Is suggestive branding…suggested?

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Declaration

I declare that this thesis presents work carried out by myself and does not incorporate, without acknowledgement, any material previously submitted for a degree or diploma in any university. To the best of my knowledge, it does not contain any materials previously published or written by another person except when due reference is made in the text and all substantive contributions by others to work presented, including jointly authorised publications, are acknowledged.

Larissa Mae Bali

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Abstract

This thesis aims to establish the prevalence of suggestive brand names, and the prevalence and effectiveness of suggestive Distinctive Brand Assets. Prevalence refers to how often suggestiveness is seen in the market in various contexts (i.e., different categories, industries, and countries). Effectiveness relates directly to how well-known the suggestive Distinctive Asset branding is ('Fame') and how well it is associated with the correct brand ('Uniqueness').

Whilst there are many strategies a marketer could adopt, almost three-quarters of industry practitioners see suggestive brand names as a better alternative to non-suggestive brand names (Romaniuk, 2022). Although literature has explored suggestiveness for over one hundred years (Viehoever, 1920), including seminal branding work by Keller et al. (1998) and more recent research (Gunasti et al., 2020), there has been little evidence of their usage in the market (Arora et al., 2015), and nothing on the effectiveness of suggestive Distinctive Assets as a branding tool.

Specifically, this thesis provides two studies with original contributions:

- Determining the prevalence of suggestive names and non-name elements (Distinctive Assets, e.g., logos) across different categories, industries, and countries.

- Examining the effectiveness of suggestive Distinctive Assets as a branding tool, including quantifying the performances among asset types (e.g., logo vs tagline) in different categories and industries.

- Undertaking and assessing a novel approach to data collection through artificial intelligence, harnessing GPT-3.5, GPT-4, GPT-4V and GPT-4o.

The first study determines the prevalence of suggestive brand names, and the prevalence and effectiveness of suggestive Distinctive Assets.

Study 1: How prevalent are suggestive brand names and Distinctive Assets? An AI-human approach

Study 1 examines 4,611 brand names across 244 categories in three industries and three countries to understand the prevalence of suggestive brand names across various contexts. Data is collected through scraping brand names from major online retailers in Australia, the United States and the United Kingdom. The study determines if marketers' beliefs on the importance of suggestive branding (Romaniuk, 2022) translate into implementation. The results indicate that suggestiveness is seen in market, however less commonly than non-suggestive counterparts, constituting an average 28% of the brands in the market. When extending, for the first time, an examination of 597 Distinctive Assets across 12 categories, four industries, and three countries – finds suggestiveness comprises, on average, 38%.

The prevalence of suggestive direct and indirect branding is low. However, the most prominent variance was for direct branding across industries, wherein durables scored the lowest prevalence (10%), followed by consumer goods (20%), and services substantially higher (56%). Further, the sub-optimal outcomes for suggestive Distinctive Assets substantiate the choice not to implement suggestive branding. Across all industries analysed, suggestive assets perform inferior to non-suggestive assets – although differences in Fame and Uniqueness performance are minor. Study 1 thus finds that whether a marketer uses suggestive or non-suggestive branding should not have a revolutionising impact on their brand.

This study was undertaken at an overarching level in the context of Distinctive Assets. As a study on the effectiveness of suggestive Distinctive Assets had never been undertaken before (nor had a prevalence study), it was essential to establish initial benchmarks. A deeper exploration into the data is necessary to determine whether, under different circumstances, suggestive or non-suggestive Distinctive Assets may be more effective. Thus, study 2 examines the effectiveness across Distinctive Asset types.

Study 2: Evaluating Suggestive Distinctive Asset Types

Study 2 quantifies the effectiveness (i.e., Fame and Uniqueness) for all Distinctive Asset types (e.g., taglines and logos) and compares the performance between suggestive/non-suggestive elements. The Distinctive Asset data is expanded to 1,162 assets across 21 categories and four industries to determine these findings robustly. These were secondary data collected from independent studies commissioned by a market research company. The second study aims to determine whether there are instances wherein suggestive Distinctive Assets may be of benefit to use as opposed to non-suggestive, and vice versa. Findings indicate circumstantial benefits in using suggestive Distinctive Assets, as there are with non-suggestive.

Overall, findings show that shape-based Distinctive Assets performed the strongest and colour the worst, with the rest of the asset types performing similarly (i.e., audio, word, story, face, and design-based elements). When analysing suggestiveness, shape had small and medium effect sizes (Fame: d=0.48 Uniqueness: d=0.66) and word-based assets produced medium and large effect sizes (Fame: d=0.62 Uniqueness: d=0.84), with both asset types performing best as non-suggestive. Conversely, audio and design assets performed best as suggestive. Study 2 offers deeper insights into the results of Study 1, highlighting that suggestive and non-suggestive Distinctive Assets each have their place in branding strategy, with effectiveness contingent on type.

These two studies formulate the crux of this thesis. Each was initially written as a pilot study, peer-reviewed, and presented as a conference paper at the Australian and New Zealand Marketing Academy (ANZMAC) 2023 in Dunedin, New Zealand. Study 1 has been accepted into the International Journal of Market Research. Study 2 is under review in the Journal of Advertising Research. Both journals are A-Level on the Australian Business Deans Council 2022 list. One further conference paper on GPT-4(Visual) has been presented at the Informs Society for Marketing Science (ISMS) 2024 in Sydney, Australia. Each study is presented in this thesis.

The findings derived from this thesis deliver critical implications:

- As a minority of brand names (28%) and Distinctive Assets (40%) are suggestive, marketers should re-evaluate whether their beliefs are adequately reflected through their end branding strategy.
- Use of a human-in-the-loop approach has effectively reduced monetary costs and increased the efficiency of data collection, so future researchers can endeavour to adopt a similar method in their research.
- The exploratory nature of the studies has meant several foundational benchmarks have been established; thus, the groundwork has been laid for future researchers to replicate and extend upon the research.
- The differences in performance across Distinctive Asset types indicate that marketers should tailor their branding strategies to favour the more effective types.

Contents

Tables

Figures

Chapter 1
Introduction

Chapter overview

Chapter 1 aims to summarise the contents of this thesis. At first, it discusses the importance of exploring suggestive brand names and non-name elements in branding practice. Then, it outlines the two studies comprising this thesis, accompanied by their respective research questions, methods, and key findings. A top-level summary of the thesis is subsequently provided, followed by the structural contents of each chapter.

1 Thesis Overview

1.1 Research Background

Researchers have explored suggestive brand names for over 100 years (Viehoever, 1920). However, the area has only gained traction in marketing in the past two decades, following the work of Keller et al. (1998). The extant research focuses on one aspect of branding: the name. To date, researchers have neglected suggestive non-brand name elements (i.e., Distinctive Assets). Distinctive Assets include any branding element that is not the name (e.g., jingles, slogans, and logos). For both the name and Distinctive Assets, suggestive branding involves deliberately embedding a product and/or category-related attribute or benefit to leverage existing memory structures – adapted from Keller et al. (1998). Burger King is an example of a suggestive brand, containing a suggestive name and suggestive Distinctive Asset (i.e., its logo).

Marketing practitioners see value in using suggestive brand names; 73% believe suggestive names are of better use than non-suggestive names when launching a new brand (Romaniuk, 2022). With almost three-quarters of marketers upholding this view, there is a natural belief that suggestive brands would be used in the market. However, this has yet to be observed. Knowledge on the matter is limited to one study using a small data set, with findings indicating that 15% of the top 500 global brand names are suggestive (Arora et al., 2015). These initial and limited findings show a disconnect between marketers' beliefs about suggestive names and their use in practice.

Not only do we need more research into the prevalence of suggestive brands, there is also a notable lack of research into the effectiveness of suggestive branding. We can measure performance in many areas of marketing, for instance, through market share or distribution, to understand the size of a brand and compare it to others (Wilbur & Farris, 2014). Specifically, metrics like Fame and Uniqueness can be used to determine the strength of a brand's Distinctive Assets relative to its competitors (Romaniuk & Nenycz-Thiel, 2014). These measures can subsequently inform marketers of the strength of suggestive and non-suggestive branding elements.

Human power, combined with artificial intelligence (i.e., a human-in-the-loop approach), can guide the processing of large amounts of data more accurately, quickly, and cost-efficiently (Wu et al., 2022). Thus, the guidance and power of artificial intelligence enables the analysis of an expansive dataset to calculate the prevalence of suggestive branding.

Subsequently, this thesis aims to robustly determine how often suggestive branding elements are used and how their effectiveness as a branding vehicle compares to non-suggestive alternatives.

1.2 Research questions, methods, key results and implications

This thesis comprises two studies that determine the prevalence and effectiveness of suggestive branding from an overall and specific level. Each study is outlined below with the research questions, method and key findings.

1.2.1 Study 1: how prevalent are suggestive brand names and Distinctive Assets? An AI solution

This first study aims to robustly determine the prevalence of suggestive branding in the market and the effectiveness of this strategy. As such, data for over 4,000 brand names and almost 600 Distinctive Assets was analysed. Multiple industries were included (i.e., consumer goods, durables, services, and retailers) across three key countries (i.e., Australia, the United Kingdom, and the United States) to ensure both breadth and depth in data quality. Artificial intelligence (Chat GPT-4) was employed to code for brand name suggestiveness, subsequently reviewed by humans (human-in-the-loop approach), and human researchers were solely used to code for Distinctive Asset suggestiveness.

1.2.1.1 Research Questions

RQ1: What is the prevalence and variance of suggestive brand names?

RQ2: What is the prevalence of suggestive Distinctive Assets?

RQ3. What are the Fame and Uniqueness scores of suggestive and non-suggestive Distinctive Assets, and are there any differences between them?

1.2.1.2 Method

The study included 4,611 brand names across 244 categories and diverse industries, collected from major online retailers (e.g., Coles and Woolworths for Australian consumer goods). After data collection, artificial intelligence classified them as either suggestive or non-suggestive. To determine the best approach, GPT-3.5, GPT-4, and research assistants were tested against the benchmark identified by researchers and experts, with GPT-4 found to be the closest performing. Chat GPT-4 was prompted with the definition of suggestive branding and other critical information, such as the category and accompanying list of brands. The results of GPT-4 were then reviewed, utilising a human-in-the-loop approach to distil the most accurate results. For the 597 Distinctive Assets, human coders applied the same process (classifying each element as suggestive or non-suggestive) since GPT-4 needed more sophistication to process all this data efficiently. The process allowed for data collection on the prevalence of suggestive branding.

The Distinctive Asset dataset came from an internal repository, which also provided Fame and Uniqueness metrics; these metrics were subsequently used to determine whether suggestive or non-suggestive Distinctive Assets scored the strongest.

