (Pauwels & van Ewijk, 2020; Rappaport, 2014; Wu & Rappaport, 2014), which is why most research is done with aggregated data over time rather than at an individual level (Pauwels & van Ewijk, 2020). Thus, the relationship between CMMs and individual CICs is still unquantified. Most studies focus on weekly or monthly aggregate data to identify trends in CMMs and sales. However, there is a risk of bias and limitations to the relationships explored due to the aggregation of data (Leone, 1995; Chung & Kaiser, 2002). The only exception is a study conducted by Dotson et al. (2017) examining the relationship between CMMs and brand search. This study demonstrates that those with more positive attitudes are more likely to search for a brand by name; however, the understanding is limited as brand searches account for a small proportion of website visits.

1.4.5 Which CMMs are Important

> *more research is needed to learn the best ways to model the consumer decision journey and shed light on whether there are models that are more appropriate than the decision funnel. (Marketing Science Institute 2014, p. 4)*
>
> *This is an important agenda because attitudinal and transactional metrics are not highly correlated, and thus brands run the risk of focusing on the*

wrong performance metric in conducting their marketing valuations.

(Hanssens & Pauwels, 2016, p. 182)

There is a growing consensus that using CMMs is still critical in determining the effectiveness of advertising. However, debate exists about which CMMs should be used and in what order, especially given the rise of digital advertising. The Marketing Science Institute (2016) has asked if the 'Old Rules' of Awareness, Interest, Desire and Action still apply. Based on the hierarchy of effects (HOE) model (Lavidge & Steiner, 1961; Lewis, 1908), consumers sequentially go through cognitive, affective and conative stages before making a purchase. The order of cognition, affect, and action is fixed in this traditional approach. Measures representing these phases have been used by Hanssens et al. (2014) and Srinivasan et al. (2010), although at an aggregate level a true hierarchy is not represented; once data are averaged across individuals, we can see that all of the elements are important, but not if consumers progress through each stage in turn. When results are averaged across consumers, there is a risk of aggregation bias (Abhishek et al., 2015) and valuable information is lost. For example, identifying nonlinear effects (Srinivasan et al., 2010).

The simultaneous or state-space approach recommended by Vakratsas and Ambler (1999) is an alternative to the HOE model. This approach suggests that affect (A), cognition (C), and experience (E) are all important, but advertising impacts them simultaneously rather than sequentially. This approach was empirically extended by Bruce et al. (2012) and Valenti et al. (2022), proposing an integrated approach that allows alternative sequences to exist but does not force a simultaneous response. Both studies fall under the FMCG category. While Bruce et al. (2012) discovered that Experience-> Cognition-> Affect provides the best explanation, this model only applies to a single brand. Valenti et al. (2022) used this approach on 178 FMCG brands and discovered that the most consistent order was Affect->Cognition->Experience. However, the measures used indicate that liking was a leading indicator of advertising awareness. Combined with the four weekly data aggregations these findings suggest a significant lag between a consumer being exposed to advertising and then becoming aware of it raising questions as to if the method applied is the most appropriate. Moreover, both of these studies have focused on how firm-initiated communication affects CMMs; it is unclear what impact including CICs would have.

The final perspective, that of brand salience (Romaniuk & Sharp, 2004), later updated to mental availability (Sharp, 2010), differs in that it is less about how consumers respond to advertising and more about what marketers should focus on to increase sales. Those with higher levels of mental availability are more likely to think of a brand in a buying situation. If this applies to CICs, we expect those with more positive CMMs to be more likely to visit a brand website, but they should not have to go through different stages. Top-of-mind awareness is often used to represent mental availability in empirical studies (Stocchi et al., 2021) while this may not be a comprehensive approach to capturing the construct a critical part is that the measures look at a cognitive approach to measuring the response to advertising. This cognitive approach has been used in the empirical models of Cain (2022) and Dotson et al. (2017), and while these models demonstrate the importance of CMMs, it is unclear whether the model fit would improve if measures of affect were included.

1.5 Key Contributions

The key contributions of this research are across two key areas. Firstly, providing theoretical contributions by improving our understanding of how CMMs help explain who is likely to visit a brand website and secondly methodological contributions by proposing a novel approach to data collection that allows observable (website visits) and unobservable (CMMs) data to be collected for the same individuals. Together these contributions offer an approach to evolve the use of CMMs in performance measurement that is better suited to reflecting the importance of longer-term brand building activity. Finally, I demonstrate the practical implications for managers and how this research may influence their approaches to measuring advertising performance.

1.5.1 Theoretical

This research extends previous studies (Katsikeas et al., 2016; Vakratsas & Ambler, 1999) by demonstrating the relationship between soft (unobservable) CMMs, such as liking and familiarity, and hard (observable) website visit metrics (representing CICs) on the path to purchase. Although there is a growing body of research on the most important metrics (e.g., Mintz, Gilbride et al., 2021; Mintz & Currim, 2013, 2015) and frameworks for understanding when to use them (e.g., Katsikeas et al., 2016; Morgan et al., 2022), few studies have examined these metrics together. This research aims to add to the literature and advance the future research agenda in this field.

Second, I identify a key empirical gap in the lack of understanding of CMMs and CICs within this framework (in particular, website visits). Given the budgets now spent driving consumers to a website, this is an important agenda. Furthermore, the emphasis on the most common intermediate metrics responds to the call from Morgan et al. (2022) to begin exploring the benefits and drawbacks of various approaches to accountability rather than the current practice of beginning with the need to demonstrate a financial return.

Although the work of Hanssens et al. (2014), Hanssens and Pauwels (2016), Pauwels and van Ewijk (2020), and Srinivasan et al. (2010) have significantly improved our understanding of this area using aggregated time-series models, focusing on the end output of a sale, this approach risks problems of aggregation bias (Shellman, 2004), ignores important dynamics such as nonlinearity (Srinivasan et al., 2010) and frequency of response effects, as well as limiting what we can understand about combinations of CMMs held by individuals. Using respondent-level data, I demonstrate that the commonly used marketing funnel (awareness, consideration, preference) is not the best way to represent CMMs and that there is no evidence of an individual sequence in CMMs; rather, we should use rating scales of familiarity and liking as key metrics, allowing for different responses among individuals rather than a simple consistent path. This is in contrast to previous research that focuses on the sequence of advertising (Bruce et al., 2012; Valenti et al., 2022), which revealed a dominant sequence. My findings also reaffirm the importance of cognition, affect and experience as key measures aligning with the perspective of Vakratsas and Ambler (1999) but differ from the approach of Cain (2022), Dotson et al. (2017) and Sharp (2010), who take a more cognitive view of the role of advertising.

This research also demonstrates that CMMs are more important than past behaviours. While it is widely assumed that past behaviour is the best predictor of future behaviour (Tanusondjaja et al., 2016), my research shows that positive CMMs are a better predictor of the likelihood of interacting with a website than the commonly used approach of new or returning users in an online environment.

I am able to assess how mindset metrics can predict the likelihood of a consumer visiting a brand website and how many times they are likely to visit using the hurdle model proposed by Dotson et al. (2017), which is not possible in a single model with aggregate data because the frequency is lost in data collection. While Dotson et al. (2017) examined this relationship in the context of brand search, they only found CMMs significant for the frequency of visits in the smartphone category, whereas I find them significant across the three focus categories: hotel booking, airlines and retail.

Individual data allow for the testing of nonlinear relationships. Nonlinearity was not tested because of the binary nature of the scale used by Dotson et al. (2017). I found no evidence of diminishing returns but rather an exponential relationship in which the more positive the mindset, the more likely respondents are to visit, with those with at least high positive CMM (Top 2 scores on a five-point rating scale) accounting for 85 % of all website visits across all categories.

To complete this research, I propose a novel approach to data collection. Approaches to data collection are also important for creating value (Morgan et al., 2022; Petersen et al., 2009). Data linking has been a significant challenge in combining attitudes and behaviours at the respondent level (Wedel & Kannan, 2016). While there has been a body of work that focuses solely on customers, few studies have investigated how to link CMMs and online behaviours to measure the broader impact of brand building activity.

Dotson et al. (2017) collected data in collaboration with Google. This is problematic for two reasons: first, it limits the amount of data available owing to privacy concerns, and second, it is not a common approach available to managers. My research adopted a novel approach to data collection and coding, employing a market research panel to achieve a high granularity level without using cookies. This lays the groundwork for future research in this field. Using an innovate approach to data collection, I obtain data at an individual level to match CMMs and website visits (CICs) for individuals across three categories of airlines, hotel bookings, retail and 27 different brands.

1.5.2 Application

The results have several practical implications for managers, including guidelines for metric use. First, the research demonstrates the role of CMMs as antecedents to online behaviours. This shows the importance of combining key reporting metrics to fully understand the impact of advertising. It is especially important that advertising focusing on brand building be measured using CMMs rather than online behaviours. Because online behavioural uplift is driven by people with a strong positive mindset towards the brand, capturing this uplift is a unique dynamic. Increased clicks may not be seen drive incremental sales because they are less likely to come from new potential customers. Advertising directed at websites with the strongest behavioural response targets those with favourable attitudes towards the brands. This is especially important for smaller brands, which may not be able to build their brands if their investment is heavily skewed towards performance metrics.

Second, in terms of tracking CMMs using a simultaneous approach of capturing liking and familiarity rather than assuming a sequence of mindset metrics that consumers go through is beneficial. These metrics allow marketers and their agencies to see how brand building activities are shifting consumers in terms of affect and cognition, to capture non-linear effects and understand how we expect behavioural

Finally, the size of the impact of CMMs relative to past behaviour show the importance of accounting for these measures in experimentation. Whilst (Romaniuk, 2011) have suggested that tracking for CMMs should be split into users and non-users my research demonstrates that when interpreting behavioural metrics we should consider existing attitudes towards the brand.

Chapter 2: Market Context – Brand and Performance Divide

2.1 Introduction

The rapid digitisation of media has seen one of the most dramatic shifts in the marketing landscape (Hanssens, 2018). The change has come not only from the online media channels but the ecosystems around advertising in the form of advertising and marketing technology (often referred to as AdTech and MarTech).

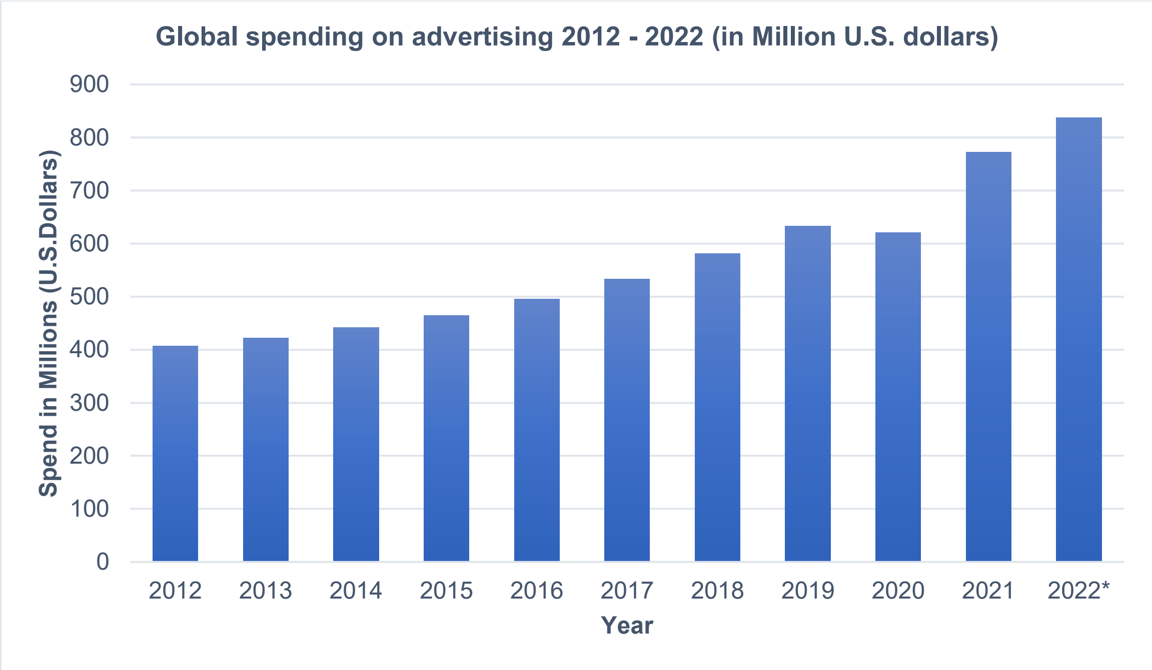
This digital marketing world is known for its jargon and complexity (Smallwood, 2016). Therefore, before reviewing the substantive literature examining what we know about performance metrics, I provide some market context of the data and how advertising performance measurement is driving decisions. This chapter provides an overview of the digital marketing environment, its impact on measurement, and the utilisation of online digital metrics beyond performance evaluation. The main focus is on the increasing division between short-term and long-term marketing strategies and how this fragmented approach to measurement is causing difficulties in decision-making and driving a focus on a narrow set of easy to collect indicators of advertising performance.

2.2 The Growth of Digital Media and Metrics

Total spending on advertising has nearly doubled since 2012. Figure 2-1 shows the growth in global expenditure.

Figure 2-1

Advertising Spending Worldwide, 2012–2022 (in Billion USD)

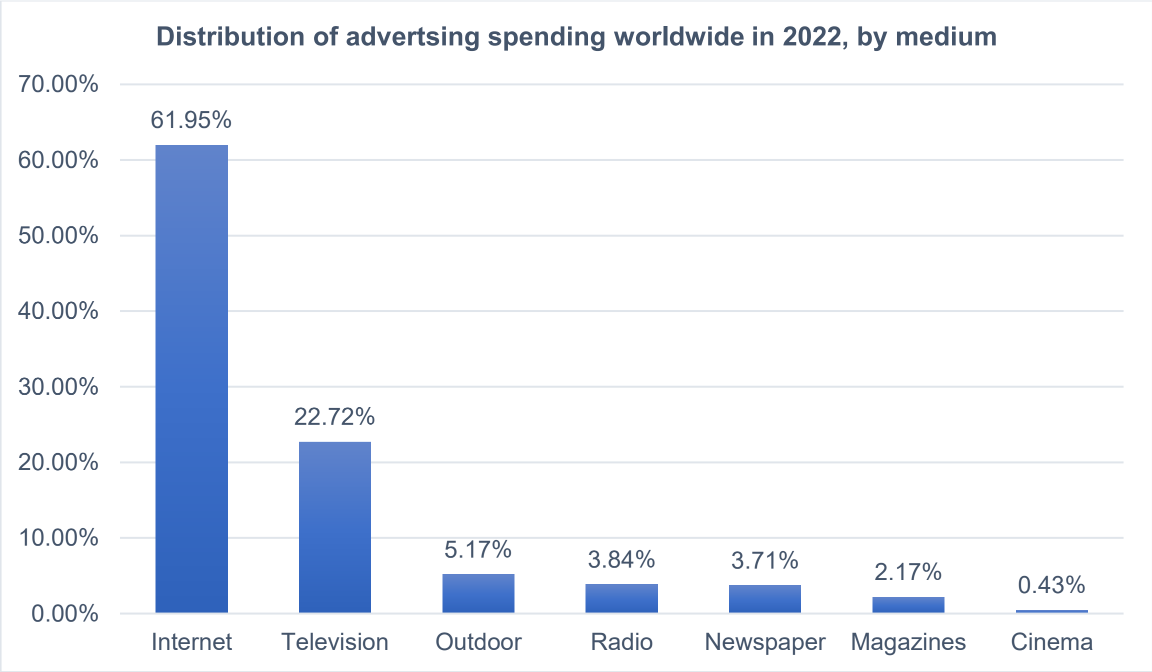


Source: Zenith. (June 8, 2022). Advertising spending worldwide from 2000 to 2024, by region (in million U.S. dollars) [Data]. In Statista. Retrieved November 12, 2022, from https://www-statista-com.ezproxy.library.sydney.edu.au/statistics/1174981/ advertising-expenditure-worldwide /?locale=en

Much of that growth comes from digital advertising. It is estimated that advertising spending was less than USD 8 billion in 2000 and is expected to have grown to over USD 600 billion by the end of 2023 (Zenith, 2022c). Figure 2-2 shows that, compared to other media channels, online advertising now accounts for more than 60% of total media spending, while television accounts for only 22.7% of total spending.

Figure 2-2

Distribution of Advertising Spending Worldwide in 2022 by Medium

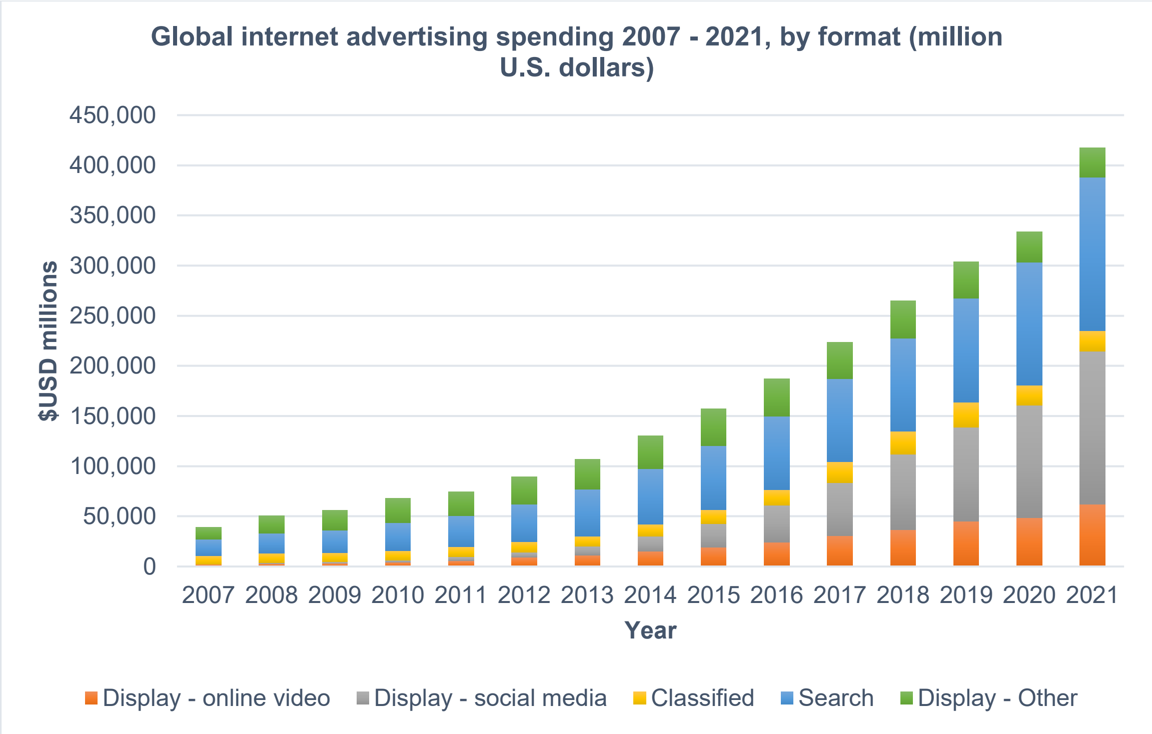


Source: Zenith. (June 8, 2022). Distribution of advertising spending worldwide in 2022, by medium (in million U.S. dollars) [Data]. In Statista. Retrieved November 12, 2022, from https://www-statista-com.ezproxy.library.sydney.edu.au/statistics/376260/global-ad-spend-distribution-by-medium/?locale=en

As internet advertising itself has many different components, Figure 2-3 shows how the online channels are further split, including the major areas of search marketing, display advertising and paid social media. Search and social media spending are the two dominant media channels, and both are still growing. With Google dominant in search and display advertising and Facebook dominant in social media, it is easy to see how these companies have become so powerful in the modern media landscape.

Figure 2-3

Spending by Digital Media Channel



Source: Zenith. (June 8, 2022). Internet advertising spending worldwide from 2000 to 2024, by format (in million U.S. dollars) [Data]. In Statista. Retrieved November 12, 2022, from https://www-statista-com.ezproxy.library.sydney.edu.au/statistics/276671/global-internet-advertising-spending-expenditure-by-type/?locale=en

The digitisation of information, which allows computers to process it easily, has altered how advertising performance is measured. As digital channels continue to shape the marketing landscape, it emphasises the importance of using appropriate metrics to measure and interpret advertising performance. The rise of big data has been the driving force behind this transformation. Most of these data consist of 'hard' behavioural measures that are directly linked to online media and are frequently observational. The significance of these data differences is further discussed in Chapter 5.

While the availability of data significantly impacts our ability to report consumer responses to advertising, another significant consequence of digitisation is the ability to use that information in real-time (Busch, 2014). As a result, individual-level reporting and signals are faster and more frequent and can be used in ‘knowledge-based decision-making’.

Data are assuming an increasingly central role in organizations, as marketers aim to harness data to build and maintain customer relationships; personalize products, services, and the marketing mix; and automate marketing process in real-time. (Wedel & Kannan, 2016, p. 97)

Online advertising, particularly search marketing, plays an important role in directing consumers to a brand’s website, where they can click on ads or search links, visit the site, and potentially make a purchase. Due to the availability of data on consumer website visits, businesses have been encouraged to use this valuable information on individuals (Kannan & Li, 2016). Marketers can now track the progression of advertising exposure to website visits and purchases, allowing them to assign a monetary value to digital advertising exposure, which has contributed to an increase in spending on digital media channels (Ritson, 2017). Despite the growth of digital channels, many commonly used metrics, such as page views and likes, are not directly related to real business success and are often referred to as ‘vanity metrics’ because they make activities look good and are simple to report (Rogers, 2018). This enables managers to selectively use metrics based on the level of improvement that can be demonstrated rather than on returns to the business.

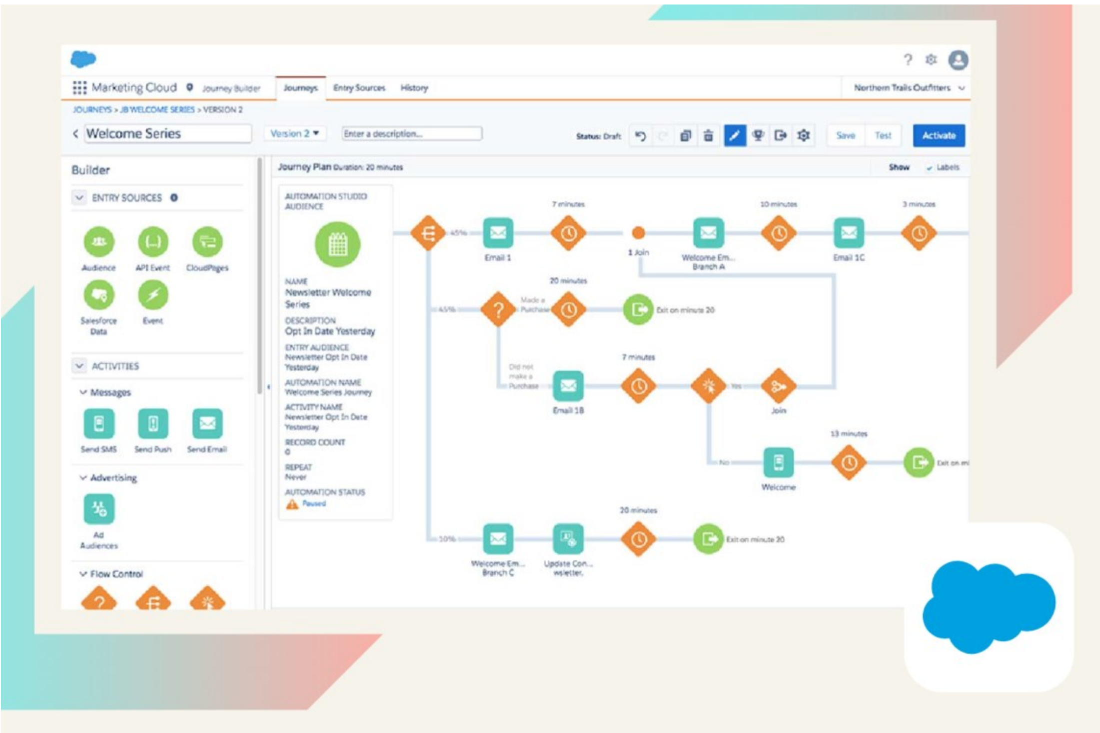
2.2.1 Influence of Automation

Automation drives the use of easy -to-calculate and readily available metrics for targeting, personalising and fuelling new buying models. Spending on marketing automation software globally is set to hit USD 3.2 billion (Brooker, 2022), including systems such as Salesforce, Marketo and Hubspot, and is expected to increase further (Gartner Research, 2021; The CMO Survey, 2022). Fundamentally, these tools allow marketers to automate sequential tasks dictated by a set of rules. These tasks could include sending an email to customers who click on an advertisement or customising a landing page on a website for return visitors. The more data that are fed into these systems, the more complex the rules become.

According to a CMO study (2022), nearly 55% of marketers track digital performance in real-time (Mela & Moorman, 2018), and much of this real-time data is used to fuel marketing automation; thus, there is an inherent link between performance media, as measured by views and clicks, and media automation. This automation is not based on complex models driven by conceptual frameworks and theories of how advertising works but on signals that can be used to personalise and target media. Because these decisions must be made in milliseconds, computational efficiency is critical (Paulson et al., 2018). Owing to the need for efficiency, simple models that can be implemented quickly have been developed. Figure 2-4 shows an example of the Sales Force Marketing Cloud interface, where emails are automatically sent to new customers after they sign up to receive a marketing list for a brand. It is unknown whether the customer enjoys the emails, but behavioural signals, such as unsubscribing or open rates, are used to determine the next step.

Figure 2-4

Example of Salesforce Marketing Cloud Interface

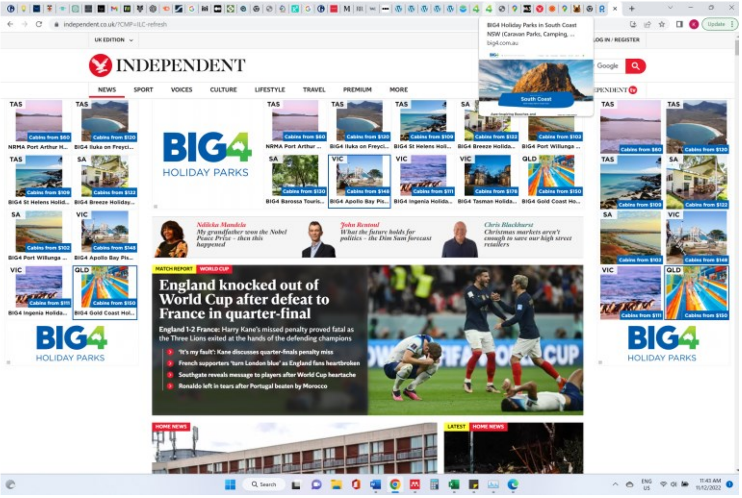


Source: Scheiner (2022).

Another example is the use of retargeting; after a consumer visits a website, display advertisements are shown to them to prompt them, as illustrated in Figure 2-5 after visiting a website to find a campsite, display advertisements of key brands are delivered to an individual user based on that original website visit.

Figure 2-5

Example of Retargeting Advertisement



These data that are created are considered signals of intent (Hamilton, 2022) and can be related to the brand, as shown in the above example, or they can be category related (Binet & Field, 2017). It is difficult to imagine such actions based on brand-tracking data, at least in their current form. However, the metrics that inform these actions are simple to collect and widely available (Morgan et al., 2022). The drive for automation has been a key influence behind the metrics that have been used. The ability to obtain data quickly is fundamental to the functioning of the technology platforms and therefore a visit to a website has become a critical signal for targeting and personalisation in these systems.

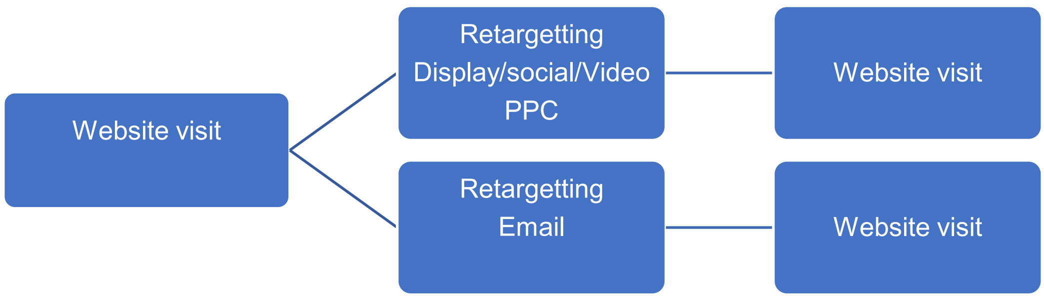
2.2.2 Targeting and Personalisation

> *Big data has been transforming the media industry for some time, but perhaps in no more significant way than in the growing application of advanced audience data. (ComScore, 2017)*

The mantra of media planning has long been to reach ‘The right person, at the right time, with the right message’. However, in the pre-digital era, the reality was that targeting was fairly crude (Cheong et al., 2010). The approach that prevails is to classify customers based on brand purchase behaviour (Danaher et al., 2003; Ehrenberg et al., 2004; Jones, 1998; Scriven & Goodhardt, 2012; Sharp, 2010); this behaviour can then be profiled against other dimensions, such as demographics, to define an audience to target with media). For television, this could mean finding shows that the target audience was more likely to watch (for example, men are more likely to watch sports) or for OOH having higher-end products in the central business district. The digital ecosystem provides many more ways to target advertising messages. First targeting individuals (the right person), second, personalisation (the right message) and third when they are in the market (often seen as the right time). Data allow marketers to see how consumers move through the journey to a sale and to target interventions to those they believe are the most valuable. For example, if a consumer visits a website, it is assumed that they are in the market; they can then be targeted with additional advertising in an attempt to close the sale. Because of the heavy reliance on online behavioural data, website visits are critical to marketers' ability to measure performance. The stages are shown in Figure 2-6 using a simple flowchart.

Figure 2-6

How a Website Visit Can Feed Further Advertising



Overall, metrics based on website visits have become central to research, and targeting has been the focus. For example, Andrews et al. (2016) examine contextual targeting, Chen and Stallaert (2014) and C. H. Park and Park (2016) examine behavioural targeting, and Matz et al. (2017) examine psychological targeting. While this creates a great opportunity for brands, in theory, it also creates certain issues. The success of these activities is judged by the number of people who click on a specific advertisement. Therefore, when attempting to maximise clicks from a given spend, the real focus shifts to identifying those most likely to click, assuming that this is the best response. The perceived risk is that this could focus on existing customers when research has shown that the best growth comes from acquiring new customers rather than targeting existing ones (Binet & Field, 2013; Sharp, 2010). This aligns with existing research showing that users respond more strongly to advertising (Zantedeschi et al., 2013). According to Vaughan et al. (2016), brand users are 2.4 times more likely than non-users to recall brand advertising. As a result, the risk of personalisation is twofold: Those who already have a strong relationship with the brand are more likely to be exposed to advertising through digital targeting, and because once users see an advertisement, they are more likely to notice it, we spend a higher percentage of the advertising budget on those who require less convincing. While it could be argued that this group are low-hanging fruit and thus makes sense, it is unclear whether this has been assessed in current measurement approaches. The risk is heavily targeting those who would have purchased anyway rather than bringing in new users. To avoid spending too much money on those who already think positively about a brand, it is critical to understand the role of the metrics being used, especially when subsequent actions (such as retargeting activity or which advertiser to spend more money with) are driven by automated routines. Understanding the role of various CMMs in the context of personalisation is critical because different marketing activities influence these factors (Bruce et al., 2012).

2.2.3 Consumer-initiated media contacts

While firms initiate traditional media channels, such as television and OOH advertising (Pauwels et al., 2016), digital media channels can be initiated by the firm, such as in display or video advertising, or by the consumer, such as in search advertising. While website visits are central to the measurement of advertising performance, for consumers to action to visit a website rather than waiting for a display advertisement, they will either type in a URL or visit a search engine such as Google and type in a search term for either the brand or category of interest. As a result of the greater emphasis on digital channels, new advertising classifications have emerged. While firms are used to driving advertising, consumers now play an active role. Thus, consumer-initiated versus firm-initiated advertising must be considered (de Haan et al., 2016; H. Li & Kannan, 2014; Wiesel et al., 2011).

CICs generally considered include search, website visits and referrals) are media channels used to acquire information about a brand, purchase or enable a consumer to purchase online (Srinivasan et al., 2016). In the pre-digital era, information search can be considered in-store browsing (Maity & Dass, 2014), looking up suppliers from paper directories, or seeking recommendations/word-of-mouth (Ortinau et al., 2013). These offline activities are not associated with advertising budget investments or tracked as standard metrics. Therefore, consumer-initiated media channels receive a significant portion of the media budget in the digital age. For example, paid search budgets now exceed USD 160 billion globally, accounting for 22% of total digital media budgets (Statista, 2022b). Spending on Search Engine Optimisation (SEO) is expected to reach USD 51.25 billion in 2020 (The Business Research Company, 2022), significantly increasing overall investment in consumer-initiated activities. This has increased the value of understanding how they work because they are not only an intermediate effect but also a significant cost area for firms.

CICs require a different approach for managers from a buying perspective, as they have less control over investment decisions than they do for FICs. For paid search, marketers determine which words to bid on and how much they are willing to spend (H. Li et al., 2016). This means that spending can vary depending on demand, and it is common to set daily spending limits to avoid overspending. Budgeting is even more complex for SEO, which does not have a fixed cost and is instead driven by activities such as content creation and page optimisation (Yoong, n.d.). Despite these complexities, little is known about what motivates consumers to search for a brand online or to visit a website.

Marketing performance models assume that consumers are in the market and treat advertising as a precursor to sales, regardless of whether advertising is initiated by the firm or by the consumer (H. Li & Kannan, 2014).

Treating CICs in the same way as treating FICs is statistically problematic because CICs have an inherent selection bias (Blake et al., 2015). Since firms cannot control who is exposed and who is not exposed to communication, the only solution that does not require complex modelling is to turn the search off completely, as in the work of Blake et al. (2015). With a better understanding of antecedents to CICs, alternative solutions for measuring the ROI from these advertising channels may be developed.

2.2.4 The Change in How We Can Buy Media

Technology has finally advanced to the point where marketers can use real-time data in a way that is both meaningful to customers and profitable for companies. (Boudet et al., 2017)

With technology enabling greater automation, how advertisers pay for these contacts has shifted. Digital advertising signals have also paved the way for the widespread use of alternative payment approaches for media inventory. Traditionally, media was purchased on a cost per mille (CPM) basis, with marketers paying for the number of consumers who had the opportunity to see (OTS) the advertisement. Although the OTS is calculated differently for each media channel (ComScore, 2017), the overall approach to purchasing remains the same. Marketers are said to pay for their eyeballs in this manner.

A digital landscape with clearly measurable actions, such as clicks, views, or sales, opens the door to new ways of paying for advertising. The automating and tracking of digital activity has enabled advertisers to pay media vendors only for certain actions; The automating and tracking of digital activity has enabled advertisers to pay media vendors only for certain actions; for example, this could be based on Cost per Click (CPC), where every click receives a set payment, or a Cost per Action (CPA), where action deemed to drive the conversion receives the reward. While CPM is the traditional approach to buying media, the most common alternative is CPC (ANA, 2021) and this is the way most paid search is bought.

This method has been dubbed a significant advancement in the field of advertising accountability (J. Shin et al., 2016). These approaches to buying are prolific in digital advertising, with claims that if consumer are not interested in your advertising, you no longer need to pay to reach them. The various buying models are frequently the same measures used for automation via real-time bidding (RTB), which allows advertisers to buy media in by auction in real-time. Spending is optimised using common media metrics, such as CPM, CPC, CPA and CTR. As a result, we have seen a shift towards a behavioural approach.

According to a survey conducted by the ANA (2021) among leading marketers, financial and online metrics are the most commonly used. Table 2-1 summarises the top 10 measures. The most popular metrics are cost per thousand (CPM), CPC, unique reach, ROI and site visits. This list excludes all the softer mindset metrics associated with brand building, instead focusing solely on advertising exposure or behavioural responses.

Table 2-1

Top Metrics Used for Reporting as Found in ANA Survey to Marketers

Order	**KPI**	**Percentage of marketers currently using the KPI**
1	CPM (cost per thousand)	83%
2	CPC	77%
3	Unique Reach	77%
4	ROI/ROAS Based on spending or lift	76%
5	Site Visits	72%
6	Viewable impressions	71%
7	CTR (Click through rate)	70%
8	Conversion	69%
9	CPV (cost per view)	69%
10	Completes, Completion rate	68%

Source: ANA (2021, p. 5).

Yet it has become clear all is not what it seems with these measures and there is a risk that advertisers are paying for clicks and sales that would have happened anyway

(Blake et al., 2015). One of the big challenges for understanding what has happened is that many of our online interactions are initiated by consumers not by firms as is traditional for advertising and most of the models built do not take into account this variation in likelihood for consumers to initiate contact with a brand. Surprisingly there is very little research that even considers how we should capture these differences.

The challenge for marketers is to compare a click to a view because there is no way to compare the various costing models. For example, TV costs are determined by demographic factors, whereas search costs vary according to the number of individuals searching for a specific term. The average global cost to reach 1,000 eyeballs for linear TV is $20.01 (Brownsell, 2022) USD. The average CPC for search ranges from $1.36 for real estate to $8.67 for legal services (Wordstream, n.d.). With one click often costing more than 100 times as much as a single view we want to be sure that clicks are worth the additional value and understand when we should be using this measure.

Understanding which consumers are most likely to initiate contact with a brand is an important step towards developing this comparison. This thesis investigates the metrics used in digital reporting, focusing on brand websites as the centre point for data creation (In CPC, clicks are the actions that take a consumer to a website, while in CPA, the actions take place on the brand website). This study differs from previous research (Cain, 2022; Hanssens et al., 2014; Pauwels & van Ewijk, 2020; Srinivasan et al., 2010) in that it examines the mindset or brand attitudes of consumers who make those clicks, establishing a valuable link between our traditional view of advertising (changing consumer perceptions) and the more recent perspective of driving a behavioural response.

2.3 A Growing Divide: ‘Brand’ and ‘Performance’ Marketing

> *Reconciling brand and performance is key to marketers being taken more seriously at a C-Suite level. (Greg Stuart, CEO MMA Global)*

Aside from the significant differences in how advertising space is purchased for online and offline channels, a more philosophical divide has emerged as marketers have begun to consider the roles played by different channels in the customer journey. This has created divided streams of marketing commonly referred to as brand and performance.