1.2.1.3 Key findings

Suggestive brand names had an average prevalence of 28%, with most industries scoring lower (i.e., consumer goods and durables) and some raising the score (i.e., services). The prevalence of suggestive Distinctive Assets was higher at 38%. Suggestive Distinctive Assets performed weaker than non-suggestive ones across all industries, as indicated by Fame (27% vs. 43%) and Uniqueness (30% vs. 63%). Thus, despite being preferred by marketers (Romaniuk, 2022) and proposed as a viable option in literature (Gunasti et al., 2020; Keller et al., 1998), suggestive branding was less prevalent and effective.

1.2.2 Study 2: What Distinctive Brand Assets work best? Using an AI-human approach to evaluate assets according to type and suggestiveness

Study 2 builds on Study 1 by examining the intricate differences in Distinctive Asset performance based on asset type. While Study 1 does this on an aggregate level, this study addresses whether suggestive Distinctive Assets are effective to use in specific circumstances. Visual assets (e.g., logos) and auditory assets (e.g., jingles) are processed differently in memory (Crutcher & Beer, 2011), which may impact the effectiveness of suggestive branding. The study solely used humans for data collection of Distinctive Asset type effectiveness and incorporates a human-in-the-loop approach (with Chat GPT-4o) for the suggestiveness of Distinctive Assets.

1.2.2.1 Research Questions

RQ1: What are the Fame and Uniqueness scores across Distinctive Assets?

RQ2: To what extent, if any, do visual-based Distinctive Assets perform better than word or audio-based Distinctive Assets?

RQ3: What, if any, are the differences in the performance of suggestive and non-suggestive Distinctive Asset types?

1.2.2.2 Method

This study analyses 1,162 assets, containing seven asset types, across 21 categories (e.g., salty snacks and cars), four industries (i.e., consumer goods, durables, services, and retailers), and three countries (i.e., Australia, the United Kingdom, and the United States). The same internal data repository is used as in Study 1. However, almost double the amount of data is analysed. The Distinctive Assets are then classified into asset types (i.e., shapes, story, word, face, design, colour, and auditory). The performance of each of the asset types is then determined to compare their effectiveness on an overall level.

From there, all Distinctive Assets are classified into suggestive or non-suggestive elements (excluding colour assets, which are all non-suggestive). Replicating the process from Study 1, a human-in-the-loop approach was undertaken, wherein three suggestiveness experts coded for Distinctive Asset suggestiveness separately, then discussed differences and created a final benchmark. The benchmark was used to compare against GPT-4o, and any differences were reviewed by the primary researcher to produce a final classification list. The performance of different suggestive and non-suggestive asset types is then extracted to determine whether suggestive assets perform better/worse than non-suggestive assets.

1.2.2.3 Key findings

Overall, the average Distinctive Asset scores Fame and Uniqueness of 26% and 54%, respectively, with a slight positive skew, meaning that an asset will often score beneath these percentages.

The visual-based asset, shape, was the top performer in Fame and Uniqueness metrics, and colour-based assets were the lowest performers. Most visual-based assets (i.e., shape, story, and design) scored higher than word and audio elements, confirming the picture superiority effect. However, face and colour, also visually based, scored lower. Apart from shape and colour, all other element types (i.e., story, design, word, audio, and face) performed similarly; therefore, differences between these asset types were negligible. Subsequently, the picture superiority effect, for the most part, holds.

Specifying into suggestive and non-suggestive Distinctive Asset types, shape and word-based elements were statistically significant, and both performed better as non-suggestive. Audio assets performed more effectively as suggestive, and story, face, and design assets performed similarly regardless of suggestiveness.

1.2.3 Implications

Through the two core studies that formulate this thesis, important implications for both academics and practitioners are found:

Prevalence results from Study 1 indicate that all suggestive branding elements (name and Distinctive Assets) are seen less often than non-suggestive ones (28% and 40%, respectively). However, almost three-quarters of marketing practitioners believe being meaningful (or suggestive) is a better alternative. Subsequently, there is a mismatch between beliefs and execution when it comes to suggestive branding, and marketers should endeavour to minimise that gap to ensure their branding strategy adequately reflects what they aim to achieve.

Both studies use a novel 'human-in-the-loop' approach to data collection, effectively reducing time and monetary costs whilst boosting accuracy. Past research on brand suggestiveness used small samples and datasets, avoiding any issues that would arise at a larger scale. However, the trifecta success demonstrated through these two studies should prompt future researchers to adopt a similar method, where possible.

Study 2 determines differences in the performance of Distinctive Asset types, which again differ based on their suggestiveness. Considering this new information, marketers should leverage specific Distinctive Asset types based on their performance and suggestiveness.

Both studies are highly exploratory and thus provide several foundational benchmarks on the prevalence and effectiveness of branding elements that academics can use in replicative studies and practitioners can use when determining their branding strategies.

1.3 Structure of the thesis

Chapter 1 summarises the thesis before succinctly detailing the contents of Study 1 and Study 2. It provides a top-level summary of the rest of the thesis.

Chapter 2 explores the memory literature relevant to understanding how suggestive branding works and the differences in Distinctive Asset types. Specifically, it unpacks the overarching theories: Associative Network Theories and Interference Theory.

Chapter 3 comprises of Study 1, which explores the prevalence and effectiveness of suggestive branding elements.

Chapter 4 consists of the standalone abstract on GPT-4V(isual), accepted and presented at a conference.

Chapter 5 contains study 2, an extension of study 1, wherein suggestive Distinctive Assets are broken down by type, and their respective effectiveness is explored. Study 1 and study 2 are isolated due to being submitted to two high-ranking academic journals. As such, they are autonomous in their abstracts, introductions, backgrounds, research questions/hypotheses, methods, results, and discussions.

Finally, Chapter 6 discusses Studies 1 and 2, containing critical academic and industrial implications. It also discusses the limitations of the studies and the scope for future research in the field.

Chapter 2
How Memory Works

Chapter overview

Chapter 2 explains how memory works. It explores key memory theories, including the Associative Network Theories and Interference Theory. Unpacking how the brain works provides an understanding of the benefits and drawbacks of suggestive branding, including brand names and various Distinctive Assets (i.e., non-name element types).

2 How Memory Works

To understand how suggestive branding can be beneficial or limiting, it is important to comprehend how consumers' brains work. In doing so, two key memory theories are explored - Associative Network Theories and Interference Theory. Also discussed are other memory theories that assist or argue with the critical theories explored.

2.1 Associative Network Theories of Memory

Many known theories explain how memory works, such as Associative Network Theories (Collins & Quillian, 1969), Information Processing Theory (Atkinson et al., 1968), Dual Coding Theory (Paivio, 1971), and Levels of Processing Theory (Craik & Lockhart, 1972). However, the most suitable theory for understanding memory is the Associative Network Theories of memory (ANT), with its wide usage and acceptance empirically supported for decades (e.g., Anderson & Bower, 1980; Collins & Quillian, 1969; Romaniuk, 2013; Vaughan et al., 2021). ANT posits that each piece of information (including any brand-related information) stored in memory is represented as a node, all interlinked, forming a weblike associative network (Anderson & Bower, 1979; Collins & Loftus, 1975; Collins & Quillian, 1969).

2.1.1 Linkage to Suggestive Branding

Keller, Heckler & Houston (1998) found that both suggestive and non-suggestive names can be beneficial, depending on the brand's objective. ANT underpins the way suggestive branding can be helpful. Brand knowledge consists of many separate items of brand information that connect to form a network (Collins & Quillian, 1969; Vaughan et al., 2021). Specifically, suggestive branding directly links specific attributes and a brand (Keller et al., 1998). The way these nodes interact with one another and how information gets retrieved is termed Spreading Activation, which occurs when one node is activated and then spreads to other related nodes within the network, all of which have the propensity to be retrieved from memory (Anderson, 1983). The speed at which the spreading occurs depends on the strength of the connections between nodes; thus, if the nodes are only slightly related, then the likelihood of retrieval decreases.

Within a branding context, the stronger the connection between brand-related information and the brand, the easier it is for Spreading Activation to occur, allowing a consumer to retrieve that brand from memory (Hutchinson & Alba, 1991). Often, it is not the brand that gets activated first but rather a need that a brand can fulfil (Romaniuk & Sharp, 2021); for instance, conveniently needing a pair of glasses may lead a consumer to think of Specsavers as they advertise home visits (Figure 1). Furthermore, a brand that uses suggestive branding by associating with an attribute directly related to the brand develops a semantic connection, subsequently making it easier to retrieve the brand from memory (Keller et al., 1998); for instance, when needing a pair of glasses, Specsavers may immediately come to mind (Figure 1).

Specsavers is an example of a brand that taps into suggestiveness with multiple branding elements; its name is suggestive (i.e., combining ‘spectacles’ and ‘savings’), its logo is in the shape of a pair of glasses, and its tagline reinforces its name ‘should’ve gone to Specsavers’. The congruency of the link between the associations means that the information can be learned and remembered more easily (Keller, 1993). Therefore, suggestive branding theoretically makes retrieving the brand from memory easier due to the deliberate embedding of related links to evoke a brand directly in the consumer's mind (Keller et al., 1998).

2.1.2 Application of Associative Network Theories

Figure 1 illustrates a network of memories for someone who needs a pair of glasses. Suggestive branding elements have the benefit of directly linking to their potential needs, for instance, affordability – Specsavers, or even the general need for glasses – Specsavers, both suggested elements captured within the brand name. An abstract but still suggestive glasses-shaped logo may be thought of when prompted by the need for a pair of glasses. That being said, non-suggestive brands can still forge connections through other means, like advertising (Vaughan et al., 2021). Therefore, whilst Specsavers promotes affordability in its name, Boots promotes its glasses through advertisements.