In many disciplines, there is a direct link between an action and a return (Pauwels & Reibs, 2015); however, linking marketing activities to a sale has been a key challenge for CMOs for many years (O'Sullivan & Butler, 2010) and this has been seen as a barrier to demonstrating returns. The additional challenge is that there is not a consistent view on what the goal of advertising is.

Marketing managers have a range of objectives with different associated performance metrics (Hanssens & Pauwels, 2016; Katsikeas et al., 2016), and the long- and short-term effects of advertising have been extensively researched (Leone, 1995). The evolved metrics now available through automation and different buying models have resulted in some practical differences. Despite this, most approaches to digital measurement are focused on the short term, although it is acknowledged that focusing on a direct link between advertising and sales 'undervalues the dual contribution of advertising to growing sales and building brands' (Bruce et al. 2012).

FICs are typically measured in terms of the cost of eyeballs and the resulting shift in CMMS, whereas CICs are measured in terms of actions that are typically either a click or sale. Different 'streams' of marketing have evolved as the skills and tracking required for digital marketing differ substantially from traditional offline channels, such as television and print. Binet & Field (2017), who have a large practitioner following, propose a classification of brand building vs sales activation; the conceptualisation is shown in Table 2-2.

Table 2-2

Definitions of Roles of Advertising and the Difference Between Brand Building and Sales Activation

Brand Building	Sales Activation
Creates mental brand equity	Exploits mental brand equity
Influences future sales	Generates sales now
Broad reach	Tightly targeted
Long term	Short term
Emotional priming	Persuasive messages

Source: Binet and Field (2017, p. 11).

Brand marketing is typically associated with brand equity and awareness measures (Anderson et al., 2022). Binet and Field (2013) conclude that emotional metrics are better predictors of long-term performance associated with brand building, and rational metrics are better predictors of short-term sales performance by describing brand advertising as longer-term emotional priming and sales activations as short-term activating to exploit brand-building work. According to this definition, more traditional media channels, such as television and OOH advertising, are better for brand building, whereas digital channels are better for sales activation.

Sharp (2010) proposes that physical and mental availability, and these concepts are popular alternatives. Improving physical availability necessitates making products as easy to purchase as possible, while mental availability refers to how likely a brand is to be thought of in a buying situation. The essence is the same; marketing has two core roles: one is slow-moving, building a predisposition towards a brand, and the other is sporadic, capitalising on that predisposition when a consumer is in the market.

The ability to target consumers in the market is critical to marketing performance. The performance marketing association (PMA) industry association defines the discipline as follows:

> Performance Marketing is a comprehensive term that refers to online marketing and advertising programs in which advertisers (a.k.a., 'retailers' or 'merchants') pay marketing companies (a.k.a., 'affiliates' or 'publishers') when a specific action is completed, such as a sale, lead or click. (The *PMA*, n.d.)

The focus on completed actions demonstrates a clear alignment of performance marketing with digital advertising and the metrics associated with digital marketing. While performance marketing focuses on putting a monetary value on marketing investment, as illustrated in Table 2-1 , many of the most common metrics are still intermediate success measures, with clicks and site visits being two of the top five. As a result, a brand website becomes central to measuring digital performance. First, customers click on advertisements to access the websites. When a customer visits a website, their activity can be tracked using tools such as Google Analytics, which provides individual-level insights into the customer's path to purchase.

There is a growing understanding that the conventional methods of evaluating advertising "underestimate its dual effects on both increasing sales and strengthening brand identity"' (Bruce et al., 2012). Advertising has a greater impact when measured by its intermediate effect on mindset metrics, allowing for both direct and indirect responses to advertising. The indirect effect is captured in the vector autoregressive model through the use of lags, meaning advertising can not only directly impact sales by raising them when present but also indirectly affect CMMs, which then impact sales. Pauwels and van Ewijk (2020) estimate a higher advertising elasticity using this method than Dinner et al. (2014), who focus on the direct link between advertising and sales both online and offline or Joo et al. (2016), who investigate the direct relationship between TV and search.

While brand and performance measurement are well conceptualised that is advertising can influence feelings towards a brand or brand equity (Cramphorn, 2006) and build the likelihood of being thought of in a buying occasion (Sharp, 2010), as well as being judged through financial performance and sales, as expected by many CEOs and CFOs

(Petersen et al., 2018) or online metrics. Approaches to measuring differences are not well operationalised in the context of the role of online metrics. This is problematic for managers because marketers are much more confident in demonstrating short-term impacts versus long-term impacts, with 51.4% of marketers saying they can quantitatively demonstrate short-term impacts versus only 32.1% for long-term impacts (The CMO Survey, 2021).

Clicks and CTRs are still commonly used to measure brand-building campaigns (Florès, 2014), rather than CMMs, which are the mainstay of the brand-building activity or the longer-term component (Bruce et al., 2012; Cain, 2022). It is difficult to fully quantify the impact of advertising without first understanding how they relate.

Chapter 3: Conceptual Development – Where CMMs and CICs Fit in Performance Modelling.

3.1 Introduction

This literature review is divided into three parts. First, with a focus on advertising performance measurement and the associated metrics, I explore the influence that online performance metrics have had in terms of the approaches now used to measuring advertising performance. After establishing the conceptual process for measuring digital advertising performance, I assess where the approaches fit in the most commonly used holistic measurement frameworks. In particular, I want to know if they account sufficiently for the role consumers play in initiating interactions with brands. This demonstrates the lack of a conceptual framework in the current approaches to measuring digital performance.

Second, to better understand potential issues, I propose a framework for evaluating the functioning of advertising in the context of performance measurement. This framework outlines the key areas to consider for marketing performance models and allows me to identify gaps in our understanding of how advertising affects CMMs, particularly the role of CICs.

Finally, in the third part, I evaluate key performance measurement techniques (brand tracking, market mix modelling, and digital attribution modelling) and the literature aligned with those approaches to understand how we expect consumers to respond to advertising input. This analysis shows the limited empirical understanding of the relationship between CMMs and CICs.

3.2 Benefits and Problems of Key Digital Performance Metrics and Models

Marketing gains higher status with managers when it is seen as accountable (O'Sullivan & Butler, 2010). Access to data to enable a link between advertising exposure and a behavioural response has been a challenge in a non-digital landscape (Pauwels & Reibs, 2015), and digital behavioural data has been welcomed as a solution. Detailed clickstream variables (the data collected from each online click that is made) have been described as '*the most important when classifying customers according to their online purchase behaviour*' (van den Poel & Buckinx, 2005). These data are regarded as the next evolution in data-driven marketing, providing greater visibility of customer-level data (Wedel & Kannan, 2016

3.2.1 The Appeal of Digital Performance Measurement - Creating a Chain from Exposure to Clicks to Sale

Clicks now drive many of the most heavily used marketing metrics, such as CTR and CPC, which influence marketing investment decisions (Fulgoni, 2016). For example, they determine which advertisements should be invested in (Bruce et al., 2017), which search terms should be bid on (Klapdor et al., 2014; Simonov & Hill, 2021), what order advertisements work best (C. H. Park & Agarwal, 2018) and what the ideal frequency levels of advertisements should be (Försch & de Haan, 2018). However, despite widespread adoption, clicks have been widely criticised as metrics; it has been shown that clicks are not correlated with sales (Smallwood, 2016) and that they are not needed for advertising to have an impact (Briggs & Hollis, 1997; Fulgoni & Mörn, 2009). Clicks remain popular largely because they are available for all forms of online advertising (Bucklin & Sismeiro, 2009), whether a purchase is ultimately made online or offline. However, it is important to remember that a click is not the end of the tracking. These clicks take consumers through to websites where further actions can be recorded; hence, they are of particular importance where a purchase is eventually made online (Sismeiro & Bucklin, 2004).

Figure 3-1 shows the flow of this information; when online consumers are exposed to an advertisement, the exposure is recorded, any click is then tracked (currently through the use of cookies), and if a consumer goes on to purchase, this is also recorded as an event.

Figure 3-1

Implied Process for Modelling Digital Effectiveness

Technology has solved the problem of directly linking advertising to sales in an eCommerce context, digital marketing has now allowed companies to gain new visibility into the parts of the consumer journey that register in ad server log files. These data typically comprise of timestamped views of an advertisement (referred to as impressions), clicks and conversions where these 'actions' occurred. Conversions are a specific tag that registers the completion of a journey, which could be a visit to a website, a request for a quote, or a purchase if a product is available online.

The process of being exposed to an advertisement, potentially browsing and then making a purchase is not necessarily different to the offline world, the difference is the availability of data to capture these stages; that is, clickstream data enables researchers to examine phenomena that were previously impractical (Bucklin & Sismeiro, 2009). Digital advertising and the technology surrounding it have made a single source of data between advertising and exposure available at scale.

3.2.2 The Problem - the Illusion of Accountability

The widespread availability of 'single source' data linking exposure to behaviour has significantly altered performance measurement practices. Attribution modelling is one of the most widely used and researched approaches (eMarketer, 2016). Although H. Li and Kannan (2014) provide a comprehensive analysis of these issues, I give a brief overview for context. When the data are accessible via digital log files, it is theoretically possible to analyse the clickstream data to determine which advertisements result in a sale. Figure 3-2 shows a hypothetical example of the type of data available for converting pathways.

Figure 3-2

Hypothetical Example of Ad Server Log File

	Interaction 1	Interaction 2	Interaction 3	Interaction 4	Interaction 5	Interaction 6
Customer 1	**Direct to site**	**Conversion**				
Customer 2	Brand Search	**Brand Search**	**Conversion**			
Customer 3	Display	Video	**Generic search**	**Conversion**		
Customer 4	Display	Display	Generic search	Direct to site	**Direct to site**	**Conversion**
Customer 5	**Display**	**Conversion**				
Customer 6	**Brand Search**	**Conversion**				

We can see which advertisements each of the six potential customers were exposed to. The conversion is highlighted in red, indicating that the consumer made a purchase (or completed an equivalent activity, for example, requested a quote). This example shows only the channel (as seen in Google Analytics), but the raw data contain more information on exact time, creative execution, and placement. The most common model, last-click attribution (Robertshaw, 2017), credits the channel before the conversion with the sale. For customer 1, 5 and 6, there is only one interaction before the conversion; so, this is the channel that is credited with the sale, for customer 5 that would be display and customer 6 brand search. In the case for customer 2 that would be brand search and customer 3 generic search.

It is estimated that 85% of companies with over 100 employees using digital marketing use some kind of digital attribution model (Benes, 2018) because models are built into tools such as Google Analytics, an example of which is shown in Figure 3-3.

Figure 3-3

Example of Google Analytics Path Output

	Default Channel Grouping Path	Conversions		Conversion Value	
1.	Email × 2	106	(26.63%)	A$6,162.00	(21.96%)
2.	Email → Direct	37	(9.30%)	A$1,780.00	(6.34%)
3.	Email × 3	27	(6.78%)	A$1,125.00	(4.01%)
4.	Direct → (Other)	15	(3.77%)	A$2,217.60	(7.90%)
5.	Social → (Other) → Social → (Other)	12	(3.02%)	A$813.00	(2.90%)
6.	Email × 4	10	(2.51%)	A$445.00	(1.59%)
7.	Email × 2 → Direct	8	(2.01%)	A$496.00	(1.77%)
8.	Organic Search → (Other)	8	(2.01%)	A$701.00	(2.50%)
9.	Direct → Email	5	(1.26%)	A$790.00	(2.82%)
10.	Email × 3 → Direct	5	(1.26%)	A$235.00	(0.84%)

Despite the high usage and popularity of last-click reporting, there is widespread agreement that this method is misleading (Kannan et al., 2016). In terms of dynamics, the last click has been compared to a commission-based salesperson (Spinnakernordic, n.d.), where they receive full credit for the sale, regardless of what motivates the customer to visit the store. While approaches are constantly evolving last-click attribution along with data are available still widely used by Google (*About Attribution Models*, 2023) showing how central these types of models still are to reporting.

As only a small percentage of advertising exposures result in a click or a conversion (Fulgoni & Mörn, 2009) there is still an implication that much of the advertising has not worked because no sale is generated. Thus, they have been criticised for having a narrow focus (Hanssens & Pauwels, 2016). The last click model has remained popular, not because of a philosophical or theoretical belief in how advertising works but because of the ease and speed with which it can be analysed (Kannan et al., 2016) and because it provides an impression of accountability. Much research has focused on developing different statistical models that include additional media exposure before the last click rather than on better understanding which consumers are more likely to visit a website. In other words, in the example shown in Figure 3-3, the other channels in the path should be rewarded for their contribution. Improvements have been made, such as using Markov chains (Anderl, Becker et al., 2016; H. Li & Kannan, 2014), probit models (Danaher & van Heerde, 2018), and a bagged logistic regression (Anderl et al., 2016). Nevertheless, using the same data, they reallocate the contribution weights to those channels that appear earlier in the process

Attribution models have been criticised for failing to account for offline media channels (Lemon & Verhoef, 2016), but the issues go much deeper. ROI should be a function of profit from the specific investment, but it is frequently calculated based on total profit rather than just incremental profit to the activity (Bendle & Bagga, 2016). Despite improved approaches to attribution modelling consistently finding that last-click attribution underrepresents firm-initiated channels such as display and email (Anderl, Becker et al., 2016; H. Li & Kannan, 2014) and overrepresents customer-initiated channels such as search and type in which the consumer goes directly to the firm's website, they have failed to provide a realistic view of the marginal returns from advertising. The simplicity of the calculation helps explain why so many companies can now claim to measure ROI (as reported by ANA, 2021). The inaccuracy of this approach may also help explain why ROI-based measures are less useful than CMMs (Mintz, Gilbride et al., 2021).

Disappointing results were obtained when an out-of-sample test was used by Li and Kannan (2014, p. 52), demonstrating the lack of robustness of attribution modelling: specifically, when paid search was removed, the model failed to account for the interaction between paid and organic search effectively, and overall conversions did not decline as much as expected as consumers found another route to the website. Furthermore, widely different conclusions have been demonstrated in an experimental setting. Blake et al. (2015), demonstrated that when brand search was turned off for eBay, it had a negligible impact on the number of people who visited the website. Suggesting traditional approaches can over estimated brand search results by over 4000%; that is, people will find their way to the website whether they are clicking on a paid advertisement on not. When people want to visit a brand's website, they will; a key job of marketing is to make them want to visit in the first place, this aligns to the view of brand building.

One of the major issues is that the models do not distinguish between firm-initiated advertising, such as display and video and customer-initiated activity. For example, it is atheoretical that the customer searches for a specific brand with no prior input (or knowledge), yet the modelling allocates 100% of the conversion to a brand search if this is the last action before a purchase. Due to the nature of these data, none of these models accounts for the consumer's prior relationship with the brand. They merely look to allocate the contribution of the stages in the digital journey. Moreover, the models appear to be driven by the modelling techniques relevant to the data structure rather than an appropriate theoretical approach to understanding how advertising works. Within this single-source environment, much less is known about the role of other antecedents, such as traditional advertising or mindset metrics. Yet until we build our understanding of what those factors are it is unlikely that we can effectively understand how different media channels have performed.

3.2.3 Why are CICs Central to the Problems?

In a digital landscape Srinivasan et al. (2016) classify firm-initiated channels as display and email and Consumer-initiated as search, website visits and referrals. Search, website visits and referrals cannot be seen as distinct as they are all related to website visits (a search is a precursor, and a referral takes place on a brand or third-party website) suggesting that those actions that are a result of consumers looking to visit or be directed to a website are the most consistent definition of a CIC.

CICs differ from FICs in several aspects. First, whereas firms traditionally control when and where their advertisements are viewed, CICs result from consumer action (Wiesel et al., 2011). Second, CICs are used for communication with a company which may include requesting or searching for information, including technical advice or facilitating feedback (Bowman & Narayandas, 2001). Third, depending on whether customers initiated the interaction, it is possible to determine whether they were aware of the brand through the initiation (Anderl, Schumann et al., 2016) i.e., whether brand or generic search terms were used. This is a valuable categorisation, as there is a recognised cost difference to the firm between these forms of contact (Cheng et al., 2018).

The involvement of customers in a CIC makes understanding its impact more difficult than in an FIC. Firms can manipulate FIC for experimentation purposes; however, this is more difficult for CICs. For example, while paid search can be removed, SEO cannot. Furthermore, if one type of CIC is removed (e.g., paid search), a consumer can switch to another alternative and still reach the brand website. In their experiments, both Blake et al. (2015) and H. Li and Kannan (2014) show that removing paid search does not prevent consumers from visiting a website; instead, they find other ways to visit, such as through SEO links or direct type in. CICs occur only when a consumer requests them, and they have some control over the channels with which they interact. To account for these in models, we need to better understand how consumers use CICs, and a clear distinction between CICs and FICs should be made in statistical models. Furthermore, there is a clear value of understanding the overall consumer objective, in terms of visiting the website, before focussing on which channel is used to reach the website.

3.3 What We Know About Antecedents to CICs

A key stream of literature in understanding consumer search has looked to understand consumer motivations of consumer search for example Lewis & Marvel (2011) look at changes in search volumes in relation to price changes, Bronnenberg et al. (2016) explore different features of a camera that consumers search for and Kim et al. (2010) investigate different sequences of search and the relationship to search costs, however area of research does not look at the impact of advertising on the search but rather understanding the search patterns themselves. In fact, it has been suggested that search is more commonly studied with price (Honka, 2014)

Within the advertising space there is a clear distinction between FICs and CICs. Despite the absence of comprehensive frameworks that account for CICs, they are still included in several performance models. Some research that utilises observable data aims to understand the drivers of customer search behaviour and website visits. Joo et al. (2016) studied the increase in brand searches resulting from television advertising and discovered that FICs could drive CICs. However, this reflects only a short-term increase and not a long-term increase.

Regarding unobservable data, Dotson et al. (2017) attempt to address this by demonstrating that mindset metrics are good predictors of brand searches. Using aggregate time-series data, Pauwels and van Ewijk 2020) using aggregate timeseries data show that CMMs are more enduring, while search and website visits play a shorter-term contextual role. The latter two studies make a case for a long-term perspective on CMMs, but the differences highlight the importance of a conceptual framework. Pauwels and van Ewijk (2020) employ both CMMs and CICs in their models, demonstrating that both attitudes and behaviours are antecedents to purchase but also share dual causality. This extends their previous work, (Pauwels & Ewijk, 2013), that captured the same dynamics. This approach is consistent with the belief that advertising has an indirect brand-building effect (Bruce et al., 2012).

Therefore, we can expect both FICs and CMMs to be an antecedent to CICs, but also that once a consumer has visited a brand website it is also possible for CMMs to change. So, for example we see for a digital attribution model that the only action accounted for prior to a click is advertising exposure. Consequently, there is a high risk that the results will be biased due to the lack of affect, cognition and past experience measures, as Vakratsas & Ambler (1999) pointed out many years before digital attribution existed. Where this is the case experimentation becomes an important approach to performance measurement (Blake et al., 2015).

3.4 Where CICs Fit in Holistic Measurement Frameworks

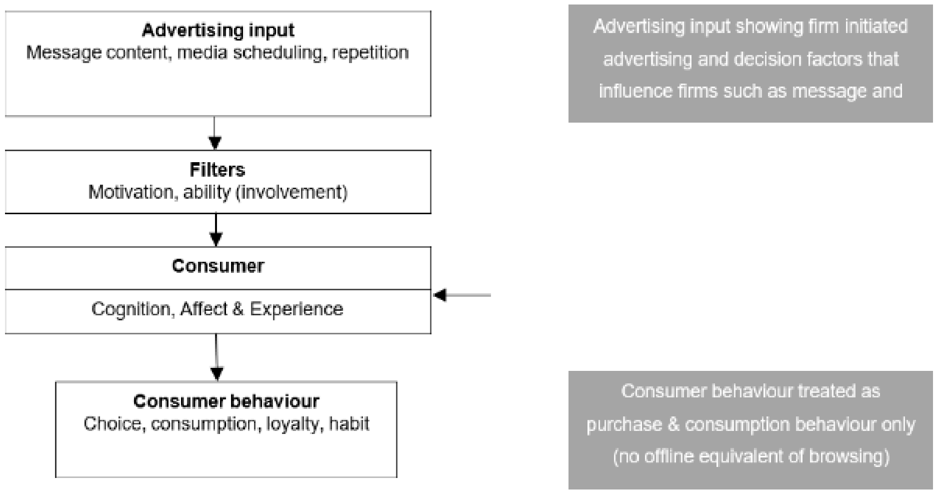
> *It is more important than ever before to begin with a conceptual framework that identifies the relevant constructs and specifies how they interrelate.*
> *(Malthouse & Li, 2017, p. 233)*

With the ever-increasing volume of metrics, frameworks such as this one are critical in developing our understanding (Morgan et al., 2022) and aligning the metrics we report on (Rappaport, 2014). When measuring advertising performance, it is widely accepted that it is preferable to have a range of metrics that focus on different elements of an overall causal chain or hierarchy (Ambler, 2003; Ambler & Roberts, 2008; Lehmann, 2006), as this provides a structure that can link intermediate metrics with an ultimate goal. Therefore, it is critical to agree on the framework for measurement before the activity begins (Rappaport, 2014), and KPIs across multiple dimensions should be included in the framework (Barwise & Farley, 2004). These dimensions could be as simple as the input (advertising) and output (consumer response) variables (Ambler et al., 2004), but it is recommended that perception, performance and financial metrics be balanced (Munoz & Kumar, 2004). Hence, frameworks typically include multiple stages with intermediate metrics. Further studies are necessary to establish the links between the stages of the chain and to integrate the entire chain into a multi-equation framework (Lehmann, 2006).

Two key studies that have used a synthesis of the literature to understand how advertising works are widely accepted. First, Vakratsas and Ambler (1999) proposed the framework shown in Figure 3-4. Advertising can influence cognition, affect and experience, which affect consumer behaviour. In terms of measurement, the approach would then be to collect metrics from each stage to build models or run experiments to understand how to link the input variable advertising spend with the eventual output, in this framework, a customer choice or purchase. The works of Hanssens et al. (2014) and Srinivasan et al. (2010) linking advertising spending to CMMs to sales are examples.

Figure 3-4

Framework for Assessing How Advertising Works



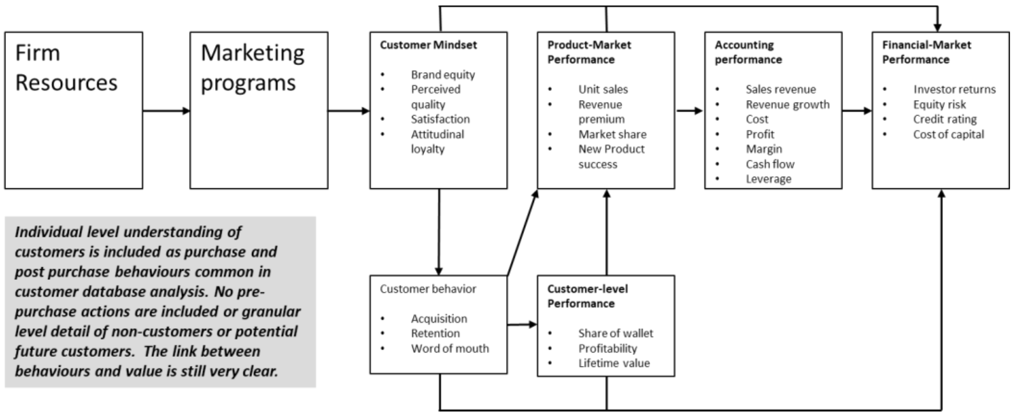
Source: Adapted from Vakratsas and Ambler (1999, p. 26).

Similarly, Lehmann (2006) proposed additional stages of financial performance and firm valuation after customer behaviour; this demonstrates the financial element required to capture mechanisms such as profitability, which is critical for budget allocation. Gupta and Zeithaml (2006) use a similar framework in their research on customer satisfaction but keep the behavioural stage as a measure of what customers do; while this is not specifically tied to online behaviours and could equally relate to sales, this broader view aligns with the existing empirical work that the dominant relationship is one where attitudes precede behaviours.

Katsikeas et al. (2016) proposed an updated framework for measurement, as shown in Figure 3-5.

Figure 3-5

Proposed Stages for Marketing Performance Measurement review of Katsikeas (2016)



Source: Adapted from Katsikeas et al. (2016, p. 3).

The importance of customer-level performance in the link between operational and organisational performance are highlighted in this framework or outcome chain. Katsikeas et al. (2016) proposed various measures ranging from operational to organisational performance while being more prescriptive about the actual measures used. Despite the clear metrics aligned to each stage, this framework does not include widely used online performance metrics. This is a significant omission, given their dominance as measures of advertising performance.

This relates to the first research gap: there is no comprehensive measurement framework of advertising that includes both firm inputs and outputs and acknowledges the role of CMMs and CICs in combination. This is an important step in allowing marketers to choose metrics for specific activities and to understand the potential consequences of those decisions. While Pauwels and van Ewijk (2020) focused on their empirical measurements, they did not consider the broader context of firm investment points or the evolution of media costing models. As discussed in the review of digital performance models, these elements are critical for understanding when different metrics should be used.

3.5 Summary of Existing Frameworks

Although these frameworks offer useful guidance on how marketers should measure advertising performance, CICs are missing from the dominant frameworks and metrics proposed. This is partly because CICs are a more recent addition to marketing history. Many of the core marketing models used were developed before significant levels of investment in consumer-initiated media channels were observed. Given the importance of CICs in performance measurement, this is a considerable gap, which is particularly noteworthy because of the lack of a conceptual framework for digital attribution models.

Understanding the relationship between different metrics is important because there is not always a high correlation between the variables (Hanssens & Pauwels, 2016), meaning they can move in different directions and become difficult to interpret. These indicators should not be interpreted in isolation; rather, understanding how they are expected to fit together is required (Ambler, 2003; Hanssens & Pauwels, 2016).

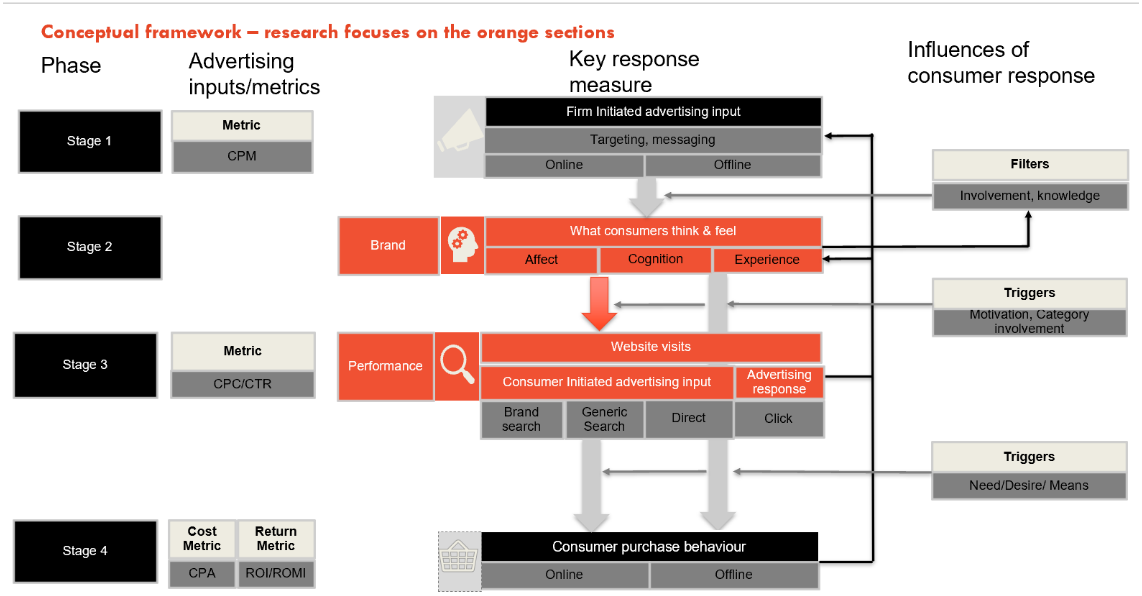
3.6 A New Conceptual Measurement Framework Including CICs

Historical frameworks (Katsikeas et al., 2016; Vakratsas & Ambler, 1999) no longer accurately reflect commonly used metrics because customer behaviour is now observed as both a website interaction and a sale. Previously, advertising investment decisions were made solely based on FICs at the start of the framework; however, with CIC investment, investment decisions are now made at two points. A website visit represents a cost for the firm, as does a consumer's search for a brand or click on advertisements.

The starting point used for the conceptual framework is that proposed by Vakratsas & Ambler (1999). It includes the core intermediate measures between inputs to and outputs from advertising. To improve on these conceptual models and to more effectively measure digital advertising performance, our conceptual framework of how advertising works needs to evolve. Figure 3-6 shows the proposed framework. I look at this primarily from a data perspective and what that means for the data we need to capture, but by including the links and feedback loops it is possible to observe what the possible paths through the framework a consumer may have. For example, they may start with a trigger or motivation rather than Firm initiated advertising, in the case of an offline purchase there is no requirement for advertising to play any role.

Figure 3-6

Proposed Framework for Consumer-Initiated Advertising



3.7 The Components of the Conceptual Framework

The proposed framework outlines the sequential process we measure response to advertising that is not to say that all models will include all elements, but it is important to understand the consequences of not including any individual part on our interpretation of results. Although it may appear complex initially, the proposed framework comprises well-known stages in advertising responses. The proposed framework provides a structure for understanding knowledge gaps, the significance of different stages in the process, and potential biases and challenges in measuring advertising performance by presenting it as a single framework that considers the metrics used, the presence of feedback loops, and cost considerations for advertisers.

We begin with firm-initiated advertising input in **Stage 1.** Although difficult to verify, it is estimated that we are exposed to between 6,000 and 10,000 advertisements per day (Carr, 2021), with more conservative estimates suggesting 300–500 advertisements per day (Sanders, 2017). It is impossible to believe that most of these are actively processed, let alone elicit a behavioural response from a consumer. Consequently, consumers spend most of their time in the loop between **stages 1 and 2**, with the size of the response moderated by the filter variables of knowledge and involvement. This stage is most commonly measured through brand tracking, which involves asking consumers a series of questions about their thoughts, feelings and behaviours towards a brand.

Stage 3 is when the consumer response becomes observable; these are actions that a consumer makes that are not a sale. This stage is where CICs appear in the framework and where marketing measurement shifts from common brand metrics to performance metrics.

Finally, in **stage 4,** a purchase is made. If a purchase is made offline, for example, in a retail store, the website stage can be bypassed. For an online purchase, a website must be visited. There are four key components of this proposed framework distinguish it from previous proposals.

3.7.1 The Addition of Customer-Initiated Advertising

While Anderl, Schumann et al. (2016) propose a taxonomy that divides CICs into brand and generic categories, I add a category of Direct. Consumers who visit a brand's website directly have a significant advantage. First, there is no PPC cost, and second, it eliminates exposure to competitor communication. Furthermore, by breaking Direct contacts into a third and distinct category, it acknowledges potentially different inputs into statistical models. That is, the drivers of brand search, generic search, and direct-to websites may change, or at the very least, they may differ in size.

The incorporation of CICs into this framework has significant implications. The most fundamental difference is that, unlike traditional advertising, the firm does not control exposure. If there is no consumer interest in visiting a brand website driving CICs, the advertising budget will go unspent even if firms have allocated a larger budget. It also demonstrates that we expect consumers to interact differently with digital channels based on brand attitudes and previous brand experience. Firm spending now occurs in two distinct stages: Stage 1, the traditional firm-initiated stage, and Stage 2, the consumer-initiated stage, in which consumer actions drive a cost to firms as they pay for the actions. Recognising dual-cost inputs is essential for budget allocation decisions. For example, suppose we treat CICs as an independent variable controlled only by firms, not consumer demand. In that case, we should expect bias in our models because an increase in CMMs can lead to an increase in CIC demand.

It is an important recognition that **marketing costs** are no longer just at the start of the process but also driven by consumers. This is how the distinction can be made between firm-initiated and consumer-initiated advertising. Then the returns are captured at the purchase stage of the framework.

3.7.2 Segmenting Online and Offline Purchasing

In I distinguish between online and offline purchases in the consumption phase, recognising that online purchases are tracked and measured differently than offline sales. The framework proposed by Vakratsas and Ambler (1999) suggests that the aspects of choice, consumption, habit and loyalty should be acknowledged in the purchase stage. Although these are critical considerations, they have received less attention in the field of performance measurement. The distinction between online and offline purchases is because online purchases are linked to individuals, whereas offline purchases are rarely tracked in this way (unless through a loyalty program that creates a digital record), and they produce a different signal for advertisers.

Similar to online website visits, online purchases can provide an identity that can then be used for future advertising communications in the form of first-party data, creating a feedback loop in the system which must be included for online interactions. Therefore, it is important to separate not just the website visits but also online and offline purchases. The idea of feedback loops is not new, Keller and Lehman (2006) recognising the importance in the brand value chain model. Vakratsas and Ambler (1999) include a feedback loop between brand usage. Pauwels and van Ewijk (2020) discuss the dual causality between CMMs and online behaviours. It is logical that if a consumer visits a website, that, in turn, should have an impact on CMMs even if a purchase is not made.

3.7.3 Consideration of Triggers as Well as Filters

According to Vakratsas and Ambler (1999), there is a stage for filters that influences consumer responses. Filters are important because they influence how a consumer responds to an advertisement. This is particularly important in terms of the effect of advertising exposure on consumers' likelihood of noticing an advertisement. For example, brand users are more likely to notice advertising than non-users (Romaniuk et al., 2017; Vaughan et al., 2016), and there are different levels of interest for those in the market (Petty et al., 1983).

The proposed framework emphasises the separation of filters and triggers. That is unless there are some internal or external triggers, such as owners wanting information about their products (Dotson et al., 2017), a desire to purchase (Etco et al., 2017), or a general interest in the category (J. Park & Chung, 2009), there will be no interaction. Without a trigger, there will be no consumer-initiated advertising input, and as a consequence, there is no observable data. In this sense, until a trigger is added to the system, consumers will be in a cycle between stages one and two, where they are exposed to advertising messages that may impact their thoughts and feelings about a brand but will not progress.

According to Protheroe et al. (2020), the trigger is present before a purchase and is not a phase but a constant presence. I consider the trigger the input required for action to occur. This could be internal to the consumer; for example, I enjoy exploring new holiday destinations or being externally visible. For example, I recently moved house, so I will need a new internet connection or a marketing stimulus, such as this brand is now on sale. These potentially observable external triggers are popular with advertisers for targeting and making up a significant portion of third-party advertising data. As a result, I included these triggers and filters as separate streams of inputs to be considered in a broader measurement framework.

An additional catalyst is required to proceed to the purchase stage. The signals differ depending on whether the purchase is made online or offline. While 59% of people conduct an online search before making a purchase (Google & Ipsos, 2019), stage three may be skipped entirely in the case of an offline purchase. As a result, the triggers between stages two and three and stages three and four are not necessarily the same. For instance, I may visit the Tesla website to gather information about cars without intending or having the means to purchase, but this visit will provide feedback on my thoughts and opinions about the brand.

3.7.4 Clear Delineation of Brand and Performance Marketing

The framework formally distinguishes between brand and performance metrics. By doing so, we can provide more clarity on the distinction between them and better understand how they relate to each other. I have also considered the definitions that should be used to help with this distinction.

I propose the following definitions:

Performance marketing is a stream of advertising where exposure to activity is directly linked to an observable consumer response in a specified period, and performance and value are measured based on the cost of those actions.

In contrast, an important function of advertising is maintaining brand associations for the next time a person is in a purchasing situation (Briggs & Hollis, 1997). Thus, brand advertising should be viewed as:

Brand marketing is a stream of advertising where exposure to advertisements aims to elicit an unobservable response that may

manifest as an observable response at an unspecified point in the future.

These definitions are not channel-specific, and just because a channel is considered better for performance marketing does not mean that it cannot elicit a brand response; for example, search advertising may lead to a website visit that improves the attitude towards a brand even if an immediate sale is not made. These definitions are important from a measurement perspective because they help clarify the data collection methods (for observable and unobservable measures) and measurement periods. This is significant in empirical measurement, where the impact of CMMs must be captured first, followed by a behavioural response observed over a specified time period.

There is an understanding that improving consumer attitudes towards a brand can lead to increased sales (Srinivasan et al., 2010). However, this long-term impact is built not by a single advertisement but by all interactions with a brand over time; therefore, the best period to capture that response must be considered. It is also worth noting that the loop allows for a response that does not require a customer action, but only a shift in mindset, meaning that these data frequently go unobserved (Gupta & Zeithaml, 2006).

3.8 How The Popular Approaches to Performance Measurement Relate to The Proposed Conceptual Framework

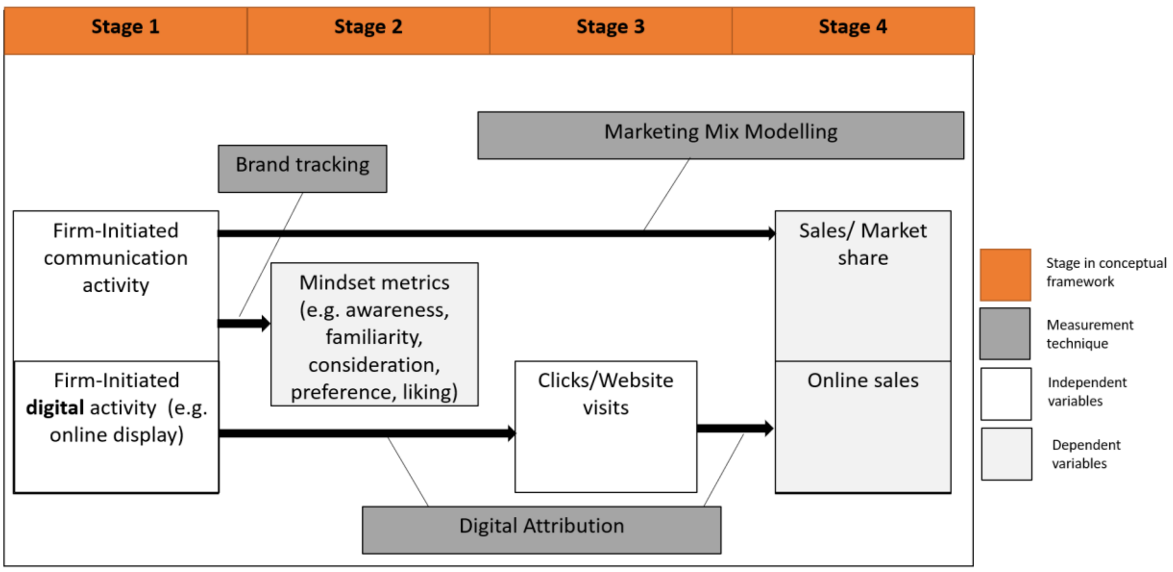
While frameworks are important for developing our understanding of the processes that are happening and the metrics to capture, reporting alone is often not enough, and therefore, metrics are used in marketing performance models. These models are essential for understanding the relationships between metrics and for calculating popular metrics, such as ROI (Pauwels & Reibs, 2015). To better understand the gaps in our empirical understanding, I compare the conceptual framework proposed in section 3.5 with current empirical understanding of marketing performance models. If they are taking the expected paths, they should align. According to Roberts (2000), models that measure advertising performance have three components: the phenomenon being measured, the toolkit or models used, and the decisions to be made.