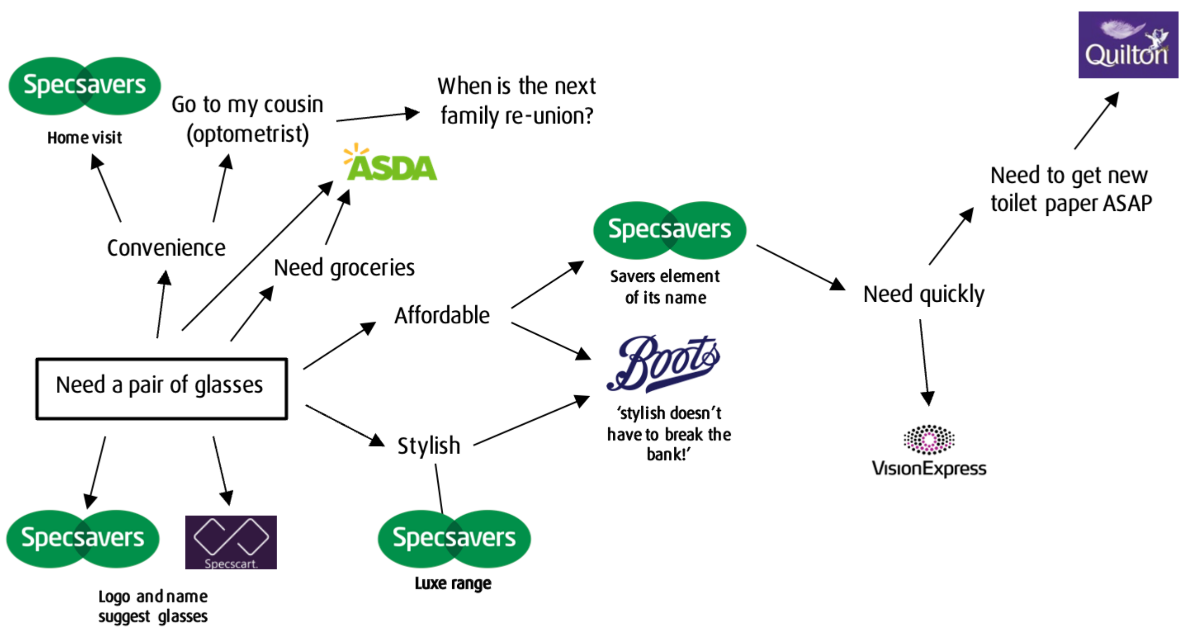

Figure 1: Associative Network for Glasses

Multiple strategies can potentially form links to the associated attribute (Vaughan et al., 2021); the challenge for brands is forming strong links to reach the threshold required to be retrieved in one's memory (Anderson, 1983). Though other branding vehicles like non-suggestive elements can be employed to build strong links, suggestive branding is theoretically advantageous because it reduces cognitive load immediately and directly creates a meaningful association (Carlston, 2007).

2.2 The Picture Superiority Effect

Sitting within ANT is the Dual Coding Theory, which finds memories can be stored as verbal or non-verbal, or a combination of both (Paivio & Csapo, 1971). Non-verbal memories tend to be remembered better, known as the picture superiority effect, seen in critical works, including Childers and Houston (1984) and Paivio and Csapo (1973). Initial studies focused only on comparisons between words and pictures; however, future studies have found that not only words but also audio are inferior to visually based memories (Cohen et al., 2009; Crutcher & Beer, 2011; Ho et al., 2022). Within the context of Distinctive Assets, it is seen that as a subsequent result, visual, word and audio-based assets are stored differently within memory.

2.2.1 Visual, Word and Audio-Based Distinctive Assets

Visual Distinctive Asset types include story (e.g., the specific cartoon style of Redbull's advertisements), face (e.g., George Clooney for Nespresso), shape (e.g., Nike's logo), design (e.g., clear Apple stores), and colour assets (e.g., Coca Cola's red). Word-based Distinctive Asset types can come in the specific form of taglines, fonts, and words. For example, Disneyland's famous tagline: 'the happiest place on earth'. Finally, audio Distinctive Assets can either be sound or music-based, for instance, the Beach Boy's 'Wouldn't it be nice' song used in Cadbury's advertising.

The comparison of the memory effect of words and images has long been explored (Shepard, 1967), and images have always reigned superior in terms of being remembered (Childers & Houston, 1984; Ho et al., 2022). As such, there are decades of confirmation on the picture superiority effect. Specifically, words and pictures can be verbally encoded to memory, but how the encoding occurs differs (Paivio, 1971). The mental advantage of visual assets is providing a vivid and distinct portrayal of the specific brand element that allows for a richer dual encode to memory than words, as the latter cannot tap into as many sensory elements (Paivio & Csapo, 1973). Visual elements benefit from dual-coding, wherein people first see an image and visually encode it, then encode it symbolically in a verbal manner (Crutcher & Beer, 2011). Such a process is impossible with audio or word-based elements, as there is nothing to encode visually, so they can only be processed verbally. Generally, studies investigating the comparative recall of both types find that pictures perform best (Cohen et al., 2009; Paivio et al., 1968). The indication is that, as a subsequent result, visual Distinctive Assets like logos could outperform word or audio-based assets like taglines due to the memory advantages they carry. As found through Interference Theory, specific marketing strategies can also inhibit brand recollection.

2.3 Interference Theory of Memory

Interference Theory is a sub-component of the ANT - referring to when one node interferes with the recollection of another node within an associative web of related information (Murnane & Shiffrin, 1991). There are two primary types of inference: proactive (struggle to remember new information due to past information) and retroactive (struggle to remember past information due to new information) (Postman & Underwood, 1973). For example, if a brand wants to be known for being stylish but now also wishes to be known as affordable, style and affordability would be two separate nodes of information competing to be linked to the brand. Although ANT establishes that memory is a web of interconnected nodes, Interference Theory indicates that how well each node will be recalled can vary substantially (Mensink & Raaijmakers, 1988).

2.3.1 Linkage to Suggestive Branding

In the context of the Interference Theory, Keller et al. (1998) found that a non-suggestive name is better suited than a suggestive name, as its meaninglessness ensures it can never be incongruent with a given attribute. The finding that non-suggestive branding can be beneficial is underpinned by Interference Theory, which suggests that pre-existing semantic links formed by a suggestive brand will make it challenging for new, unrelated links to be established in memory (Postman & Underwood, 1973). Since non-suggestive brands cannot form semantic links, there is no interference with pre-existing links formed (Murnane & Shiffrin, 1991). For example, Specsavers has branched into hearing aids but might have trouble creating a link for this product category when strong links have already been made to glasses. Therefore, it has been proposed that suggestive branding has the benefit of forming strong semantic links to related nodes; however, it becomes difficult to reposition the brand in an unrelated direction, as the pre-existing links make it challenging to create any new associations (Keller, 1991; Keller et al., 1998).

2.3.2 Combatting Interference Theory

As memories vary from person to person, researchers have found that Interference Theory does not consistently impact memory. Further studies demonstrate that suggestiveness can be effective even in incongruent circumstances (Lam et al., 2013; Sen, 1999). Additionally, other memory theories suggest that interference is not the sole cause of difficulty in retrieving information. The number of associations linked to the target information affects retrieval (Alba & Marmorstein, 1987; Krishnan, 1996). Thus, if the target node (the brand) is connected to more nodes (attributes/branding identity/consumption occasions), it has a higher chance of being retrieved. However, this approach does not always yield positive outcomes, as a node with many associations is more likely to be connected to competitor brands (Burke & Srull, 1988; Heil et al., 1994). Such mental competition would subsequently decrease the likelihood of the target brand being retrieved.

Another factor that affects retrieval is time (Ebbinghaus, 1913). The longer a brand goes without being seen, the harder it is to retrieve it from memory. To overcome interference, Specsavers could increase new linkages between hearing aids and the brand while maintaining existing linkages with glasses/spectacles. These two differing connections must be balanced to not overpower each other. The balance can be achieved by ensuring both benefits from recency effects (Riebe et al., 2008), wherein the mental salience of both hearing aids and glasses is continually refreshed in the minds of consumers by Specsavers. These memory theories can be seen as providing two strategies that suggestively named brands can use to increase the likelihood of retrieval - despite potential interference challenges.

Memory interference will differ from person to person, as all consumers have gone through different experiences (Morin, 2011). New information is constantly being learnt; therefore, the brain is considered plastic and everchanging. Older people are still learning about new brands and buying them (Mecredy et al., 2023; Phua et al., 2018). Whether the latest information is retained or forgotten depends on the person's mental capacity (cognitive reserve) (Stern, 2002) and experience with the brand (Phua, Page, et al., 2023). Some may have strongly encoded memories that are difficult to override, while others may be more flexible to change (Craik & Lockhart, 1972). The plasticity of memory is something marketers have limited control over. However, people learn through their environments and marketers can leverage this through advertising and branding efforts (Morin, 2011). Whilst the current marketing literature acknowledges the influence of suggestiveness on memory (Gunasti et al., 2020; Keller et al., 1998), there remains a gap in understanding how suggestive branding is used in the market and its proven effectiveness. Chapter 3 details this through Study 1 of this thesis.

Chapter 3
How prevalent are suggestive brand names and Distinctive Assets? An AI-Human approach

Accepted into the International Journal of Market Research (i.e., Australian Business Deans Council 2022 - A-Level).

Bali, L. M., Anesbury, Z. W., Phua, P., & Sharp, B. (2024). *How prevalent are suggestive brand names and Distinctive Assets? An AI-human approach.* International Journal of Market Research, 14707853241251954.

The pilot study was accepted and presented at ANZMAC 2023.

Bali, L. M., Anesbury, Z. W., Phua, P., & Sharp, B. (2023). *GPT-4: faster, cheaper, more accurate brand suggestiveness coder*. ANZMAC.

Please note that this journal is UK-based; thus, Chapter 3 contains English (UK).

Chapter overview

This chapter details Study 1. The study adds to the current body of research by analysing a greater breadth and depth of data to determine the prevalence of suggestive names robustly. Furthermore, it is the first to explore the prevalence of suggestive Distinctive Assets and contributes by using a novel approach for data collection, harnessing artificial intelligence to produce insights.

3 How prevalent are suggestive brand names and Distinctive Assets? An AI-Human approach

3.1 Abstract

Despite the concept of a suggestive brand name existing for over one hundred years (Viehoever, 1920), the prevalence of suggestive vs non-suggestive brand names has not been documented. Previously, to do so extensively would have taken considerable time and money. We now show that artificial intelligence can replace manual coding with increased accuracy. We found the coding performances of Chat GPT-4 are 34% more accurate than GPT-3.5 and 44% more accurate than human coders. Systematically expanding our research to over 4,600 brands from consumer goods, services, and durables in major English-speaking markets (United Kingdom, United States, and Australia), we find that overall, slightly more than a quarter of all brand names are suggestive - ranging from 10% of durables to 56% of service brands. Further, we expand the suggestiveness research to non-brand name elements of almost 600 Distinctive Assets (e.g., colours, logos) across consumer goods, services, durables, and retailers (in the same three countries), finding that two in five are suggestive. The brand name and Distinctive Asset prevalence distributions are positively skewed, with most categories falling beneath the respective averages. Furthermore, regarding performance, on average, suggestive Distinctive Assets display lower levels of Fame and Uniqueness than non-suggestive Distinctive Assets.

3.2 Introduction

Suggestive branding was introduced in the early 1900s (Viehoever, 1920) and became popularised following the seminal work of Keller et al. (1998). Suggestive brand names involve deliberately embedding a product and/or category-related attribute or benefit to leverage existing memory structures (Keller et al., 1998). An excellent example of a suggestive name is *Specsavers*, which contains category (Specs) and product (savers) contexts. Opposingly, non-suggestive names are more abstract or unrelated (e.g., *Knorr* spices). Within marketing literature, brand suggestiveness definitions closely align with the seminal paper (Keller et al., 1998), with subsequent studies adopting attribute (Sen, 1999), feature (Muzellec, 2006), or benefit (Kohli et al., 2005; Lam et al., 2013) classifications.