> *To be phenomenologically appropriate, the model must be faithful to the processes that are occurring in the marketplace. To be methodologically admissible, it must be rigorous and internally consistent. Finally, for application it must be useful, which includes being accessible to the manager as well as addressing the questions that she has to answer in directing her marketing investment and energies. (Roberts, 2000, p. 128)*

Using these principles, I examine the most commonly used approaches to performance measurement. While the previous diagram shows the common approaches practitioners use, Figure 3-7 shows how the key literature adds to these approaches. The stages identified in the conceptual framework are labelled as stages 1 through 4. The key metrics are highlighted in blue, and the white boxes represent common performance models.

Figure 3-7

How Key Metrics Align to Commonly Used Performance Measurement Approaches



Marketing mix modelling (MMM) and brand tracking, as linked by Srinivasan et al. (2010), and, more recently, digital attribution models, as discussed at the beginning of this chapter, are the most commonly used approaches. Table 3-1 shows a review of the identified core literature and the path taken to demonstrate how it relates to the conceptual framework proposed in Figure 3-6. I include an evaluation of the data used, research questions and contributions, how the impact of advertising is quantified, and limitations of the research approach from which I seek to understand the research gaps. I paid less attention to the brand-tracking element in this review because there is no behavioural element, but it is included because it is an important intermediate metric in this research.

Table 3-1

How the Measurement Approaches, Research and Conceptual Framework Align

Measurement stream	Path (numbers indicate stages from the conceptual framework)	Associated research	Data	Focus of research/ Research question	Key contribution/Benefit	Quantification	Limitations
Brand tracking	**Media -> CMMs 1->2**		**Survey data, individual response to multiple questions**	**Linking digital exposure to brand metrics**	**Key intermediate metric linking**	**Uplift in metric per spend**	**Does not have financial outcome, therefore, has lower influence as a metric**
	1->2	(Vaughan et al., 2016)	Survey data from multiple studies covering usage and advertising awareness	Do users remember more than non-users?	Demonstrates the differential impact of advertising on those closer to a brand	Brand users are 2.4 times more likely to be aware of advertising	Limited to users and non-users which can be a problematic distinction in many categories
MMM (aggregate)	**Marketing Inputs -> Sales 1->4**		**Usually, weekly aggregated data across all elements of marketing mix (sales, advertising, price, distribution etc.)**	**ROI on advertising on sales**	**Liking advertising spend to sales or market share**	**Clear ROI for each media channel**	**High level of aggregation does not take into account customer differences or targeting. Endogeneity risk with CICs**
	Marketing inputs -> CMMs -> sales	(Srinivasan et al., 2010)	Aggregate time-series data over 7	Do mindset metrics help improve	Demonstrated that there is clear improvement in including CMMs in	Impact of increase in mindset metric on sales	Long time period impractical for many marketers. Aggregation over a long time period

Measurement stream	**Path (numbers indicate stages from the conceptual framework)**	**Associated research**	**Data**	**Focus of research/ Research question**	**Key contribution/Benefit**	**Quantification**	**Limitations**
	1->2->4		years, monthly aggregation	marketing mix models	particular to help improve our understanding of base-level sales. Show a strong impact of liking		subject to aggregation bias, do not find significant effects from brand awareness and have to substitute advertising awareness which is a very different measure
	Marketing inputs -> CMMs -> sales **1->2->4**	(Bruce et al., 2012)	251 weeks of aggregate data	Introducing an integrated approach to the use of CMMs to allow for HOE or simultaneous impact	Quantify advertising dual contribution in driving direct and indirect effects	Advertising elasticity through direct and indirect route	Single FMCG brand is used. The questions relate to the advertising rather than the brand, which is not in line with traditional HOE constructs
	Advertising -> search -> sales 1->3->4	(Dinner et al., 2014)	Weekly aggregate data, over 103 weeks	Understanding the different impacts on online and offline sales	Traditional advertising increases the impressions but reduces the CTRs of brand search. Online channels drive high levels of offline sales	Impact of advertising on sales across online and offline retail	Results over a short time period only focus on the direct impact of advertising on search
	Marketing inputs -> CMMs -> sales **1->4**	(Reimer et al., 2014)	Weekly data over 87 weeks and customer level data for 500,000 individuals	Understanding how different segments respond to marketing inputs	Innovative approach to combine individual level data with aggregate level data to provide greater granularity of findings	Advertising elasticity by segment	Website usage is used as a segment variable therefore no changes over time are taken into account as segments are fixed

Measurement stream	Path (numbers indicate stages from the conceptual framework)	Associated research	Data	Focus of research/ Research question	Key contribution/Benefit	Quantification	Limitations
	Marketing Inputs -> Sales 1->2->4	(Hanssens et al., 2014)	Aggregate time-series data over 7 years, monthly aggregation	How can CMMs help with budget allocation	Propose concepts of potential and stickiness and responsiveness to help understand which CMMs to focus on	Impact of increase in mindset metric on sales	Aggregate data so cannot see the impact of changing response for individuals. We cannot independently more mindsets.
	Marketing mix -> Online activity ->Sales 1->2->4	(Srinivasan et al., 2016)	Aggregate weekly data over 40 weeks	Using CICs as an intermediate stage in marketing mix model	Combining online metrics and survey responses improves the prediction of sales.	Increase in sales from advertising investment	Overestimation of the impact of website visits. It appears to double count search clicks as they inevitably lead to a website visit. Impressions would have been more appropriate.
	3->**2**->4	(Colicev et al., 2018)	Daily aggregate data for 273 days	Linking social media to brand awareness	Demonstrating impact of social media on different stages of the CDJ	% Change in shareholder value	Averaged across individuals so do not control for brand relationship of individuals (e.g., customer satisfaction will not be high if they are not a user). Uses users posts as CICs so although they are initiated by the consumer the impact is against all those that are exposed to the reviews. This is very different to the way search behaves.

Measurement stream	**Path (numbers indicate stages from the conceptual framework)**	**Associated research**	**Data**	**Focus of research/ Research question**	**Key contribution/Benefit**	**Quantification**	**Limitations**
	1->**2->3->**4	(Pauwels & van Ewijk, 2020)	Weekly aggregate data over 108 points	Distinction between CMMs and CICs in impact on sales	Dual causality of mindset metrics to online behaviours. Attitudes have more enduring impact; behavioural measure are contextual. Across a large range of industries.	Elasticity on sales and cross elasticity between variables	Aggregate level response only. Website visits and search overlapping metrics leading to potential problems with allocation recommendations. Many brands FMCG
	1->**2->3->**4	(Cain, 2022)	Weekly aggregate over 100 observations	How to build a mechanism to demonstrate brand-building role of advertising	Combining CMMs with path to purchase model. Demonstrating the persistent brand-building nature of advertising through the use of CMMs	Elasticity on sales and cross elasticity between variables	Aggregate-level response, only uses measures of cognition to capture CMMs
	1->2->4	(Valenti et al., 2022)	7 years of monthly data	Order of effects Affect, cognition and Experience between advertising and mindset metrics	For FMCG brands the dominant sequence of effects is affect, cognition, experience. Cognition is the most responsive	Elasticity on sales and cross elasticity between variables	Testing individual-level constructs at an aggregate level, therefore relying on changes over time. This risks endogeneity problems. They conclude that liking comes before advertising awareness which is conceptually more aligned with usage making consumers more likely to notice an

Measurement stream	Path (numbers indicate stages from the conceptual framework)	Associated research	Data	Focus of research/ Research question	Key contribution/Benefit	Quantification	Limitations
							advertisement. No account for creative execution, which should be influential in the order of response.
Attribution modelling (Respondent level)	**Digital Advertising -> search/Click -> Website visit -> Sales 1->3->4**		**Longitudinal event data at a cookie level**	**Development of digital attribution models**	**Highly individual-level response for targeting, selecting publishers or testing different creatives**	Conversions per channel	**Theoretically unsound, assumes all sales are advertising driven, does not account for any influence external to the click stream**
	1->3->4	Abhishek et al., 2012	Longitudinal event	Is there evidence of different phases in purchase funnel	Use of a hidden Markov chain to demonstrate stages of the purchase funnel in clickstream data.	Conversions per channel	Assumed purchase data rather than a sale.
	1->3->4	H. Li & Kannan, 2014	Longitudinal event	Can we improve from last-click attribution	Testing for spill over and carryover in an attribution model. Substitution on organic search if paid search removed.	Conversions per channel	Out of sample forecast was still weak
	1->3->4	Anderl, Becker et al., 2016	Longitudinal event	Can we improve from last-click attribution	High-order Markov walk. Testing for spill over and carryover in an attribution model	Conversions per channel	No account for anything other than digital data
	1->3->4	Danaher & van Heerde, 2018	Longitudinal daily aggregation	Does attribution improve budget allocation	Using a probit model to demonstrate how budget allocation would change	Conversions per channel	Not reflective of how budget allocation decisions are made. Mangers take cost into

Measurement stream	Path (numbers indicate stages from the conceptual framework)	Associated research	Data	Focus of research/ Research question	Key contribution/Benefit	Quantification	Limitations
							account not just look at percentage contribution
	TV -> Search 1->3	(Joo et al., 2016)	Individual-level data on search aggregated to hourly intervals	TV advertising increases the use of brand search over generic keywords but does not drive category search or CTRs	No evidence for an increase in volume overall but brand search terms increase at the expense of generic terms	Uplift in search volumes after TV advertisement	When looked at over a short period, the impact is very small; there is no accounting for longer-term or indirect effects
	Digital exposure -> website visit 1->3->4	(Fulgoni & Mörn, 2009)	Individual-level data on advertising exposure and clicks and sales	How online display impacts clicks to a website	Online display works even without a click showing uplift in web visits and sales even if no visible interaction	Uplift in web visits & sales for exposed vs non-exposed	Treats FICs and CIC as equal input
Impact of CMMs	CMMs-> brand search **2->3**	(Dotson et al., 2017)	Individual-level data, with single survey.	Mindset metrics are a strong predictor of online brand search	Mindset metrics are a strong predictor of online brand search	Those with a positive mindset are 7 times more likely to search for a brand by name	Only focus on brand search, a small part of overall website visitation. No measure of affect, unclear on the overall impact as most consumers would hold multiple attitudes as they are considered on a binary level.

The objective of these studies is to help demonstrate the impact of advertising spending; they use different data and models; therefore, advertising impact is measured in different ways.

By representing the main approaches to measuring marketing performance as the four individual stages and then comparing it to the conceptual framework (shown in the second column of the table), it is possible to see where the focus of empirical work has been. The analysis in Table 3-1 can be used to show where the focus of the empirical work on marketing performance measurement is. This analysis is used to direct the empirical focus and design of my research.

3.8.1 The Empirical Focus in Advancing Performance Measurement Approaches

Several key observations are made:

When intermediate metrics are included, most are either CMMs or CICs, but not both, limiting our understanding of the relationship between these two critical areas.

In comparing the new conceptual framework to mainstream approaches to marketing performance measurement, we can see that MMM captures the cost and return stages in the framework shown on the right-hand side of Table 3-1. This has been described as a direct approach to performance measurement (Vakratsas & Ambler, 1999) in which only observable data are considered, with no intermediate metrics included.

The MMM work has been extended to include intermediate metrics to capture indirect paths. Bruce et al. (2012) Hanssens et al. (2014), Srinivasan et al. (2010), and Valenti et al. (2022), focus on the inclusion of CMMs, whereas in the case of digital attribution work, this involves CICs via search clicks and website visits, and an intermediate metric is implicit in the modelling approach.

Thus, while intermediate metrics are commonly used as performance metrics in performance models, the area of the conceptual framework with the least research is that which contains the link between stages 2 and 3. As an extension to aggregate-level MMM, two key studies have been identified that fit into this area (Cain, 2022; Pauwels & van Ewijk, 2020), both confirming that CMMs help represent longer-term brand-building responses to advertising. However, only one study explicitly addresses this link (Dotson et al., 2017). This provides a unique perspective because the discrete CMMs used provide visibility of the likelihood of searching based on various combinations of brand attitudes. For example, they compare the likelihood of a visit for those with no positive attitudes to those with all seven tested attitudes being positive. However, this study has limitations. Most notably, it only examined the relationship with brand search, which accounts for a small portion of total website visits. A brand search is chosen because it is expected to have a strong link with CMMs (Pauwels et al., 2016), and the measure of brand search share is gaining popularity among marketers (WARC, 2020). However, an overall website visit is important, as with all online activities. In fact, the most cost-effective routes for a marketer are those that go directly to a website, which has received little attention in the effectiveness literature. My conceptual framework demonstrates the importance of the overall metric, which determines the dependent variable in my empirical work.

The second notable observation of the study from Dotson et al. (2017) is the lack of any measure of affect in the mindset metrics tested. Srinivasan et al. (2010) discover that liking has a significant impact and that it is critical to include measures of cognition and past behaviour (Vakratsas & Ambler, 1999). While the approach proposed in this study can provide clear insight into understanding CMMs and CICs, more research on mindsets is needed.

Most research on the relationship between CMMs and CICs has used a market mix modelling approach.

The distinction between individual and aggregate data is critical. While traditional attribution models (Abhishek et al., 2012; Anderl, Becker et al., 2016; H. Li & Kannan, 2014) are conducted at an individual level, and advances in this area have primarily focused on the different statistical models that can be applied rather than the different variables that can be included; thus, CMMs have largely been ignored in this stream of literature. Abhishek et al. (2012) attempted to infer the marketing funnel stages (awareness, consideration, and purchase) using a hidden Markov model; however, these were unobserved stages rather than explicit survey measures.

Rather, advancements in incorporating CMMs into marketing performance models have come from the MMM approach. Before the widespread use of digital marketing, data availability posed a significant barrier to behaviourally driven analytics. Direct marketing customer databases were one of the few sources of customer-level transaction data (Wedel & Kannan, 2016). The only option was aggregate-level sales data, such as total weekly sales. The aggregation over time led to econometrics being a key method for understanding the relationship between sales and advertising (Vakratsas & Ambler, 1999). This is an important consideration when evaluating previous work as it becomes clear that the work done is driven by data availability rather than a philosophical perspective on how the relationships should best be captured.

There are limitations to what can be explored with temporal aggregation of data

While MMM has advantages beyond data availability, such as measuring seasonality, understanding how media should be laid down over time (or flighted as it is often referred to) (Dawes et al., 2018), and how long advertising effects last (L. A. Wood & Poltrack, 2015), the techniques used are not without criticism. In particular, problems with aggregation bias in sales response models are recognised. First, the estimated carryover effect of advertising can be seen to change purely due to the data aggregation period, resulting in different and 'sometimes incorrect' conclusions on advertising effectiveness (Leone, 1995). Second, aggregate data can overestimate the size of search effects (Joo et al., 2016). Moreover, when comparing daily data to monthly data using a vector autoregressive model, Shellman (2004) found opposing results. Although it is impossible to confirm without testing the models, results for models presented by Srinivasan et al. (2016) suggest possible endogeneity issues due to aggregation bias. The detailed results from the empirical model, which incorporates searches, website visits, and Facebook likes and dislikes into a traditional MMM shows a large variation in results. Notably each paid search generates 40.25 sales and a visit to the website 0.87; this means that a paid search is 46 times more likely to result in a sale than visiting a website via another route. Yet, as paid search is measured through clicks each paid search results in a website visit, meaning not only are these duplicated but the disparity in magnitude is hard to explain theoretically. These results do not align with the findings of Blake et al. (2015) and H. Li and Kannan (2014) in experimental conditions, which show that when paid search is removed, consumers frequently revert to organic search through unpaid listings, suggesting it is not as effective as models tend to suggest.

When different approaches yield conflicting results, there is a cause for concern. This analysis demonstrates the importance of being able to replicate across different levels of data aggregation. My research contributes to this by comparing the granular individual-level results with previous aggregate results. However, there are also other benefits of individual level data beyond replication.

Individual-level data are widely used in digital marketing analytics (Anderl, Schumann et al., 2016). Data decisions should be theoretically motivated (Shellman, 2004), but practical considerations frequently drive them. Because advertising exposure and impact are at the individual level, this is the best way to evaluate the impact (Tellis & Weiss, 1995), and individual-level data is especially important when it comes to targeting consumers with advertising messages. Targeting is important not only for advertisers to reach the 'right' customers, but it has also become an important part of the performance measurement landscape as advertising platforms allow for random experiments (Zantedeschi et al., 2017).

Individual-level data are also important for order effects; for example, C. H. Park and Agarwal (2018) examine the order effect of different search advertising using individual-level data and nonlinear effects (Srinivasan et al., 2010). However, this is not possible with aggregate approaches.

Prior research on CMMs has been based on data availability.

A final concern with aggregate data is that data access difficulties limit which CMMs are tested empirically. In general, data access and availability have had a substantial impact on the research and analytical approaches used by managers (Wedel & Kannan, 2016). Studies that have used long time periods of continuous tracking, such as research by Hanssens et al. (2014), Srinivasan et al. (2010) and Valenti et al. (2022), rely on seven years and thus used the measures that were available in ongoing brand tracking, such as it is unclear if (Cain, 2022) purposefully excludes a measure of affect. While several studies have examined the order of CMMs (Bruce et al., 2012; Valenti et al., 2022), none have examined various combinations of CMMs. Only one study reviewed in Table 3-1 (Dotson et al., 2017) created a specific survey.

My research develops a survey using traditional brand-tracking data, allowing me to test different CMMs and their combinations to better understand how they can help explain website visits.

3.9 Summary

New methods for evaluating advertising performance have emerged, owing to the abundance of digital metrics. While detailed clickstream data that show the specific routes to purchase are frequently included in digital performance measurement, the issue is that widely used digital models do not account for consumers' attitudes and perceptions of a brand. The development of digital performance measurement models has been based on accessible data rather than on a conceptual understanding of advertising. The importance of considering the antecedents of CICs has been overlooked.

Although mindset metrics and website visits are two of the most commonly used performance indicators, there is little understanding of how they relate and can be used in combination (Pauwels & van Ewijk, 2020), especially at the individual level. Much prior research has focused on whether and when CMMs should be used; however, there has been little research on how mindset metrics should be best captured to help understand CICs.

Chapter 4: The Relationship Between CMMs And Website Visits

4.1 Introduction

Despite the long history of examining each CMMs and behaviours separately this gap is even more noticeable in the digital ecosystem where little research has been conducted on the relationship between mindset metrics and online behaviour. The significance of CMMs as a bridge between the antecedents of CICs, and advertising performance was highlighted in the first part of the literature review. However, as discussed in Chapter 3, our understanding of the relationship between CMMs and CICs is limited. Few studies that link CMMs to online behaviour have focused on which CMMs are important in predicting brand interactions online.

Whilst the previous chapter explored the metrics from the role, they play empirically in modelling This chapter explores how CMMs have been incorporated into previous theoretical models to better understand how they should be used in the context of website visits. Given the scarcity of research in this area, I examine not only prior research that includes online behaviours but also sales, looking for possible explanations for any differences.

4.2 Approaches to Representing the Brand-Building Component of Advertising in Response Models

While there are various perspectives on how advertising influences consumers (Vaughan et al., 2021), most include the notion that advertising influences mindset as a precursor to behaviour when they are in a buying situation. CMMs capture brand feelings, which are not short-term effects (Cramphorn, 2006; Pauwels & van Ewijk, 2020); rather, they are conceptually used to capture the brand-building component of advertising response (Anselmsson & Bondesson, 2015; Bruce et al., 2012; Cain, 2022; Valenti et al., 2022). This indirect impact is consistent with Keller (1993), who argues that consumers with a higher level of consumer-based brand equity (CBBE) are expected to be more responsive to advertising. This has been empirically validated by Datta et al. (2017), who demonstrated that brands with higher CBBE have higher advertising elasticity, as expected.

These consumer mindset measures are commonly captured through brand tracking and survey-based polling of respondents. CMMs have been used to capture the brand-building component of advertising response, but there is still disagreement about which metrics should be included and how they relate to one another. This is important as results are highly dependent on the specific metrics used (Morgan et al., 2022).

Valenti et al. (2022) have identified three different approaches to measuring the impact of advertising on CMMs as classical, simultaneous and integrated, where classical represents the traditional hierarchy of cognition, affect and then behaviour; simultaneous accounts for cognition, affect and past behaviour, but no order is enforced; and the integrated approach where alternative hierarchies can exist. These viewpoints are consistent with those of Vakratsas and Ambler (1999), who conclude that affect, cognition and past experience (ACE) are all required otherwise results will be biased.

An alternative perspective is that the cognitive path is the most important (Cain, 2022; Dotson et al., 2017; Sharp, 2010). This approach is most often associated with the concept of brand salience or mental availability (Romaniuk & Sharp, 2004; Sharp, 2010). The measures used here do not include measures of affect but rather cognitive measures, such as brand awareness or top-of-mind awareness. Despite its widespread use of the concept of mental availability there is a lack of research testing the construct empirically. Determining the exact measures to capture this concept has been challenging, and it is therefore considered practically difficult to implement by practitioners (Hurman, 2022).

4.3 Theoretical and Empirical Evidence of Advertising Response

Table 4-1 summarises some of the most commonly used models driving CMMs, which were proposed using a combination of theoretical frameworks, empirical models and literature synthesis.

Table 4-1

Overview of Commonly Used Hierarchies and Associated Metrics

Year	Approach	Reference	Model	Approach	Common associated measures	Order C – Cognition A – Affect B – Behaviour E – Experience	Summary of Model
1908	Conceptual	(Lewis, 1908)	AIDA Awareness, Interest, Desire, Action	Classic	Brand Awareness Brand Consideration	C-A-B	First, to describe how consumers may move through stages on the path to purchase.
1961	Conceptual	(Lavidge & Steiner, 1961)	Awareness – knowledge – liking – preference – conviction – purchase	Classic	Brand awareness, familiarity, liking, preference, purchase intent, purchase	C-A-B	A development on AIDA Liking and preference are suggested as the key additional measures which bring in an important emotional element to the model
1974	Conceptual	(Ehrenberg, 1974)	Awareness – Trial – Reinforcement- (ATR)	Cognitive	Awareness Trial Repeat purchase (buy regularly)	C-B–A	Looks at advertising as having only a relatively small impact on driving sales. Introduces the idea of repeat purchase and needs to reinforce after initial purchase for long-term sales success.
1993	Conceptual	(Keller, 1993)	CBBE	Classic	Brand Awareness or Familiarity	C-A-B	The higher the level of CBBE the more likely a consumer is to both respond to advertising and to purchase a brand. First a consumer needs knowledge of a brand and then they make judgements.
1999	Synthesis of literature	(Vakratsas & Ambler, 1999)	Simultaneous Affect, cognition and past experience	Simultaneous		(C&A&E)-B	Allows for integrative and simultaneous models depending on the situation, factors

Year	Approach	Reference	Model	Approach	Common associated measures	Order C – Cognition A – Affect B – Behaviour E – Experience	Summary of Model
							such as product category, or level of involvement or context may impact the order
2004	Conceptual	(Romaniuk & Sharp, 2004)	Brand Salience	Cognitive	Top-of-Mind awareness	C-B	Those with higher levels of brand salience are more likely to purchase
2009	Conceptual	McKinsey (Court et al. 2009)	Consider, reconsider, purchase, evaluate	Cognitive	Brand Consideration Purchase	C-B-C	Shift from HOE to CDJ (customer decision journey). Introduce a feedback loop, arguing that awareness is no longer a prerequisite for purchase due to the impact of eCommerce. The loyalty loop can bypass future considerations. As a result, the number of brands considered active consideration is often increased.
2010	Conceptual	(Sharp, 2010)	Mental availability	Cognitive	Brand Salience	C-B	Likelihood of thinking of a brand in a purchase situation
2010	Empirical	(Srinivasan et al., 2010)		Classic/simultaneous	Liking, advertising awareness, consideration	(C&A) -B	While the metrics are representative of a hierarchy, the measures themselves do not enforce one (you can consider a brand without being aware of advertising)
2012	Empirical	(Bruce et al., 2012)		Integrated	Advertising response (attention, messaging) Brand recognition Liking	E-C-A	Allows inclusion of lags to advance simultaneous approach

Year	Approach	Reference	Model	Approach	Common associated measures	Order C – Cognition A – Affect B – Behaviour E – Experience	Summary of Model
					Purchase intent		
2013	Conceptual	(Munchbach et al. 2013)	Discover, Explore, Buy, Engage	Cognitive	Search, Consider, purchase	B-B	Allows for more active involvement now available through digital channels.
2017	Empirical	(Dotson et al., 2017)		Cognitive	Brand awareness, familiarity, consideration, purchase intent	C-B	Higher CMMs result in greater likelihood of searching for a brand
2020	Empirical	(Fortenberry & McGoldrick, 2020)		Classic	Awareness, interest, desire, influence, retention, loyalty	C-A -B	Evidence of hierarchy through to loyalty and retention
2022	Empirical	(Cain, 2022)		Cognitive	Brand Awareness, Brand Consideration	C-B	Awareness and consideration lead behavioural measures of website visits and
2022	Empirical	(Valenti et al., 2022)		Integrated	Liking, advertising awareness, brand awareness, Purchase intent	A-C-E	For FMCG the most prominent order is affect, cognition and then experience. Cognition is the most responsive to advertising

The combination of conceptual and empirical representations of CMMs provides a framework for various approaches that should be tested to determine which CMMs should be considered.

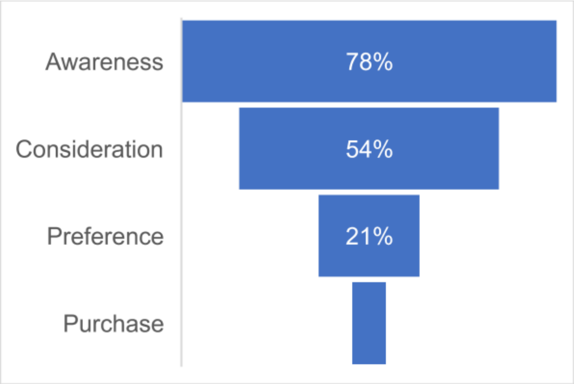
4.4 Perspectives of CMMs' Role in Advertising Response and Responsiveness

Since the seminal work of Simon (1955), proposing a framework for individual or group decision-making, the consumer decision journey has become a key part of consumer behaviour research. Funnels have been a widespread feature of marketing performance measurement, greatly influencing the metrics that marketers capture. This has evolved into an important framework for understanding consumers' reactions to advertising (Abhishek et al., 2012; Lemon & Verhoef, 2016; Wiesel et al., 2011). Despite being one of the first marketing models, the AIDA 'marketing funnel' remains one of the most popular (Ritson, 2017).

Marketers have long been interested in tracing the steps a customer takes towards making a purchase. The AIDA model from the early 1900s has served as a fundamental guide for marketing strategy and metrics. Figure 4-1 depicts a representation of this model, often referred to as a 'funnel' due to the decreasing number of consumers at each stage as they progress from awareness to action. The HOE funnel approach is based on the idea that customers go through cognitive, affective and conative stages before purchasing (Smith et al., 2008). These models assume that customers proceed sequentially through each stage until they make a final purchase decision. Each stage is assumed to have fewer customers than the previous stage because they eliminate options before making final purchase decisions.

Figure 4-1

Hypothetical Funnel Based on AIDA Model



Hanssens and Pauwels (2016), observed it is logical to assume a hierarchy from awareness to consideration to purchase. The path could be virtually simultaneous with a first-time purchase, or it could be over a much longer period of time. This logic aids in preserving the hierarchy. By comparing conversions from one level to another across brands, this ‘funnel’ creates a comparative tool that allows brand managers to identify points of focus.

These funnels are based on survey data and display aggregated information. The idea is that I must first be aware, then consider, then prefer Brand A to others, and finally make a purchase. Several conditions can be used to represent this with survey data. For each measure, the data are **binary**; respondents either meet the condition or do not, hence we count how many people are aware and present this as a percentage. Once a consumer is aware, we must focus on making them consider, so the implicit role is to focus on all those who are already aware of a brand and provide them with a reason to consider it. A purchase is the percentage of the population that has purchased, not the number of purchases.

Simplified consumer decision process models (Dierks, 2017) are becoming more important in terms of how people are targeted through media and linked to brand equity (Lehmann et al., 2008). However, there is a widespread belief that the AIDA hierarchy does not accurately reflect the actual consumer decision-making process (Cramphorn, 2015;

Ehrenberg, 2000). There is an ongoing debate about the stages of the funnel and its existence (Vakratsas & Ambler, 1999). This distinction is critical when determining which consumer decision-making models (CMMs) are required to comprehend website visits. The observations from the alternative models evaluated in Table 4-1 provide additional guidance on which CMMs should be empirically tested.

4.4.1 Most of the Empirical Work Looks at How CMMs are Impacted by Advertising, or the Not the Subsequent Behavioural Response That is Important for CICs

Prominent studies investigating the sequence of advertising impacts evaluate the link between firm-initiated advertising and CMMs in stages 1 and 2 in the conceptual framework. However, as discussed in Chapter 3, advertising exposure is now driven by consumers and firms, so we need to understand not only which CMMs firm-initiated advertising can easily shift but also which CMMs advertisers should try to shift to get consumers to create CICs. This stage is better represented by the concepts of mental availability (Sharp, 2010) and CBBE (Keller, 1993), which consider how likely a consumer is to respond to advertising, given a level of CMMs. However, previous research has focused on sales response rather than a likely increase in CICs (e.g., Datta et al., 2017; Stocchi et al., 2021)

This additional stage of CICs is an important consideration for marketers, especially those in the eCommerce industry. As demonstrated by the conceptual framework and analysis of budget splits by media channels, attracting consumers to a brand website now accounts for a sizeable portion of the advertiser budget. However, no research has examined whether there is a sequence in the way CMMs influence website visits. This is critical for developing our understanding of the antecedents of CIC. If there is a hierarchy in measures, only those closest to the behavioural action should have a strong significant impact.

4.4.2 Hierarchies in Aggregate vs Individual Data

Empirically a traditional HOE approach is still widely used, for example Fortenberry and McGoldrick, (2020) and they regarded as a useful tool in problem diagnosis. Consequently, HOE models have remained popular (Ritson, 2016, 2019). Although it is conceptualised as a series of stages consumers go through, it has largely been tested at an aggregate level.

Bruce et al. (2017) and Valenti et al. (2022) used aggregate timeseries data to test the sequences. This means that leads and lags between variables are tested rather than looking for a hierarchy of attitudes held, where some attitudes, such as awareness, must be held before a consumer can consider. This is shown in the VAR model if one of the metrics changes during the following period. Thus, no metric combinations have been investigated.

Considering the specific metrics used by Valenti et al. (2022), they use an average of advertising awareness and brand awareness for cognition. They find that affect leads cognition. However, given brand awareness of brands is often stable over time (Hanssens et al., 2014), this effectively means that advertising awareness is shown to follow liking, which if described in this way raises more concerns than cognition follows affect. We know that users are more likely to like a brand (Sharp, 2010) and that they are more likely to notice advertising (Vaughan et al., 2016), which could explain the findings because advertising uplift is expected to be higher with more users or more consumers who are attracted to the brand. Companies such as Millward Brown, which creates awareness index (AI) models, do not anticipate a lag between advertising exposure and awareness (Brown, 1991). Therefore, more research is required into the mechanism that could drive these results based on specific survey questions. This highlights the of understanding differences at the individual level.

4.4.3 Not All Approaches Include Cognition and Affect

While the view that cognition and affect need to be accounted for (Vakratsas & Ambler, 1999) has strongly influenced empirical models, as evidenced by the use of HOE, simultaneous and integrated models in Table 4-1, this view is not universal. Another perspective argues for a more cognitive approach (Cain, 2022; Court et al., 2009; Dotson et al., 2017; Sharp, 2010). Sharp (2010) considers the role of advertising best measured through mental availability, defined as 'a brand's propensity to be noticed and/or thought of in buying or consumption situations'. This is a common phrase in business practice. Measures of mental availability concentrate on cognitive measures of awareness and association rather than brand judgements (Stocchi et al., 2021). This approach is used in studies that rely on measures, such as brand awareness, top-of-mind awareness (Hakala et al., 2012), and consideration or sharing of associations (Stocchi et al., 2021).

This cognitive perspective has also been adopted in changes to marketing funnel metrics. Although alternative funnels have been underdeveloped for many years, the digital landscape has brought the funnel and discussion of the stages a customer goes back into vogue. Court et al. (2009) proposed a model that included a loyalty loop and introduced a stage for reconsideration as part of the evolution. The digital economy raises the possibility that the availability of online information results in the addition of previously unconsidered brands. While there is no evidence that this would not happen in a physical store, it is especially relevant in the digital realm because consumers can bypass evaluation and purchase a brand directly. This scenario is unlikely in a traditional retail setting where consumers are exposed to other brands on store shelves (branded stores and exceptions). While they contend that the marketing funnel is no longer appropriate (Court et al., 2009), they maintain that there are attitudinal stages that are drivers of online behaviour and sales.

The empirical models developed using this approach by Dotson (2017) and Cain (2022) both show the same intermediate role for CMMs, except that no measure of liking or preference is included. As alternative versions of the model, including affect, are not compared it is not possible to determine whether these models can be improved. Nonetheless, this is an important distinction in metric selection.

4.5 Testing the Three Key Perspectives

If we are to use CMMs as important intermediate metrics it is important to understand which CMMs we use and on what scales we measure them, in order to better account for CMMs in our understanding of how advertising works. The analysis has provided three clear approaches that need to be considered. By testing them all on a single data set a comparison can be made on the benefits of each.

4.5.1 Testing the Notion of Hierarchy of Advertising Effects at Individual Level

Although analysis of aggregate time-series data have significantly progressed our understanding, aggregate data limit what can be explored. We know there is more variation across customers than across time, (Srinivassan, 2010). Investigating these metrics at the respondent level will better understand which metrics to use and how to represent them. This also enables the investigation of nonlinearity in the scales employed. Table 4-2 shows the data requirements for enforcing a funnel using a three-stage sequence.

Table 4-2

Grid of HOE Metrics Required for a Sequence to be Present

	Awareness	Consideration	Preference
Option 1	0	0	0
Option 2	1	0	0
Option 3	1	1	0
Option 4	1	1	1

If we consider a hierarchy that goes from awareness to consideration to preferences if a hierarchy exists, then only the four options in the table should be possible. Option 1 is those who are yet to reach the first stage. Since these consumers are unaware of a brand, any behavioural interaction with it, such as a website visit or purchase, is highly unlikely. Option 2 is where a consumer first becomes aware of a brand, but there is no consideration at this point. Option 3 is where they consider it, and finally, it becomes the preferred brand. It should not be possible to prefer a brand that is not considered or to consider a brand that a consumer is unaware of. How the question is posed is critical here; if, instead of prompted brand awareness, an alternative metric, such as advertising or top-of-mind awareness, is used, the concept of a hierarchy or funnel is no longer valid. It is entirely possible to prefer a brand without being aware of the advertising. This is important at the individual level, where we are not looking for patterns over time (as with time-aggregated data) but rather for the entire set of CMMs that an individual holds.

The first approach tests the following to maintain a hierarchy within the measures at the individual level:

Approach 1: Awareness -> Consideration -> Preference

4.5.2 The Cognitive Approach

The cognitive approach, largely driven by mental availability, is frequently captured as top-of-mind awareness (Hakala et al., 2012), which, while not fully capturing the complexity of brand salience, is easy to capture (Romaniuk & Sharp, 2004).

Regardless of how the CDJ concept influences it, consideration is an important part of the cognitive approach (Cain, 2022; Court et al., 2009; Dotson et al., 2017). While not traditionally part of brand salience, consideration allows for multiple levels of connection to a brand when combined with awareness). Consequently, the second approach to testing is as follows:

Approach 2: Awareness -> Consideration -> Top-of-Mind Awareness

4.5.3 Simultaneous and Integrated Approach

An alternative to a hierarchy is to consider different dimensions or spaces, as described by Cramphorn (2006) and Vakratsas and Ambler (1999). While HOE models and associated metrics are pervasive, many argue that this is because of convenience rather than a strong representation of the path to purchase. After a thorough review of over 250 articles that investigate these advertising effectiveness models of firm-initiated media channels, (Vakratsas & Ambler, 1999) assert that it is critical to assess cognition, affect and behaviour when measuring advertising performance; otherwise, the results will be biased.

They also suggest that these metrics should not be in an enforced order, favouring hierarchy-free models.

According to Nyilasy and Reid (2009), practitioners agree that there are plausible explanations for most orders in HOE models that either affect, cognition or conation could start (Barry & Howard, 1990), which would indicate that enforcing an order is not appropriate, Cramphorn (2006) goes argues more strongly against this approach describing HOE models as "one of the more notable red herrings in marketing history".

To allow for simultaneous or integrated approaches to be measured for individuals' different scales need to be used. Brand awareness, recall and familiarity are used interchangeably (Krishnan et al., 2013). Familiarity is frequently used when scale or depth is required. Using scales, we effectively allow respondents to be 'more aware' or have 'greater liking' towards a brand.

Advertising is not the only factor that can influence CMMs. Consumers' previous interactions with a brand are also important in determining whether they will likely interact with the brand in the future (Vakratsas & Ambler, 1999). Conventional wisdom holds that behaviour is the best predictor of behaviour (Sharp, 2010, Tanusondjaja et al. 2016). This is supported by Pauwels and van Ewijk (2020), who find that when online behaviours are added to market mix models, they make a larger difference than CMMs. Furthermore, the behavioural approach is dominant in digital performance measurement. Formisano et al. (2020) criticise the behaviouralist approach, arguing that cognition and affect are not solely driven by behaviour. If this is the case, we can expect both CMMs and past behaviour to play a role in models of website visits. Capturing the different elements becomes an important question when looking to balance metrics between attitudinal and behavioural.

The final approach differs from the first two in that it incorporates a measure of past experience, as proposed by Vakratsas and Ambler (1999). The purpose of this is to recognise that those who have interacted with a brand will have more well-formed opinions. Prior research has used survey data to measure experience, such as Valenti et al. (2022), who used purchase intent, and Bruce et al. (2012), who use past usage, but both of these studies look at sales as a dependent variable. In this model of website visitation, I include a measure of previous website visitation.

A non-hierarchical structure requires that an order is not enforced, that a consumer has a higher level of cognition than affect, or vice versa. There are some critical questions to ask to remove an enforced hierarchy.

Because a scale is required to capture this, the third approach is tested as follows:

Approach 3: Liking & Familiarity & Past Experience

While this approach focuses on measures of liking, familiarity and past experience testing within empirical models, I first test liking and familiarity to compare all mindset combinations and then add a measure of past experience to test the relative importance of attitudes and behaviours.

4.6 Summary

The previous chapter emphasised the significance of considering CMMs as a precursor to website visits in the context of brand building and performance evaluation. This chapter examines the relevant CMMs and whether a specific order influences consumers' likelihood of engaging with a brand online. Three approaches to assessing the impact of CMMs have been identified: the classical hierarchy approach, the cognitive hierarchy approach, and a simultaneous approach that considers both cognition and affect.

4.7 Research Questions

Online behavioural metrics should not be viewed as a replacement for mindset metrics; rather, used together, CMMs can help inform who is likely to visit a website and, in doing so, provide a mechanism for linking traditional advertising to the online ecosystem. Based on a review of the existing literature and the proposed conceptual framework, I develop three research questions to address the overall objective of the research, which is to better understand the role of CMMs in website visitation to provide better guidance to marketers on how to understand and interpret the most prominent metrics for assessing consumer advertising response. By developing a research design from the ground up rather than relying on available data, valuable insights into the most critical areas for development with future data capture will be provided.

All the research questions seek to predict the likelihood of an individual visiting a brand website and how we can do so with knowledge of their attitudes and past behaviours.

1) **RQ1: Which CMMs best explain website visits, and is a sequence of CMMs supported?**

Following the AIDA model and cognitive perspective I evaluate whether the hierarchy is the best way to understand the role of CMMs or the alternative investigate approach using dimensions of cognition and affect.

2) **RQ2: Do CMMs combined with a behavioural measure provide a better prediction of who is likely to visit a website than past behaviour alone?**

We know that past behaviour is a strong predictor of future behaviour and that there is a complex relationship between cognition, affect and past experience. Although aggregate research has shown that incorporating CMMs into models to predict future sales is beneficial, we do not know whether this is true at the individual level. CMMs may help with the ‘why’ but provide little predictive value.

3) **RQ3: If CMMs are important what is the relative importance of CMMs and behaviours?**

If CMMs are important the final question addresses the relative importance in understanding CICs. The goal of furthering this area of research is to determine how consistent it is across different categories. Is it always necessary to use the same metrics, or should they be category-specific?

Chapter 5: Methods – Considerations and Previous Studies

5.1 Introduction

This chapter begins by analysing the challenges for data collection, specifically the differences between observed behaviour and unobserved survey data. Subsequently, previous solutions to these challenges are discussed. Despite the lack of research on advertising performance measurement, the customer satisfaction domain provides a wealth of information because customer identities are known; this knowledge is used to develop a research methodology. First, we consider the value of the individual-level data. This is followed by an overview of the various data characteristics of CMMs and website visits to understand the key challenges. Finally, I look at how these problems have been solved before and the implications for this study.

5.2 Challenges of Linking CMMs and Behaviours

Despite research demonstrating the benefits of utilising behavioural and attitudinal data in together to understand and predict brand sales (Srinivasan et al., 2010; Vakratsas & Ambler, 1999), effectively combining these two types of data has been identified as a significant challenge for studies in this area (Pauwels & van Ewijk, 2020). Additionally, the complexities of the available data can in part account for some of the limited research combining attitudes and behaviours (Rappaport, 2014; Wu & Rappaport, 2014). Consequently, research in this area is either conducted separately, with brand metrics associated with brand-building activities and behavioural metrics associated with sales-driving activities, or researchers rely on proxies available in the data. For example, claimed behaviour or behavioural intentions are frequently used as measures in survey research (Heath & Feldwick, 2008; Petersen et al., 2018).

Using surveys to measure claimed behaviour is a common practice; however, there is a high level of criticism for the approach, including that correlation can be a result of the measurement process (Bolton, 1998) and that claimed behaviour differs from actual behaviour (Rundle-Thiele, 2009). While this can be mitigated to some extent through analysis (Rindfleisch et al., 2008), claimed behaviour lacks the accuracy and fidelity of collecting actual behaviour. It is also likely that inaccuracy is not random, for example, light users tend to over-report, whereas heavy users tend to under-report (Collopy, 1996).

Despite the recognition of the benefits of using actual behaviour, there is only a small amount of research combining survey data with data that have captured actual behaviour, either for online interactions or sales, key examples are (Cain, 2022; Hanssens et al., 2014; Pauwels & van Ewijk, 2020; Srinivasan et al., 2010, Valenti et al.2022), and even fewer that do so at an individual level (Dotson et al., 2017). Typically, data are either considered separately (Wu & Rappaport, 2014) or modelled at an aggregate level (e.g., Srinivasan et al., 2016). Although aggregate data significantly simplify the problem, we lose the ability to see any path to purchase or individual actions. To develop the approach used for this research, it is necessary to assess prior research in the area and review the different data characteristics for attitudinal and behavioural data, classified as observable and unobservable constructs by Gupta and Zeithaml (2006). Unobservable constructs in this study are CMMs. Observable constructs are when these preferences are revealed through the behavioural action of website visits, the key metric for CICs.

5.2.1 Behavioural Data – Observed Effects

Behaviours have clear signals that can be observed and are commonly captured by firms for accounting purposes, for example, how many sales have been made or number of website visits. Website visits are an easily trackable behaviour, aided by the use of technology. It has been estimated that there are around 7 billion searches per day (Firestorm SEM, 2019), demonstrating the volume of available data. A large amount of data means that small-scale custom solutions are not widespread; rather, much of the data used for observation come from large-scale technology companies that offer tools, such as Google Analytics, providing off-the-shelf solutions to track website analytics. While this makes the data relatively cheap and widely available, Dotson et al. (2017) were able to access data for multiple brands specifically for this research through a partnership with Google, which means that data are generally only available for single brands, which restricts our ability to understand the generalisability of the results.

5.2.2 Survey Data – Unobserved Effects

Survey data are usually customised and flexible to individual research projects (Dibb & Simkin, 2010), considered 'small data' (Lam et al., 2017), which means that it is very common to customise the scales used based on study objectives. While the measures can be wide-ranging in surveys, we generally capture information that it is not possible to collect through observation, as suggested by Hulland et al. (2018) p.92 *'it is difficult to imagine how certain topics could be studied without directly asking people questions*', or as classified by Gupta and Zeithaml (2006), perceptual measures of what customers think are considered unobservable metrics. Brand awareness and familiarity are good examples of measures that do not have observed alternatives.

Apart from the unobservable nature of mindset metrics, another key characteristic that impacts the measurement of brand attitude is that they can be considered enduring (Pauwels & van Ewijk, 2020). Conceptually, this is critical for capturing data, as it does not need to be captured at a specific time. Traditionally, to create continuous data for CMMs, the same respondent is not repeatedly asked about brand awareness; rather, a different sample is recruited for each survey wave. This is a critical distinction, as individual-level data cannot simply be aggregated to create time-series data if we want to conduct the analysis at the respondent-level granularity. Therefore, merging surveys with behavioural tracking data becomes challenging when surveys are administered to individuals at a specific time, whereas behavioural data can be collected longitudinally. Consequently, most survey research adopts a cross-sectional design, as highlighted by Hulland et al. (2018), who found that over 92% of articles published in the Journal of the Academy of Marketing Science (JAMS) utilised this approach.

5.3 Where, Who and When Considerations in Data Collection for CMMs and CICs

Independently the collection of online behaviours and brand attitudes have well-developed approaches and associated data sources. However, there are key differences that inhibit their combined use. Assessing how the different data sources have been used individually reveals more about the attributes of the data and the challenges of data collection, demonstrating the benefits of the different data types and contrasts the collection and use of data.

While the conceptual framework captures differences in the data, data collection is critical for the study design. This are the differences between a) when data are collected, b) where data are collected and c) from whom data are collected. This is discussed in the following sections.

5.3.1 Where the Data are Sourced from – Source

The use of two separate data sources nullifies the risk of CMV bias and also enhances CI ability by reducing the likelihood of rival method-based explanations. (Rindfleisch et al., 2008, p.274)

While behavioural data are considered easy to collect, this is only the case when technology is in place; for example, the offline equivalent of collecting footfall traffic is not consistent and widespread (ANA, 2021). The prevalent collection of behavioural data relies on existing technological solutions or partners to capture data. Google Analytics (GA) is the most widely used tool for tracking behavioural website data (W3Techs, 2023). However, there is no link back to the consumer to enable surveys to be easily administered.

In contrast, the dominant approach to collecting survey information is via online panels, where personal information about the respondents is collected. This approach uses smaller sample sizes (McDaniel & Gates, 2010), and while data can be captured over time through brand tracking, it is often only at a single point in time. When data are collected over time, different respondents are used for each survey to avoid repetition (Valenti et al., 2022).

5.3.2 Who the Data are Collected from – Sample

Survey data are concerned with samples for specific research questions (Hulland et al., 2018). This means it is common to emphasise who will receive the survey and how representative the sample is for the research objectives (Fulgoni, 2014). Although it is common to remove at least some of the respondents because they did not meet the selection criteria or because data were missing (Hulland et al., 2018), this has not been observed in studies focusing on observed behavioural data. In particular, it is difficult to determine whether all online website visits have been recorded (Facebook & Datalicious, 2017). The equivalent of non-response or non-observed behaviour is viewed as a technological issue rather than a problem with the respondents in this scenario.

The sample size of survey data captured using questionnaires sent to individuals is smaller relatively; because it is common to incentivise each respondent separately, there is a direct relationship between the cost and sample size. Conversely, with tools such as Google Analytics, all respondents are tracked at no additional cost once tracking is set up. The data have some known quality issues, mainly because the identifier is based on cookies rather than people (Facebook & Datalicious, 2017). However, this is considered as a representation of total website visits. Tracking tools allow the signal to be observed if the device visits the website again; therefore, return visits or the frequency of visits can be captured (Fulgoni, 2014).

5.3.3 When Data are Collected – Cadence

While the era of big data refers to data volume, velocity and variety, the reality is that the signal is sporadic for individual customers. Many people do not visit a website at all, and even for those who do, there may be a long gap between visits, often followed by short bursts of repeated visits (C. H. Park & Park, 2016). Furthermore, the nature of website visits necessitates that the mechanisms, processes and technology used to capture them be in place at all times and triggered by observed behaviour. Behavioural data are passively captured, meaning consumers are often unaware they are being tracked, allowing for continuous tracking.

In contrast, survey data can be collected anytime, which may affect the outcome. The fact that brand attitudes persist means that continuously being able to capture information about an individual is not critical; rather, the focus is on collecting a valid sample of people at a specific point in time (Hulland et al., 2018).

5.3.4 Key Data Attributes that Should be Considered

Table 5-1 summarises these characteristics and challenges: Contrasting the data characteristics of website behavioural and mindset metrics; this contrasts the behavioural and attitudinal metrics across the previously identified key data dimensions.

Table 5-1

Contrasting the Data Characteristics of Website Behavioural and Mindset Metrics

	Behavioural metrics	**Attitudinal mindset metrics**	**Challenge**	**Consideration**
When	The signal is Sporadic and Instantaneous (if not captured in real-time, the chance to observe is missed)	Enduring, persistent and slow-moving	Continuous tracking through technology is required for behaviours; for Attitudes, the consideration is at what point to collect data and how often	Data Cadence
Where	Mechanically collected, data collection has little impact on the behaviour	Self-reported or consciously reported.	Repetition is not a problem for behavioural data, but repeating survey measures can be	Data source/capture
Who	Census	Sample	Although a sample is sufficient for the research, all behaviour linked to that individual must be available.	Sample size
	Self-selected by engaging in monitored activity	Proactive recruitment	It must start with either a tracking technology and then determine how to administer a survey or get survey respondents to allow behaviour tracking.	Sample Frame
	Largely unidentifiable	Strongly identifiable	While there is no need to have personal information for the research, identifying individuals for matching purposes is critical	Identity

These attributes will be used to assess prior research that has linked observed behaviours with survey results. These attributes and their implications for study design are reviewed below.

5.4 Previous Research on Combining Data – When, Where and Who Considerations

To merge data from diverse data sources, it is crucial to identify common attributes, such as time, which is present across all the data. However, merging data across individuals is more complicated and requires unique identifiers for each person. The complexity of merging increases as datasets become more diverse. Companies are now prioritising merging data across individuals and implementing CRM systems to create a 'golden record' or a 'single source of truth' for customers. (Verhoef et al., 2010; Amalina et al., 2020). Individual visibility across all business areas allows for greater detail in the analysis. This includes factors such as the time between purchases (Fader et al., 2005; Liu-Thompkins & Tam, 2013) and identifying homogeneous groups of customers (Malthouse & Calder, 2006). Because of the benefits of single source data (data from the same individuals), much attention has been paid to how to achieve it, particularly in the case of media exposure and sales (Cannon et al., 2007), where the sources are different, but both are observable factors. Attitudes and behaviours have received less attention.

Despite the challenges of combining observed and unobserved data, several studies have used data from a single source for behaviour and attitudes. Table 5-2 summarises key studies. Two studies covering both customers and non-customers have been identified to assess CMMs along the path to purchase; however, customer satisfaction research focusing only on those with a purchase history with a brand can provide guidance. While there is little evidence that using survey data within CRM systems is a common practice, there are more opportunities in this area because surveys require large customer databases with personal contact information.

Petersen et al. (2018) conducted a comprehensive review of studies on customer satisfaction. This review covers a subset of those that use surveys and actual behaviours but focuses on the models and data collection approaches rather than the key findings of the research. Furthermore, several recent instances have been identified, and each study has used a unique technique for data capture, focus categories and data handling in models. These studies provide critical insights into data collection methods that can address the challenges associated with surveys and behavioural observation data. The continuous collection of behavioural data has proven extremely beneficial for precise quantification. Rather than allowing claimed purchases or actions, all studies examined captured behaviour this way.

Table 5-2

Prior Research with Both Behavioural and Attitudinal Data

Research questions	Attitudes considered	Data Collection Approach	Model	Data	Categories	Benefits	Limitations	Authors
Are customers who hold positive attitudes towards a brand more likely to search for the brand?	Recognition Recall Familiarity Consideration Purchase intent	Partnership with Google allowing a pop-up survey to be matched to online behaviour	Hurdle model. DV number of visits Cross-sectional approach	DV Count IV's binary indicators Control variables metric Attitudes measured once	Telco Automotive	Can see multiple brands Large sample size	Only able to assess brand search. Cannot see search terms. Data access controlled by Google	(Dotson et al., 2017)
What type of digital and traditional information is used along the path to purchase?	Stage in the purchase cycle is identified through Early, Mid, Late, and Final.	Six weeks of tracking using a panel that allows online behavioural to be measured through an installed app. 5-minute weekly survey. Sample size 662 – Auto 541 Smartphone 703 pizza	Poisson	DV Count visits IV stage	Auto Smartphone Pizza	Multiple brands	A bespoke panel had to be set up for the research	(Wu & Rappaport, 2014)

Understanding the impact of CMMs on customer behaviour and customer profitability	Customer satisfaction Perceived quality Attitudinal loyalty	Data from loyalty program allowing spend levels to be matched with an annual survey where customers have an account login Mindset measures use a multi-item scale (3 items, 7-point scale)	conditional mixed Process (CMP)	DV – Gross margin IV Past mindset Past behaviour Marketing efforts Factor scores are used	B2B High-tech B2C Telco	Long time period Detail on customer-level profitability	Only a Single brand Reliant on predetermined questions Only possible to see those with an ongoing relationship with the brand Does not show online interactions	(Petersen et al., 2018)
The link between satisfaction and length of the relationship	Customer satisfaction	22 Months Sample from a customer database 650 customers	Proportional hazards regression	Duration of relationship Satisfaction	Telco	Two survey waves Considerable time period as all historical sales records are available	Only a single brand	(Bolton, 1998)
Establishing the link between past usage, satisfaction and future usage	Customer satisfaction	Use of customer database over six months 184 entertainment	Tobit Mixed model	Usage Satisfaction Pay equity	Entertainment Telco	Multiple waves of survey and behaviour allowing causal inference Customised survey	Only focus on customers Limited survey information	(Bolton & Lemon, 1999)

How relative satisfaction impacts the likelihood of staying with a firm	Satisfaction, likelihood to recommend, renew & increase share	Sample 405 customers Two years	Logistic regression	DV - Repatronage Relative satisfaction Likelihood to stay (index)	Credit cards	Able to consider in a competitive context	Heavy use of indexes makes it complex to understand what to change	(Bolton et al., 2000)
Satisfaction thresholds in relation to repurchase	Customer satisfaction Repurchase intention	100,400 Survey 33 months after purchase	Probit model with latent variables	Repurchase behaviour Satisfaction & Repurchase intention - 5-point scale Demographics Dummy coding for satisfaction	Automotive	Very large sample Identify nonlinear effects	Pre-existing survey results rather than customised. Survey time is fixed, but repurchase can vary a lot	(Mittal & Kamakura, 2001)
Relationship between satisfaction and churn under different trigger situations	Customer satisfaction Customer Commitment	17 months Fixed line 712 Mobile 1503 Modem 303 Broadband 197	Principal components Churn model	Churn Triggers Satisfaction (1 -10) Commitment	Telco	Detailed qualitative pre-study Test for nonlinearity but find only linear results	Survey timing was driven by time with company meaning they took place at different times for each respondent	(Gustafsson et al., 2005)
Positive customer churn	Customer satisfaction and dissatisfaction	1,369 customers Four months	Competing-risk regression	Churn Satisfaction & Dissatisfaction	Online dating	Utilise level of interaction as IV, i.e. observational data not just used as DV	Single brand, very specific to online dating industry (few categories have	(Dechant et al., 2019)

							positive & negative churn)	

The ability to capture data in the most appropriate way for the data type is a critical component of this research design. That is, observable data should be observed rather than claimed, whereas unobservable data should be elicited from respondents through a survey. Hence the study design has two key components to capture: website visits (observable) and CMMs (unobservable). Various design options have been considered, all in the context of when the data are collected, where they are collected, and from whom they are collected.

5.4.1 Where the Data are Collected from – Source of Data

Starting with a pre-existing source has a clear advantage in that it allows access to existing behavioural data, which the customer satisfaction studies in Table 5-2 take advantage of. In the context of this research, a particular advantage is the ability to look at past experience (i.e. behaviours before the survey) as used by Bolton (1998) and Bolton and Lemon (1999). Furthermore, because customer databases contain personal information for individuals, including email addresses, it is a relatively simple process to contact customers and link them back through an email address.

In customer satisfaction research, an existing customer panel is frequently an accessible source for collecting survey data. Understanding the broader impact of CMMs on online behaviour requires more than a focus on customers, as the goal of advertising activity is frequently to gain new customers. Hence, for a more comprehensive population sample, this source is not suitable.

Dotson et al. (2017) use a partnership with Google to overcome the requirement for a broader sample base by linking IP addresses or accounts of survey responses. However, owing to privacy concerns, Google manages the matching process, and online behaviour is restricted to brand searches. Online brand searches account for a small percentage of website visits (Anderl et al., 2016), limiting the scope of the research. Wu and Rappaport (2014), conversely, use a more traditional research panel provider that has used technology to track online actions, as well as the ability to send surveys. Although this method does not allow for large sample sizes, it allows for observing all online interactions across various brands and categories. Participants are specifically recruited for the study, which incurs costs and may influence consumer behaviour because they must use passive tracking apps to capture their actions.

As a result, there are two options for getting started: finding a technology provider with access to behavioural data that can also conduct consumer surveys. This is consistent with the approach used in customer satisfaction literature (Bolton et al., 2000; Bolton & Lemon, 1999), in which consumer databases containing sales records served as the starting point. The problem with this approach is that behavioural data, such as searches or sales, are typically collected to provide data to individual brands. Consequently, data constraints exist. For example, detailed data from a system such as Google Analytics limits access to a single brand unless specific access is obtained. While this is appropriate for research purposes, it does not help extend the data collection approach to something most marketers can achieve.

The alternative approach adopted was to use a research panel with the primary focus on custom surveys for individuals but that also has the ability to track online behaviours for a subset of the research panel members. To explore the critical questions of which CMMs should be used and why, a survey must be customised. Based on the requirement to customise the survey and consider data collection approaches that can further the ability to combine observed and unobserved data, this research collects data from a research panel rather than traditional clickstream sources, such as Google Analytics. This allows for greater visibility of all passively captured behaviours and greater control over the survey length.

5.4.2 Who – Survey Sample

Customer databases can be used as key sources of behavioural data and as samples for survey data in customer satisfaction research. This means some of these studies have access to large customer databases, for example, Mittal and Kamakura

(2001), with over 100,000 customers. These databases are established by firms to manage customer relationships; thus, while in some studies, such as Petersen et al. (2018), the survey can be customised, in many cases, the customer data have already been collected, and there is little ability to customise the inputs for research purposes (e.g. Gustafsson et al., 2005; Mittal & Kamakura, 2001). Because of this reliance on data from individual firms, research is frequently based on a single firm, as in the case of Gustafsson et al. (2005). It is preferable to be able to look across multiple brands and categories to understand the broader relationship between users and non-users. Although this results in a smaller sample size, it ensures that the data captured are flexible and that there is full access to the raw data.

TEG Rewards was selected as the data partner. TEG Rewards (now TEG Insights) has a large marketing research panel built in conjunction with their ticketing business which is the largest in Asia (TEG, n.d.). Given their impressive access to customer data, they are uniquely positioned to develop capabilities for capturing behavioural observations. They have a pre-recruited panel of respondents with a passive capture application installed on their devices which scrapes the long URL for every website interaction for panel members who have opted in. The data that I am then able to collect have three distinct advantages.

a) Since the data collection app is already installed on respondents' devices, there is no need for a pre-recruitment stage. This significantly reduces the risk and cost of data collection. Because of the ongoing tracking of consumer activity, their online visits before the start of the research are captured and available for analysis. This allows for an analysis of search behaviours before the survey, which is useful in the category selection phase and a critical measure of past experience in the models.
b) The tracking app records all website visits of the panel member, allowing us to see both visits to competitor websites and (once the data is coded) the path a consumer took to reach the website (e.g., direct to the website, brand search, etc.). It also provides visibility for overall online usage, which is an important control variable, as will be discussed later.

c) Because these are known individuals rather than IDs, demographic information on individuals can also be accessed.

5.4.3 When

While the behavioural data captured will be longitudinal; in most of the customer satisfaction literature attitudinal data are measured once or twice. As a result, the timing of the survey in relation to behavioural tracking becomes critical. The conceptual framework presented shows attitudes as antecedents to behaviour. Mindset metrics, primarily customer satisfaction, were conceptualised in this way all of the 41 cases reviewed by Petersen et al. (2018). This is also the case in the brand research work of Wu & Rappaport (2014). Hence the survey responses must be collected **before observing the behaviour** of website visits, which is the dependent variable.

Tracking behavioural data after the survey has been conducted over as little as six weeks in the case of Wu and Rappaport (2014) and as long as 33 months in the case of Mittal and Kamakura (2001). Various factors can be seen to determine the length of the period. Mittal and Kamakura (2001) accessed a survey the firm had already conducted, so there was no control over the timeframe. The phasing of the surveys was based on the time customers are expected to purchase a new vehicle, as the sample size and frequency of purchases influence the duration of behavioural responses (Gustafsson et al., 2005). In research involving churn models, customers must be allowed to leave a company, and churn rates are critical for ensuring adequate data variation. The same is true for count models, which require sufficient product usage time to allow for multiple interactions, thus generating the necessary data variation for modelling.

The tracking period was shorter in the two studies that did not use customer databases. There are three possible explanations for this finding. First, a key consideration is an appropriate time to ensure that behaviours reflect current brand attitudes. Dotson et al. (2017) suggest that eight weeks is appropriate because the longer the period, the more potential changes to the starting brand attitudes. Second, the dependent variable is online website visits, which have lower barriers to entry than sales because there are numerous non-purchase reasons to visit a brand’s website (Pallant et al., 2017). Because website visits occur more frequently than sales visits, observing customer interactions takes less time.

As this research will look at visits to a website, the time frame of the research needs to reflect a sufficient period to allow multiple interactions. However, as website visits are more frequent that sales, it will follow prior research utilising a shorter tracking period. The time period selected for the post-survey work reflected that of Dotson et al. (2017), who used an 8-week period. The standard period for retention of cookie data is 30 days; therefore, the 8-week period allows greater flexibility but not so long that we would expect large changes in CMMs. This period also corresponds to Pauwels and van Ewijk’s (2020) findings, who discovered that attitudes lead to behaviours for up to eight weeks.

Chapter 6: Empirical Study Design and Methodology

6.1 Introduction

The methods section describes the approaches to be used to answer each research question. The study design, data collection and data analysis methods are highlighted. The complexity in collecting data for both attitudes and online behaviours is a consideration and a methodological differentiator for this research. My approach contrasts with those of others, such as Colicev et al. (2018), Hanssens et al. (2014), Pauwels and van Ewijk (2020), and Srinivasan et al. (2010), who have used aggregate time-series data. This study requires data to be collected from the same individuals; therefore, I have used web scraping technology and a research panel. Various data sources have been carefully considered, as detailed in Chapter 5, to use survey data and behavioural data in the most appropriate ways.

The first part of this chapter covers these data collection decisions. Many of these difficulties stem from the differences in observable and unobservable data characteristics, which necessitate different approaches to data collection, as discussed in the previous chapter. The most important aspect of this study is that behavioural data must be collected over time to observe the sporadic interactions of an individual with a website, as opposed to survey data, which allows us to engage with consumers at a defined point in time. These differences have implications for both **data collection** and appropriate **modelling** approaches. The second part of the chapter reviews the data collected and explains the statistical modelling selection process.

6.2 Data Collection Approach

Figure 6-1 shows the data collection design, timing and capture. The two main components are continuous behavioural data collection and two point-in-time surveys.

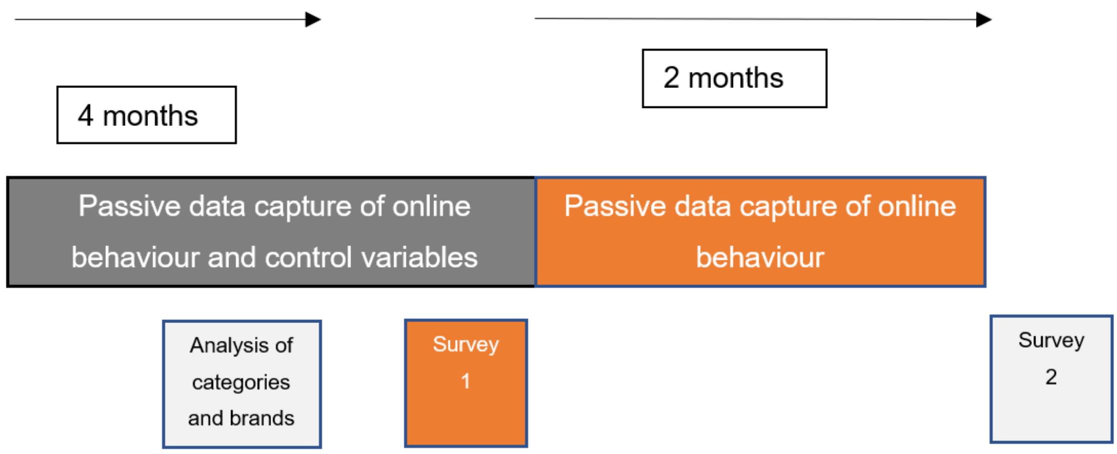
Stage 1: Capture of control variables and finalisation of survey brands.

Stage 2: The survey is distributed to all respondents covering the key brands in the selected categories.

Stage 3: At the end of the period, a second survey is conducted to measure changes in CMMs over time, as well as in the context of this research, to check for stability over time and for future research.

Figure 6-1

Study Design, Including Timings and Data Capture



Note. The orange sections represent the key variables used in the model, the dark grey section is used for the control variables, and the light grey sections represent the data check stages.

6.3 Survey Design

The surveys are used to collect the CMMs to be tested within the model. These are self-reported responses to specific brand questions that can be tailored and customised to the needs of those using the data. The aim of the survey is to capture common brand metrics aligned to those used in brand tracking. A survey is designed to collect these metrics for specific brands. Key studies in this area have used aggregate time-series data and have therefore relied on pre-existing surveys supplied by consultancies; for example, Colicev et al. (2018) used syndicated research from YouGov, and Pauwels and Ewijk (2013) were able to access brand-tracking data from GfK and Millward Brown. Therefore, the metrics used are based on brand health metrics that large market research companies have traditionally used.

Given the extensive research on measuring these concepts in market research, approaches to developing these scales should be considered. Table 6-1 shows the main metrics and data types previously used. To supplement these metrics, the survey component of this research draws on the concepts of cognition, affect and past behaviour identified by Vakratsas and Ambler (1999) as important components of balanced measurement.

Table 6-1

Review of Prior Survey Measures of Research Looking at Use of CMMs

Study	**CMMs Cognition**	**CMMs Affect**	**Past behaviour experience**
(Hanssens et al., 2014; Srinivasan et al., 2010)	Ad awareness, Consideration	Liking	(Base level in model)
(Bruce et al., 2012)	Memorability, Recognition	Liking	Claimed usage
Dotson et al. (2017)	Recall, Recognition, Familiarity, consideration, Purchase intent	No measure	Ownership
(Colicev et al., 2018)	Advertising awareness Received WOM Consideration Purchase intent	Customer satisfaction	Current customer perceptions on value
(Pauwels & van Ewijk, 2020)	*Unaided Brand Awareness, Consideration*	*Preference*	*Use regularly*
(Cain, 2022)	*Brand awareness, Brand Consideration*	*No Measure*	(Base level in model)
(Valenti et al., 2022)	*Average prompted brand awareness and advertising awareness*	*Liking*	*Past Purchase & Purchase intent*
The present study	Brand awareness, advertising awareness, Consideration, Top-of-mind awareness	Liking Preference	Past website visits

The metrics used in previous research in this area demonstrate strong consistency, partly due to the use of the same dataset (e.g., Hanssens et al., 2014; Srinivasan et al., 2010). Because I aim to determine whether variations exist at the individual level, I stick to previous metric choices while ensuring that the list of measures is sufficiently extensive to include various brand awareness and affect measures. The benefit of my research approach is that, first, I can consistently test combinations of CMMs across different categories. Second, the measure of past experience is an actual behavioural measure, as opposed to another claimed measure captured in the survey.

Each of the metrics examined in this research is discussed further below, and a summary of the questions posed is shown in Table 6-2.

Brand Awareness: While more complex measures of brand equity were not included in this research, brand salience has emerged as the most common cognition metric (Binet & Field, 2013; Romaniuk & Sharp, 2004; Samuel, 2017; Sharp, 2010). Traditionally, promoted brand awareness and top-of-mind awareness have been used to measure salience (Sharifi, 2014). As seen in studies such as Dotson et al. (2017), awareness can be prompted or unprompted, with the latter characterised as recognition. The issue with awareness-based metrics is that they rely solely on the brand name as a cue for memory, although memory is influenced by multiple cues, as Romaniuk and Sharp (2004) point out. However, in the context of this study, where searches are conducted using either brand or category names, brand awareness is a suitable and practical measure that can be assessed in both prompted and unprompted forms.

Familiarity: An alternative measure to brand awareness is that of familiarity, which has an established link with liking (Sharp, 2010). Although Girard et al. (2017) treat familiarity and awareness as the same construct, research has found that familiarity can distinguish more than brand awareness, which, especially for large brands, shows very little variation, particularly for prompted brand awareness (Hanssens et al., 2014). When attempting to determine the number of visits a respondent makes to a website, the additional variation provided is expected to be superior to the binary metrics.

Consideration: Consideration is the most consistently used measure across all the historical research reviewed. While consideration is a common survey metric, it has also been captured as an observable behavioural metric based on search data (Protheroe et al., 2020) and modelled using sales data (Nierop et al., 2010). According to the decision model of Court et al. (2009), consumers can add or remove brands from the consideration phase during the information search stage. This is the consideration phase in customer journey analysis where consumers are expected to visit a website.

Liking: Several methods have been proposed to measure the affect construct, which is related to the various emotions an advertisement can elicit. However, the key theme in the literature is liking (du Plessis, 2005; Lavidge & Steiner, 1961; Srinivasan et al., 2010). It has also been suggested that liking should be captured in the context of competing brands (Samuel & Alagon, 2013). The attitudinal survey uses liking as the primary measure of affect, but preference is also tested for comparison within the funnel.

Preference: Brand preference has also been widely used to track affect (Dyson et al., 1996; Lavidge & Steiner, 1961; Pauwels & Ewijk, 2013). While liking can be measured in isolation or comparison with other brands, preference is always in the context of the competitive set, so this must also be defined.

Advertising awareness. While understanding the role of advertising awareness is not a core objective of this study, it has been used as a substitute for brand awareness (e.g. Hanssens et al., 2014; Srinivasan et al., 2010) and in combination with brand awareness by Valenti et al. (2022). Therefore, it is included for comparison purposes.

Table 6-2

Summary of Survey Questions

Question	Scale	Measure
When thinking about category x, which is the first brand or company that comes to mind?	Open-ended response	Top-of-mind brand awareness
Which other brands or companies come to mind?	Open-ended response	Unprompted brand awareness
Which of the following brands are you aware of?	Select all that apply	Promoted Brand awareness
Thinking of brand x, how familiar would you say you are:	5-point rating scale (not at all, slightly, moderately, very, extremely)	Familiarity
Which of the following brands have you seen advertising for in the last 2 months?	Select all that apply	Advertising awareness
Which of the following brands would you consider when next purchasing in category x	Select all that apply	Liking
Which brands in category x do you prefer? Please rank in order of preference	Ranking	Preference

The full survey is provided in Appendix 1.

6.3.1 Sample Size and Characteristics

The size of the TEG reward panel largely determined the sample size. The behavioural tracking panel was limited to 400 people who opted in for and agreed to install the tracking device on their desktop, mobile or both devices. Although this sample size is smaller than that of many studies based solely on behavioural data, it is not uncommon in survey-based research. For example, Zantedeschi et al. (2017) use a panel of 300 respondents for their customer satisfaction research, whereas Bolton et al. (2000) use 405 respondents. However, in this research there are 3 categories and each respondent answers questions for 27 brands this provides a much stronger base for analysis than single brand customer satisfaction-based research.

A further description of the sample is also provided in Appendix 1.

6.3.2 Fieldwork

The survey was conducted using the Qualtrics survey tool. The survey length was approximately six minutes, with each respondent answering the results for the three categories. Table 6-3 lists the survey timing and responses. Given the importance of travel in my research, it is important to note that all fieldwork was completed before the global COVID-19 pandemic.

Table 6-3

Fieldwork Details

	Start	End	Responses
Survey 1	6 May 2019	26 May 2019	290
Survey 2	1 July 2019	20 July 2019	281

Respondents were asked to complete the survey for each of three categories, there was some level of non-completion however respondents were included in a category if they answered all the key questions for that category. This means there is some minor variation between categories, with respondents missing one or two categories.

Two surveys were conducted; however, the analysis was based solely on the results of the first survey. The second survey was used to confirm the expectation that brand attitudes are slow-moving measures, and it will be used in future research that goes beyond the research questions addressed here. Appendix 1 presents a comparison of the two surveys

6.3.3 Selection of Categories

The siloed approach to measurement using CMMs and CICs results in divergence in categories across different research streams. Bruce et al. (2012) and Valenti et al. (2022)

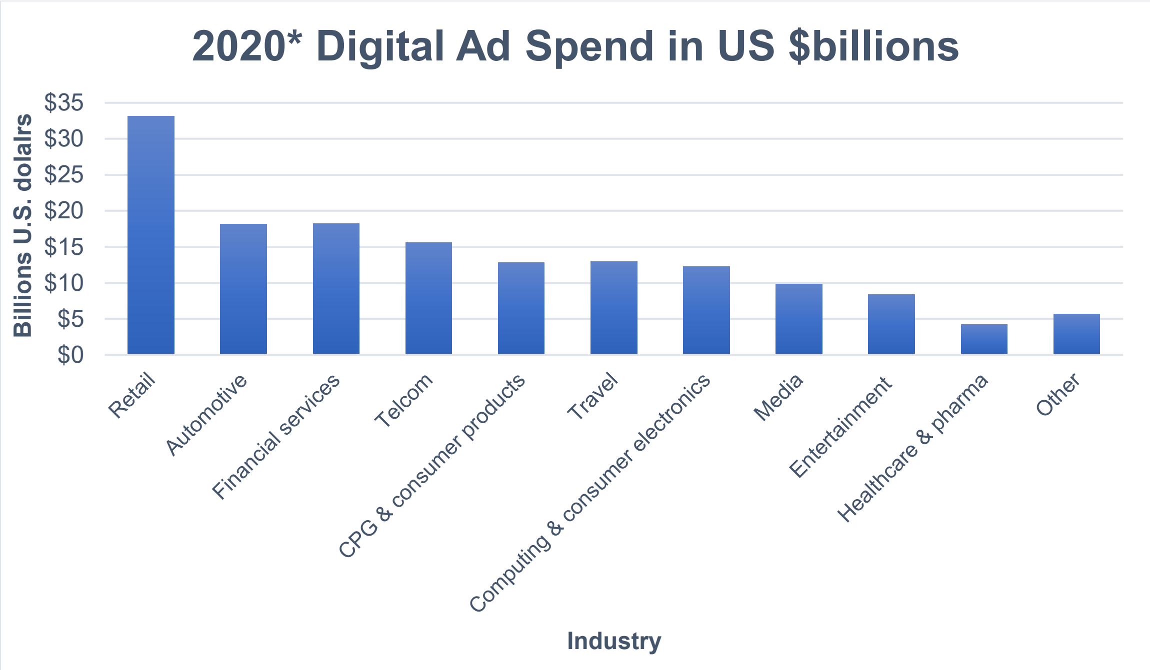
concentrate on FMCG categories, where scanner data have resulted in readily available sales data (Wedel & Kannan, 2016). However, FMCG brands have lower website visits than higher involvement categories and do not have the same access to online sales data (Pauwels & van Ewijk, 2020). Because category and product involvement are thought to play a role in the path taken (Pauwels & van Ewijk, 2020; Vakratsas & Ambler, 1999), research on website visits has focused on higher involvement eCommerce brands.