Minimal knowledge exists to demonstrate *how often* suggestive names are used in different industries, categories, and countries and *how effective* they are in each circumstance. However, marketing practitioners value suggestive brand names instead of non-suggestive alternatives (Romaniuk, 2022). Although marketers claim they value suggestive names, there is confusion about the translation into practice. The most extensive study explores the popularity of brand name types used by the top 500 brands in the United States and finds that suggestive names make up 15% (Arora et al., 2015); contradicting industry beliefs (Romaniuk, 2022).

Twenty-five years after Keller et al. (1998) argued for implementing suggestive brand names, studies have primarily examined the effects on recall and attitudes, citing memory theories to understand findings (Sen, 1999). Thus, focusing on the intricacies of suggestive naming, neglecting the *if* and *when* they should be used. Although exploring prevalence through brand name type popularity has indirectly occurred (Arora et al., 2015), more extensive suggestiveness research is required to confidently establish whether the gap between marketer beliefs and implementation exists.

Undertaking prevalence research on a large scale is traditionally timely and costly, with tedious collection posing risks to accuracy. Thus, our study is the first to demonstrate the viability of employing artificial intelligence, specifically GPT-4, to solve this problem. Due to the help of artificial intelligence, brand name prevalence has been determined for over 4,000 brand names, over 200 categories, across three industries (i.e., consumer goods, services, and durables), and three dominantly English-speaking countries (i.e., United Kingdom, United States, and Australia) wherein GPT-4 performs best (Learnship, 2023; Ray, 2023).

Furthermore, current research is adept at exploring suggestive brand *names*. However, Distinctive Assets also contribute to branding success (Zaichkowsky, 2010). Distinctive Assets are the non-name elements that make up a brand's identity (e.g., logos, slogans, characters) (Romaniuk & Sharp, 2016). The current study adds to the extant literature by expanding into suggestive Distinctive Assets (e.g., the Burger King burger logo) and determining their prevalence in four distinctly varied industries (i.e., consumer goods, services, durables, and retailers (Saji et al., 2013)) across three English-speaking countries (i.e., United Kingdom, United States, and Australia).

Although exploring the prevalence of a suggestive name is a critical first step, there is further value in exploring suggestive Distinctive Assets; their Fame and Uniqueness can measure their strength. Such measurements discern whether suggestive Distinctive Assets outperform non-suggestive equivalents (or vice versa), providing practical insights into their comparative effectiveness. Subsequently, our findings give insights into the efficacy of these branding practices in different sectors. Hence, marketers can refine their strategies and make informed decisions rooted in country, industry, and category-specific knowledge regarding *how often* and *how well* suggestive brands perform.

3.3 Background and Research Questions

3.3.1 Brand Name Suggestiveness and Associative Network Theories

The Associative Network Theories (ANT) (Collins & Quillian, 1969) and the Spreading Activation Theory (SAT) (Anderson, 1983) are often applied to explain how suggestiveness operates in consumer memory. Similar to memory structures, brand knowledge is conceptualised as a collection of nodes or items of brand information that are interconnected by links to form an associative network (Anderson & Bower, 1980; Collins & Quillian, 1969; Romaniuk, 2013; Vaughan et al., 2021). 'Suggestiveness' can be classified as attributes (represented as nodes) that attach to a brand, forming a direct link (Keller, 1987). The number of connections impacts the probability of retrieval (Alba & Marmorstein, 1987; Krishnan, 1996). More links mean more pathways and a higher chance of node activation (Romaniuk, 2003). The quality and quantity of node connections differ among people and change over time (Hutchinson & Alba, 1991).

Hence, suggestive brands should have a mental advantage over non-suggestive brands. For example, the Specsavers brand name (i.e., saving on spectacles) and Distinctive Assets (i.e., the glasses-shaped logo) tap into suggestiveness. The congruency of the link between associations should mean the information is learned and remembered more easily (Keller, 1993). However, non-suggestive brands can still forge connections through other means, like advertising (Vaughan et al., 2021).

Brand Name Suggestiveness and Interference Theory

Conversely, interference theory demonstrates the potential drawbacks to suggestive naming strategy (Keller et al., 1998; Lam et al., 2013). The theory is concerned with information containing a strong link that impedes information that has not formed as strong a connection (Murnane & Shiffrin, 1991; Postman &

Underwood, 1973). For example, when a brand expands into a new category, suggestive attribute/s may not transfer well and become non-suggestive with the risk of confusion (Keller et al., 1998).

Keller et al. (1998) found suggestive names performed poorly compared to non-suggestive names when the associated attribute was inconsistent with the name's suggestion (e.g., using LifeLong Luggage being stylish). Thus, using a non-suggestive name is recommended. Although brands will not benefit from forming immediate connections to target information, they have directional flexibility (Keller et al., 1998). However, subsequent studies question this advice, inferring these challenges can be overcome (Lam et al., 2013), or they are non-issues (Sen, 1999), perhaps due to memory interferences differing from person to person, attributed to having varying experiences (Morin, 2011), and learning new information (Ellis & Lambon Ralph, 2000).

Meanwhile, Sen (1999) found that names suggesting a product's attribute are more readily remembered than names suggesting a category connection. The findings were against Keller et al. (1998)'s recommendation that specific brand names will struggle when applied to unrelated brand extensions, as product suggestiveness is more specific than category suggestiveness. Over a decade later, Lam et al. (2013) found a middle ground to the contention between Keller et al. (1998) and Sen (1999). The study explained suggestive names are limited in their abilities, but extendibility issues can be combated with careful marketing strategy. Should a brand wish to extend beyond a product benefit tied to its name, it can leverage the parent brand name that relates to the category, which links to more general associations, receiving the advantages of a suggestive name, whilst remaining unattached to a specific attribute, that would otherwise leave a brand pigeon-holed.

3.3.2 Brand Name Suggestiveness and Attitudinal Responses

Other research on brand name suggestiveness pays greater attention to the attitudinal response of the consumer (e.g., Djedi, 2018; Lee & Ang, 2003). Akin to previous studies, Lee and Ang (2003) found that suggestive names not only receive greater recall but a more positive attitudinal response than non-suggestive names. Djedi (2018) found that the strength of the attributes linked to a suggestive name overpowered any other information provided and could lead to negative perceptions. Subsequently, this study introduced the potential for suggestive names to have negative connotations associated with the direct link.

Gunasti et al. (2020) investigated how product consumption journey situations compete with suggestive brand names for attention when incongruent with one another (e.g., products with high tartare concentration but misguided naming - cavity protection). Results varied, finding the brand name was favoured in situations before (ingredients on pack) and after product use (emotions after watching a clip). However, product usage experiences (printing quality) outpowered the name. The findings primarily tie into the fact that, on average, shoppers spend less than 13 seconds purchasing from a category online and offline (Anesbury et al., 2016; Hoyer, 1984); thus, the true product performance is not always known.

3.3.3 Limitations of Brand Suggestiveness Research

Previous suggestiveness research exhibits limitations. Research has over-relied on student samples (e.g., Gunasti et al., 2020; Kara et al., 2020; Lam et al., 2013; Sen, 1999), fictitious brand names (e.g., Djedi, 2018; Gunasti et al., 2020; Keller et al., 1998; Sen, 1999), and small sets of data with less than ten names (e.g., Djedi, 2018; Gunasti et al., 2020; Kara et al., 2020; Keller et al., 1998; Lam et al., 2013; Lee & Ang, 2003; Sen, 1999). These practices are advantageous to researchers through substantially reducing time and monetary costs (Espinosa & Ortinau, 2016). However, they minimise the applicability of results to the real world (Yoon, 2013).

Rather than focusing on how findings relate to practice, these studies primarily focused on brand name intricacies analysis, with links to memory theories (Gunasti et al., 2020; Keller et al., 1998; Lee & Ang, 2003; Sen, 1999), or differences in attitudes (Djedi, 2018; Kara et al., 2020), subsequently never establishing their usage.

3.3.4 Brand Suggestiveness Prevalence Research and Pitfalls

Arora et al. (2015) is the only study to document suggestive name prevalence across 11 categories (from consumer goods, durables, and services) and 500 brands, though only in the United States. The study finds that 15% of these brands are suggestive; however, to establish the prevalence of suggestive names robustly, the data must include more brands, categories, and countries to provide generalisable results across different conditions (Barwise, 1995; Bass, 1995).

Consumer goods contain hundreds of categories and tens of thousands of brand names (e.g., one Australian online supermarket has 2,626 brands from 124 categories in the pantry section alone (Woolworths, 2023)). In this instance, manual coding would take over seven hours and cost over £130 (i.e., ten seconds per brand at £20 per hour), a figure doubled to calculate inter-coder reliability. Expanding the research to online platforms, services, and durable goods would exponentially increase expenses. However, this problem may be solved through an alternative: artificial intelligence (AI). GPT-3.5 is free, and GPT-4 has a low monthly fee. If artificial intelligence can assist with manual coding, researchers and managers can use it for traditionally expensive, time-consuming, monotonous coding tasks – providing cheaper, faster, and potentially more accurate results.

3.3.5 A 'Human-In-The-Loop' Approach

Artificial intelligence continues to improve (Gemini, 2024; OpenAI, 2024) - in complexity and efficiency (IBM, 2024; Stanford University, 2023). Consequently, usage in academia (Dogan et al., 2023; Livberber & Ayvaz, 2023), industry (McKinsey & Company, 2023; Watson, 2022), and general population's day-to-day life (Office for National Statistics, 2023) is rising. However, artificial intelligence still cannot operate reliably alone; thus, several streams employ a coveted approach referred to as 'human-in-the-loop', including medicine (Bien et al., 2018), law (Enarsson et al., 2022), and business (Metcalf et al., 2019). Human-in-the-loop combines artificial intelligence with human power (Holzinger, 2016) to distil more accurate results than either could attain individually (Wu et al., 2022).

Marketing academia is beginning to tap into the power of AI (Kim et al., 2023); therefore, this study leverages AI to answer our first research question:

RQ1: *What is the prevalence and variance of suggestive brand names?*

3.3.6 Exploring Suggestive and Non-Suggestive Distinctive Assets

Although there has been academic exploration into suggestive brand names (Keller et al., 1998; Lee & Ang, 2003), suggestive Distinctive Assets (examples shown in Figure 2) offer many advantages (Zaichkowsky, 2010), yet have received no scholarly interest, with just one industry article relating to the area (Luffarelli et al., 2019). Unlike direct branding, which solely includes the brand name, several types of Distinctive Assets exist (Gaillard, 2007; Keller, 2012). For example, logos such as the McDonald's Golden Arches are used as an identification symbol or design, while the M&M characters act as mascots for the brand.