For this research, three categories were chosen to test for robustness across different product areas. Because the sample size is limited by panel size, I limit the research to three to keep the survey short. To determine the categories, I use a combination of three data sources: first, common categories from prior digital research; second, digital advertising spend levels because these are likely to be the categories that rely the most heavily on clicks and website visits for reporting; and finally, TEG data that shows visitation rates by category and brand.

Common categories for prior research include lodging (Anderl, Becker, et al., 2016; H. Li & Kannan, 2014) online retail (Anderl, Becker, et al., 2016; Blake et al., 2015; Danaher & van Heerde, 2018) automotive (Abhishek et al., 2012; Dotson et al., 2017) and telecommunications (Dotson et al., 2017). These categories provide some direction. In addition, categories with a higher focus on performance marketing tend to have higher digital spend levels (*eMarketer, 2019)* The data below in Figure covering digital spend by categories broadly aligns with the categories used in prior research, with retail showing by far the largest spend.

Figure 6-2

Digital Advertising Spend by Channel in billion USD



Note: Forecast spend

Source: Data obtained from eMarketer (2019)

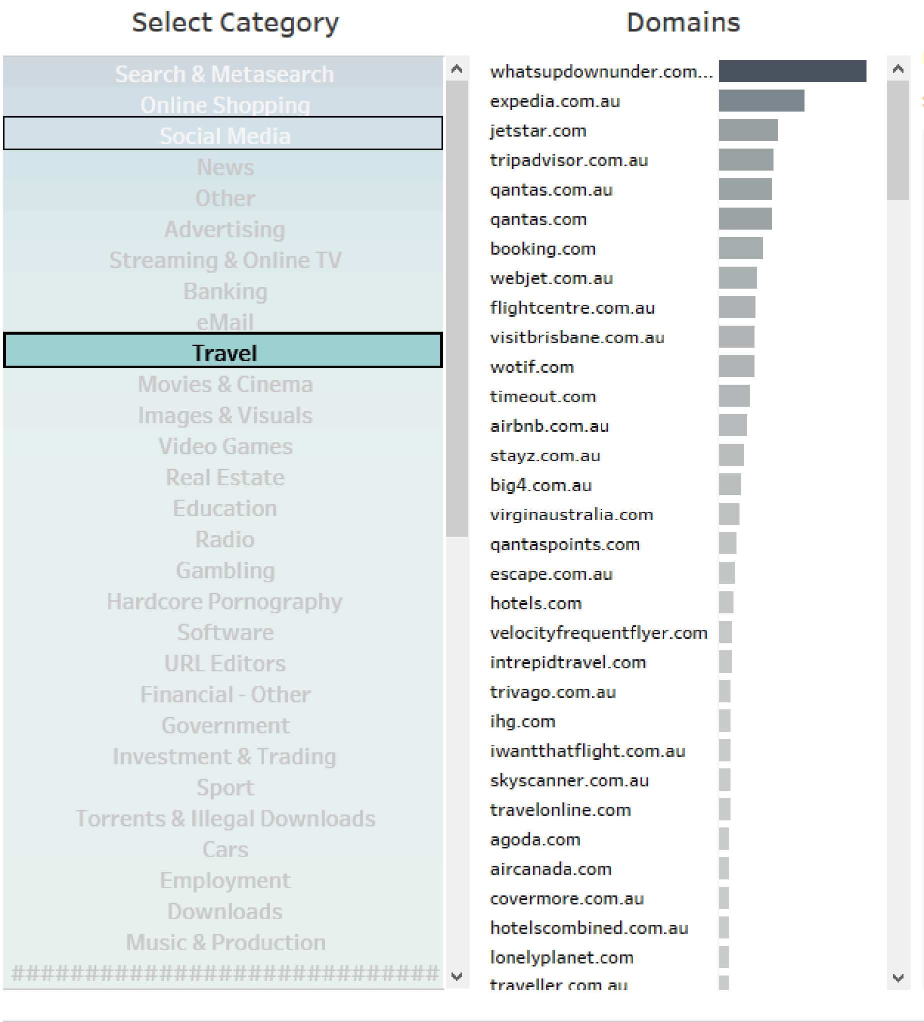
Therefore, empirical research should focus on eCommerce where website visits play an important role in the purchasing process. Dotson et al. (2017) focused on the automotive and telecommunications industries, but I aim to broaden the learning to include other industries. Furthermore, the prolonged buying process in their research may have been a reason that there was limited consistency across categories in the count stage of the model, therefore I opt for categories where we can expect higher visit frequency.

While automotive, financial services, and telecommunications are high-spending industries, I avoided them for various reasons. First, while these categories may be expected to have a high level of interaction with a website, it is more likely that this interaction is functional rather than about a purchase; for example, for finance and telecommunications companies there may be a requirement to visit the website to pay bills or check payments. Second, because new purchases are rare in these categories, information search visits should be much fewer than transactional visits. As a result, these categories were not used, and emphasis was placed on categories with more frequent purchases and the potential for regular browsing behaviour. Brands were selected using the same procedure.

Finally, Figure 6-3 shows sample data of relative visitation levels for travel using TEG data for the final category decision. These data were used to guide category and brand selection in the survey. Three survey categories were selected based on higher levels of visitation: airlines, online hotel bookings and retail.

Figure 6-3

Example of Visitation Data Available from the TEG Rewards Internal Reporting



6.3.1 Selection of Brands

Understanding the volume levels of website visits for brands is one of the benefits of using an established panel. While behavioural tracking data are available for all websites consumers visit, survey questions must be predetermined, meaning categories and brands must be selected for the research. Thus, assessing interaction levels of respondents with different categories is advantageous before deciding the focus of the research.

The brands selected for each category were selected based on visitation levels as well as category definitions (for example, whatsupdownunder.com.au is the highest site in terms of visitation, as shown in Figure 6-3, but is an information and content website rather than eCommerce). Table 6-4 shows the selected brands.

Table 6-4

Summary of Brands and Categories

Hotel Booking	Airlines	Retail
• Wotif • Booking.com • Trivago • Expedia • Webjet • TripAdvisor • Flight Centre • Agoda • Skyscanner • Hotels Combined	• Qantas • Virgin Airlines • Jetstar • Emirates • Singapore Airlines • Air Canada • Tiger Air • Air New Zealand	• Amazon • David Jones • Myer • Kmart • Big W • Target • eBay • Harvey Norman • JB Hi-Fi

6.4 Behavioural Data Overview

The raw data from passively tracked online behaviour are obtained from a web scraped URL, resulting in a long string URL form that must be coded before analysis. Given the long-form structure of the data, processing is required to extract metrics suitable for modelling. When attempting to understand performance, several key metrics are frequently used, the most important of which is total visits (Florès, 2014). While previous research frequently looked at page views rather than overall visits, it has been argued that page views are no longer appropriate because pages on mobile-optimised websites are poorly defined (Wedel & Kannan, 2016).

The metrics captured across key brands in the relevant categories for this research are:

- Site visits (with timestamps for each URL) are used to generate the dependent variable and the measure of past experience
- Device (desktop, mobile or both) used as a control variable.

This information is extracted from each respondent for each brand included in the survey. The coding exercise used to extract the data is described in Appendix 2.

6.4.1 Measuring Past Behaviour

A measure of past behaviour is required to align with the key elements proposed by Vakratsas and Ambler (1999). The measure of past behaviour represents previous interactions with the brand. Survey metrics captured these in previous research by Bruce et al. (2012) and Valenti et al. (2022). However, there are known issues with claimed behaviour, such as increased responses to more socially desirable questions and a lack of perfect recall (Rundle-Thiele, 2009). Light users will have the greatest deviations, and usage may be inflated (Nenycz-Thiel et al., 2013), and there is a risk of common method bias when data are collected from the same source (Rindfleisch et al., 2008).

Given the context of digital behavioural measures, it is also important to consider the data used in digital reporting. The most common distinction in digital reporting is between visitors and non-visitors hence this is used for the measure of past experience.

6.4.2 Control Variables

Measuring response at the customer level rather than the aggregate level necessitates using some level of control variables to account for individual differences. Dotson et al. (2017) employed a claimed measure of category interest and a measure of brand ownership. I did not account for these because my dataset uses a measure of past behaviour as an alternative. There are two main control variables based on the available data.

1. Overall, internet usage represents heavy or light internet users, as heavy internet users are more likely to visit any individual site and are more likely to be exposed to advertising (Huang & Lin, 2006).
2. I have tracked device behaviour because we can expect different patterns of behaviour between desktop and mobile visits (Sakas & Giannakopoulos, 2021).

6.4.3 Summary of data

Using these measures, a single data file has been created. The behavioural data were combined with survey data after being transformed into a single flat file for each respondent. A summary of the measures is shown in Table 6-5.

Table 6-5

Summary of Key Available Data Tested Within the Models

	Measure	Data type
Customer mindset metrics (CMMs)	Top-of-Mind awareness	Binary measure
	Spontaneous awareness	Binary measure
	Prompted Brand awareness	Binary measure
	Familiarity	5 – point scale
	Liking	5 -point scale
	Advertising awareness	Binary measure
	Preference/first choice	Ordinal & Binary
Behavioural metrics	**Total Website visits in research period (DV)**	Count
	Total website visits in control period	Count/Binary
	Duration of visits	Time
	Device (Desktop, Mobile, Both)	Categorical

6.5 Descriptive Analysis and Model Development

This second part examines the collected data and discusses the model selection process used to answer the research questions. This research has three main research questions:

4) **RQ1: Which CMMs best explain website visits, and is a sequence of CMMs supported?**
5) **RQ2: Do CMMs combined with a behavioural measure provide a better prediction of who is likely to visit a website than past behaviour alone?**
6) **RQ3: If CMMs are important what is the relative importance of CMMs and behaviours?**

This modelling stage aims to investigate how CMMs influence consumer website visit behaviour. Each question builds on the one before, and the same modelling approach is used for all questions. The exploratory analysis aids in the selection of a modelling approach. The descriptive section is divided into three categories: behavioural data (including the dependent variable of survey visits), mindset metrics and control variables. The analysis is performed at the category level to align it with the structure of the models. Some analyses have also been conducted at the brand level to demonstrate brand variations.

6.5.1 Website Visits – Dependent Variable

Understanding whether a consumer interacts with a brand's website and what motivates this interaction is a critical first step in determining how to increase the level of interaction. Driving these metrics would become a key objective for firm-initiated media.

Figure 6-4 shows histograms of the visits for each category. Each category represents all the brand respondents.

Figure 6-4

Histograms of the Number of Category Visits

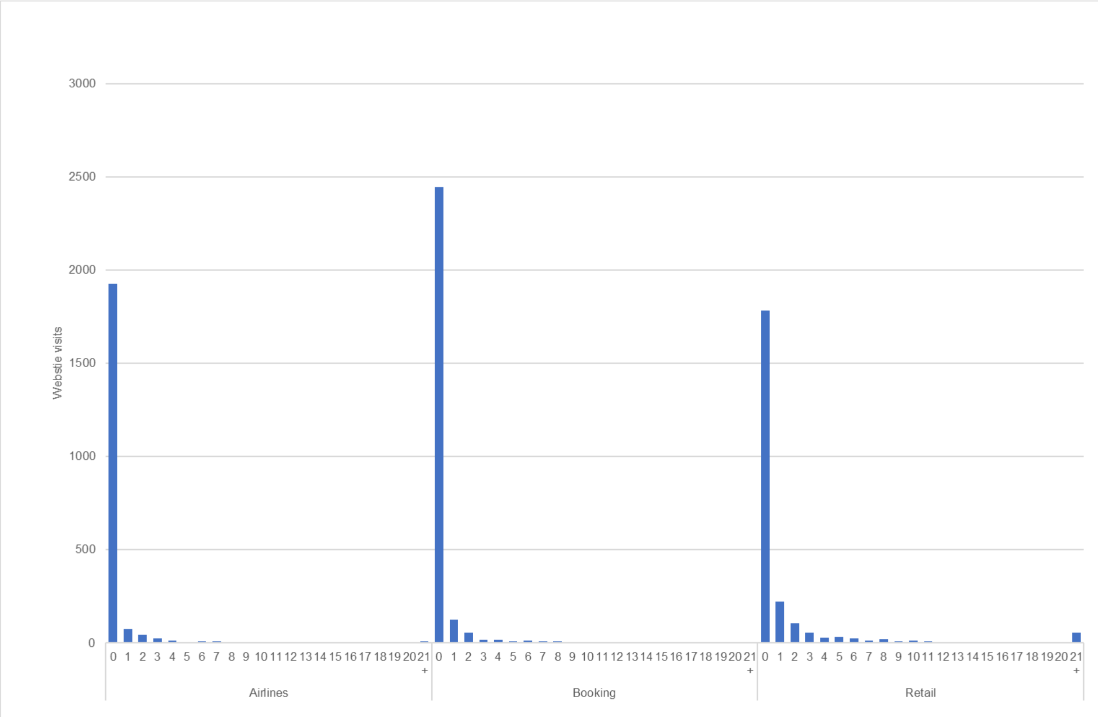


Table 6-6 shows the key descriptive data. The first measure reflects the number of times respondents visited websites in each category for the dependent variable, which is in the period after Survey 1.

Table 6-6

Key Descriptive Statistics of Online Website Visit Data, Including Control Period and Test Period Split by Category

	Airlines		Hotel Booking		Retail	
	Mean	*Std Dev*	*Mean*	*Std Dev*	*Mean*	*Std Dev*
Website visits						
Total visits after the mindset survey (DV)	0.50	2.66	.39	4.10	2.08	9.74
Indicator of website visitation	.10	.304	.10	.296	.26	.437

The mean visitation levels in the table show some clear differences between categories. The most notable distinction is the higher level of retail visits. This is unsurprising, given that the broader category allows for more search or purchase opportunities. The mean visitation levels for hotel booking and airlines are similar; however, the hotel booking category has a greater variation. This is because, fewer people visit it.

Overall, CICs as measured by website visits have a highly skewed distribution (Dotson et al., 2017; H. Li & Kannan, 2014; C. H. Park & Park, 2016). It is expected that many people will have no interaction with any given website, whereas a few will have a high level of interaction. This pattern is supported by the data, with most people not visiting.

A high level of zeros is important for model selection because it indicates that the Poisson model is not appropriate (Feng, 2021). Instead, zero-inflated models are popular where there are structural zeros and sampling zeros (Hofstetter et al., 2016). Dotson et al. (2017) used a hurdle model to account for excess zeros in their modelling. The model is divided into two stages: the first estimates whether consumers are likely to visit a website, and the second uses a negative binomial distribution to estimate the number of visits. This model assumes that there is a single process that first determines whether a consumer visits a website and how frequently they will visit. An alternative is the zero-inflated Poisson or Negative Binomial (ZIP/ZINB) model.

In the ZIP/ZINB model, the first model is a count stage with Poisson or Negative Binomial regression, followed by logit regression to estimate the excess number of zeros (Institute for Digital Research and Education, n.d.). This differs from the hurdle model, which conceptually determines whether an event will occur at all and how many times it will occur (Dotson et al., 2017). The conceptual difference between the two-stage approach is critical; it has been observed that the results are often similar; hence the selection is often viewed as theoretical (Hofstetter et al., 2016). Owing to this simpler interpretation, hurdles are frequently preferred (Zeileis et al., 2008). In marketing science literature, for example, a negative binomial is frequently used (Ehrenberg et al., 2000; Scriven & Goodhardt, 2012). Consequently, this approach is adopted.

An analysis of the visitation levels of each brand in the survey was performed to gain a deeper understanding of the differences between brands. I examined the average visitation using the hurdle model, as shown in Table 6-7.

Table 6-7

Website Visitation by Brand

		Percentage of respondents that visit in the modelling period	*Average visitation (if they visit)*	*Standard Deviation*
Airlines	Qantas	24.00%	10.86	22.583
	Virgin Airlines	16.50%	4.86	7.122
	Jetstar	*10.50%*	*4.04*	*3.667*
	Tigerair	4.50%	3.62	4.388
	Singapore Airlines	3.70%	2.6	2.319
	Emirates	3.00%	2	0.756
	Air New Zealand	0.70%	3.5	0.707
	Air Canada	0%	0	0
Hotel Booking	Trip Advisor	18.10%	3.43	6.195
	Booking.com	15.50%	3.29	2.814
	Flight Centre	10.70%	1.9	1.319
	Expedia	8.10%	2.5	4.748
	Hotels Combined	2.20%	2.84	2.918
	Skyscanner	6.60%	2.11	2.784
	Webjet	6.30%	3.18	2.157
	Trivago	5.50%	1.73	1.033
	Wotif	5.50%	1.6	1.056
	Agoda	3.70%	4.2	3.36
Retail	Amazon	33.00%	4.98	6.993
	eBay	51.70%	20.44	31.369
	Big W	21%	2.59	2.365
	David Jones	7.90%	5.76	9.828
	Target	21.70%	3.62	4.388
	Myer	15.70%	3.6	5.7
	Harvey Norman	14.20%	2.84	2.918
	JB Hi-Fi	27%	5.67	11.171
	Kmart	20.20%	2.43	2.328

In the airline category, the likelihood of visiting and visitation rates is higher for local airlines. For context, Qantas, Virgin Airlines, Jetstar and Tigerair provide domestic and international services, whereas Singapore Airlines, Emirates, Air New Zealand, and Air Canada provide only international flights. Interestingly, while Virgin Australia had the highest visitation, Qantas, the national carrier, had the highest visitation frequency.

Booking.com and TripAdvisor both have visitation levels of more than 30% of respondents in the hotel booking category. While only 16% of respondents visited Webjet, the average frequency is still greater than 4.

Within the retail category, eBay has the highest percentage of respondents who visited and the highest frequency of all brands in the research. Amazon, another online-only retail brand, is popular and frequently used. JB Hi-Fi, an electronics retailer with a strong online presence, has high levels and frequent visits. The other retail stores included are more generalist in nature, and department stores show less variation in the average visitation frequency, despite significant differences in overall visitation, ranging from 17.2% for David Jones to 33% for Target.

These patterns are largely consistent with the prediction by Sharp (2010) that bigger brands have a higher visitation frequency. However, some differences were identified, such as the hotel booking category, where all visitation frequencies were comparable. These models help determine whether different levels of familiarity and liking can explain these differences.

6.5.2 CMMs and Control Variables

Table 6-8 summarises the independent variables for the three core areas. First, behavioural measures are based on core behavioural measure visits before Survey 1. Second are the survey-based attitudinal measures for cognition and affect, followed by control measures.

Table 6-8

Core Constructs for Modelling

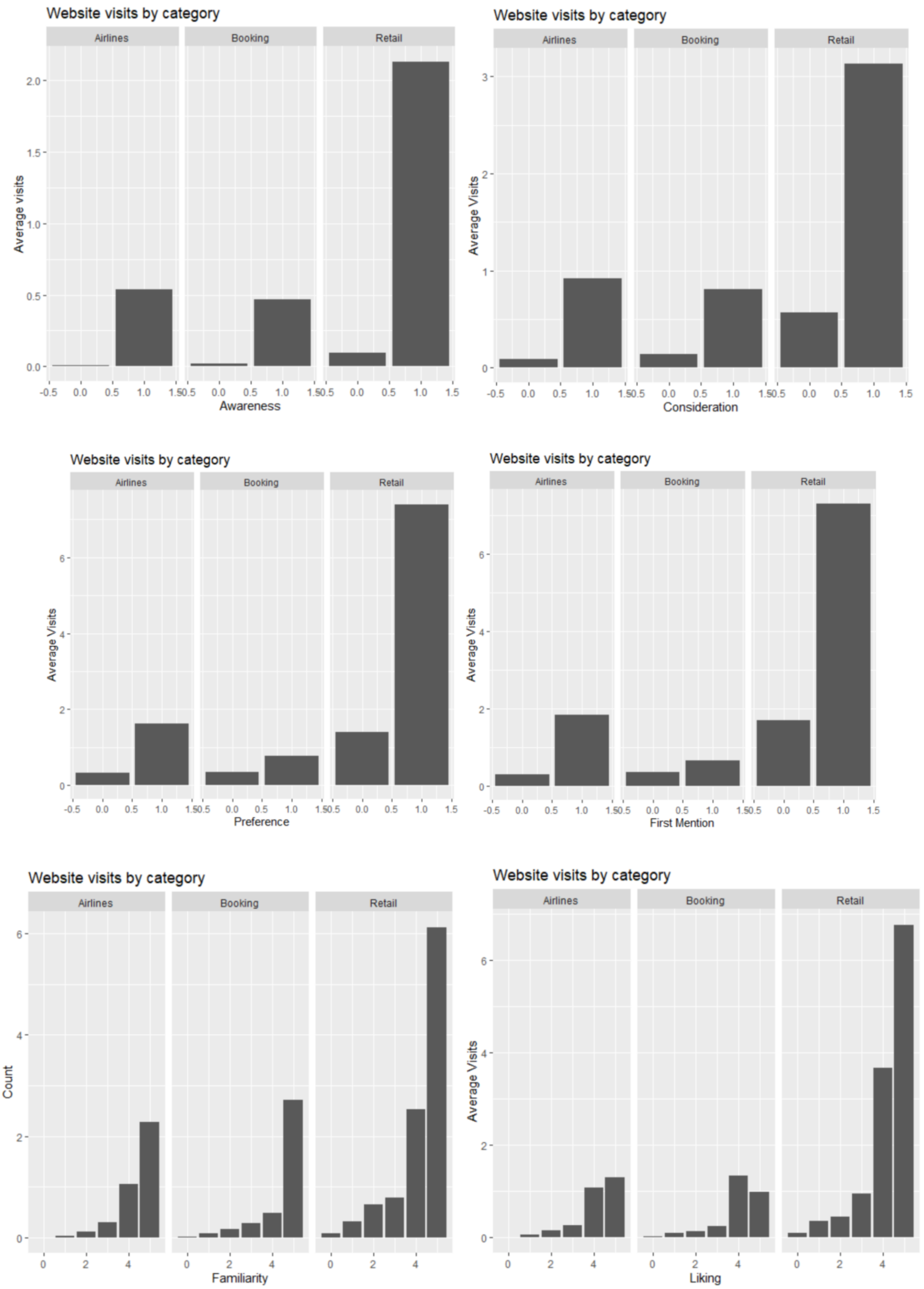
Behavioural measure	If a website was visited in the three months pre-period (Jan – April)
Attitudinal measures	Prompted Brand Awareness
	Top-of-mind brand awareness
	Familiarity
	Consideration
	Advertising awareness
	Liking
Control measures	Total Visits to any website (a measure of overall internet usage)
	The device used for tracking

As described in Section 4.4, models will be built to compare different combinations of these inputs. First, I will build attitudinal models to determine which CMMs best explain website visits. This will be done as follows; First a HOE sequence based on awareness, consideration and preference; then, a cognitive based sequence on awareness, consideration and top-of-mind awareness; and finally, independent dimensions of liking and familiarity. Second, I will include a measure of past behaviour to represent past experiences.

Figure 6-5 shows a univariate analysis of the average visitation based on each CMM for each variable.

Figure 6-5

Average Visits by CMMs for Each Model Being Tested



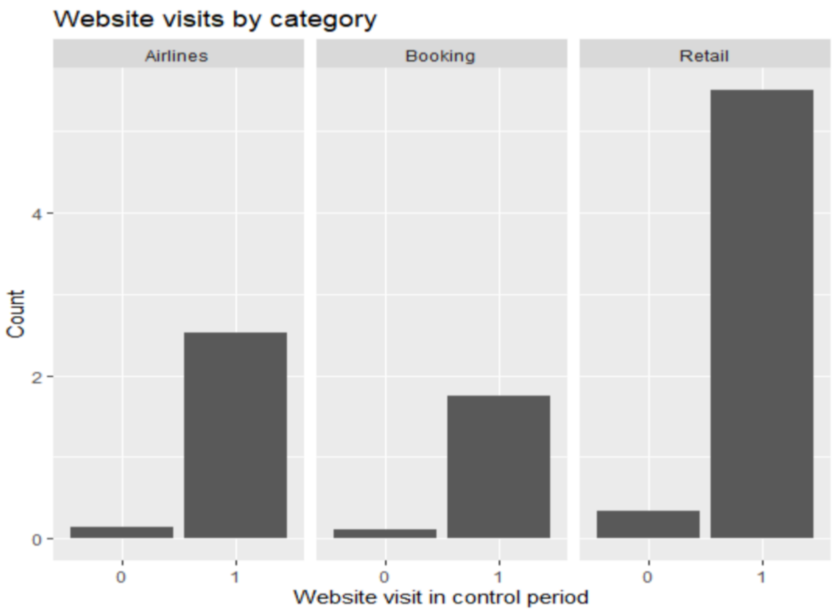
These charts show a clear pattern for all mindset metrics, indicating that visitation increases with higher attitude levels. The one outlier is that in the hotel booking category, those with the highest level of liking (rating of 5) had a slightly lower level of visitation than those in the previous category (rating of 4). In contrast, those with the highest level of familiarity had a much higher visitation rate. Overall, these charts show that this relationship is in line with expectations.

The four-month period preceding Survey 1 serves as a control for past behaviour. This enables a comparison of those who have visited versus those who have not aligned with the new or return visitor common in tools like Google Analytics.

Figure 6-6 shows that those who did not visit during the control period have a very low chance of visiting during the modelled period. This implies that most website visitation is habitual, casting further doubt on the value of advertising designed to entice consumers to visit a website.

Figure 6-6

Website Visitation in Control Period (0) vs Modelled Period (1)



It is necessary to include several control variables to quantify the impact of mindset metrics on website visitation. First, there are structural differences in data collection across respondents since they chose which devices the behavioural tracking app would be installed on. As there are three options for this; desktop, mobile or both, two dummy variables are included to account for where the respondent has installed the app. Furthermore, it is important to account for how active each respondent is; this research follows the approach by Dotson et al. (2017) of including a measure for all website visits, regardless of category.

Table 6-9

Control Variables

	N*umber of respondents*
Control variables	
Desktop	171
Mobile	54
Desktop + Mobile	42

Table 6-9 shows the number of respondents in each group.

6.6 Multicollinearity Checks

The models include measures for alternative CMMs, and while there may not be a strong correlation over time (Hanssens et al., 2014), a correlation at the individual level is expected. People tend to like what they are familiar with and be familiar with brands they like (Sharp, 2010). The correlations with key CMMs are shown in Table 6-10.

Table 6-10

Correlations with key CMMs

Correlations

Category		Awareness	Consideration	Preference	Top of Mind Awareness	Liking	Familiarity	Past Visit	Future Visits
Airlines	**Awareness**	1	.284**	.109**	.101**	.636**	.527**	.115**	.053*
	Consideration	.284**	1	.343**	.309**	.598**	.501**	.241**	.157**
	Preference	.109**	.343**	1	.516**	.374**	.367**	.213**	.162**
	Top of Mind Awareness	.101**	.309**	.516**	1	.310**	.371**	.261**	.189**
	Liking	.636**	.598**	.374**	.310**	1	.695**	.264**	.145**
	Familiarity	.527**	.501**	.367**	.371**	.695**	1	.358**	.206**
	Past Visit	.115**	.241**	.213**	.261**	.264**	.358**	1	.361**
	Future Visits	.053*	.157**	.162**	.189**	.145**	.206**	.361**	1
Hotel Booking	**Awareness**	1	.366**	.159**	.142**	.817**	.736**	.129**	.042*
	Consideration	.366**	1	.348**	.247**	.529**	.513**	.178**	.079**
	Preference	.159**	.348**	1	.410**	.328**	.307**	.124**	0.032
	Top of Mind Awareness	.142**	.247**	.410**	1	.236**	.253**	.063**	0.020
	Liking	.817**	.529**	.328**	.236**	1	.833**	.214**	.081**
	Familiarity	.736**	.513**	.307**	.253**	.833**	1	.267**	.103**
	Past Visit	.129**	.178**	.124**	.063**	.214**	.267**	1	.147**
	Future Visits	.042*	.079**	0.032	0.020	.081**	.103**	.147**	1
Retail	**Awareness**	1	.187**	.056**	.042*	.439**	.387**	.090**	0.032
	Consideration	.187**	1	.234**	.147**	.518**	.447**	.228**	.129**
	Preference	.056**	.234**	1	.325**	.350**	.271**	.175**	.195**
	Top of Mind Awareness	.042*	.147**	.325**	1	.183**	.168**	.154**	.145**
	Liking	.439**	.518**	.350**	.183**	1	.679**	.260**	.174**
	Familiarity	.387**	.447**	.271**	.168**	.679**	1	.247**	.175**
	Past Visit	.090**	.228**	.175**	.154**	.260**	.247**	1	.229**
	Future Visits	0.032	.129**	.195**	.145**	.174**	.175**	.229**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

In the traditional funnel metrics of awareness consideration and preference, the correlations are significant however all are below 0.4 suggesting a low to moderate level. Significant correlations are seen between liking and familiarity across all the categories. When the correlation is greater than 0.8, it is generally assumed that there is a risk of multicollinearity (Kim, 2019). While the correlations are strong, the airline and retail categories fall short of this threshold; however, the hotel booking level is 0.833. It will be necessary to consider the VIF to assess the problem of multicollinearity. A VIF of less than five indicates that multicollinearity is not an issue in the model (Pergelova et al., 2010). VIFs (see Appendix 3) show a maximum of 3.3 for the hotel booking category, and all are less than five. Therefore, no further transformations are made. While transformations could have been used to overcome multicollinearity, this increase the complexity of interpretation, so the models are built using familiarity and liking as individual variables on the original 5-point scale.

6.7 Model Specification

The dependent variable is the number of website visits following the first survey. While the frequency of visits is also important, it is expected that those who visit more frequently will have stronger brand attitudes. The model will be count based as a result of this.

While Poisson regression is widely regarded as the standard for count modelling, Sengupta et al. (2021) investigate various models for predicting Airbnb bookings, including Poisson and negative binomial hurdle regressions. They discover that the negative binomial has the lowest AIC. This is consistent with the results of Dotson et al. (2017). Hence a negative binomial distribution is used in the modelling.

The number of visits is predicted in two stages, as shown in Equation 1. First, whether the threshold of zero is crossed and, if so, how many times.

$$P(Y_i = y_i) = \begin{cases} p_i & y_{i=}0 \\ \frac{1-p_i}{1-\left(\frac{r}{u_i+r}\right)^r} \frac{\Gamma(y_i+r)}{\Gamma(r)y_i!} \left(\frac{\mu_i}{\mu_i+r}\right)^{y_i} \left(\frac{r}{\mu_i+r}\right)^r & y_i > 0 \end{cases} \quad (1)$$

(Feng, 2021)

Where y_i is the outcome

λ is the expected count for i[th] respondent.

Π is the probability of increased zeros.

The regression model is shown in Equation 2.

$$Log\left(\mu_{ij}\right) = \widetilde{\alpha_i} + x_{ij}\tilde{\beta} + z_{ij}\tilde{\gamma} + w_{ij}\tilde{\vartheta} \qquad (2)$$

Where:

I represents each individual consumer.

j represents each individual brand.

μ_{ij} represents the number of visits to each brand website for each person.

x_{ij} is a vector of brand attitude variables representing affect and cognition.

z_{ij} is a vector containing the past behaviour variable.

w_{ij} is a vector containing the control variables.

The models are estimated using R in R Studio. For model estimation, I use the pscl package to estimate the hurdle model, as discussed by Zeileis et al. (2008) The hurdle model works as a two-stage process first to predict if a respondent will visit the website and then a count process to estimate for those who have visited how many times they visit.

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Chapter 7: Results

7.1 Introduction

The results chapter will address each of the research questions in turn. First, I investigate the role of the two alternative sequences (awareness, consideration, preference and awareness, consideration and top-of-mind awareness) in predicting website visits and compared models these to a model including the two independent measures that represent cognition and affect using familiarity and liking. This will assist in determining the best way to incorporate mindset metrics into respondent-level modelling. Second, I investigate the relative importance of past behaviour and CMMs in determining the likelihood of a consumer visiting a brand's website. Finally, I discuss the relative importance of behaviour and CMMs in determining a consumer's likelihood of visiting a brand's website. Each question builds on the previous one and provides a comparison of the models. This analysis achieves the overall research objective of understanding the role of CMMs in website visitation to aid metric selection and interpretation.

7.2 RQ1: Which CMMs best explain website visits, and is a sequence of CMMs supported?

The first research question investigates the concept of a sequence or heirarchy versus independent cognition and affect measures. This is a critical first step in determining how to best represent mindset metrics in respondent-level modelling. While time-series analysis must aggregate mindset metrics across people to produce a total percentage or mean score for each period, respondent-level data allow for a more granular treatment of survey data and assessing different combinations of attitudes.

Based on the three key perspectives supported by the literature (discussed in Chapter 4), I test three alternative approaches, one of which includes an HOE approach, another more cognitive in nature, and finally, a dimensions-based approach.

Approach 1: Awareness -> Consideration -> Preference

Approach 2: Awareness -> Consideration -> Top-of-Mind Awareness

Approach 3: Familiarity and Liking

7.2.1 Model Results – Which CMMs Best Explain Online Behaviour

As described in Chapter 6, all models are estimated using a hurdle model. Figure 7-1 shows the results of this model. The coefficients for each model are reported along with the standard error below in brackets. Each model has two parts because I used a hurdle model. The first column in each model is the count component (how frequently a consumer visits, if they visit at all), and the second column is the hurdle component, indicating whether a consumer is likely to visit. A respondent must first pass the 'hurdle', and then we estimate how many times they will visit.

Figure 7-1

Comparison of Models: Hierarchy vs Dimension Models by Category

Airlines

	Hierarchy Aw-Con-Pref		Hierarchy Aw-Con-TOM		Independent - Liking & Familiarity	
	count	zero	count	zero	count	zero
Intercept	−15.279	−11.616***	−14.363	−11.467***	−6.159***	−11.660***
	(131.154)	(1.239)	(115.549)	(1.232)	(1.382)	(0.788)
Total Internet Usage	0.358***	0.648***	0.329**	0.640***	0.334**	0.611***
	(0.106)	(0.073)	(0.100)	(0.072)	(0.106)	(0.071)
Awareness	10.183	1.622	9.908	1.628		
	(131.149)	(1.029)	(115.545)	(1.028)		
Consideration	1.348***	1.332***	1.370***	1.456***		
	(0.344)	(0.210)	(0.343)	(0.207)		
Preference	0.559	1.035***				
	(0.293)	(0.202)				
Desktop & Mobile	0.211	−0.154	0.203	−0.163	0.163	−0.163
	(0.284)	(0.207)	(0.282)	(0.205)	(0.275)	(0.210)
Mobile	−2.600**	−1.574***	−2.549**	−1.503***	−2.739***	−1.548***
	(0.823)	(0.376)	(0.811)	(0.369)	(0.797)	(0.369)
Local Airlines	1.106**	2.069***	0.752*	1.956***	1.048**	2.053***
	(0.395)	(0.227)	(0.378)	(0.231)	(0.376)	(0.238)
Log(theta)	−1.486*		−1.440*		−1.302*	
	(0.578)		(0.561)			

Top of Mind Awareness			0.440	0.627**		
			(0.269)	(0.201)		
Affect (Liking)					0.276	0.582***
					(-0.19)	(0.110)
Cognition (Familiarity)					0.467***	0.363***
					-0.151	(0.098)
AIC	**1882.8**		**1900.1**		**1865.87**	
BIC	**1978.3**		**1995.6**		**1950.1**	
Log-Likelihood	**-924.4**		**-933.1**		**-917.9**	
N	**2031**		**2031**		**2031**	
Significance: *** = p < 0.001; ** = p < 0.01; * = p < 0.05						

Retail

	Hierarchy Aw-Con-Pref		Hierarchy Aw-Con-TOM		Independent - Liking & Familiarity	
	count	zero	count	zero	count	zero
Intercept	−14.279	−9.226***	−14.863	−9.129***	−6.713***	−8.938***
	(104.403)	(0.850)	(88.158)	(0.848)	(1.481)	(0.472)
Total Internet Usage	0.347***	0.669***	0.334***	0.658***	0.315***	0.652***
	(0.056)	(0.045)	(0.056)	(0.045)	(0.055)	(0.045)
Awareness	1.449	1.618*	1.552	1.631*		
	(1.419)	(0.747)	(1.431)	(0.747)		
Consideration	0.647**	0.889***	0.720***	0.967***		
	(0.215)	(0.125)	(0.217)	(0.123)		
Preference	0.804***	0.854***				
	(0.237)	(0.167)				
Desktop & Mobile	1.013***	−0.46	1.021***	−0.55	0.831***	−0.80
	(0.246)	(0.143)	(0.250)	(0.142)	(0.228)	(0.145)
Mobile	0.244	−0.400*	0.275	−0.398*	0.58	−0.503**
	(0.289)	(0.172)	(0.291)	(0.171)	(0.279)	(0.174)
Local Airlines	1.501***	1.255***	1.671***	1.269***	1.583***	1.473***
	(0.196)	(0.129)	(0.191)	(0.131)	(0.183)	(0.129)
Log(theta)	−10.958		−11.533		−3.174*	
	(104.391)		(88.144)		(1.314)	
Top of Mind Awareness			0.743**	0.609**		
			(0.286)	(0.209)		
Affect (Liking)					0.497***	0.323***
					(0.116)	(0.073)
Cognition (Familiarity)					0.196*	0.317***
					(0.094)	(0.062)

AIC	**4958.1**	**4908.8**	**4911.2**
BIC	**5055.5**	**5078.3**	**4997.2**
Log-Likelihood	**-2462**	**-2473.4**	**-2440.6**
N	**2280**	**2280**	**2280**
Significance: *** = p < 0.001; ** = p < 0.01; * = p < 0.05			

Hotel booking

	Hierarchy Aw-Con-Pref		Hierarchy Aw-Con-TOM		Independent - Liking & Familiarity	
	count	zero	count	zero	count	zero
Intercept	−16.233	−8.530***	−15.722	−8.538***	−16.299	−7.951***
	(111.244)	(0.653)	(76.374)	(0.653)	(170.998)	(0.545)
Total Internet Usage	0.303*	0.500***	0.326*	0.501***	0.190	0.487***
	(0.148)	(0.056)	(0.149)	(0.056)	(0.143)	(0.056)
Awareness	1.452	2.129***	1.503	2.124***		
	(1.013)	(0.426)	(1.016)	(0.426)		
Consideration	2.048***	0.439**	1.988***	0.488***		
	(0.289)	(0.150)	(0.278)	(0.146)		
Preference	−0.516	0.513**				
	(0.353)	(0.194)				
Desktop & Mobile	0.334	−0.214	0.370	−0.215	0.529	−0.145
	(0.383)	(0.188)	(0.387)	(0.188)	(0.388)	(0.190)
Mobile	−0.379	−1.647***	−0.375	−1.654***	−1.241	−1.657***
	(0.963)	(0.395)	(0.980)	(0.395)	(0.821)	(0.396)
Log(theta)	−12.822		−12.76		−13.112	
	(111.232)		(76.356)		(170.992)	
Top of Mind Awareness			−0.605	0.486*		
			(0.377)	(0.207)		
Affect (Liking)					0.255	0.416***
					(0.237)	(0.099)
Cognition (Familiarity)					0.711***	0.209*
					(0.160)	(0.085)
AIC	**2369.8**		**2371**		**2326**	
BIC	**2457.7**		**2458.9**		**2399.6**	
Log-Likelihood	**-1169.9**		**-1170.5**		**-1148.7**	
N	**2592**		**2592**		**2592**	
Significance: *** = p < 0.001; ** = p < 0.01; * = p < 0.05						

The funnel-based models each have three CMMs in both stages, the alternative approach has two CMMs in each stage, so in total there are 16 CMMs. The mindset metrics are significant in 14 of the 16 cases where mindset metrics are included, overall, this supports the use of these models; therefore, I go on to assess which model is the strongest. This first research question focuses on determining the best approach to measuring mindset metrics within the respondent-level model. To compare the models, I use the AIC, a common measure for comparing model alternatives, for example, as used by (Sengupta et al., 2021). Identical results would also be found with the BIC and log-likelihood, two alternative measures of fit, however for simplicity and clarity I will focus on the single measure of the AIC in the following tables. The AIC is a positive number, with a lower number representing a better fit. The AIC is calculated using the formula

$$\mathbf{AIC = 2k - ln(L) \quad (3)}$$

Where L is the likelihood and k is the number of parameters.

The AIC is a positive and relative measure; therefore, I only compare within the categories (that is, the fit of the airline category cannot be compared to the retail category). As the AIC is measured on an additive scale, I look at the absolute difference rather than the percentage change. Typically, a difference of 10 or more is strong evidence of a "better" model (Burnham & Anderson, 2004). Table 7-1below shows the AICs for each category model.

Table 7-1

AICs for Category Models Assessing a Hierarchical Model to Independent Measures of Affect and Cognition

	Hierarchical model Aw->Con->Pref	Hierarchical model Aw->Con->TOM	Independent Attribute model Liking & Familiarity
Airlines	1883	1900	**1866**
Hotel booking	2370	2371	**2326**
Retail	4958	4981	**4911**

Note. The lowest AIC is highlighted in bold, showing the independent attribute model superior for all categories.

The results show that for each market category, the model using the independent dimensions for affect and cognition provides a better explanation than the HOE versions of the model. While the logic of the hierarchy exists, the models are consistently stronger when independent attributes are used. The largest impact is in the retail category, where the AIC is 47 points lower, followed by hotel booking, where the improvement is 44 points, and finally, airline, where the improvement is 17 points. The consistency of these results demonstrates that the independent attribute model outperforms the respondent-level data model.

It is also worth noting that neither of the two proposed hierarchical approaches has a clear winner. In the retail category, the preference-based alternative has a lower AIC, there is no difference in the AIC for hotel booking (an AIC change of less than two indicates no significant difference), and the cognitive-based hierarchy has a lower AIC in the airline category. The lack of consistency in the results of the proposed hierarchies suggests that using independent dimensions is advantageous.

7.2.2 The Role of Awareness in Understanding Website Visits

Whilst the consistency of results across the categories demonstrates that an enforced sequence is not the strongest approach, the logical nature of the progression means that there are still some valuable insights from the result. Of particular importance is that brand awareness is significant in the models for each category. The impact of brand awareness can be seen in the hurdle stage of the models. In the hotel booking category, brand awareness has a significance level of 99.9%, and an odds ratio of exp (2.1), meaning those who are aware are 8.4 times more likely to visit a brand website; this is consistent in both the preference and top of mind versions of the model.

For comparison, consideration has an odds ratio of 1.6. Within the retail category, brand awareness is significant at the 95% level with an odds ratio of 5.1 compared to consideration with an odds ratio of 2.4 (preference model) and 2.6 (top-of-mind model). Finally, although the airline model is only marginally significant with a probability value of 0.11, it shows a consistent odds ratio of 5.1. For airlines, consideration is much more important than in the other categories, with an odds ratio of 4.3. The exploratory analysis showed that hotel booking is the category with the lowest levels of awareness. This is a possible reason why brand awareness plays a bigger role in this category; For example, it is unlikely that awareness was very important for Qantas, where there is near universal awareness (over 99%).

In my research, while awareness is only significant in the count component of the model, consideration is consistently significant across all three categories and two versions of the hierarchy. This makes sense and is in line with the idea of the hierarchy that brand awareness is important when assessing if someone visits a website. However, a deeper connection is needed for a consumer to visit multiple times. The difference could be driven by the categories selected, for my research the categories were specifically chosen to be ones where repeat purchase could be made within a short time frame for heavy users, for smartphones and vehicles we would expect a longer time between purchases.

An important comparison of these findings is to the time-series models proposed by (Hanssens & Pauwels, 2016; Srinivasan et al., 2010), where they could not show a significant impact of brand awareness despite favouring its inclusion conceptually. The main reason suggested was the lack of variation in brand awareness for individual brands over time. This finding demonstrates the benefits of using respondent-level data to align more closely with brand awareness's theoretical role compared to time series research findings. It is also noteworthy that advertising awareness, which was used as a substitute in the time-series approach, was only significant in the hurdle component of the airline's model (results shown in Appendix 3), suggesting this may not be an appropriate substitute.

7.2.3 Implications for Measurement of Mindset Metrics

While the awareness component of the brand funnel provides learning on how the metrics work, this was not the preferred model. However, this relationship is captured within the independent dimensions model when we use respondent level data, in that those that are unaware have a zero level of familiarity. A binary measure imposes a threshold that needs to be passed (for example, moving a potential customer from awareness to consideration), and once the threshold is passed, the metric changes, meaning different metrics for different respondents. However, a scale for individuals allows for more gradual improvement for the same objective. Rather than using a funnel, liking and familiarity should be used to best understand likelihood of visiting a website.

7.3 RQ2: Do CMMs combined with a behavioural measure provide a better prediction of who is likely to visit a website than past behaviour alone?

Having determined the best approach to include mindset metrics into the model, I now consider their relative contribution compared to measures of past behaviour. As suggested by Vakratsas and Ambler (1999), it is important to include a measure of each dimension, cognition, affect and past experience. Behavioural data has become dominant in reporting and assessment of digital advertising channels, so it is important to establish if mindset metrics add something over measures of past behaviour.

I test three versions of the model, one with only a behavioural measure, the number of visits in the control period, one with only mindset metrics, liking and familiarity as used for the first research question and one with both mindset metrics and past behaviour. This follows the approach and comparisons of Srinivasan et al. (2010). The measure I use for prior visits is a binary indicator representing whether a respondent visited in the control period before the survey was conducted. The binary variable is selected as this is the most representative of measures used in digital performance tracking and provides simplicity of interpretation. In addition, the long tail of multiple visits could risk spurious results as we expect regression to the mean for high visiting customers not visiting in the following period (Hess & Doe, 2013).

7.3.1 Model Results: CMMs and Past Behaviour

In Chapter 6, the models are estimated using the hurdle model in Equations 1 and 2. Table 7-2 summarises these findings. Models are presented for each category. The first set of results shows the behavioural model, the second the mindset model, and the final set shows combined model. Each model has a zero column, which is the hurdle component that predicts whether a respondent will visit the website at all and a count component that predicts how frequently a respondent will visit. Furthermore, each model has the same three control variables, a measure of overall website usage and a binary indicator to reflect whether the passive tracking app has been installed on the respondents' mobile or both mobile and desktop, leaving desktop only as the base case to account for some of the category differences. The airline model has a control variable representing the local airline brands as they have a much higher chance of usage (Simarmata et al., 2016), and the retail model has a binary indicator for stores that are online only, meaning consumers do not have a retail alternative if wanting to interact with these brands.

Table 7-2

Comparison of Behavioural Only, Mindset Only and Combined Models by Category

Airlines

	Behaviour Only		Mindset Only		Combined	
	count	zero	count	zero	count	zero
Intercept	−2.05*	−7.601***	−6.159***	−11.660***	−4.611***	−10.124***
	(1.43)	(0.712)	(1.382)	(0.788)	(1.262)	(0.857)
Past Experience	1.98***	2.492***			1.164***	1.996***
	(0.39)	(0.190)			(0.324)	(0.199)
Total Internet Usage	0.55	0.425***	0.334**	0.611***	0.152	0.497***
	(0.06)	(0.077)	(0.106)	(0.071)	(0.106)	(0.079)
Desktop & Mobile	0.29	−0.228	0.163	−0.163	0.206	−0.265
	(0.85)	(0.219)	(0.275)	(0.210)	(0.259)	(0.225)
Mobile	−2.26**	−1.027**	−2.739***	−1.548***	−2.668***	−1.150**
	(0.11)	(0.379)	(0.797)	(0.369)	(0.788)	(0.385)
Local Airlines	0.62*	1.407***	1.048**	2.053***	0.921*	1.502***
	(0.80)	(0.237)	(0.376)	(0.238)	(0.370)	(0.252)
Log(theta)	−1.57*		−1.302*		−1.036*	
	(0.57)		(0.509)		(0.423)	
Affect (Liking)			0.276	0.582***	0.136	0.410***
			(0.190)	(0.110)	(0.177)	(0.121)
Cognition (Familiarity)			0.467**	0.363***	0.448**	0.228*
			(0.151)	(0.098)	(0.140)	(0.107)
AIC	**1805.7**		**1865.9**		**1749.**	
BIC	**1878.7**		**1950.1**		**1844.7**	
Log-likelihood	**-889.9**		**-917.9**		**-857.6**	
N	**2031**		**2031**		**2031**	

Significance: *** = p < 0.001; ** = p < 0.01; * = p < 0.05

Retail

	Behaviour Only		Mindset Only		Combined	
	count	zero	count	zero	count	zero
Intercept	−13.749	−6.007***	−6.713***	−8.938***	−6.062***	−7.779***
	(150.754)	(0.401)	(1.481)	(0.472)	(1.335)	(0.484)
Past Experience	1.519***	1.665***			1.065***	1.408***
	(0.294)	(0.125)			(0.278)	(0.130)
Total Internet Usage	0.141*	0.456***	0.315***	0.652***	0.180**	0.492***
	(0.072)	(0.046)	(0.055)	(0.045)	(0.067)	(0.048)
Desktop & Mobile	1.428***	0.063	0.831***	−0.080	1.077***	−0.025
	(0.271)	(0.146)	(0.228)	(0.145)	(0.250)	(0.150)
Mobile	0.444	−0.195	0.058	−0.503**	0.215	−0.316
	(0.294)	(0.177)	(0.279)	(0.174)	(0.286)	(0.182)
Online Business	1.561***	1.007***	1.583***	1.473***	1.405***	1.082***
	(0.196)	(0.132)	(0.183)	(0.129)	(0.187)	(0.136)
Log(theta)	−13.108		−3.174*		−3.049**	
	(150.753)		(1.314)		(1.166)	
Affect (Liking)			0.497***	0.323***	0.451***	0.233**
			(0.116)	(0.073)	(0.117)	(0.076)
Cognition (Familiarity)			0.196*	0.317***	0.188*	0.254***
			(0.094)	(0.062)	(0.095)	(0.064)
AIC	**4879.0**		**4911.2**		**4777.0**	
BIC	**4953.5**		**4997.2**		**4874.4**	
Log-Likelihood	**-2426.5**		**-2440.6**		**-2371.5**	
N	**2280**		**2280**		**2280**	
Significance: *** = p < 0.001; ** = p < 0.01; * = p < 0.05						

Hotel Booking

	Behaviour Only		Mindset Only		Combined	
	count	zero	count	zero	count	zero
Intercept	−10.490	−5.710***	−16.299	−7.951***	−14.574	−7.165***
	(42.543)	(0.517)	(170.998)	(0.545)	(126.011)	(0.572)
Total Internet Usage	−0.005	0.346***	0.190	0.487***	0.121	0.381***
	(0.134)	(0.059)	(0.143)	(0.056)	(0.139)	(0.060)
Past Experience	2.149***	1.776***			1.105***	1.463***
	(0.278)	(0.146)			(0.325)	(0.154)
Desktop & Mobile	0.423	−0.099	0.529	−0.145	0.486	−0.102
	(0.369)	(0.196)	(0.388)	(0.190)	(0.385)	(0.200)
Mobile	−1.749*	−1.286**	−1.241	−1.657***	−1.388	−1.380***
	(0.867)	(0.397)	(0.821)	(0.396)	(0.844)	(0.400)
Log(theta)	−11.021		−13.112		−12.069	
	(42.528)		(170.992)		(126.003)	
Affect (Liking)			0.255	0.416***	0.089	0.391***
			(0.237)	(0.099)	(0.256)	(0.101)
Cognition (Familiarity)			0.711***	0.209*	0.624***	0.068
			(0.160)	(0.085)	(0.171)	(0.089)
AIC	**2305.7**		**2326.4**		**2227.4**	
BIC	**2370.1**		**2402.6**		**2315.3**	
Log-Likelihood	**-1141.8**		**-1150.2**		**-1098.7**	
N	**2592**		**2592**		**2592**	
Significance: *** = p < 0.001; ** = p < 0.01; * = p < 0.05						

As for the second research question, the main objective is to assess the impact of including mindset data in a model to predict behaviours. The models are again compared using AIC; the summary is shown below in Table 7-3. As it is common practice to use behaviour to predict behaviour, I have used this as the base model. The AICs for the mindset-only and full combined results are then compared to this base level.

Table 7-3

AIC for Models Comparing Behaviour Only, Mindset Only and Both Behaviour and Mindset Metrics

	Behaviour only (Base Model)	Mindset only	Full Combined
Airlines	1806	1866	**1749**
Hotel Booking	2306	2326	**2227**
Retail	4879	4911	**4777**

Note. The lowest AIC is highlighted in bold, showing the independent attribute model superior for all categories.

The results are consistent across categories; for each category, the combined model with both a behavioural measure and mindset metrics has the lowest AIC. Furthermore, the results are consistent with those of time-series modelling (Hanssens & Pauwels, 2016; Srinivasan et al., 2010). Finally, according to Table 7-2, showing the significance levels for each variable, affect and cognition are important in each model. This confirms that both cognition and affect, as measured by familiarity and liking, are important in understanding both the likelihood of visiting a website and how frequently, even when accounting for past behaviour, mindset metrics improve explanatory power.

7.3.2 Discussion of Results in Comparison to Previous Work on the Importance of Mindset Metrics

Mindset metrics have been consistently shown to improve model fit when included in time series analysis, (e.g. Hanssens & Pauwels, 2016; Srinivasan et al., 2010). However, it was unclear if this is the case with respondent-level data. As previously discussed, the respondent-level approach aligns more closely with constructs such as mental availability proposed by (Sharp, 2010) and consumer-based brand equity (Keller, 1993) in the context of brand sales. These constructs suggest that those with strong brand knowledge are more likely to think of a brand in a buying situation or respond to advertising. In the context of website visits, we expect those with greater knowledge of a brand to be more likely to visit a brand website.

However, if the behaviour is strongly habitual, past behavioural will be the strongest predictor of future behaviour, (Pauwels & van Ewijk, 2020; Romaniuk & Nenycz-Thiel, 2013) therefore it is not necessarily the case that both are needed. The assessment of past behaviour was not achievable in past individual-level modelling. Although (Dotson et al. (2017) used a similar approach to building the model, their research had to rely on claimed brand ownership as a measure of behaviour as there was no behavioural tracking data prior to the survey. This meant no comparison between attitudes and behaviours as independent variables was possible.

7.4 RQ3: If CMMs are important what is the relative importance of CMMs and behaviours?

While the first two research questions were important in determining the appropriate structure of the model, the overarching aim of the empirical stage is to understand the relative importance of the different inputs and to test for robustness across the three categories. I evaluate the coefficients from the modelling to understand the relative importance of the measures of cognition, affect and past behaviour. The functional form of the model enforces an exponential relationship on the results; a polynomial approach was tested for greater flexibility, and each level of the mindset metrics was modelled as a dummy variable. The nonlinear component was not significant in the polynomial version. The version with individual metrics exhibited a similar pattern to the presented model but with fewer degrees of freedom and less stability. Consequently, I present my findings using a five-point rating scale for liking and familiarity.

7.4.1 Relative Importance of Cognition, Affect and Past Behaviour

The model results presented in Table 7-4 show the combined models for the three different categories for ease of comparison.

Table 7-4

Coefficients for the Selected Combined Model by Category

	Airlines		Retail		Hotel Booking	
	count	zero	count	zero	count	zero
Intercept	−4.611***	−10.124***	−6.062***	−7.779***	−14.574	−7.165***
	(1.262)	(0.857)	(1.335)	(0.484)	(126.011)	(0.572)
Total Internet Usage	0.152	0.497***	0.180**	0.492***	0.121	0.381***
	(0.106)	(0.079)	(0.067)	(0.048)	(0.139)	(0.060)
Past Experience	1.164***	1.996***	1.065***	1.408***	1.105***	1.463***
	(0.324)	(0.199)	(0.278)	(0.130)	(0.325)	(0.154)
Affect (Liking)	0.136	0.410***	0.451***	0.233**	0.089	0.391***
	(0.177)	(0.121)	(0.117)	(0.076)	(0.256)	(0.101)
Cognition (Familiarity)	0.448**	0.228*	0.188*	0.254***	0.624***	0.068
	(0.140)	(0.107)	(0.095)	(0.064)	(0.171)	(0.089)
Desktop & Mobile	0.206	−0.265	1.077***	−0.025	0.486	−0.102
	(0.259)	(0.225)	(0.250)	(0.150)	(0.385)	(0.200)
Mobile	−2.668***	−1.150**	0.215	−0.316	−1.388	−1.380***
	(0.788)	(0.385)	(0.286)	(0.182)	(0.844)	(0.400)
Local Airlines	0.921*	1.502***				
	(0.370)	(0.252)				
Log(theta)	−1.036*		−3.049**		−12.069	
	(0.423)		(1.166)		(126.003)	
Online Business			1.405***	1.082***		
			(0.187)	(0.136)		
AIC	**1749.21**		**4777.04**		**2227.41**	
BIC	**1844.7**		**4874.5**		**2315.3**	
Log-Likelihood	**-857.6**		**-2371.5**		**-1098.7**	
N	**2031**		**2280**		**2592**	

Significance: *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$

The variables of interest are the behavioural measure, a binary indicator of whether a respondent visited the website in the control period, and the variables for familiarity and liking, measured on a five-point rating scale. Table 7-5 shows odds ratio and increase count for past behaviour across the categories. The hurdle component shows the reflects the increased chance of visiting a website if a respondent visited in the control period compared to those that did not; the count component represents how many more visits are likely to be achieved. The impact of prior visitation is the greatest in the airline category and smallest in the retail category. This order is the same for both the count and the hurdle component. The count component is relatively similar across all three categories ranging from an increased visitation rate of 2.9 for retail to 3.2 for the airlines category.

Table 7-5

Log Odds Ratio and Increase in Count of Prior Visitation by Category

Prior Visit	Hurdle	Count
Airlines	**7.4**	**3.2**
Hotel Booking	**4.3**	**3.0**
Retail	**4.1**	**2.9**

Note. Significant terms are in bold.

To compare the impact of mindset metrics on past behaviour, I look at the combined impact of the mindset metrics shown in Table 7-6. I look at the highest level of liking and familiarity. For the hurdle component in all three categories, the importance of mindset metrics is much greater than previous behaviours. In the airline category, those with the highest level of familiarity and liking (which accounts for just under 4% of all ratings) are 24.2 times more likely to visit and will visit 18.4 times more, when compared to the people with no positive views towards the brand. Again, the hurdle is lower for hotel booking and retail, with an increase in odds of 9.9 for hotel booking and 11.4 for retail. Overall, the influence of the mindset metrics is 2 to 3 times greater than the behavioural measure.

Table 7-6

Combined Log Odds Ratio and Increased Count for Maximum Positive Mindset Metrics

Combined Mindset Impact (Rating 5)	Hurdle	Count
Airlines	24.2	18.4
Hotel Booking	9.9	35.3
Retail	11.4	24.4

The final set of results in Tables 7-7 and 7-8 shows the odds ratios for the mindset metrics of liking and familiarity. For comparison in these tables, I have shown the odds ratio if a respondent provides a rating of five with a base level of 0 (i.e., no brand awareness). For those with the highest level of liking, the odds of visiting a website are much higher for both the airline and hotel booking categories, with hurdle impacts of 7.8 and 7.1, respectively, compared to 3.2 for the retail category. Conversely, liking has a greater impact on the count component of the retail model, with a 9.5 increase in visitation frequency compared to 1.5 for hotel bookings and 2.0 for airlines.

Table 7-7

Log Odds Ratio and Increase in Count of Liking level of Five by Category

Liking (rating 5)	Hurdle	Count
Airlines	**7.8**	2.0
Hotel Booking	**7.1**	1.5
Retail	**3.2**	**9.5**

Note. Significant terms are in bold.

The trend is reversed for hotel booking and airlines for the familiarity component. The influence of familiarity is much greater for the count phase for airlines and hotel booking, with the count of visits increase of 9.4 and 22.6, respectively. Again, there are differences in the retail category, with familiarity slightly more influential in the hurdle stage than in the count stage.

Table 7-8

Log Odds Ratio and Increase in Count of Familiarity Level of Five by Category

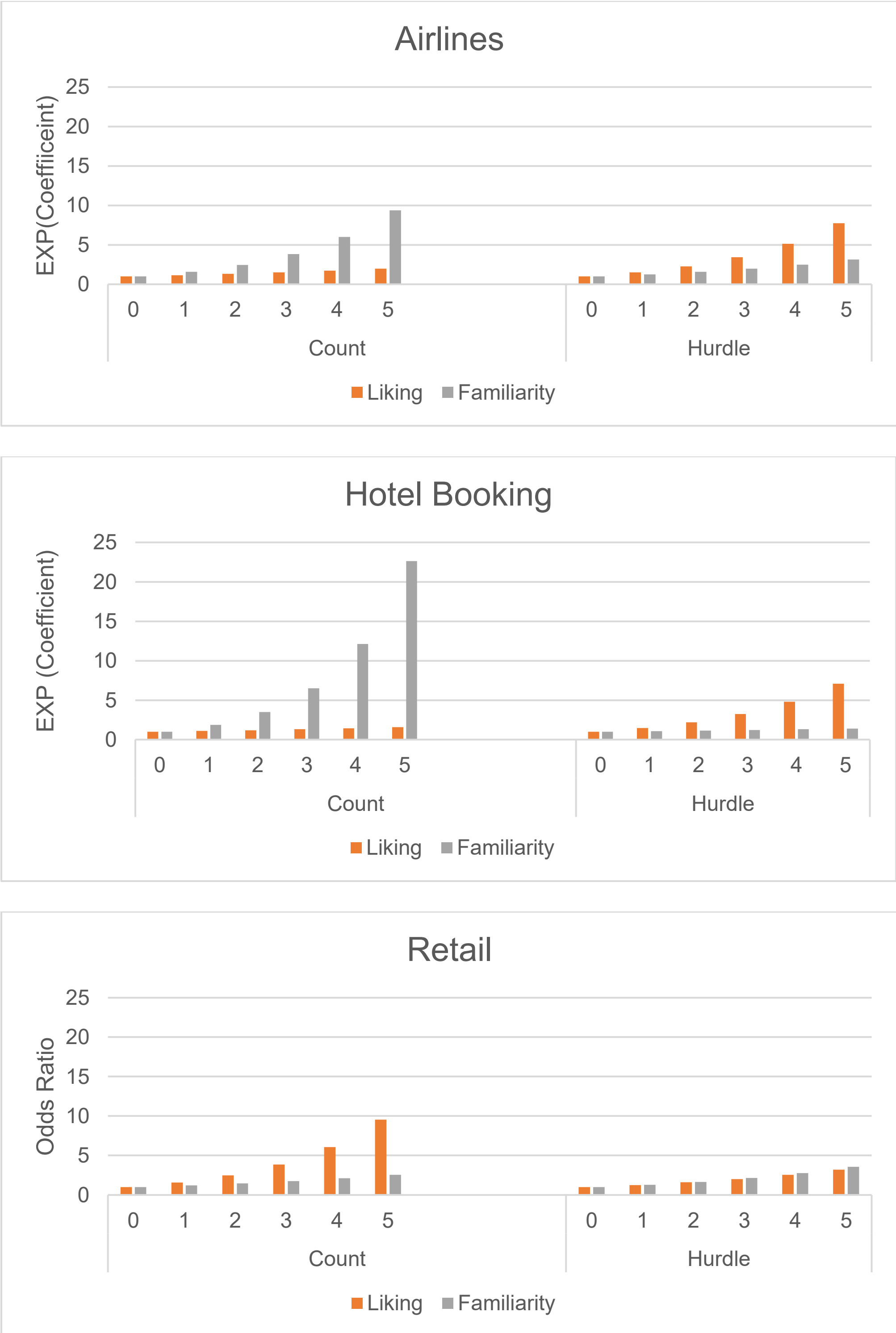
Familiarity (Rating 5)	Hurdle	Count
Airlines	**3.1**	**9.4**
Hotel Booking	1.4	**22.6**
Retail	**3.6**	**2.6**

Note. Significant terms are in bold.

To further understand the increase in visits as mindset metrics grow, these differences are charted below in Figure 7-2. As a rating scale has been used for the mindset metrics, it is possible to observe the relative impact of familiarity and liking and how they improve with each step in the rating scale. For comparison purposes, each category is shown on the same scale with an exponentiated coefficient from 0 to 25.

Figure 7-2

Relative Impact of Mindset Metrics Based on the Level of Positive Attitude for Each Category Over the Hurdle and Count Stages of the Model



The hotel booking and airline categories are similar. If respondents have visited before, liking is important for predicting whether they will return; if they have returned, familiarity becomes more important. In retail, both familiarity and liking influence the likelihood of visiting and liking influences how frequently a respondent returns to a website.

7.4.2 Discussion

These findings are important in several ways. First, while Dotson et al. (2017) discovered that those with the most positive attitudes were 7.0 times more likely to search for a brand in the smartphone category and 5.2 times more likely in the automotive category my research shows an even greater impact of CMMs. The log odds ratio of 9.9 times (for those with a liking and familiarity of 5), 11.4 times for retail and 24.2 times for airlines. Four significant differences exist between my research and that of Dotson et al. (2017) which may help explain these variations.

First, they only explored brand search as a dependent variable, whereas my research explores all website visits; therefore, the overall visit levels are higher. Given that we would expect those with more positive attitudes to be more likely to go directly to a brand website through type-in, this could explain why my research found mindset metrics to have a greater impact. Second, Dotson et al. studied high-involvement consumer purchases (smartphones and vehicles), whereas my research focuses on services and retail. While it is common to make only one purchase in the consumer durables market (Mittal & Kamakura, 2001), there is a much higher opportunity for frequent visits and brand switching in the service and retail sectors, which is especially true in the retail sector. This means I can show more consistent results for the model count stage. Further, my research included a measure of past behaviour, whereas Dotson et al. included a measure of brand ownership. In their study, the largest and most consistent predictor was if a consumer owned a product, and owning a brand cut the odds in half.

The final distinction between the two studies is that only my research included a measure of affect, including liking. This has been seen to play a significant role in all models, for hotel booking and airlines; if a consumer does not like a brand, they are unlikely to visit its website at all. In the retail category, it can be seen that familiarity has the largest impact on whether a respondent is likely to visit at all, but liking has the largest role. This new dimension in the relationship has implications for marketers because approaches to shifting liking are not always the same as those to shifting familiarity (Heath & Feldwick, 2008).

According to these findings, differences in categories influence the impact of different mindset metrics for website visits. Previous research suggests category involvement is a key driver of differences (Hanssens et al., 2014), however as all categories in this research would be classified as high involvement indicating that another factor may also drive the category effect. Visitation levels could be a plausible explanation as the descriptive analysis reveals that retail has higher visitation rates, with 67.3% of respondents having visited at least once, compared to 43.2% for airlines and 39.5% for hotel booking. Furthermore, 73% of those who visited retail visited more than one brand, compared to 53% of those who visited airlines and 56% for hotel booking. Visitation frequency is another possible factor, as retail has a greater number of consumers with multiple website visits.

Chapter 8: Discussion and Implications

In this final chapter, I discuss the implications and contributions of my research. Responding to the calls for research into the role of hard behavioural measures and soft mindset metrics from the MSI (Marketing Science Institute, 2014, 2018, 2020) as well as a better understanding of which KPIs should be measured and how? (Marketing Science Institute, 2018). My approach to answering this question has three stages. First, conceptually demonstrating where CMMs and website visits (CICs) fit into the overall performance measurement framework; second, empirically determining which CMMs should be used to assess this relationship; and finally, quantifying this relationship using a hurdle model.

Below is a summary of the empirical results from the three questions, followed by a discussion of how these results contribute to our overall knowledge and what the results mean in practice. Finally, I discuss some of the limitations of this research and future research directions in this area.

8.1 Overview of Empirical Findings

Three key research questions were asked for the empirical work. This follows the process of determining how CMMs should be measured. Do they aid in predicting website visits? If so, how important are they?

RQ1: Which CMMs best explain website visits, and is a sequence of CMMs supported?

Marketers frequently track CMMs that are related to a HOE model, which looks at the consumer response from awareness to consideration, and then at preference or top-of-mind awareness. It is considered important to go through each stage, and once a brand is preferred, it is more likely to be purchased, so each stage will have fewer purchases than the previous stage. Across all models, I find that a combination of familiarity and liking has stronger explanatory power for those who are likely to visit a website than when using an enforced sequence of metrics. Theoretically, this aligns with the view of Vakratsas and Ambler (1999) that independent dimensions should be measured and that affect and cognition are both important.

RQ2: Do CMMs combined with a behavioural measure provide a better prediction of who is likely to visit a website than past behaviour alone?

Although there is a theoretical advantage to including CMMs to capture a longer-term impact, this does not necessarily imply that it is advantageous to include them in individual-level modelling. Tests comparing models with only past visits, only mindset metrics, and the combination consistently show that the combined approach predicts the likelihood of visiting a website better in all models.

RQ3: If CMMs are important what is the relative importance of CMMs and behaviours?

The final research question investigates the relative importance of CMMs and past behaviours. While those who have visited in the past are between 4.1, in the case of retail and 7.4 for Airlines more likely to visit showing that there is a pattern of regular usage, those with the most positive mindset, as represented by the highest score for liking and familiarity are up to 11.4 times more likely to visit for retail and 24.2 times for Airlines, over 2.5 times more likely for each category.

8.2 Contributions

Understanding which metrics are used to measure advertising performance and how they interact has been a consistent focus of research (Katsikeas et al.,2016; Morgan et al., 2022). It is common for new data to accelerate and dominate the focus, as was the case with the first use of surveys, sales scanners, and digital clickstream data (Wedel & Kannan, 2016). Many studies have examined what can be learned from website visit data (e.g., Pallant et al., 2017; C. H. Park, 2017) and clicks that lead a potential customer to a website (e.g., H. Li & Kannan, 2014), while few have examined non-behavioural antecedents to website visits in terms of what makes a consumer likely to visit in the first place. Where they have, they have been limited to brand search in the case of Dotson et al. (2017) or at an aggregate level in the case of Cain (2022) and Pauwels and van Ewijk (2020). Table 8-1 summarises where the empirical research fits the existing literature, which will then be discussed in more detail.

Table 8-1

Where This Research Fits with the Current Literature

	Include CICs	Use individual-level data	Test alternative combinations of CMMs	Measure of cognition,	Measure of affect	Measure of Past behaviour	Testing for nonlinearity	Understand visit frequency	Model focus
(Srinivasan et al., 2010)	No	No	No	Yes	Yes	No	No	No	Building CMMs in Market mix models
(Bruce et al., 2012)	No	No	No	Yes	Yes	Survey only	No	No	Hierarchy Effects for FMCG brand
(Hanssens et al., 2014)	No	No	No	Yes	Yes	No	No	No	Financial implications of including CMM in market mix model
(Dotson et al., 2017)	Partial brand search	Yes	No	Yes	No	No	No	Yes	Can brand search replace CMMs
(Colicev et al., 2018)	Partial using social media as an input	No	No	Yes	Customers only	No	No	No	Does social media drive CMMs
(Pauwels & van Ewijk, 2020)	Yes	No	No	Yes	Yes	Yes	No	No	Role of attitudes and behaviours in MMM
(Cain, 2022)	Yes	No	No	Yes	No	Yes	No	No	Brand building role of CMMs
(Valenti et al., 2022)	No	No	Yes	Yes	Yes	Survey only	No	No	Sequence of CMMs in MMM
This research	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	How CMMs help explain website visits

8.3 Theoretical Contributions

In their reports from 2014 to 2020, the MSI recognised the importance of understanding the relationship between hard and soft metrics. This research contributes to the field of study in two ways. First, the proposed conceptual framework emphasises the importance of the brand website in relation to performance marketing metrics, but it also shows that the antecedents are not only firm-initiated advertising but also CMMs. Second, insights that are not attainable at the aggregate level can be gained by empirically investigating the relationship at the individual level. The hurdle model empirically demonstrates that CMMs are important predictors of online website visits.

Most studies in this area have focused on aggregate data analysis, investigating the relationship between mindset metrics and sales, as shown in Table 8-1. Only one of the primary studies, Dotson et al. (2017), utilises individual level data. While aggregate level outcomes can reveal that, on average, visits increase when consumers exhibit a more positive mindset, individual level data enables us to examine variations between them. This approach offers a distinct perspective, including the ability to compare if results align across diverse data collection approaches and to explore connections that are better suited to individual level data.

8.3.1 Inclusion of Consumer-Initiated Media Interactions in the Measurement Framework to Distinguish Between Brand and Performance Marketing Measurement Metrics

While Cain (2022) and Pauwels and van Ewijk (2020) propose conceptual frameworks that were used in their empirical work, there is a need for a broader representation of how advertising works to understand the landscape of marketing performance measurement and to evaluate models and metrics. Work of Katsikeas et al. (2016) and Vakratsas and Ambler (1999) have provided comprehensive views on how to measure advertising and marketing performance, however neither has included the important stage of Consumer initiated contacts (CICs). This is a critical gap because a key failing of digital performance models is the lack of a conceptual framework (Malthouse & Li, 2017). CICs now have significant investments behind them, as demonstrated in Chapter 2. After reviewing the literature on digital performance models, a conceptual framework that includes customer-initiated media channels is proposed to address this gap. I build on earlier work by Vakratsas and Ambler (1999). Importantly, this framework recognises that cost is now a consideration not only at the beginning of the advertising performance measurement process but also at the midpoint when consumers decide whether to interact with a brand. Because demand driven by firm-initiated activity must be considered in the consumer-initiated stage, the occurrence of cost at two points in the framework has significant implications for budget optimisation. This also emphasises the significance of understanding the factors that influence online behaviour. That is, attitudes and behaviours are important not only because they play independent roles in explaining sales (Pauwels & van Ewijk, 2020) but are now also form a distinct stage that needs to be accounted for in our advertising channel decisions.

The critical aspect of this is that recognising these various approaches to media buying based on different metrics is a key driver of the brand and performance divide. As a result of this framework, a clear distinction between brand and performance advertising can be made, demonstrating why this is a critical link for managers to understand. Furthermore, based on the development of my conceptual framework, I discover a lack of understanding between CMMs representing brand-building effects and CIC measuring performance and that this link is missing from all mainstream approaches to advertising performance measurement. This has driven the empirical stage of the thesis.

8.3.2 Empirical Findings – How CMMs Help Explain Website Visits

The empirical models focus on the stages in the conceptual framework that link the key metrics for brand advertising (CMMs) with performance advertising (website visits). Website visits are becoming an increasingly important driver of marketing performance models, but the most commonly used approaches ignore long term drivers of website visits and focus only on short-term exposure to digital advertising. Understanding predictors is critical because, unlike other forms of advertising, website visits are initiated by consumers. The use of CMMs has been identified as an important predictor.

The first research question sought to better understand how to best represent CMMs to build relationships with website visits. I focus on website visits in the eCommerce because they precede trackable sales and are the source of the most commonly used metrics for assessing online performance. Some strong, consistent patterns observed across the models show how we should best capture how CMMs relate to CICs and help advance our understanding of this relationship. The following are specific areas that I have been able to investigate due to the respondent-level approach. As I discuss each point, I reflect on why individual-level data are important for this finding.

a. Liking and familiarity best explain website visits

Previous empirical research has demonstrated the importance of CMMs at the aggregate level for understanding sales (Hanssens & Pauwels, 2016; Srinivasan et al., 2010). More recently this work has been expanded to include CICs through search and website visits (Cain, 2022; Pauwels & van Ewijk, 2020), but the focus remains on how CMMs and CICs impact sales, with little insight into the relationship between CMMs and CICs other than that it exists. Furthermore, this aggregate approach does not address the conceptual understanding of how CMMs work, namely that marketing activity can change an individual’s propensity to notice advertising, interact with a brand, or purchase a brand over time due to brand knowledge (Keller, 1993). This is different to a timeseries approach which shows on average when CMMs increase so do sales but does not allow us to understand how much more likely an individual with a positive mindset is to interact with a brand online. It is important to understand if this relationship holds at an individual level.