Figure 2: Examples of Suggestive Distinctive Assets

Distinctive Assets offer various advantages to brands; however, many do not utilise them and forego a crucial aspect of brand management (Weinburg & Lombardo 2023). First, they provide avenues for enriching consumers' brand memory. Distinctive Assets can tap into multiple senses (e.g., sight and hearing), providing flexibility in creating richer memory links (Hartnett, Romaniuk, et al., 2016). Furthermore, the range of creative devices that can be used allows brands to easily stand out amongst the 'clutter' in both retailing and advertising contexts (Bellman et al., 2019; Piñero et al., 2010), particularly where consumers pay little attention (Anesbury et al., 2016; Heath, 1999). With the value of Distinctive Assets established, it is worthwhile to benchmark their prevalence across industries, categories, and countries. Thus, the second research question is:

RQ2: *What is the prevalence of suggestive Distinctive Assets?*

3.3.7 Strength of Suggestive and Non-Suggestive Distinctive Assets

When assessing Distinctive Assets, objective measures can serve a purpose beyond determining their prevalence. The *strength* of a Distinctive Asset can be measured, allowing for performance comparisons between suggestive and non-suggestive Distinctive Assets. When strong, Distinctive Assets are brand name proxies; their strength can improve brand elicitation. The two measures of Distinctive Asset strength are Fame and Uniqueness (Romaniuk, 2018).

Distinctive Assets that contain meaning have been noted as a risky strategy due to the potential for other non-brand-related associations to be attached to the same link, creating mental competition (Romaniuk, 2018). However, meaning has been noted as a necessary strategy to create strong brand linkages (Bulmer & Buchanan-Oliver, 2004).

3.3.8 Objectively Assessing Distinctive Asset Performance

Assessing Distinctive Asset performance should not rely on gut feeling. Often, marketers use intuition to guide strategic decisions, like making a random guess at the outcome of marketing decisions (Hartnett, Kennedy, et al., 2016). Instead, we can eliminate guesswork by incorporating measures that can directly test Distinctive Asset strength (Romaniuk & Nenycz-Thiel, 2014). Results will either confirm or deny that suggestive Distinctive Assets are risky by presenting equal or greater Fame and Uniqueness metric scores than non-suggestive alternatives.

Scant amounts of publicly available data disclose the Fame and Uniqueness metric performance of real brands/categories. To the best of the authors' knowledge, Romaniuk (2018) is the only known source, and demonstrates logos received an average Fame of 32% and Uniqueness of 59%, and audio assets an average of 23% Fame and 62% Uniqueness. These results suggest that visual assets have higher levels of Fame but slightly lower levels of Uniqueness than audio assets. With the ability to measure Distinctive Asset strength, we can determine the effectiveness of a suggestive Distinctive Asset through the final research question:

RQ3. *What are the Fame and Uniqueness scores of suggestive and non-suggestive Distinctive Assets, and are there any differences between them?*

3.4 Data and Method

3.4.1 Establishing the feasibility using Artificial Intelligence

To test the feasibility of artificial intelligence as a coding tool, we examine 282 brands from ten consumer goods categories: multi-vitamins (n=44), breakfast cereals (n=43), tea (n=38), salad dressing (n=33), pizza and pasta sauce (n=28), instant noodles (n=23), coffee beans (n=22), long-life milk (n=22), honey (n=20), and Mexican food (n=9), from the two largest Australian supermarkets' websites (Gannon, 2023). Through the data, we could determine the differences in prevalence across categories.

The authors created a comparative benchmark by independently coding brands as suggestive or non-suggestive, then comparing results and reaching the final brand suggestiveness list after debate. The approach aligns well with our exploratory study for two reasons. First, we pose research questions instead of hypotheses, ensuring no preconceived notions or pre-existing agendas for the coding and consensus outcomes. Second, the authors are the most appropriate benchmark given their better understanding of what should/should not be considered suggestive against the definition. Subsequently, this brings a higher level of objectivity to the task, with authors achieving an inter-coder reliability (measured by percentage agreement) of 77%, as opposed to 63% for Research Assistants. Then, three coder groups were employed: (1) Research Assistants, (2) GPT-3.5, and (3) GPT-4. All received identical coding definitions and directions, shown in The three results were compared against the benchmark to determine the best option for coding brand suggestiveness. To measure the agreement between coder groups vs the benchmark, the inter-coder reliability (ICR) was calculated (Lombard et al., 2004). The number of 'yes' was used to attain the percentage agreement; scores between 0-20% (none), 21-39% (minimal), 40-59% (weak), 60-79% (moderate), 80-90% (strong), and >90% (perfect) agreement (McHugh, 2012). Table 1 shows that GPT-4 better matches the benchmark, scoring, on average, an ICR 22% and 27% higher than GPT-3.5 and Research Assistants. To ensure that the benchmark created and GPT-4 were the best combinations, each coder was tested against the others (Appendix B).

Table 1: Comparison of Brand Suggestiveness

	Inter-Coder Reliability against Benchmark		
	GPT-4 (%)	GPT-3.5 (%)	Research Assistants
Tea	89**	47	74*
Breakfast Cereals	88**	65*	40
Honey	85**	75*	45
Coffee Beans	82**	68*	68*
Long-Life Milk	82**	45	55
Salad Dressing	79*	76*	70*
Multi-Vitamins	77*	52	43
Average	**83****	**61**	**56**

Agreements: *** = >90% (almost perfect) agreement, ** = 80-90% (strong), and * = 60-79% (moderate).

Suggestiveness can be analysed in languages other than English. Brands can adopt an international or foreign-sounding name that aligns with their category. However, coding them for suggestiveness presents challenges. For instance, a brand like Hakubaku in the Instant Noodle category might sound non-suggestive to non-Japanese speakers. Still, it can be considered suggestive for Japanese speakers as it translates to 'White Barley'. The benchmark did not evaluate the suggestiveness of non-English brand names. Arguably, GPT-4's ability to handle sophisticated tasks demonstrated a superior level of understanding compared to GPT-3.5 (OpenAI, 2023b). Thus, an inverse result is seen, wherein GPT-3.5 and Research Assistants primarily disregarded suggestive words in other languages and, as such, were better aligned to the benchmark (Table 2). Given our examination of brands within English-speaking countries, where buyers are accustomed predominately to English, international categories are excluded.

Table 2: Comparison of 'International' Brand Suggestiveness

	Inter-Coder Reliability against Benchmark		
	GPT-3.5 (%)	Research Assistants	GPT-4 (%)
Mexican food	100***	33	44
Pizza and Pasta	64*	82**	57
Instant Noodles	39	65*	57
Average	68*	60*	53

*Agreements: *** = >90% (almost perfect) agreement, ** = 80-90% (strong), and * = 60-79% (moderate).*

We tested the consistency in GPT's results against itself on five occasions. GPT-4 is more consistent when re-prompted with the same brand list than GPT-3.5

(88% vs. 26%). The result supports that GPT-4 is the most appropriate tool for this task. Variances in language backgrounds can cause the same word to be interpreted differently (Degani & Tokowicz, 2010). Therefore, we focus on the suggestiveness of brand names within predominantly English-speaking countries to maximise the probability of more reliable and accurate coding outcomes.

3.4.2 Brand Name Suggestiveness

To address RQ1 regarding prevalence of suggestive brand names, we examined 3,897 brands from 224 categories (e.g., breakfast cereals and insurance) from diverse industry types (i.e., consumer goods, services, and durables). In line with our earlier discovery, three Western countries were chosen, wherein English is the dominant language (i.e., the United States - 78% (United States Census Bureau, 2022), the United Kingdom – 91% (Office for National Statistics, 2021), and Australia) - 73% (Australian Bureau of Statistics, 2017)). Although Chat GPT-4 is proficient across multiple languages, English is its strongest (Learnship, 2023; Ray, 2023). The deliberate diversity in data with built-in replications (Uncles & Wright, 2004) aligns with multiple sets of data approach (Bound & Ehrenberg, 1989; Ehrenberg, 1966, 1990), providing more robust results.

We audited brand name data from leading retailers' websites to accurately represent the brands available in each category and country, the specific details regarding the audit can be found in Appendix C. For example, for consumer goods categories, data was collected from Target in the United States (Statista, 2023), Morrison's in the United Kingdom (Bedford, 2023), and Coles and Woolworths (Gannon, 2023) in Australia.

The analysis approach is demonstrated using the breakfast cereals category. GPT-4 was prompted with relevant contextual information needed (shown in Appendix A) including the definition of "A brand name that conveys relevant attribute or benefit information in a particular product or category context" (Keller et al., 1998), the category of 'Breakfast Cereal", and the list of 44 available brands across two Australian supermarkets. Examples of suggestive brands include All-Bran, Corn Flakes, and Rice Bubbles, while non-suggestive brands include Cheerios, Guardian, and the Private Labels 'Woolworths' and 'Coles'. A human-in-the-loop approach (Holzinger, 2016) is then employed, with the primary researcher auditing GPT-4's results to ensure there were no objectively wrong classifications (e.g., 'Corn Flakes' being classified as non-suggestive when it is suggestive); this approach provided the highest possible accuracy in the classification.

We tested a combination of all coders used in the pilot study (Research Assistants, GPT-3.5, and GPT-4) to see how consistent each was compared to the other on their results from the seven non-foreign dominant categories. The results indicate a combination of GPT-4 and the benchmark created was the best method due to having the highest level of inter-coder reliability (83%). The best method was 22% higher than the next closest of the benchmark and GPT-3.5 (61%), and Research Assistants (57%). The combination of GPT-4 and Research Assistants (59%) and GPT-3.5 (54%) had low levels of inter-coder reliability, but the worst combination was Research Assistants and Chat GPT-3.5 (30%). We have added a table (Appendix B) to assess the inter-coder reliabilities, when research assistants, GPT-3.5 and GPT-4 are the benchmark. Time constraints meant getting all three brand experts to audit results was not possible, thus, the primary researcher was employed to do the auditing for the expanded dataset. Audit findings indicated that 12% of GPT-4's results were considered incorrect to the auditor and adjusted to ensure the highest accuracy. Overall, 51% of brands were classified as being suggestive. The process is systematically replicated for 60 additional Australian consumer goods categories (e.g., multi-vitamins, salad dressing, and coffee beans) before expanding to all categories and countries.

3.4.3 Distinctive Asset Suggestiveness

To address RQ2 and RQ3 concerning Distinctive Assets, we examine a broad set of data from a commercial research provider collected across seven years (2016 to 2022). In total, we examine 593 assets from 38 Distinctive Asset types (e.g., logos and colours) across 12 categories and three countries. The Distinctive Asset data had sample sizes ranging from 229 to 1,108 respondents. OpenAI released GPT-4V(ision) to the public in late September 2023; however, this system card comes with multiple risks due to being newly released to the market (OpenAI, 2023a). Therefore, artificial intelligence was not used to code for Distinctive Asset suggestiveness. Instead, three brand suggestiveness experts independently coded the suggestiveness of the assets before comparing and debating the differences and defining the classification. The adapted prominent brand name definition (Keller et al., 1998) was used (i.e., "a non-brand name element that conveys relevant attribute or benefit information in a particular product or category context"). The inter-coder reliability between the researchers was 77%. Where differences existed, they were quickly resolved through discussion, with human error as the root cause, which is common when undertaking a tedious task (Reason, 2000).

Distinctive Assets were tested for their prevalence and strength. Fame reflects how many people can link the Distinctive Asset to the target brand (Romaniuk & Nenycz-Thiel, 2014). Uniqueness is the share of responses the target brand attains versus competitor brands (Romaniuk & Nenycz-Thiel, 2014). These metrics are shown in Equation 1 and Equation 2.

Equation 1: Distinctive Asset Fame

$$fame = \frac{people\ who\ linked\ brand\ to\ element}{sample}$$

Equation 2: Distinctive Asset Uniqueness

$$uniqueness = \frac{times\ a\ brand\ is\ linked\ to\ element}{times\ any\ brand\ is\ linked\ to\ element}$$

To illustrate, we use the short-haul personal travel flights in Europe category. The Colour Distinctive Asset (classified as not suggestive) had 247 of the 404 respondents indicate that the correct brand came to mind when they thought of the category (i.e., 61% Fame), and of those, 213 indicated this was the only brand that came to mind (i.e., 86% Uniqueness). The process was repeated within this category for 53 assets from six brands. Overall, suggestive Distinctive Assets score an average Fame and Uniqueness of 49% and 21%, respectively. In comparison, Fame and Uniqueness scores are significantly higher for non-suggestive assets, at 76% and 35%.

3.5 Results

In answering the first research question, we find the average prevalence of a suggestive name to be 28%. There was variance across industries, as demonstrated in Table 3.

Table 3: Prevalence of Suggestive Brand Names

	Services %	Consumer Goods %	Durables %
United States *1,382 brands, 42 categories*	64	22	10
United Kingdom *1,209 brands, 129 categories*	53	15	7
Australia *2,020 brands, 73 categories*	51	21	12
Average	**56**	**19**	**10**

However, the average prevalence score only partially explains the results. Regardless of the industry, most categories fall beneath their industry average. Thus, brand names often have a lower prevalence of suggestive names than the average. Figure 3 illustrates this as an aggregate result across all industries. The outliers in Figure 3 are from the services industry, or, the consumer goods categories with very few brands.

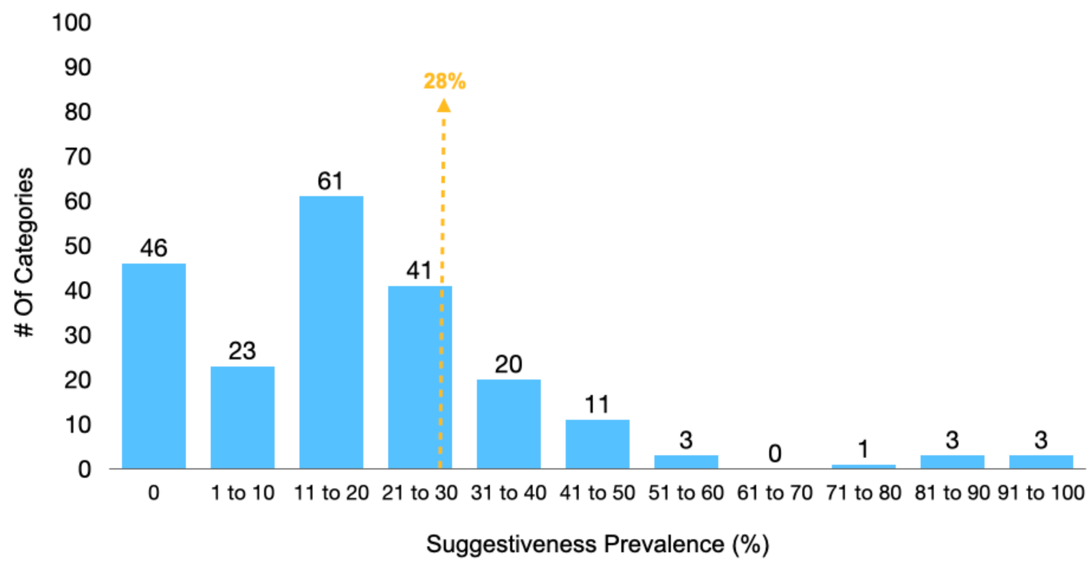

Figure 3: Suggestive Name Prevalence - Positively Skewed Distribution

The results for the second research question regarding Distinctive Assets, show that the prevalence of a suggestive Distinctive Asset is 38%, 10pp higher than brand names. Interestingly, as seen in Table 4, consumer goods have the highest prevalence and services the lowest, inverse to results for brand names. Furthermore, data was readily available for a fourth industry - retailers, and subsequently analysed.

Table 4: Prevalence of Suggestive Distinctive Assets

Industry	**Prevalence %**
Consumer Goods *22 brands, 174 assets*	51
Retailers *31 brands, 124 assets*	38
Durables *22 brands, 161 assets*	35
Services *24 brands, 137 assets*	29
Average	**38**

Like brand names, the distribution is positively skewed, with 58% of categories falling beneath the 40% prevalence, indicating that, more often than not, the prevalence of suggestive Distinctive Assets is less than 40% for a given category.

Finally, in addressing RQ3, comparing the scores between suggestive and non-suggestive Distinctive Assets, Fame results are statistically insignificant (p=0.110), and Uniqueness statistically significant (p=0.002) but with a small effect size (Cohen's d = -0.245). The results suggest that whether a Distinctive Asset is suggestive or not may have a minor influence on its Uniqueness score, while other factors should also be considered. Across the four industries, suggestive Distinctive Assets have an average Fame of 27% and Uniqueness of 54%, while non-suggestive elements score 30% Fame and 63% Uniqueness. The result is consistent in each industry, shown in

Figure 4, with non-suggestive Distinctive Assets consistently scoring marginally higher.

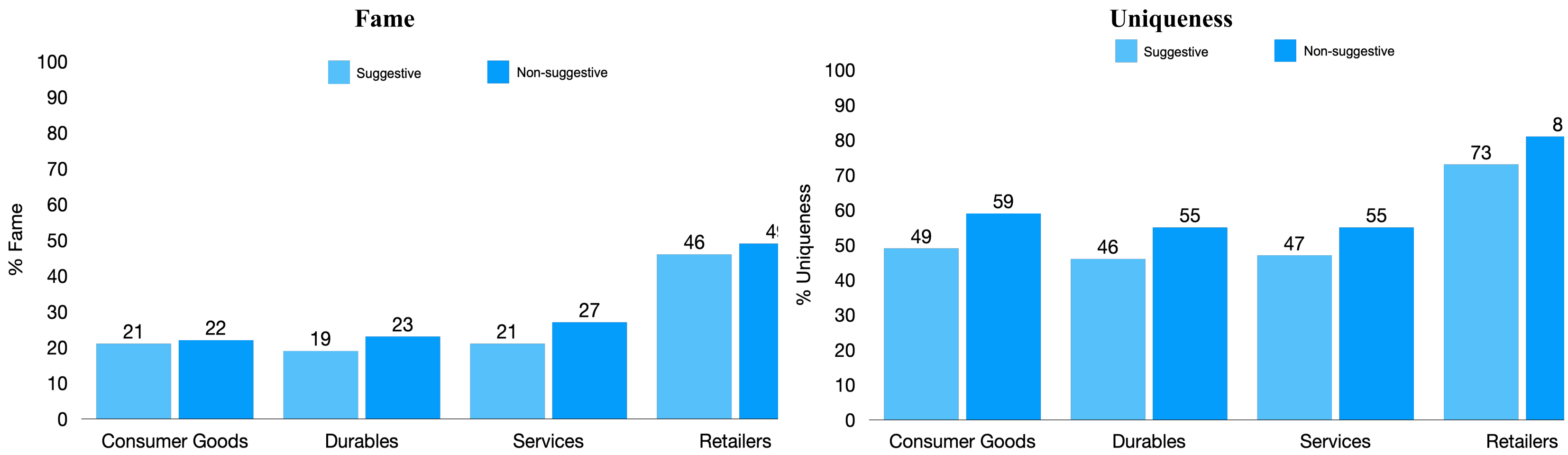

Figure 4: Fame and Uniqueness for Suggestive and Non-Suggestive Distinctive Assets

3.6 Discussion and Implications

Despite research in the area vouching for the use of a suggestive name (Kara et al., 2020; Sen, 1999), our results show that almost three-quarters of brands (72%) incorporate a non-suggestive name. With a human-in-the-loop approach involved, data collection was less fatiguing on human coders, maintaining the highest level of accuracy possible. In most categories, the prevalence of a non-suggestive name is higher than 72%, as the distribution is positively skewed. Our findings can be understood through the research that recommends suggestive names may limit the associations brands can make and thus lessen the flexibility of brand extension (i.e., Keller et al. (1998)). Therefore, suggestive names may not be a good choice; however, this result could depend on a few factors such as the category, as the service industry shows an opposing result, with a 56% prevalence of suggestive names. Services functionally differ from consumer goods and durables (Ashour, 2018); notably, their intangibility, meaning consumers cannot physically assess a product before purchasing (Lovelock & Gummesson, 2004). Therefore, other branding devices (e.g., suggestive names) may need to rely on establishing strong mental links to a service brand (du Plessis, 1994). However, other essential factors, such as the time in a market, may influence the results (Pecot et al., 2022; Phua, Page, et al., 2023). Furthermore, two categories within services had a prevalence between 91-100%, bringing the overall prevalence average up. The other category in this group was a one brand category, displaying 100% suggestiveness. Due to the use of a human-in-the-loop approach, it need be mentioned that this was the result produced at the particular point in time of the research, technology is ever-evolving so it cannot be said that this result would remain the same over time.