The time-series work of Hanssens et al. (2014), Pauwels and van Ewijk (2020), and Srinivasan et al. (2010) seek to improve sales forecasting by viewing CMMs as slow-moving long-term predictors of sales. While previous research on mindset metrics has focused on balancing the needs of the CMO and CFO (Hanssens et al., 2014) or how to replace mindset metrics (Dotson et al., 2017), my research has focused on the role of CMMs in understanding CICs. This is an important area because CMMs and website visits are the most highly utilized metrics for marketers (ANA, 2021; Mintz, Gilbride et al., 2021).

This finding has two components. First, using an enforced sequence for the most influential CMMs through a hierarchy or funnel is rejected. While the existence of a marketing funnel or sequence has been disputed on philosophical grounds (Heath & Feldwick, 2008), the concept of a funnel is widely accepted in practice. Individual data offer a unique perspective on this problem; the two proposed sequences show a cognitive-only version and a version with preference included as a measure of affect, in contrast to the third approach in which no hierarchy is enforced. My research shows that dimension-based models (using familiarity and liking) are consistently stronger than hierarchy-based models where consumers are said to progress through various stages, from awareness through to preference or top-of-mind awareness. The distinction made in my research is important because it shifts the emphasis from the top of the funnel (brand awareness), middle of the funnel (consideration), and bottom of the funnel (preference/top-of-mind awareness) as stages that must be prioritised to treat CMMs as a measure of the propensity to engage with a brand that must be consistently grown and reinforced over time, but that different consumers will have different communication needs. By using both familiarity and liking on a rating scale a hierarchy or order is not enforced. An individual may have higher level of familiarity than liking, higher liking than familiarity and may or may not have visited the website in the prior period.

Second, in testing the sequence of approaches for the cognitive path and traditional funnel, brand awareness has a significant impact at an individual level. The overall conclusion is that familiarity is a better measure of cognition than brand awareness. While modelling revealed that a funnel was not the best way to represent CMMs, brand awareness is worthy of some further discussion as this is one of the most used metrics by marketers (Mintz, Gilbride et al., 2021; Romaniuk et al., 2017) and is frequently seen as a prerequisite for advertising impact. Therefore, it is important to consider the implications of the rejection of the marketing funnel and compare this to prior research. While brand awareness is conceptually considered the key metric time series approaches several studies have used advertising awareness as a substitute for brand awareness (e.g. Hanssens & Pauwels, 2016; Srinivasan et al., 2010) or averaged with brand awareness (e.g. Valenti et al., 2022). The barrier in time-series models is not conceptual but rather that there is not enough variation in prompted brand awareness for many established brands on an aggregate level (Srinivasan et al., 2010). Looking at brands and individuals demonstrates the importance of brand awareness in understanding CICs. This is a critical step in validating the value of individual-level data. When the models do not match our conceptual understanding, it is a cause for concern concerned. Not only would we anticipate brand awareness being more important than advertising awareness, but advertising can still have an impact, even when there is no active recall (Heath & Feldwick, 2008).

According to my research, the hurdle models show that brand awareness is important in the first stage of the funnel model (i.e., if consumers visit the website) but not in the second stage (i.e., how often they visit). This supports the notion advanced by Berg et al. (2007) that brand awareness is necessary but not sufficient. Individual-level data, conversely, allow for a more nuanced understanding of awareness beyond simply whether a consumer is aware of a brand. Brand awareness and familiarity are captured as separate measures at the aggregate level; however, they can be combined into a single metric using a 5-point rating scale at the individual level.

b. Affect, as well as cognition, should be captured

The second finding is that it is important to understand both cognition and affect. Three approaches have been used in the literature: one focuses solely on cognition measures (Cain, 2022; Dotson et al., 2017; Sharp, 2010), and the other includes cognition and affective measures either as a sequence or as factors that can be impacted simultaneously. Prior research has not tested alternatives to understand their implications for model fit. My findings support the latter approach, which posits that both cognition and affect are important. This has never been demonstrated at the respondent level, as Dotson et al., (2017), who examine the relationship at an individual level only measured cognitive impact, more in line with the concept of a CDJ (Court et al., 2009) and mental availability (Sharp, 2010).

At an individual level, it is important to emphasise the role of affect because these results show that it is important regardless the level of familiarity, capturing consumers' specific paths, including becoming aware of a brand and subsequently developing positive evaluations. According to Romaniuk and Sharp (2004), positive evaluations result from increased familiarity and do not require a separate evaluation. The traditional AIDA model typically measures affect or preference only once a brand is being considered. This means that affect is not considered until a brand is on the consideration list.

Using a rating scale, it is possible to see there are many cases where affect (likability) is greater than cognition (familiarity) even at lower levels familiarity. An example from my data set is where Emirates and Singapore Airlines have higher liking than familiarity, not only for specific individuals but also on average (see section 6.4.1). My findings show that relying solely on cognitive measures when selecting metrics can lead to bias. In the case of airlines and hotel bookings, the measure of affect (liking) is more important in determining whether a respondent will visit a website. This also provides support for a rating scale-based approach rather than progressive binary indicators.

c. Overall CMMs are more important than past behaviour

Whilst there has been research looking at what motivates consumers to visit a website (e.g. Moe, 2003; Y.-H. Park & Fader, 2004) there is very little that understands this from an attitudinal perspective. Rather previous research has found that past behaviour is a better predictor of future behaviour (Pauwels & van Ewijk, 2020), and this is the approach taken by many fields of study (C. H. Park & Park, 2016; J. Park & Chung, 2009). Dotson et al. (2017), who measured responses at the individual level, did not collect brand search data before survey phase, so we do not have a comparison of behaviours and attitudes.

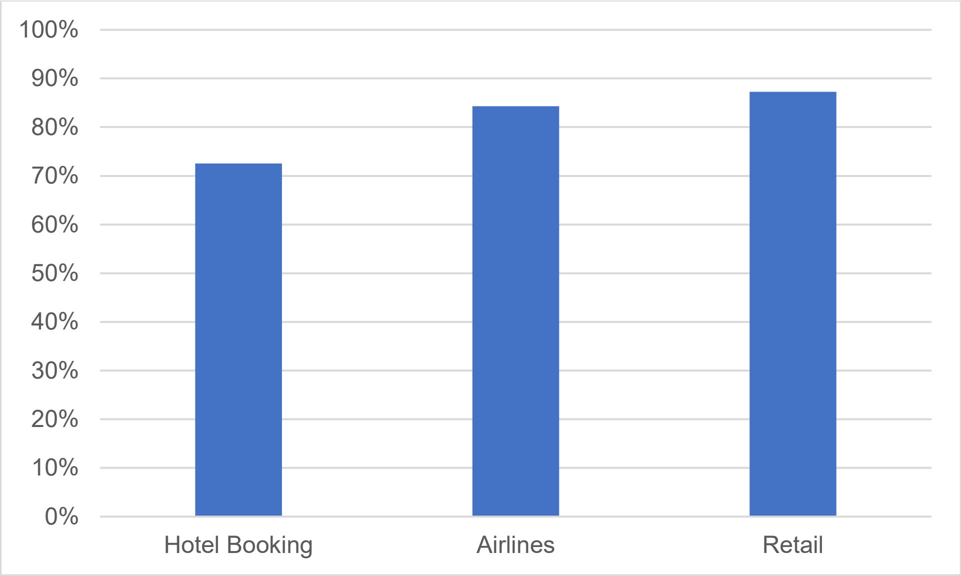
In contrast, my findings show that CMMs have a greater influence than past behaviour, especially when cognition and affect measures and past visitation are considered. My research shows that CMMs have up to three times the impact on website visitation and up to ten times the impact on the frequency of visitation for people with a positive attitude towards the brand. This demonstrates the significance of CMMs. This discovery is not visible with aggregate data.

d. Correlations do not show the extent of the relationship: A strong positive mindset is a critical indicator of likelihood to visit a website, representing our predisposition towards a brand for CICs

While Pauwels and van Ewijk (2020) argue that both CMMs and online behaviours are important because they represent different constructs (CMMs enduring and online behaviours contextual) and both are required because correlations are low, my research indicates that correlations based on time-aggregate data are not a suitable representation of the relationship. By examining individuals rather than tracking changes over time, it is clear that people who have positive feelings about a brand are more likely to interact online in the future. One could argue that people with positive attitudes have less incentive to visit a brand’s website because they already know a lot about it. My research, however, shows that people with more positive attitudes are more likely to visit a website and visit it more frequently. Furthermore, predisposition analysis indicates that those with more positive attitudes are more likely to visit. In fact, the non-modelling results show that 85% of visitors have at least one high rating of familiarity or liking, as shown in Figure 8-1.

Figure 8-1

Percentage of Website Visits from Those with High Response for Liking or Familiarity



According to the data, 85% of visits come from those with at least one strong measure (based on achieving a score of four or more on either familiarity or liking). That is not to say that those with positive attitudes will visit; they may not have the right motivations or triggers at any given time.

The selection of a time period for correlation is critical in the analysis of (Hanssens et al., 2014; Pauwels & van Ewijk, 2020; Srinivasan et al., 2010). Even though the vector autoregressive model is much more flexible than a traditional regression model it does impose a lag structure meaning that the time period for lags is based on average across individuals. While I have used a fixed time period of eight weeks in this analysis, the approach proposed is very flexible for assessment of different time periods and not implying a set aggregation period for all respondents. This could be important if assessing the role of triggers (as included in the conceptual framework) that may hit different respondents at different times.

Further, while Pauwels and van Ewijk (2020) identify a mutual temporal dependence between mindset metrics and online behaviours, this research demonstrates that the influence of this co-dependence is likely to impact only those who already have a strong positive attitude. This is will bias that exposure to a brand from those already predisposed to it.

e. **CMMs assist in determining not only whether someone will visit but also how frequently.**

One identified limitation of the MMM-based aggregate approaches used by (Cain, 2022; Pauwels & van Ewijk, 2020) is that the input variable is total visits, so we cannot understand the impact of CMMs on visit frequency. By contrast, individual-level data allow us to observe not only whether a respondent visits but also how frequently they visit; this dynamic is captured by the hurdle model.

Although this approach was used for brand search by Dotson et al. (2017), there was no consistency in the findings across categories, with familiarity and consideration being important for smartphones, but no CMMs were significant for vehicles. One possible explanation is that the selected products have long purchase cycles. In my research, I determined how different CMMs affect both the likelihood and frequency of visits. There are some differences across the categories here, with liking being more important if a respondent visits and familiarity being more important for how frequently they visit for hotel booking and airlines. In retail both metrics are important for if a consumer visits, but liking is key for regular visitation.

This finding is consistent with our understanding of purchase patterns (Goodhardt et al., 1984; Sharp et al., 2012), where we expect those with more positive mindsets to visit and visit more frequently. However, this research suggests that drivers exist in different categories. More research is needed to understand this, but one possible reason could be that affect is more important in categories with higher purchase frequency opportunities.

f. **The nonlinear effects manifest in an exponential form.**

Individual data and variations captured with visit count data allowed for the assessment of nonlinear relationships. Srinivasan et al. (2010) acknowledged the importance of understanding the potential nonlinear effects of CMMs. However, even the most recent relevant work (Dotson et al., 2017), which used binary metrics, could not demonstrate individual responses with diminishing returns because the coefficient is the average impact of each variable. In contrast, the functional form of my model, combined with the inclusion of the rating scale, allows me to identify that the impact increases exponentially with each point of increase in the scale. The rating scale used limited this increase. Various nonlinear impacts were tested, but none outperformed the multiplicative form. This shows that shifting a consumer from a level of 4 to 5 has a much greater impact than shifting from 1 to 2 on the chosen rating scale than shifting from one to two so that the biggest impact will be those with some base level of familiarity and liking.

8.3.3 Summary of Contributions

Table 8-2 shows a summary of these contributions and how they relate to our current understanding.

Table 8-2

Summary of Key Contributions

Research areas	Key studies	Current understanding	Limitations	Contributions of this research
Selection of mindset metrics to help explain behaviours	(Hanssens et al., 2014; Pauwels & van Ewijk, 2020; Srinivasan et al., 2010)	Traditions HOE metrics awareness, consideration, and preference	Used advertising awareness and not Brand awareness. Focus on sales uplift rather than drivers of CICs. Used aggregate data rather than individual-level data.	By looking at individual data rather than aggregate data I have demonstrated that separate variables of familiarity and liking are a better predictor of who is likely to visit a website. Using individual data, it can be seen that people can have higher liking than familiarity or vice versa, meaning that a hierarchy should not be enforced.
	(Cain, 2022; Court et al., 2009; Dotson et al., 2017; Sharp, 2010)	Cognitive view on role of advertising, with a focus on Brand awareness and consideration	Not including a measure of affect risks bias in the models	Demonstrate the importance of liking to understand website visits. Showing that a balance of cognition and affect is important in understanding who is likely to visit a brand's website.
How Metrics are captured	(Cain, 2022; Dotson et al., 2017)	Binary or percentage agreement with main CMMs	Only used binary metrics. Binary metrics often form a hierarchy because of the selection questions used (i.e., Need to be aware to be familiar, familiar to have top-of-mind awareness). This means once an objective is achieved for an individual, the KPI needs to change.	Using a rating scale for liking and familiarity allows for independent dimensions to be captured. This means no order is enforced and constant improvement in the same metrics becomes the goal.
Should Online Metrics replace CMMs	(Dotson et al., 2017)	Based on the relationship between CMMs and brand search, brand search is	No measure of past behaviour to test for reoccurring visitation. No consideration given to the role that the different metrics play	CMMs play an important role in measuring the role of brand advertising.

Research areas	Key studies	Current understanding	Limitations	Contributions of this research
		a candidate for an alternative metric		
Role of CMMs in frequency of visits	(Dotson et al., 2017)	Weak evidence that cognitive CMMs familiarity and consideration help explain how often a respondent searches for a brand	was only evident in smartphones, not automotive.	Demonstrate the role of CMMs in both if consumers visit and how often the visit across all three categories. Shown that the metrics do differ across categories. Familiarity is significant across all three categories and liking is only significant for the retail category.
Relative importance to behaviours	(Hanssens et al., 2014; Srinivasan et al., 2010)	Low correlation between CMMs and online behaviour	The relationship has only been assessed at an aggregate level, which is not the most appropriate way to test the conceptualisation that those with a more positive mindset are more likely to interact with a brand online.	While there may be a low correlation over time between CMMs and online behaviours, this research shows that this is more related to the temporal nature of the measures. When looking across brands, there is a strong correlation, and those with stronger CMMs are much more likely to visit a brand website

8.4 Methodological Contribution

As seen in the theoretical contributions, many differences stem from the ability to capture data at the individual level. Data collection has previously been identified as a major issue in research on attitudes and behaviour (Rappaport, 2014; Wu & Rappaport, 2014). The approach I propose advances future research in this area.

8.4.1 Novel Approach to Data Collection That Supports Models to Demonstrate Impact of CMMs in a Way That is More Reflective of Their Conceptualisation

The approach to data collection is novel and guides future research on attitudes and behaviours. The use of respondent-level data has conceptual and practical implications. The conceptual role of CMMs is to measure the predisposition to a brand; this is more accurate at an individual level, where we can link attitudes and behaviours rather than looking at averages across all individuals, as discussed in Chapter 5. As digital channels have made more personalised targeting possible, the contributions of both academia and practitioners can be viewed through this lens. Prior research has used data from search engines such as Google (Dotson et al., 2017), or in the case of customer satisfaction research, customer databases (e.g. Bolton, 1998; Bolton & Lemon, 1999; Petersen et al., 2018). My approach is unique because I use a research panel rather than data from a specific company. This method overcomes several limitations of previous research.

First, this has made it possible to collect responses from multiple brands. This is critical for assessing generalisability and capturing the competitive context, which includes the ability to examine relative differences and similarities. This has been a limitation in customer satisfaction and loyalty research, which pioneered approaches based on individual-level data for attitudes and behaviours. Furthermore, it does not limit its approach to companies with large customer databases.

Second, because I used web scraping rather than data from a search engine such as Google, I had access to all website visits, not just search visits. This allows for a broader view of CICs, as used in this research and also allows for research on which route a consumer takes to a website (e.g., brand search vs. direct type-in) and cross device analysis (i.e. desktop vs. mobile devices). As cookies become obsolete, the use of panel data will remain a viable approach to capturing these data, and the opt-in nature means there are fewer privacy concerns.

Third, using a panel allowed for capturing a pre-measure of behaviour. This helped not only with category selection but also by accounting for prior behaviour in empirical models. While Dotson et al. (2017) investigated whether online behaviours could replace CMMs, the only behavioural measure was the dependent variable of brand search, meaning previous history of generic search or search of other brands was not taken into account. This could be overcome by greater data access but data privacy concerns necessitate pre-recruitment, which significantly increases the cost of the research approach. The inclusion of a behavioural measure prior to conducting a survey helps in understanding if and when CMMs are useful. My research shows that even if accounting for past visitation the role of CMMs is an important one, accounting for a longer-term view of customers' predisposition towards a brand and providing an important link with brand advertising messages.

This method is timely, considering the evolution of digital measurements. While much clickstream data have been reliant on the use of cookies, this is about to change, with Google slated to phase out the use of third-party cookies in 2024 (Davis, 2022). This has a significant impact on the way that advertising effectiveness is reported. While it has been claimed that this will end attribution modelling in its current form, with CPC and CPA models still in use, understanding the best approaches to balancing performance remains critical for marketers, implying that new approaches will be required in the future.

8.5 Practical Implications

My research aims to improve our understanding of the relationship between mindset metrics and online behaviour. This allows us to make informed decisions about selecting and interpreting various metrics, not just in isolation but also in light of their expected interaction. In this section, I discuss how these findings may affect the use of mindset metrics by managers to comprehend the impact of marketing activities. My research has implications for managers in two key areas: first, the methods for capturing CMMs, including which metrics should be prioritised and why, and second, how these metrics should be interpreted. In light of the substantial investment in driving website traffic, this study emphasises the importance and utility of understanding the relationship between mindset metrics and website visits.

8.5.1 Which Metrics Should be Used and When

Understanding which customers interact with a brand's website and the metrics that can be used to identify them is an important stage in determining how we can increase that level of interaction. Driving these metrics would then become an important objective of firm-initiated media. My research provides evidence that CMMs remain an important component of performance measurements. This is still an important agenda item, as brand and marketing executives continue to question the value of CMMs due to the cost of collection compared to behavioural, digital data (Dotson et al., 2017; Katsikeas et al., 2016). As well as reaffirming the importance of CMMs as a key measurement for branding building activity, CMMs provide another important role in terms of targeting.

Although the primary rationale for monitoring CMMs has been the connection between FICs and CMMs, indicating an intermediate response to advertising that indirectly impacts sales, my research reveals that these metrics are crucial in identifying who is likely to engage with a brand online. Thus, interpreting the intermediate metrics of CMMs and clicks or website visits in isolation would not be ideal. This is a critical concern because the media channels used to drive website traffic, such as search, email and retargeting, now account for a sizeable portion of advertising budgets, and managers want to understand the relationship between key 'brand' and 'performance' metrics. Identifying whether a customer engages with a brand's website and the factors that drive such engagement is an important first step in determining how to increase the level of interaction. Consequently, improving these metrics becomes an essential objective of company-led media, and there are several key takeaways for those interested in tracking this relationship.

First, the metrics that should be captured are familiarity (to represent cognition) and liking (to represent affect). When practitioners are thinking about which exact CMM to capture, there has been some debate over the use of cognition and affect as key metrics. This is important as although emotional advertising measures have been shown to be more important than persuasion or brand linkage (O. Wood, 2012), cognitive measures of awareness and consideration are far more prevalent in brand tracking (Mintz, Gilbride, et al., 2021). I recommend that both cognition and affect are used, and that unlike a funnel affect is not a measure that only becomes important after a brand is considered. For example, from my work in the airline and hotel booking category, liking is an important part of visiting a website at all.

Second to establish the relationship conceptualised in this research there is not a requirement for long time periods of data as utilised in prior research (e.g. Hanssens et al., 2014; Pauwels & van Ewijk, 2020; Srinivasan et al., 2010) use continuous brand tracking over 3 to 7 years. The approach I propose can connect CMMs to online behaviour using irregular bursts of consumer research, allowing for a more time and cost-efficient approach (relative to continuous tracking) that is also more closely related to our understanding of the role of consumers' thoughts and feelings. This means linking CMMs to behaviours becomes more accessible to marketers who often do not have access to a long period of historical data.

Finally, it eliminates the need to change metrics, as Romaniuk et al. (2017) recommended and who suggest different brand awareness measures for different brands. According to my research, overall rating scales should be used instead of binary indicators representing stages in a funnel as although the sequential progression from awareness to consideration and then preference may be appealing, it is better to capture how marketing activity is growing consumers levels of cognition and affect over time.

The proposed framework connects the two most frequently used intermediate metrics in marketing: one that reflects brand marketing's goal of shifting consumer mindset, and another that relates to performance marketing, which assesses consumer actions. By transforming this conceptual framework into a statistical model, it is possible to quantify the level of advertising response, which varies for different consumers based on their brand attitudes. This approach allows marketers to evaluate the potential benefits of changing brand attitudes and better measure the impact of consumer-initiated media. The proposed framework is beneficial for marketers because it indicates which metrics should be used in different situations and can be applied to any level of data aggregation, ranging from event-level data used in attribution modelling to highly aggregated data used in brand funnels. Additionally, it is possible to assess which model elements are included or excluded for a specific model.

As a result, I would first recommend a clear distinction between the metrics used for the measuring brand building and those used for immediate performance measurement. Studies demonstrating increased CMMs for those exposed to online advertising are more appropriate than online behavioural metrics. Instead of relying on approaches such as digital attribution modelling, which assumes that all online sales result from online interactions (Danaher & van Heerde, 2018), greater use of experiments is important for performance measurement. However, existing mindset metrics should be considered when designing experiments for CICs. Consumers are unlikely to visit if they do not have a high level of familiarity or liking. This does not imply, as Joo et al. (2016) proposed, that we should expect an immediate increase in brand search due to advertising airing. This means that with consistent advertising that helps the brand become more familiar and likeable, the customer is more likely to visit a brand’s website when the time is appropriate.

It must also be considered that the potential bias in spending is not only towards existing customers but also those with the most positive attitudes towards a brand. If the role of brand advertising is to shift consumer mindsets, then we need to know which mindsets we can change. Instead of thinking about communication to move consumers from awareness to preference, we should consider barriers to different levels of the familiarity and liking relationship, such as what approaches will help move consumers with low liking but moderate familiarity. Currently, digital signals provided through clicks and website visits are increasingly used for marketing automation, including targeting. Using this digital signal will result in advertising to the most positive people, as it provides high-performance campaign metrics if campaigns are assessed based on the CTR and CPAs. This could have negative consequences over the long term.

Recognising that the objective is independent of the media channel is also critical. Attempts have been made to align media channels with brand and performance activities (e.g. Binet & Field, 2013, p. 37), which should be regarded as a loose categorisation because, while a channel has an influence (Pauwels & van Ewijk, 2020), it should not drive the objective of the communication. For example, a digital display advertisement can elicit a consumer click and thus be judged as a performance channel, but it can also be purchased and judged on a CPM basis, with a focus on changing consumer attitudes. Consequently, the measurement approach should be guided by specific campaign objectives.

Practically the individual data provides different implications as it suggests that the current approach of new and existing visitors used as a classification in tools like Google Analytics are not sufficient and more consideration should be given how we can better capture CMMs to help our understanding of how many people we expect to visit a website.

8.5.2 Who is Likely to Visit a Website (Targeting)

A key use of online visit data are for targeting or retargeting raises the question of who is being targeted and, consequently, where the investment is being made, particularly for heavy or light users (Sharp et al., 2019; Sharp & Sharp, 1997). This research enables us to consider this debate not only in terms of users but also in terms of consumer attitudes towards a brand.

Using the generic recommendation of Binet and Field (2013) that 60% of the budget should be spent on brand advertising and 40% on performance, I assume that the brand advertising will have little targeting in terms of users and non-users and that the media will be purchased against an audience that is likely to be interested in the product. This means that the budget will be allocated in the same ratio as those predisposed or not. The first column of Table 8-3 shows two examples: one where 70% of the audience is predisposed to advertising with a rating of four or higher in either familiarity or liking, and the other where only 30% are predisposed to the brand.

Table 8-3

Example of Spending Distribution Depending on How Many Consumers Have High Levels of Liking or Familiarity

	Predisposed (either Familiarity or Liking rated as four or more)	Brand spending. Random distribution of spending 100% (millions)	Brand spending. Random distribution of spending 60%	40% Performance spending. 85% to those predisposed	Total spending	Difference Historical approach
		$8	$4.8	$3.2	$8	
Predisposed	30%	$2.4	$1.44	$2.72	**$4.16**	$1.73
Not Predisposed	70%	$5.6	$3.36	$0.48	**$3.84**	$0.69
Predisposed	70%	$5.6	$3.36	$2.72	**$6.08**	$1.09
Not Predisposed	30%	$2.4	$1.44	$0.48	**$1.92**	$0.80

The second column shows how the budget would be divided if all advertising were brand based. The three following columns show how that split changes if we allocate 40% of the budget to performance spending (assuming from the average in my categories that

85% then goes towards those already predisposed to a brand). The final column compares the ratio between the two scenarios, comparing the smaller brand (with only 30% of people predisposed) to the larger brand (which 70% of people predisposed).

In the basic scenario, I demonstrate that allocating 40% of the budget to performance marketing has a greater impact on smaller brands. This can be problematic because smaller brands stand to gain the most from attracting new customers; however, they experience a more pronounced shift towards those who are already inclined, emphasising the danger of advertising following sales performance practice.

8.5.3 Messaging – How These Findings Can Help Marketing Decision-Making on CMM Objectives

Brand managers should explore which messages work best for different audiences. Table 8-4 shows examples of brands with varying levels of familiarity and liking and implications for advertising focus in terms of brand and performance balance and messaging through familiarity and liking.

Table 8-4

Approaches for Different Combinations of Familiarity and Liking

		Familiarity	
		Low	High
Liking	High	Example: Singapore Airlines, Emirates Few loyal followers with high repeat visitation.	Example: Qantas, eBay, JB HiFi These brands already have a strong CMMS. For these brands, effective approaches to minimise the cost of performance marketing will be critical as there is a much greater risk of paying for those that would have visited anyway. Therefore, approaches to getting consumers to go direct to a website become important.
	Low	Example: Skyscanner hotels combined, Agoda For the booking category, low liking is a key barrier to visitation. When there is little difference between the products' brand advertising, promoting a more affect-based response should increase CICs.	Example: Myer, Tiger Air Focus on building liking as a way to attract new users (particularly for Airlines). Expect a higher focus on performance marketing than brands with higher liking.

Table 8-4 shows that the challenge differs for brands depending on levels of liking and familiarity. Brands with low familiarity but high liking could be attributed to distribution issues (such as an airline lacking appropriate flight routes). For example, non-local airlines, Singapore Airlines, Air Canada, and Air New Zealand, have a higher liking than familiarity, which could indicate the potential for additional growth or airline routes, a physical availability problem using the language of Sharp (2010). Agoda has low liking and familiarity, which could indicate broad communication focused on building CMMs with a broad audience, as there is little risk of high-spending levels on those who are already predisposed to the brand.

At the other end of the spectrum, eBay has very high visitation rates, and it is expected to capitalise on this by using the website for much of its communication.

Consequently, they can target brand communications to a much smaller audience, potentially targeting those who have not visited the website rather than those who have. Finally, Tiger Airlines has low familiarity but high liking, indicating a more precarious position and a focus on likeability in both communications and products. While these strategies are unique to each business, it is easy to see how they might differ in different situations. These parameters should be measured and tracked and with the importance of CMMs demonstrated and their relationship with established website visits, it is possible to consider CMMs in targeting.

The critical point is that marketers need to think more broadly about what “the right message at the right time to the right person” means. It should not always be about finding people who are about to purchase and trying to maximise the chance of a conversion. The chance of a sale is very low if the groundwork is not there. It also suggests any preceding factors also needs to be acknowledged in the designing of experiments, where elements that preceded the variable of interest should be accounted for within the design. This is often not the case with experiments considering online advertising.

8.5.4 Approaches to Data Capture

For those involved in the marketing research industry my research shows the importance of continuing to develop approaches to data collection. While survey data has typically been used for collecting unobservable data (Gupta & Zeithaml, 2006) being able to combine this with actual behaviours at an individual level allows us to identify research areas that were previously impossible. Whilst approaches have been developed within the field of customer satisfaction (Bolton, 1998; Bolton & Lemon, 1999), respondents are all customers, and generally, only single brands (or subsets of brands) can be included. This limits our ability to investigate competitive interactions.

Because the data landscape is changing owing to privacy concerns, it is now an excellent time for research firms to consider new approaches to data collection and how they might aid in marketing performance measurement. While some argue that returning to

MMM is necessary because digital attribution modelling will become more difficult over time (Yordanova et al., 2022), my research demonstrates that the individual-level data we have come to associate with digital data have significant value. This research can guide a valuable approach to data capture, as the way we collect data may change in the future.

8.5.5 Summary of Practical Implications

The potential managerial impact of the research is considered in terms of the decisions summarised in Table 8-5. The first set of suggestions pertains to measurements themselves. The empirical nature of the models also shows what we expect to discover when we understand the relationship between CMMs and CICs. There are implications for marketers in both the conceptual framework and the empirical work. These findings relate to the initial trends identified in Chapter 2, such as automation, media buying models, targeting, and personalisation.

Table 8-5

Summary of Digital Advertising Decisions Where My Research Can Provide Guidance

Decisions to be made		Current approach	Recommendations from my research	Areas of further research
What to measure and when?	When to measure CMMs?	While managers still use CMMs, there is a growing question about the value of when behavioural metrics are so widely available and easy to capture. The frequency and usage of brand tracking has often been reduced.(Dotson et al., 2017; Katsikeas et al., 2016) CMO 2021 August	Brand-tracking surveys are a critical part of digital marketing performance measurement; however, continuous tracking may not be required. Rather approaches should be developed based on this research to establish a direct link with online behaviours. These fast-moving online behaviours should be able to provide an early warning system. Individual activity should be measured.	Testing how stable the relationship remains over time or among different groups of people.
	What CMMs to measure and how	Measures; HOE based measures Brand Awareness, Consideration, Preference Dominant thinking about a hierarchy as a path to purchase. (Dotson et al., 2017; Pauwels & van Ewijk, 2020)	Liking & Familiarity should be considered key CMMs and prioritised more than awareness and consideration. They should be measured on rating scales rather than as binary metrics. That is, the depth of CMM is more important than a hierarchy of measures. Think more about building the propensity to select a brand when an appropriate trigger is present	Should be tested across further categories with different purchase cycles and different levels of involvement. Further work on scales to test for nonlinearity in different situations
Metrics and buying models for brand vs performance	Buying models/Automation	CPC & CPA costing models make advertising more accountable through digital attribution models (Berman, 2017; Y. Li et al., 2019)	CPC costing models should be avoided for brand advertising. These will focus on those people that already have a strong predisposition towards the brand. Using CPC over brand metrics either as a buying model or through reporting is going to bias away from potential new users.	This research has looked at all ways that individuals can reach a website. This should be expanded to look at the differences across different channels (e.g., brand vs generic search).
Who to target	Online customer Targeting	Website visits are used as a method for retargeting with the	Now know most people who visit the website already have strong positive	My research suggests that unless uplifts are measured through a

Decisions to be made		Current approach	Recommendations from my research	Areas of further research
		assumption that this will drive additional conversions.	attitudes towards the brand, making them more liking to have an intent to purchase.	controlled experiment, it is likely only targeting those already predisposed to a brand. There is a strong risk that this diverts funds away from those that do not currently have high opinions. This may be sustainable for larger brands but not if there is a growth strategy
	Messages for different individuals	Current practice is that targeting is a greater focus on sales conversion activity rather than brand-building activity	Personalisation should not be limited to sales conversion activity	Further research is needed into the targeting of brand messages aimed to shift liking and familiarity to high levels. Understanding the differences in building high CMMs compared to maintaining high CMMs
Strategies for different situations	General rules	60% Brand/40% Performance (Binet & Field, 2013) Target light brand buyers (Sharp, 2010)	My research shows that we need to move beyond rules of thumb and build models that can optimise at a brand level.	The suggestions in Table 8-4 provide some hypotheses on how different brands should prioritise investment. Further experiments testing this would be a valuable addition.
Development of data collection approaches		Collection of observed behavioural data and unobserved survey data are largely done separately	My research shows the value of capturing attitudes and behaviours at an individual level	Best approaches to build panels, testing different time periods for behavioural response. Inclusion of additional behaviours

8.6 Limitations and Further Research

This research has limitations that must be acknowledged to understand the applicability of the findings and to guide future research. As a result, I will discuss these areas below and how future research could address these limitations. These limitations consider the data collected, categories and brands of focus and measures used.

8.6.1 Data

Although the approach to data collection allowed for observed data to be captured via non-invasive behavioural tracking and unobserved data to be collected via a simple survey, some limitations should be acknowledged. First, while the sample size is comparable to that of other studies (e.g. Bolton et al., 2000; Bolton & Lemon, 1999), more respondents would have allowed for more advanced analysis. More complex models, such as those used by Tutz (2021), were tested but did not converge. However, the exploratory analysis in Chapter 6 shows that the exponential form used in the model accurately represents the impact. One exception was observed with the booking category results indicating that those with the highest level of liking may have lower rather than higher visit levels. This could imply that there are times when increasing CMMs yields diminishing returns, resulting in lower website visitations from those with a more positive mindset. If firms have to pay for these visits, this could be a positive outcome for brands. This is an interesting area for future investigation.

Second, one advantage of the approach was that I could examine cross-device usage by looking at individuals from a panel rather than from cookie data, as is common in online research. However, due to the small sample size, only 42 respondents had a behavioural tracking device installed on both their mobile phones and desktops. Because the device on which the respondents installed the app was a free choice, it does not necessarily reflect true usage with a larger panel it would be beneficial to focus on respondents who have a tracking app on all their devices. I acknowledge that some level of self-selection bias exists. So, while I am confident that I have accounted for the differences in results between mobile devices and desktops using the indicator variable, the data were not robust enough to draw conclusions about cross-device usage, so it was treated as a control variable. A larger sample of users with multiple devices registered for tracking could be used to draw this conclusion about the impact of across-device usage. It is unclear whether there will be a difference in website visits, but Ghose et al. (2012) indicate that mobile phones are more likely to be used for research and are more sensitive to location.

Third, the period chosen for the website visits was eight weeks, which was the only period tested in this research. Shorter time periods would reduce the number of people interacting with a website, while longer periods would increase the likelihood of CMMs changing. However, with a larger sample size and longer tracking period, testing additional aggregation time periods for the dependent variable would be beneficial.

Fourth, this research only included visits to brand websites; it did not include other owned brand assets, such as social pages that are gaining popularity (Colicev et al., 2018). Although this would be an interesting addition, the coding exercise examining the path consumers took to a website suggests that this social media traffic volume is not significant enough to influence the results. While some people clicked on social media advertising in the data, there were no cases of people visiting brand social pages. This implies that my approach to data collection would be inadequate to investigate this phenomenon and remains an avenue for future research.

8.6.2 Product Categories of Focus

This research focused on eCommerce categories that have high levels of interaction from potential new customers. This decision was made based on where the research was expected to have the greatest impact and statistical reasons to provide high levels of interaction for modelling. As a result, the chosen categories were likely to exhibit higher levels of interaction patterns. Although this research extends the categories from the work of (Dotson et al., 2017), they too focussed on the high-interaction categories of telecommunications and automotives. Dotson hypothesized that the relationship would not hold so well for low involvement categories. Pauwels and van Ewijk (2020) demonstrated awareness and preference had a much lower impact in low involvement categories than high-involvement ones, and that online behaviours were more important in high-involvement categories. This is partly due to lower volumes of searches for lower involvement categories, as consumers do not routinely search for information on everyday items. However, if we consider who is interacting with a brand rather than the overall level of interaction, I hypothesise that low-interaction categories would have an even higher proportion of visitors with an existing positive mindset, implying that while very few consumers may be searching for Coca-Cola, those who do are already highly connected to the brand. This may impact the usefulness of websites for attracting new customers in low-involvement categories. It is critical to continue expanding the categories and purchase characteristics to build this knowledge and generalisability. While it is clear that positive mindset metrics are critical for understanding consumer interactions with websites, there are differences across categories. Further research is needed to determine whether liking or familiarity is more important in these situations.

Possible differences could be:

- Categories with low purchase frequency but high brand interaction, such as banking and insurance, where there is a greater emphasis on customer acquisition. In this case, we might expect past behaviour to be more important.
- Low-interaction categories, such as FMCG, where purchases do not require online visitation. In this case, the brand is purchased online, and website visits are required before making a purchase.

8.6.3 Data Favours Large Brands

Respondents in this study were not chosen based on their usage of specific brands, so larger brands naturally have more visitation data. Similar to previous research by (Dotson et al., 2017) using the same approach, results have been pooled across the brands for estimation purposes. While I tried a model version including a random effects parameter for brands, the results were less consistent or failed to converge. This means that we have higher confidence in the CMMs-website relationship for the larger brands. There is a path for further research to understand these differences better by using a broader sampling approach which would ensure a sufficient sample size for the less well-known brands.

8.6.4 What More We Need to Know for Budget Allocation

A key next question that is important to managers is that of budget allocation. **Does an increase in CMMs reduce or increase paid search costs?** Because this research aimed to link CMMs to website visits, no cost data were included. Although it is well known that advertising can shift CMMs, for example, Hanssens et al. (2014) show that advertising awareness, consideration and liking can be improved by advertising; the costs for individual brands are unknown. The second area is the cost of the CIC; the cost of that visit will vary depending on how customers access the website; for example, direct visits or type-in are cheaper than SEO, which is cheaper than SEM. To account for this, we must first determine which channels different consumers use to access a website. While Dotson et al. (2017) provide some insight into brand search, those who go directly to the website are a critical group because they are the least expensive for marketers. Marketer costs can be reduced if customers are encouraged to visit websites directly. Blake et al. (2015) discovered that removing brand search from the mix had little effect on overall visits to eBay.com, implying that they paid for people who would have visited anyway. According to my research, eBay is one of the strongest brands in terms of CMMs. Therefore, the question is whether this is true for all brands. Understanding the costs of shifting CMMs and investment is a critical next step in providing more guidance on budget allocation.