For Distinctive Assets, our results demonstrate that, like brand names, prevalence is lower for suggestive Distinctive Assets than for non-suggestive, at 38%, with a positive distribution skew. Suggestive branding may cause tactical and strategic flexibility issues for direct and in-direct brand name elements (Keller *et al.*

1998). However, we find that services have the lowest prevalence and consumer goods the highest, opposite to the brand name results. There may be less use of suggestive Distinctive Assets in services as no tangible product can be leveraged (Lovelock & Gummesson, 2004). However, consumer goods are physical products that can benefit from visually enhancing Distinctive Assets. Given, the short amount of time consumers take to select a consumer good product (Anesbury et al., 2016), Distinctive Assets may make these brands easier to spot and select (Romaniuk, 2018). Moreover, Fame and Uniqueness are measures of a Distinctive Asset's strength. Findings show that suggestive Distinctive Assets are, on average, slightly weaker (in both measures) than non-suggestive – potentially due to suggestive Distinctive Assets creating additional mental competition and interfering with already well-established memories (Murnane & Shiffrin, 1991; Postman & Underwood, 1973); for this reason, brand EXXON chose a non-suggestive name, avoiding the complications that come with being suggestive (Zaichkowsky, 2010). Although there are differences across the brand name types in their performance across Distinctive Asset metrics, the results are either statistically insignificant or have a small effect size. Thus, it does not necessarily mean suggestive branding will cause more harm than good if used in a Distinctive Asset form.

3.6.1 Academic Contributions

Our study tested a new method that combats issues with past research on suggestive brand names. We were able to extensively test and succeed with a new method, using artificial intelligence (GPT-4) to collect prevalence results on a large scale (4,000 brand names), wherein the collection process would not pose any of the traditional risks (timely, costly, human error). Our novel method allows brand suggestiveness researchers to circumvent an overreliance on student samples (e.g., Gunasti et al., 2020; Kara et al., 2020; Lam et al., 2013; Sen, 1999) and fictitious brands (e.g., Djedi, 2018; Gunasti et al., 2020; Keller et al., 1998; Sen, 1999).

Our research expanded the over 100 years of brand suggestiveness literature (Keller et al., 1998; Viehoever, 1920) from a purely text-based brand name context to one of non-brand name elements. To our knowledge, our research is the first academic study to explore the area. In doing so, our examination of many data sets across industries, categories, and markets provides researchers with robust benchmarks for the prevalence and strength (i.e., Fame and Uniqueness) of suggestive and non-suggestive Distinctive Assets.

3.6.2 Industry Contributions

The overwhelming majority of marketers (73%) stated meaningful names were of greater value than non-meaningful names (Romaniuk, 2022). However, our findings demonstrate that suggestive branding (names and Distinctive Assets) are only used one-third (34%) of the time. Although many other stakeholders are also involved in deciding on a brand name (Kohli et al., 2005) the significant disconnect suggests that beliefs do not necessarily equal behaviour, a theory that has also been confirmed for consumers (Nguyen et al., 2022; Young et al., 1998). Understanding the prominent gap may likely prompt branding practitioners to re-think their strategies to ensure their beliefs are reflected in their brands. Furthermore, the research demonstrates that suggestive Distinctive Assets perform slightly worse than non-suggestive. However, the difference is not large, nor statistically significant for Fame. Therefore, marketers should not change their Distinctive Assets from suggestive to non-suggestive; instead, we suggest prioritising a non-suggestive asset when creating a new brand or Distinctive Asset to minimise the risk of mental competition.

3.6.3 Limitations and Future Research

There are some key limitations of this research that should be overcome with future research. Although GPT-4 was proven to make significantly fewer errors than human alternatives, the task of coding for suggestiveness is innately subjective, so future researchers should take action to minimise this effect. Artificial Intelligence continues to complete tasks of increasing complexity with greater efficiency (IBM, 2024; Stanford University, 2023), thus, it is likely that soon it will be able to complete this task alone, which will be an exciting avenue for future research. Furthermore, this study explored three major Western countries, excluding any 'international dominant' categories in the consumer goods industry, e.g., Mexican food. Suggestiveness of words outside of the English language was beyond the scope, as determined by the pilot study. However, expansion into non-English speaking markets is valuable for future study. Chat-GPT is proficient in Neo Latin languages as well as English (e.g., Spanish and Italian) (Paul et al., 2023)). Also, Lam et al. (2003) mention that Chinese speakers rely more heavily on the semantic associations between words, which could indicate a potential difference between English and Chinese. Furthermore, our brand name suggestiveness research was contained to a snapshot in time and potentially subject to survival bias (i.e., brands coming in and out of the market) (Li & Xu, 2002). Future research should consider data over multiple years to capture data from new brands that may have failed (Ployhart & Vandenberg, 2010) with critical learnings to be discovered. Last, our research examined Distinctive Assets as a whole, yet there is scope for research into the nuances in suggestive Distinctive Asset performance across different asset types. Research suggests picture-based assets like logos would be easier to process than text-based assets like taglines (Childers et al., 1986), to which some benchmarks can be drawn upon as comparative measures (Romaniuk, 2018). Such Distinctive Asset research could be done with GPT-4V or a newer equivalent when the AI is sufficiently proficient and should be explored in future.

3.7 Appendix A

Prompt

Chat GPT-3.5 / Chat GPT-4 were used between 03/08/23 and 21/08/23 releases (OpenAI, 2024).

1. *"I am doing a study on suggestive brand names.*
2. *I define suggestive brand names as "a brand name that conveys relevant attribute or benefit information in a particular product or category context."*
3. *A few other criteria to consider:*
4. *'Suggestive' is based purely off of the brand name alone, and previous history of the brand is not included as suggestive.*
5. *'Suggestive' can also involve explicitly mentioning any aspect of the category in its name.*
6. *Please consider deliberating misspellings in names that aim to sound like the product or category, for example: Sno-cone to mean snow cone.*
7. *Names that need to be translated to be suggestive do not count. This is an English study.*
8. *Could you please code the following brand names as either suggestive with a '1', or not suggestive with a '2' in a table, using the definition and criteria above to guide your decision making:*
9. *The category is X*
10. **Insert list of brands*"*

Example Output

Name	GPT-4
Liddells	2
Mighty Milkology	1

1 = Suggestive and 2 = Non-Suggestive

3.8 Appendix B

Comparative inter-coder reliabilities of GPT-3.5, GPT-4 and research assistants

	Research Assistants	GPT-3.5	GPT-4	Benchmark
Research Assistants				
Chat GPT-3.5	30			
Chat GPT-4	59	54		
Benchmark	57	61	83	

3.9 Appendix C

Retailer Audit

The audit consisted of collecting brand name data from leading retailers' websites. Another criterion was that brand name lists were easily accessible on their website. As an example, for consumer goods, large grocery retailers were selected (e.g., Woolworths and Coles for Australia). Then, a full audit of the 'pantry' or 'food closet' section was completed for each of these retailers, which, for example, can consist of 13 sub-categories, like breakfast & spreads, condiments, and desserts (Woolworths 2024). Brand name data was collected for each of the sub-categories within these categories. For example, in breakfast & spreads, there are nine sub-categories within, for example, muesli & oats, savoury spread and sweet spread. In the breakfast cereal sub-category, there are 23 brand names; these are pasted into an excel spreadsheet and coded as either suggestive, or not suggestive by GPT-4. The process is then repeated for all the sub-categories in the pantry section of the retailer sites. The same audit is then completed for several additional large retailers operating in the consumer goods, services, and durables industry for all three countries.

Chapter 4

GPT-4V: a faster, cheaper, more accurate non-brand name suggestiveness coder?

Accepted and presented at the Informs Society for Marketing Science Conference 2024 in Sydney, Australia

Chapter overview

This chapter presents a pilot study on the visual capabilities of Chat GPT through its GPT-4V model, which, at the time of submission, was Chat GPT's most up-to-date visual processing model. This study determines the feasibility of GPT-4V to categorise the suggestiveness of Distinctive Assets and compares its performance to human coders who are experts in the field of suggestiveness.

4 GPT-4V: a faster, cheaper, more accurate non-brand name suggestiveness coder?

We assessed the ability of Artificial Intelligence's new visual processing capabilities to replace human coders on a time consuming and expensive task. Specifically, we used GPT-4V to classify over 500 *Distinctive Assets* (i.e., non-brand name branding elements including logos and taglines) from twelve categories and three countries as either suggestive or non-suggestive. *Brand suggestiveness* refers to a branding element that conveys relevant attribute or benefit information relevant to a particular product or category context (Keller et al. (1998)). Our results demonstrate the high potential of this early-stage model. It produced promising intercoder reliability at 75% (from comparing GPT-4V's output to a benchmark from three human coders). Surprisingly just 50% of Distinctive Assets are suggestive, going against the recommendations in academic literature (Gunasti et al., 2020; Lam et al., 2013; Sen, 1999) and marketing practitioner preference (Romaniuk, 2022). Our brand suggestiveness study demonstrates that GPT-4V might be a tool for all sorts of academic research in marketing. Already, GPT-4V provides marketing academics and practitioners with a time and cost-efficient way to produce scientific knowledge.

Keywords – Artificial Intelligence, GPT-4V(isual), Branding Elements, Brand Suggestiveness

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Chapter 5

What Distinctive Brand Assets work best? Using an AI-human approach to evaluate assets according to type and suggestiveness

Full study under review at the Journal of Advertising Research

***Please note that this journal is US-based and has been written in English (US).*

Chapter overview

This chapter reports on Study 2. The current body of knowledge is expanded by understanding the nuances in Suggestive Distinctive Asset effectiveness by exploring Distinctive Asset types (e.g., logos, slogans and jingles) and their respective performance when suggestive and non-suggestive. Akin to Study 1, this study utilises artificial intelligence to produce insights.

5 What Distinctive Brand Assets work best? Using an AI-human approach to evaluate assets according to type and suggestiveness

5.1 Abstract

Distinctive Assets (e.g., logos) generally lack meaning but can sometimes suggest a category. Using a Human-In-The-Loop (Human-AI) approach, this research examines whether type and suggestiveness influence a Distinctive Asset's strength, using Fame (how many people link a Distinctive Asset to the target brand) and Uniqueness (the share of responses the target brand attains versus competitor brands). Analysis of almost 1,200 Distinctive Assets in 20+ diverse categories in three countries over seven years reveals an average Fame of 26% and Uniqueness of 54%, with shape-based assets (e.g., logos) as the strongest asset type. Suggestive assets are most effective for auditory elements.

5.1.1 Management Slant

- We present a novel application of Artificial intelligence (i.e., GPT-4 omni) to determine the suggestiveness of Distinctive Assets.
- Overall, *Shapes* are the most effective type of Distinctive Asset, and *colors* the least effective, a finding that concurs with Ward et al.

(2020)—highlighting the power of logos, which consumers use to form a brand's unique identity.

- Assets suggestive of the product category do not outperform non-suggestive assets on average.
- Shapes (e.g., logos) and words (e.g., taglines) score higher when non-suggestive. Auditory assets (e.g., jingles) benefit from embedding product or category-related suggestions. Design (e.g., packaging design), story (e.g., advertising style), and face assets (e.g., celebrities) perform equally well when suggestive or non-suggestive.