8.6.5 Further Assessment of Online Metrics

One of the main motivators for my research, which used website visits as the dependent variable, was the lack of a theoretical foundation in attribution modelling, which relates to metrics for the existing research on which the framework is built. However, there are numerous other online metrics used by marketers. This research could be expanded to include these alternative measures, such as the time between visits, which is important for understanding buying likelihood (C. H. Park & Park, 2016), time spent on the website, and bounce rates (those that leave quickly).

8.7 Further Extensions of Research

While the limitations of my research help inform some future areas of research, the findings from the literature review and the methods used have opened some areas for future research. There are a number of clear areas for further research that are possible within the current data that has been collected, and some others that look to extend the research into other areas. Several research areas need to progress to reliably utilise behavioural data for media budget allocation decisions.

8.7.1 Link to Sales and Consideration Sets

To gain a comprehensive understanding of the impact of media, it is necessary to develop data harmonization techniques that integrate online and offline sales channels. This study focused on website visits and common CMMs as the primary metrics. The next logical step is to investigate the probability of a website visit resulting in a sale. By analysing individual-level data, we can identify which consumers made a purchase and the number of purchases made. Although we might anticipate that consumers with more positive CMMs are more likely to make a purchase, it is unclear whether there is a more complex non-linear relationship with website visits. This is because consumers who are more devoted to a brand may be able to make a purchasing decision more quickly, and with fewer website visits. Building a brand is believed to be advantageous because it reduces comparison with other brands (Formisano et al., 2020). Therefore, assessing the size of the consideration set, evaluated through online visits, can help us understand this concept more fully.

8.7.2 The Familiarity-liking Relationship

The strong relationship between familiarity and liking is well established and is visible in my data. However, much of the research has focused on unfamiliar stimuli (Inman & Rindfleisch, 1998). Sometimes, more information (or greater familiarity) can lead to a lower liking (Norton et al., 2011). As my research has shown the value of these metrics in measuring the likelihood of interacting with a brand online, there is value in further understanding the boundaries of this relationship and how it is influenced by existing knowledge, particularly the contrast between brands with little familiarity, such as Skyscanner, and those with a higher level of familiarity, such as Amazon. Further to this Copula models could provide a useful extension to the hurdle model to (Becker et al., 2022; Danaher & Smith, 2011; Papies et al., 2017) as this may help better understand any asymmetry or non-linearity in the relationship to provide more nuanced results.

8.7.3 Exploring a wider range of survey metrics

Based on the objectives of my research to understand the relationship between key marketing performance metrics a limited number of survey metrics were selected relating to brand health and HOE models. The proposed approach could be used to test a much broader range of survey metrics potentially expanding the literature to include the rich literature on consumer search and information processing which has focussed on the motivations for consumer search or different search styles. The approach could also be expanded to include richer brand imagery measures often included in brand tracking studies.

8.8 Final thesis summary

Efforts to establish accountability in digital advertising have led to the adoption of oversimplified approaches to performance measurement. This is exemplified by last-touch attribution models and the over-reliance on dominant performance metrics like clicks and click-through rates. A weakness of these approaches is that they assume online advertising is the sole driver of a website visit or sale. Little account is taken of consumers' existing inclination to purchase a particular brand or to visit a brand's website or that not all traffic emanates from digital advertising. This thesis has been motivated by the current state of advertising performance measurement driven by the digital ecosystem which has seen a strong shift towards consumer-initiated advertising communication and advertising performance measurement based on behavioural data (Wedel & Kannan, 2016) This is important for two reasons. First, as the media channels used to drive website visits through search, email and retargeting now form a significant part of advertising budgets. Second, these channels are not used to build long-term attitudes towards a brand, but rather to drive an immediate sales uplift (Binet & Field, 2017).

Traditionally long-term effects of advertising have been measured through Customer Mindset Metrics (CMMs) such as awareness and consideration. Despite website visits being one of the most frequently utilized metrics in the online advertising performance space, the connection between the CMMs of individuals and their likelihood to visit a brand's website remains largely unknown. Some existing research shows weak correlations between CMMs and online behaviours (Cain, 2022; Pauwels & van Ewijk, 2020). However, this research uses aggregate time-series data to conclude that both are important in understanding sales, rather than focus on the relationship between these two intermediate metrics. Although CMMs are linked with brand-building activities, and online behaviours tend to elicit more immediate responses, it is crucial to understand how these metrics interrelate since both are essential in assessing marketing performance (ANA 2021; Mintz et al. 2021). Despite this, little attention has been devoted to studying their interaction. Understanding if a consumer interacts with a brand website and what drives that interaction is an important first step to determining how we can increase that interaction and then minimise the cost of this interaction to marketers.

Methodologically, the thesis uses a novel approach to data collection capturing data covering six months of online website visitations and two consumer surveys to assess

CMMs at an individual level across 27 brands in three different categories (accommodation booking, airlines and retail). This allows the examination of how likely individuals with different CMMs towards a brand are to interact with it online and to assess the robustness of findings across various product types. Hurdle models use a two-stage process that first predicts who is likely to visit and then how often.

The results show that the commonly-used approaches following a hierarchy of effects of awareness consideration and preference (Hanssens et al., 2014; Srinivasan et al., 2010) or popular cognitive views of awareness and consideration (Cain, 2022; Dotson et al., 2017) are not the best way of using mindset metrics to explain website visits. Instead, separate dimensions of familiarity and liking perform better in explaining website visits. This predictability improves further when a measure of past experience is included in the model. In general, this supports the view of Vakratsas and Ambler (1999) that measures of cognition, affect, and past experience are important where firm-initiated advertising and CMMs that have been studied. However, the relationship explored here differs as I consider the link between CMMs and consumer-initiated advertising exposure. Next, in contrast to the popular perspective that behaviours are better predictors of behaviours than attitudes (Pauwels & van Ewijk, 2020), this research shows that those with the most positive mindsets are up to 24 times more likely to visit a website than those with no positive attitudes, while those who have visited before are only 7.4 times more likely to visit in the future than non-visitors.

These results have clear implications. First, I demonstrate the continued importance of CMMs despite the widespread shift towards behavioural metrics both for industry and academia. This is particularly important for digital advertising, where there has been a temptation to use behavioural metrics regardless of campaign objectives. Since having robust CMMs is crucial, digital advertising must demonstrate its capability to affect them. Second, my research demonstrates that CMMs should not only encompass measurements of brand salience, which pertain to awareness and familiarity with a brand, but also gauge how much consumers like the brand. Although these metrics are interrelated, their distinctions are crucial in determining whether a consumer is likely to visit a brand's website and how frequently. Third, by demonstrating both conceptually and empirically the role of CMMs in digital performance metrics, I help reduce the silos within advertising performance measurement. This helps delineate which metrics should be used and when. It also highlights the risk of using cost-per-click or cost-per-action approaches to buying media, as these buying models can result in greater spending against those already more inclined to purchase. Finally, the robust relationship between CMMs and website visits necessitates their inclusion in the analysis of standard online metrics, such as clicks and click-through rates. Stronger clicks or visits are likely due to the exposure of advertisements to an audience that already has a favourable disposition towards the brand. These individuals require minimal persuasion and are the most likely to pay attention to the advertising. The influence of CMMs on the probability of visiting a brand's website underscores the significance of controlled experiments that demonstrate response uplift, and the mindset of customers should be factored into the experimental design.

Overall, this research demonstrates the importance of using both behavioural metrics and CMMs together to understand the impact of advertising. This is important not just to help unify the approach to measuring online and offline channels, where offline channels are disadvantaged because of the lack of a direct link to a sale, but also to better understand the benefit of advertising beyond an immediate sales uplift. Understanding this relationship is a critical first step towards developing modelling approaches that reflect both investment in firm-initiated advertising contacts and those driven by consumers. By employing the proposed data collection approach, there are additional opportunities to investigate the path that consumers follow to reach a website, the variations among brands, and the association between website visits and sales on an individual level.

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Appendix 1: Survey Details

The survey was conducted using Qualtrics survey tool. A link was produced and sent to TEG insights so they could distribution to their panel members. Only and Identifier code was supplied so the survey data could be matched to the behavioural data and no personal identifiers were shared. Ethics approval was obtained through UNSW with Dr. Rahul Govind as the lead investigator.

An invite was sent out to all the panel members and follow up reminders were also sent to maximise the response rate. Below in the next three sections are the invite email, the participant information sheet and the survey.

Invite

Dear XXX

We would like to invite you to participate in a short survey

There are no right, or wrong answers so be honest and open with your responses. We hope you enjoy participating in our research.

The survey will take approximately XX minutes of your time to complete.

If you agree to participate and to provide thoughtful and honest answers, please click Next >> to begin the survey.

Participant information sheet

ONLINE PARTICIPANT INFORMATION STATEMENT
Brand attitudes and online behaviours
Rahul Govind

1. **What is the research study about?**
You are invited to take part in this research study. The research study aims to understand how brand attitudes influence online behaviours. It will help marketers better understand the importance of building positive brand attitudes. You have been invited because you are a member of Purkle passive panel, therefore through this survey we will be able to see how your brand attitudes relate to your online activity.

2. **Who is conducting this research?**
The study is being carried out by the following researchers:
    - Vince Mitchell, Professor of Marketing, University of Sydney
    - Kate Gunby PhD student, university of Sydney
    - Rahul Govind, Senior Lecturer, University New South Wales

3. **Inclusion/Exclusion Criteria**
You have been selected for this study because you are part of the Purkle Passive panel. There are no further requirements for you to participate.

4. **Do I have to take part in this research study?**
Participation in any research study is voluntary. If you do not want to take part, you do not have to.

5. **If you decide you want to take part in the research study, you will be asked to:**
Read the information carefully (ask questions if necessary);
Complete the online questionnaire.

6. **What does participation in this research require, and are there any risks involved?**
If you decide to take part in the research study, we will ask you to complete an online questionnaire. The questionnaire will ask you questions about your attitudes towards a selection of brands in three different categories It should take approximately 10 minutes to complete. You will be rewarded in Purkle dollars valued at $3, this will be administered by TEG Insights in the normal way.

7. **What are the possible benefits to participation?**
We hope to use information we get from this research study to benefit marketers by helping them understand how brand attitudes influence online behaviour.

8. **What will happen to information about me?**
Submission of the online questionnaire is an indication of your consent. By clicking the 'I agree to participate' button you are providing your permission for the research team to collect and use information about you for the research study. Your data will be kept for a period of 5 years after the publication of the research results. We will store information about you in non-identifiable format in a password protected computer in the researchers' locked office. Your information will only be used for academic research publication and presentation in a non-identifiable form.

9. **How and when will I find out what the results of the research study are?**
The research team intend to publish and/ report the results of the research study in a variety of ways. All information published will be done in a way that will not identify you. If you would like to receive a copy of the results you can let the research team know by including your details in the space provided in the consent form. We will only use these details to send you the results of the research.

10. **What if I want to withdraw from the research study?**
If you do consent to participate, you may withdraw at any time. You can do this by closing the questionnaire. If you withdraw from the research, we will destroy any information that has already been collected. Once you have submitted the questionnaire however, we will not be able to withdraw your responses as the questionnaire is anonymous.

11. **What should I do if I have further questions about my involvement in the research study?**
The person you may need to contact will depend on the nature of your query. If you require further information regarding this study or if you have any problems which may be related to your involvement in the study, you can contact the following member/s of the research team:
Research Team Contact

Name	Rahul Govind
Position	Sr. Lecturer
Telephone	02 9385 1284
Email	r.govind@unsw.edu.au

12. **What if I have a complaint or any concerns about the research study?**
If you have a complaint regarding any aspect of the study or the way it is being conducted, please contact the UNSW Human Ethics Coordinator:
Complaints Contact

Position	Human Research Ethics Coordinator
Telephone	+ 61 2 9385 6222
Email	humanethics@unsw.edu.au
HC Reference Number	HC190247

Declaration

- I understand I am being asked to provide consent to participate in this research study;
- I have read the Participant Information Sheet, or it has been provided to me in a language that I understand;
- I provide my consent for the information collected about me to be used for the purpose of this research study only.
- I understand that if necessary, I can ask questions and the research team will respond to my questions.
- I freely agree to participate in this research study as described and understand that I am free to withdraw at any time during the study and withdrawal will not affect my relationship with any of the named organisations and/or research team members;

Survey for Brand attitudes and behaviours study

1. When you think about <category X> which is the first brand or company that comes to mind? (Solo)
2. Other than the company you mention above for <Category X>online which other brands or companies come to mind? (List)
3. Which of the following brands are you aware of? (Multi-select)

Brand 1	
Brand 2	
Brand 3	
Brand 4	
Brand 5	
Brand 6	
Brand 7	
Brand 8	

4. Thinking of <brand x> how familiar would you say you are:
(Pipe those aware of. Solo per brand)

	Not at all	Slightly	Moderately	Very	Extremely
Brand1					
Brand2					
Brand3					
Brand 4					
Brand 5					
Brand 6					
Brand 7					
Brand 8					

5. Which of the following brands have you seen advertising for in the last 2 months? (Multi-select)

Brand 1	
Brand 2	
Brand 3	
Brand 4	
Brand 5	
Brand 6	
Brand 7	
Brand 8	

6. Which of the following brands would you consider when next purchasing <category x>? (multi-select)

Brand 1	
Brand 2	
Brand 3	
Brand 4	
Brand 5	
Brand 6	
Brand 7	
Brand 8	

7. Thinking of the <Category x> how much do you like the following brands? (SOLO for each brand)

	Not at all	Not really	A little	A lot	Like enormously
Brand1					
Brand2					
Brand3					
Brand 4					
Brand 5					
Brand 6					
Brand 7					
Brand 8					

8. Which brand/s in <category x> do you prefer? Please rank in order of preference.

Brand 1	
Brand 2	
Brand 3	
Brand 4	
Brand 5	
Brand 6	
Brand 7	
Brand 8	

9. Could you please indicate which of the following statements best applies to the following brands? (SOLO for each brand)

	- Never used	Have used it but not any more	Use Sometimes	Use Regularly	Use most often	The only brand I use
Brand1						
Brand2						
Brand3						
Brand 4						
Brand 5						
Brand 6						

Brand 7						
Brand 8						

***Note Demographic information to be collected via existing respondent profiles therefore they are not asked as part of the survey*

Lists have been selected based on visitation rates as shown by existing TEG Insights data from passive data capture. Lists have been limited to maximise survey response rates

Category 1: Online travel booking

Wotif.com

Booking.com

Trivago

Expedia

Webjet.com

Tripadvisor

Flightcentre

Skyscanner

Agoda

Category 2: Online retail

eBay

HarveyNorman

JBHiFi

Amazon

David Jones

Myer

Kmart

BigW

Target

Category 3: Airlines

Qantas

Virgin

Jetstar

Emirates

Singapore

Canada

Tiger airways

Air New Zealand

Comparison of survey 1 and survey 2 results

For ease I have tested for significant differences between survey one and survey two using a paired t-test (McDaniel & Gates, 2010). The expectation is that there will be little change between the two surveys and that not all shifts will be in the same direction. Only respondents who answered both surveys are included in this analysis.

Table A1-1

Brand Liking change survey 1 to survey 2

Paired Samples Test

Brand	Paired Differences Liking			t	df	Significance
	Mean Difference	Std. Deviation	Std. Error Mean			Two-Sided p
Agoda	**-0.03**	0.97	0.07	**-0.50**	207	0.62
Air Canada	**-0.01**	1.26	0.09	**-0.11**	207	0.91
Air New Zealand	**-0.01**	0.92	0.06	**-0.22**	209	0.82
Amazon	**0.13**	0.88	0.06	**2.15**	205	0.03
Big W	**0.06**	1.02	0.07	**0.81**	210	0.42
Booking.com	**0.08**	1.08	0.07	**1.08**	209	0.28
David Jones	**0.05**	1.00	0.07	**0.76**	209	0.45
eBay	**0.07**	0.79	0.05	**1.22**	208	0.22
Emirates	**0.11**	0.95	0.07	**1.68**	207	0.09
Expedia	**0.09**	0.97	0.07	**1.28**	210	0.20
Flight Centre	**0.15**	0.94	0.06	**2.38**	216	0.02
Harvey Norman	**0.08**	1.03	0.07	**1.07**	208	0.28
Hotels Combined	**-0.08**	1.13	0.08	**-0.98**	208	0.33
JB Hi-Fi	**0.09**	0.97	0.07	**1.27**	210	0.20
Jetstar	**0.08**	0.92	0.06	**1.20**	210	0.23
Kmart	**0.05**	1.06	0.07	**0.71**	211	0.48
Myer	**0.03**	0.94	0.06	**0.51**	210	0.61
Qantas	**0.07**	0.94	0.06	**1.02**	212	0.31
Singapore Airlines	**0.04**	0.94	0.06	**0.59**	210	0.56
Skyscanner	**-0.03**	0.72	0.05	**-0.58**	208	0.56
Target	**-0.03**	0.94	0.07	**-0.51**	207	0.61
Tigerair	**0.08**	0.80	0.06	**1.37**	208	0.17
TripAdvisor	**0.14**	1.04	0.07	**1.98**	212	0.05
Trivago	**0.07**	0.95	0.07	**1.08**	212	0.28
Virgin Airlines	**0.10**	0.75	0.05	**2.02**	211	0.04
Webjet	**-0.01**	0.89	0.06	**-0.15**	210	0.88
Wotif	**0.00**	1.01	0.07	**0.00**	207	1.00

Table A1-2

Brand Familiarity change survey 1 to survey 2

Paired Samples Test

Brand	Paired Differences Familiarity			t	df	Significance
	Mean	Std. Deviation	Std. Error Mean			Two-Sided p
Agoda	**-0.06**	0.82	0.06	-1.10	207	0.27
Air Canada	**-0.02**	0.92	0.06	-0.38	207	0.71
Air New Zealand	**-0.03**	0.88	0.06	-0.47	209	0.64
Amazon	**0.02**	0.90	0.06	0.31	205	0.76
Big W	**0.02**	1.26	0.09	0.22	210	0.83
Booking.com	**0.10**	0.94	0.06	1.55	209	0.12
David Jones	**-0.01**	1.21	0.08	-0.17	209	0.86
eBay	**0.01**	0.89	0.06	0.23	208	0.82
Emirates	**0.13**	0.97	0.07	1.94	207	0.05
Expedia	**0.18**	0.92	0.06	2.83	210	0.01
Flight Centre	**0.19**	1.00	0.07	2.85	216	0.00
Harvey Norman	**0.05**	1.21	0.08	0.63	208	0.53
Hotels Combined	**-0.03**	1.05	0.07	-0.39	208	0.69
JB Hi-Fi	**0.06**	1.05	0.07	0.78	210	0.43
Jetstar	**0.03**	0.92	0.06	0.52	210	0.60
Kmart	**0.04**	1.35	0.09	0.41	211	0.68
Myer	**0.04**	1.25	0.09	0.49	210	0.62
Qantas	**0.14**	0.92	0.06	2.15	212	0.03
Singapore Airlines	**0.04**	0.91	0.06	0.68	210	0.50
Skyscanner	**0.06**	0.70	0.05	1.18	208	0.24
Target	**0.04**	1.23	0.09	0.45	207	0.65
Tigerair	**0.16**	1.02	0.07	2.24	208	0.03
TripAdvisor	**0.24**	1.03	0.07	3.46	212	0.00
Trivago	**0.13**	1.03	0.07	1.80	212	0.07
Virgin Airlines	**0.03**	0.86	0.06	0.48	211	0.63
Webjet	**0.09**	0.93	0.06	1.41	210	0.16
Wotif	**0.03**	0.92	0.06	0.53	207	0.60

Survey characteristics

The below tables show the survey characteristics and provide a deeper overview of the data.

Table A1-3

Brand Level Liking and Familiarity Descriptive Statistics

	Mean	Std Dev
Total online activity	8342	11878
Visits for selected brands	.98	6.36

Table A1-4

Respondent Gender

Gender	Percentage of respondents
Male	48.6%
Female	41.1%
Unknown	9.9%

Table A1-5

Distribution of Respondent age

Age range	Percentage of respondents
21 - 30	7.5%
31 - 40	20.6%
41 - 50	26.5%
51 - 60	15.8%
61+	19.8 %
Unknown	9.9%

The key survey metrics of liking and familiarity are used as measures of affect and cognition, respectively. Each is measured on a five-point rating scale. Details can be seen in Table A1-6.

Table A1-6

Brand Level Liking and Familiarity Descriptive Statistics

Airlines				
	Mean Liking	*Mean Familiarity*	*Std. Dev Liking*	*Std Dev Familiarity*
Brands				
Qantas	3.74	3.72	.869	1.010
Virgin Airlines	3.44	3.24	.978	1.134
Jetstar	*2.72*	*3.07*	*1.031*	*1.120*
Tigerair	1.94	2.24	1.042	1.140
Singapore Airlines	3.26	2.48	1.164	1.341
Emirates	3.19	2.43	1.064	1.189
Air New Zealand	3.04	2.18	1.087	1.180
Air Canada	1.90	1.21	1.451	1.103

Hotel Booking				
	Mean Liking	*Mean Familiarity*	*Std. Dev Liking*	*Std Dev Familiarity*
Brands				
Trip Advisor	3.01	2.86	1.119	1.300
Booking.com	2.90	2.86	1.203	1.371
Flight Centre	2.85	2.89	1.026	1.171
Expedia	2.73	2.64	1.180	1.361
Hotels Combined	2.26	2.0	1.026	1.171

Skyscanner	1.40	1.31	1.727	1.696
Webjet	2.67	2.64	1.114	1.248
Trivago	2.87	2.68	1.041	1.196
Wotif	2.45	2.64	1.329	1.450
Agoda	**1.31**	**1.23**	**1.530**	**1.528**

	Retail			
	Mean Liking	*Mean Familiarity*	*Std. Dev Liking*	*Std Dev Familiarity*
Brands				
Amazon	2.80	2.66	1.157	1.292
Ebay	3.70	3.85	.973	1.070
Big W	3.19	3.24	.979	1.256
David Jones	2.47	2.52	1.118	1.282
Target	3.11	3.25	1.102	1.316
Myer	2.85	3.03	1.102	1.316
Harvey Norman	2.83	3.02	1.001	1.188
JB Hi-Fi	3.61	3.65	.941	1.076
Kmart	**3.45**	**3.46**	**.981**	**1.161**

The patterns seen at the category level are largely replicated when looking at a brand level. That is for airlines; Liking is generally higher than familiarity; the exception to this is the budget airlines of Tiger and Jetstar. Within the booking category, the levels are very similar, with only Wotif showing lower levels of liking. For the retail sector, liking is generally lower than familiarity, with Amazon the only brand where liking is higher. Amazon may be somewhat different in the Australian market as although it is a widely used and well-known brand, it only officially launched in Australia in 2017 (*Mashable, 2017)*

Appendix 2: Set-up Process for Behavioural Data

Raw Passively Captured Data Tables

To extract the key metrics selected, the data needs to be cleaned, in particular the passive data, which comes in a highly individual-level form. The behavioural data have been exported from TEG SQL database. This provides a number of tables with the core data. Each of these is discussed below, and then a detail of how these data are manipulated is provided.

The core data are shown in Table 6: Web Page Views shows the data in the main table. This creates the foundation of the data for analysis as each visit for each respondent is included. This data contains 8,077,463 cases showing the number of visits across all websites that our respondents made on desktop.

Table A2-1

Web Page Views

Data	Description
Panel ID	ID for respondent number
URLs	Full URL
Used at	Timestamp
Duration	How long the respondent was active on the website
Id	ID to link to aggregated Web visits data

To complement the core table, a simplified version is also provided, shown in Table A2-2; the data included is the same, except the Domain is given rather than the full URL, e.g. qantas.com.au rather than https://www.qantas.com/au/en/frequent-flyer/log-in.html?referrer=https%3A%2F%2Fwww.qantas.com%2Fau%2Fen%2Ffrequent-flyer%2Fyour-account%2Fbookings.html. This is useful for identifying which brand a website is linked to. These data aggregate all page views during a website visit and, therefore, has a lower number of cases, 890,686.

Table A2-2

Web Visits

Data	Description
Panel ID	ID for respondent
Domain	Domain
Used at	Time Stamp
Duration	How long the respondent was active on the website
Page views	Calculated field of pageviews
Id	ID to link to aggregated Web visits data

The third table provided covers the search terms. The measures are shown in Table A2-3. These data have extracted the search terms from the URL.

Table A2-3

Search Terms

Data	Description
Panelist_ID	ID for respondent
Device_ID	ID for device
URL	Webpage only
Domain	Domain
App_ID	ID for App used
Used_At	Time Stamp
Connection	Wifi or through network
Duration	Time on
ID	Visit ID
Search term	Search extracted

The final two tables, Table A2-4 and Table A2-5, provide the data for non-desktop visits. Table A2-4 provides the visits for the non-desktop users. The app category is used as the basis for which category a brand is in.

Table A2-4

App Visits

Data	Description
Panelist_ID	ID for respondent
Device_ID	ID for device
App_Name	Name of the App
App_os	The operating system for the App
App_ID	ID for App used
Used_At	Time Stamp
Connection	Wifi or through network
Duration	Time on
App_Cat	Category of the App
App_Id	ID code for App

The key difference with mobile data is that the long URL is not captured, so we only know the domain that is visited.

Table A2-5

Mobile Views

Data	Description
Panelist_ID	ID for respondent
Device_ID	ID for device
Domain	Domain
Used_At	Time Stamp
Connection	Wifi or through network
Duration	Time on

Merging data

The full webpage visits data are used as the full URL is required to understand where the visitors came from. This is then merged with the more aggregate data of website visits using respondent ID and time. This provides the domain which is used to classify if the brand is a target for the research (collected in the survey). App and Mobile data are appended to this file so that all visits for respondents are captured in a single file. This provides a single file with the following metrics:

Key variables in both files:

- Panelist_ID
- URL
- Duration
- Used_At
- Connection
- App_Name
- App_Category

This file is then sorted by respondent ID and time so that a full picture of online activity can be assessed for each respondent.

Figure A2-1 depicts an example of passively captured behavioural data.

Figure A2-1

Example of Data to be Used for the Study.

url	used_at	active_seconds	Gender	Age	State	Metro Regional	Birth date	region	postcod	household type	marital status
oddschecker.com/horse-racing	17/03/2017 19:19	6	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
tab.com.au/racing/2017-03-17/MOONEE-VALLEY/MVA/R/7	17/03/2017 19:19	2	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
odds.com.au/odds/horse-racing/australia/moonee-valley_96328	17/03/2017 19:19	6	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
webmd.com/digestive-disorders/tc/diverticulitis-topic-overview#1	17/03/2017 19:19	22	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
crownbet.com.au	17/03/2017 19:19	1	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
ezydvd.com.au	17/03/2017 19:19	11	male	40	QLD	R	1/02/1977	Other QLD	4210	Family household	Single
odds.com.au/odds/horse-racing/australia/moonee-valley_96328	17/03/2017 19:19	1	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
crownbet.com.au	17/03/2017 19:19	5	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
cardgamesolitaire.com	17/03/2017 19:19	2	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
ezydvd.com.au	17/03/2017 19:19	23	male	40	QLD	R	1/02/1977	Other QLD	4210	Family household	Single
google.com.au/?gfe_rd=cr&ei=5ZvLWLTvEY7r8wfytLiYCg&gws_rd=ssl#q=diverticulitis&*&spf=39	17/03/2017 19:19	12	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
crownbet.com.au	17/03/2017 19:19	2	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
crownbet.com.au/racing	17/03/2017 19:19	14	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
google.com.au/?gfe_rd=cr&ei=5ZvLWLTvEY7r8wfytLiYCg&gws_rd=ssl#q=can+diverticulitis+cause	17/03/2017 19:19	30	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
ezydvd.com.au/search?q=the+baron&t=all	17/03/2017 19:19	26	male	40	QLD	R	1/02/1977	Other QLD	4210	Family household	Single
crownbet.com.au/racing/horse-racing/moonee-valley/20170317/race-7-545504-20634608	17/03/2017 19:20	30	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
ezydvd.com.au/search?q=the+champions&t=all	17/03/2017 19:20	18	male	40	QLD	R	1/02/1977	Other QLD	4210	Family household	Single
topix.com/forum/health/diverticulitis/TVV4UEPQ86IJSJP98	17/03/2017 19:20	2	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
facebook.com	17/03/2017 19:20	10	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
facebook.com/photo.php?fbid=10154863899440310&set=a.105478635309.123163.649935309	17/03/2017 19:20	20	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
ezydvd.com.au/search?q=the+champions&page=2	17/03/2017 19:20	20	male	40	QLD	R	1/02/1977	Other QLD	4210	Family household	Single
facebook.com	17/03/2017 19:20	4	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
facebook.com/groups/IWBSS?multi_permalinks=620634588060450&notif_t=commerce_interes	17/03/2017 19:21	8	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
facebook.com/groups/IWBSS/forsaleposts?story_id=620170528106856&__xt__=27.%7B%22vie	17/03/2017 19:21	20	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
jbhifi.com.au/movies-tv-shows/tv-shows?q=the%20baron&	17/03/2017 19:21	14	male	40	QLD	R	1/02/1977	Other QLD	4210	Family household	Single
jbhifi.com.au/movies-tv-shows	17/03/2017 19:21	26	male	40	QLD	R	1/02/1977	Other QLD	4210	Family household	Single
facebook.com/groups/IWBSS?multi_permalinks=620634588060450&notif_t=commerce_interes	17/03/2017 19:21	10	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
facebook.com/groups/IWBSS/forsaleposts?story_id=620620984728477&__xt__=27.%7B%22vie	17/03/2017 19:21	4	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
facebook.com/groups/IWBSS/permalink/620620984728477?sale_post_id=620620984728477	17/03/2017 19:21	2	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
facebook.com/groups/IWBSS/permalink/620170528106856?sale_post_id=620170528106856	17/03/2017 19:21	10	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
betfair.com.au/exchange/plus#/golf/market/1.130296973	17/03/2017 19:21	1	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
jbhifi.com.au/computers-tablets	17/03/2017 19:21	48	male	40	QLD	R	1/02/1977	Other QLD	4210	Family household	Single
betfair.com.au/exchange/plus#/golf/market/1.130296972	17/03/2017 19:21	9	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto
facebook.com/groups/IWBSS/permalink/620620984728477?sale_post_id=620620984728477	17/03/2017 19:21	40	male	48	VIC	M	22/11/1968	Melbourne	3121	Family household	Married De facto
au.yahoo.com/?p=us	17/03/2017 19:22	2	male	47	VIC	M	22/01/1970	Melbourne	3054	Family household	Married De facto

Identifying key brands

All coding has been completed using SPSS, which allows for a mixture of automated coding and manual intervention. Having full visibility of the raw data has been key to this process. As URLs have a fixed format, it has been possible to identify if the website is for a key brand by coding the data where the URL contains the brand name, for example, Qantas. Most of the brands have multiple URLs that can be used, for example, amazon.com and amazon.com.au; although there is some difference to the advertiser, we do not want to count these as different visits; therefore, the latter part of the domain is excluded from the coding. Virgin has a frequent flyer program called Velocity, and this is also included as a visit to Virgin.

Some cleaning is still required after this process. Not all the site visits are to key sites, for example, Aws, as this is often used for storage in particular with s3 (use of S3 buckets) producing URLs including Amazon.

's3-ap-southeast-2.amazonaws.com/com.pureprofile.sp/Projects/Decipher/190106/14-TigerCrustPepperoni.png'

These have been removed from the visits as these are not real visits to a website and are more related to data collection that occurs on a website. There are also associated brands that are outside the category of interest, for example, virgin money and virgin active. These have been classified as an associated visits to enable easy distinction. Prime video is not included as Amazon but is treated as an affiliate relationship.

Determining a visit occasion

Through the data set, we can see each page and associated URL visits. To create the dependent variable of the number of visits, a visit needs to be defined. Two options were considered firstly to count the number of days in the time period that a respondent visited. The problem with this approach is that it is common for respondents to have multiple visits to a website in a day through different routes, e.g. firstly, brand search and then a direct visit. Hence to allow for consistency and extension of the research to include the route to the website, a visit is defined in line with the approach taken in Google analytics (n.d.)

- A time window of 30 minutes has been applied. If a visit occurs after this break, it is classified as a new visit.
- Except if a search occurs within a 30-minute window, this will be counted as a new visit.

Other information

Previously collected information about the respondent is also available but has not been utilised as part of this research.

- Gender
- Age
- Marital status
- Metro/Regional
- State
- Postcode
- Household type
- Pets

This final data set provides details of each visit a respondent has made. As part of this research, I have calculated the total number of visits before and after the survey for each brand that was included in the survey, I have also summarised the total visits that a respondent has made to any website. From this data it is possible to understand the time between visits, how many visits are made to a category in total and total share of visits. Further coding allows us to see the route a respondent has taken to the website, for example direct to website, branded search generic search or through advertising clicks. This data availability has been taken into account for the recommendations of further research.

Appendix 3: Additional Model Detail

Two sets of models have been run that were not included in the final output. Firstly, a linear regression is run to show the VIF scores demonstrating that they do not cross the threshold of five. Secondly hurdle models were run using advertising awareness for comparison with the aggregate models of (Hanssens et al., 2014; Srinivasan et al., 2010) showing that this is not a suitable replacement for brand awareness when modelled at an individual level.

VIF checks

The complex causality within mindset metrics does present a risk of multicollinearity. The most common approach to testing for this within models is using the Variance Inflation Factor (VIF), shown in the following equation (Tamura et al., 2019). Caution should be taken for values greater than 5.

$$VIF = \frac{1}{1-R^2} \tag{4}$$

As R^2 is not used as a measure within hurdle models, therefore models were run independently to check the VIF scores. Despite the correlations being somewhat high the VIF scores are within the acceptable range therefore both liking and familiarity are maintained in the models.

Table A3-1

Linear Regression Results to Show VIF for Each Model

Category		Collinearity Statistics Tolerance	VIF
Airlines	Past Experience	0.764	1.310
	Affect (Liking)	0.461	2.169
	Cognition (Familiarity)	0.402	2.486
	Mobile	0.870	1.149
	Mobile & Desktop	0.898	1.113
	Total Internet Usage	0.804	1.243
	Local Airlines	0.749	1.335
Hotel Booking	Past Experience	0.846	1.182
	Affect (Liking)	0.304	3.286
	Cognition (Familiarity)	0.297	3.369
	Mobile	0.895	1.117
	Mobile & Desktop	0.926	1.080
	Total Internet Usage	0.811	1.234
Retail	Past Experience	0.699	1.430
	Affect (Liking)	0.529	1.891
	Cognition (Familiarity)	0.530	1.887
	Mobile	0.874	1.145
	Mobile & Desktop	0.902	1.109
	Total Internet Usage	0.716	1.397
	Online retail only	0.916	1.092

a. Dependent Variable: Visit frequency

As an additional check I have conducted a crosstabulation of liking and familiarity shown in Figure A3-2, Although there is a strong number of cases on the leading diagonal (especially those cases with no familiarity or liking) there are plenty of cases with both a liking level higher than familiarity and a familiarity level higher than liking. This suggests indicates that the approach without a funnel should be able to explain more variation as it is a dynamic that cannot be account for without two independent scales.

Table A3-2

Crosstabulation of Liking and Familiarity to Check for Variation

Affect and Cognition Crosstabulation

Category			Cognition **0**	**1**	**2**	**3**	**4**	**5**	Total
Airlines	**Affect**	**0**	153	0	0	0	0	0	153
		1	0	69	49	23	13	1	155
		2	0	118	109	52	18	5	302
		3	0	134	254	220	108	27	743
		4	0	23	76	163	217	49	528
		5	0	1	3	17	52	77	150
	Total		153	345	491	475	408	159	2031
Hotel Booking	**Affect**	**0**	465	1	1	6	1	0	474
		1	0	53	25	11	5	2	96
		2	0	113	172	109	29	5	428
		3	0	81	345	456	166	17	1065
		4	0	1	22	116	213	85	437
		5	0	0	1	7	21	63	92
	Total		465	249	566	705	435	172	2592
Retail	**Affect**	**0**	54	0	0	0	0	0	54
		1	0	67	32	23	8	5	135
		2	0	86	116	91	26	15	334
		3	0	44	212	374	237	72	939
		4	0	3	29	130	299	146	607
		5	0	0	4	15	42	150	211
	Total		54	200	393	633	612	388	2280

Models with Advertising awareness

Advertising awareness was also included in the models to test for significance as a comparison to prior research. As this did not align with the theoretical approaches of how advertising works it is not included as a key model. However, it can be seen that advertising awareness is not significant. That is it may play a role in driving other CMMs but it is not important in our understanding of who is likely to visit a website.

Table A3-3

Model with advertising awareness included across each category

	Airlines		Retail		Accommodation Booking	
	count	zero	count	zero	count	zero
Intercept	−3.471**	−8.776***	−13.678	−7.072***	−15.098	−7.166***
	(1.167)	(0.795)	(62.928)	(0.457)	(158.448)	(0.572)
Total Internet Usage	0.136	0.464***	0.033	0.429***	0.118	0.380***
	(0.106)	(0.078)	(0.073)	(0.046)	(0.138)	(0.060)
Past Experience	1.257***	2.372***	1.859***	1.678***	1.118***	1.465***
	(0.330)	(0.195)	(0.282)	(0.125)	(0.327)	(0.154)
Advertising Awareness	0.167	−0.132	−0.032	−0.247	0.262	0.058
	(0.264)	(0.208)	(0.208)	(0.128)	(0.304)	(0.164)
Cognition (Familiarity)	0.483***	0.420***	0.265*	0.240***	0.586***	0.066
	(0.144)	(0.101)	(0.106)	(0.063)	(0.175)	(0.089)
Affect (Liking)	0.008	0.187	0.448***	0.256***	0.139	0.390***
	(0.179)	(0.112)	(0.128)	(0.075)	(0.263)	(0.101)
Desktop & Mobile	0.212	−0.291	1.253***	−0.013	0.512	−0.101
	(0.270)	(0.217)	(0.267)	(0.147)	(0.384)	(0.200)
Mobile	−2.585**	−1.078**	0.584	−0.269	−1.434	−1.380***
	(0.797)	(0.382)	(0.321)	(0.178)	(0.845)	(0.400)
Log(theta)	−1.125*		−11.861		−12.485	
	(0.451)		(62.924)		(158.442)	
AIC	1794.59		4891.52		2230.52	
N	2031		2280		2592	

Significance: *** = p < 0.001; ** = p < 0.01; * = p < 0.05