Keywords: Artificial intelligence, Human-In-The-Loop, Distinctive Assets, Suggestiveness, Branding, Advertising

5.2 Introduction

Distinctive Assets are the non-name elements used in ad copies (e.g., jingles and logos), packaging, and storefronts. They are highly regarded branding tools, as seen recently in industry (Evans & McKinven, 2024; Lepitak, 2024; Tucker, 2023) and academia (Fiocchi & Esfahani, 2023; Velykytė, 2023; Ward et al., 2020). Forming a significant part of a brand's identity (Romaniuk, 2018) Distinctive Assets are crucial to branding (Zaichkowsky, 2010) and advertising strategy (Rodgers & Thorson, 2012). Due to their importance, they have the power to *make* or *break* a brand. A key example is when poor branding strategy led to an approximate $100 million loss for Gap (Williams, 2021) due to an unnecessary redesign of one of its well-known Distinctive Assets - its logo. Other examples include Tropicana (Andrivet, 2015) and JC Penney (Olenski, 2012). Understanding how Distinctive Assets work for various types (e.g., logos and taglines) and the influence of suggestiveness is crucial to creating compelling advertising copy.

Strong Distinctive Assets can be built up and maintained in memory by tapping into multiple senses (Romaniuk & Nenycz-Thiel, 2014). Subsequently, they can help brands be noticed in cluttered environments on shelves (Piñero et al., 2010) and in advertising (Bellman et al., 2019). Rather than taking the time to read packaging, consumers can quickly scan for a particular asset/s to find what they are looking for. Geico Gecko is a prime example of a strong asset, with 87% of category buyers knowing the asset (Fame), and 98% of those buyers link it to Geico (Uniqueness) (Romaniuk, 2018). Assets like these can become so synonymous with a brand that they replace the name (e.g., McDonald’s removing their name from their signage) (Phua & Hartnett, 2021). Due to their importance, research is needed on the differences in performance of the varying *types* of Distinctive Assets to determine whether strategies should be adapted accordingly.

There has been a recent resurgence of brand suggestiveness research (Bali et al., 2024; Gunasti et al., 2020), and demonstrated practitioner value (Romaniuk, 2022). Traditionally, research has focused on suggestive brand *names* (e.g., Keller et al., 1998; Sen, 1999), and not a non-brand name context (i.e., Distinctive Assets). To define suggestive Distinctive Assets we adapt the definition from Keller et al. (1998), that is, integrating elements relating to a product or category-related attribute or benefit to leverage existing memory structures. An example is the burger-shaped Burger King logo, which is suggestive, given the primary product is burgers. Such examination is possible at scale via a Human-In-The-Loop approach, where humans code for suggestiveness; subsequently, Artificial Intelligence (AI) undertakes the same activity at a cheaper cost and with potentially higher coding accuracy (Gómez-Carmona et al., 2024; Wu et al., 2022). As a result, this presents an opportunity to investigate the influence of suggestiveness for various asset types. The outcome of this research offers practical guidance, to help create or prioritize the type and suggestiveness of Distinctive Assets that have a larger potential for more effectiveness and memorability.

The current study explores performance (i.e., Fame and Uniqueness) across different Distinctive Asset types (Romaniuk, 2018; Ward et al., 2020)—shapes (e.g., logos or packs), words (e.g., taglines or fonts), and audio-based (e.g., jingles or popular songs). Further, we examine the influence of suggestiveness on asset type performance, taking a novel AI-human approach.

5.3 Background and Research Questions

5.3.1 Distinctive Assets

With alternative names being used, including brand elements (Keller et al., 2008), it is not easy to pinpoint precisely where Distinctive Asset research originated. Aaker (1991), a prominent author in the field, discussed the importance of building branding elements to develop brand equity. The term 'Distinctive Assets' was coined when research became more specific and explored the different types of assets advertisers use in their creatives (e.g., Hartnett, Romaniuk, et al., 2016; Olson, 2004). Assets are broadly grouped into three main types: visual, audio, and word-based.

These core types include various assets such as colors, shapes, stories, words, faces, designs, and audio (Romaniuk, 2018; Ward et al., 2020).

Notable literature exists in the research area of Distinctive Assets, from foundational discussions on what they are and how they work (Romaniuk & Hartnett, 2010) to academically written yet practitioner-focused books providing extensive knowledge of how a brand can implement effective branding strategies (Romaniuk, 2018). Further discussions have focused on their legal weighting as trademarkable branding elements (Hoek & Gendall, 2010), or how they can be harnessed to create mental shortcuts (Keller, 2005). Research has extended to analyzing specific asset types for their Uniqueness potential (Zaichkowsky, 2010), with certain assets seen to face less competitive intensity and thus have a greater chance of being uniquely owned than others (Ward et al., 2020).

There are two core measurable metrics to determine the strength of a Distinctive Asset. **Fame** - how many people can link the Distinctive Asset to the target brand, and **Uniqueness** - the share of responses the target brand attains versus competitor brands (Romaniuk & Nenycz-Thiel, 2014). Despite these metrics being used in academia (Romaniuk, 2018) and industry (Blaess, 2023), there is a notable lack of benchmarks for the average Fame and Uniqueness scores, let alone across the various Distinctive Asset types. So, our first research question is:

RQ1: *What are the Fame and Uniqueness scores across Distinctive Assets?*

5.3.2 Visual, Word, and Auditory Distinctive Assets

While no overall benchmark on Distinctive Asset performance exists, there is undoubtedly no benchmark on the various types of assets. Extant literature has long suggested that visual assets should perform better than other assets (Ho et al., 2022; Paivio, 1971). The Picture Superiority Effect finds pictures are better remembered than words and audio for immediate and delayed recall. For instance, an examination of over 270 university students found the mean delayed recall of semantic information to be 25% faster (7.5 vs. 6.0) for pictures and words versus words alone; while sensory information was 600% greater (6.0 vs. 1.0 – out of ten items) (Childers & Houston, 1984). In the context of Distinctive Assets, many picture elements can be harnessed as logos and characters. Therefore, picture-based Distinctive Assets should have a higher propensity to have mental advantages over sound and word-based Distinctive Assets (Costley & De Wald, 1991). Additional research found 76% higher levels of information recall for audio than words (44% vs. 25%) (Crutcher & Beer, 2011); thus, sound should have an advantage over word-based assets. More specifically, the existing literature suggests that visual-based assets should have memory advantages over auditory or word-based elements and that audio should outperform words. For a contextual example, the order of superiority should subsequently be logos, followed by jingles, and then slogans.

Research has begun to demonstrate differences in the performance of different asset types. Specifically, Ward et al. (2020) analyzed the unique ownership of nine asset types measured through the competitive intensity of the assets (i.e., Herfindahl–Hirschman index (HHI) (Hirschman, 1964). Results found that character, followed by logo and font, had the lowest competitor intensity (0.69, 0.61, and 0.60) and, as such, the greatest potential for unique brand ownership. On the other hand, color had the highest competitive intensity and lowest potential for unique ownership (HHI of 0.31). Notably, the study was limited to visual assets, and subsequently, there is a desperate need to examine other assets used by advertisers. Audio assets can be used in media that visual assets cannot, including formats like radio, which are advantageous because they can help extend the reach of campaigns and build more associations to the brand in memory (Clift, 2016; Michelon et al., 2020; Simmonds et al., 2020).

Overall, the Picture Superiority Effect suggests that visual Distinctive Assets would have higher Fame and Uniqueness scores than word and audio assets (Childers & Houston, 1984). Despite substantial backing from the literature (Childers

& Houston, 1984; Cohen et al., 2009; Crutcher & Beer, 2011), we are still unaware if this effect holds true in the context of Distinctive Assets, given the lack of systematic analysis. Additionally, we do not know the comparative effectiveness of visual, audio, and word-based assets, which can be measured through their Fame and Uniqueness scores. Therefore, the following research question establishes if the prior psychological research holds for Distinctive Assets:

RQ2: *To what extent, if any, do visual-based Distinctive Assets perform better than word or audio-based Distinctive Assets?*

5.3.3 Suggestive Distinctive Assets May Improve Memory Processing

Suggestive Distinctive Assets are defined as indirect branding elements that deliberately embed a product and/or category-related attribute or benefit to leverage existing memory structures – adapted from Keller et al. (1998). For example, a suggestive Distinctive Asset would be the glasses logo used by the brand Specsavers, indicative of its category. A non-suggestive Distinctive Asset would be the Apple logo, indicative of fruit, not the technology category.

Findings from seminal suggestive work by Keller et al. (1998) indicate that the effectiveness of a suggestive brand name has *circumstantial* benefits. For product benefit statements relating to the product itself, a suggestive name was found to be useful (e.g., LifeLong Luggage described as hard-wearing), as opposed to inconsistent (e.g., LifeLong Luggage described as fashionable). Performance was gauged based on ad recall; however, testing suggestiveness performance using different metrics, such as Fame and Uniqueness, would add further depth to the field of study.

A suggestive asset that embeds a semantic product or category-related meaning can decrease mental load by providing a shortcut for remembering the brand (Keller, 1993; Keller et al., 1998). This ease of memory can lead to greater recognition and Fame for suggestive assets. Providing a 'hint' to the brand by making its branding meaningful is possible through a suggestive asset. In this way, the inherited mental disadvantage of an audio asset may be overcome by making these assets suggestive (Crutcher & Beer, 2011).

However, a suggestive asset may receive a lower Uniqueness score due to the potential for increased mental competition (Keller et al., 1998). The heightened competition stems from the suggestive elements overlapping with other memories not related to the brand. For instance, a suggestive cartoon germ asset for a household disinfectant brand may *also* be associated with hospitals and sickness (unrelated items), as a germ is not unique to the brand; this may cause memory interference (Postman & Underwood, 1973).

Artificial intelligence (AI) is gaining traction in the marketing literature, and is a research priority for prestigious advertising journals (Campbell, 2024). Applications in the advertising sphere come from different perspectives, including discussions on the power of generative AI (Campbell, 2023) and deepfakes (Campbell et al., 2022), how to use it to benefit the consumer (Ferraro et al., 2024; Wu & Wen, 2021), the risks associated (Sands, Demsar, et al., 2024), and how advertisers can leverage AI responsibly (Sands, Campbell, et al., 2024). As AI continues to improve in its abilities, it can now take on image-processing tasks (Gemini, 2024; OpenAI, 2024). The skills of GPT-4o can subsequently be harnessed through a 'Human-In-The-Loop' approach to data collection (Gómez-Carmona et al., 2024). The subjectiveness of suggestiveness coding can be minimized using human power in combination with AI as the results are established through two mediums (humans and GPT-4o). By coding this way, the accuracy and quality of the data also improve (Bali et al., 2024). Therefore, the conclusions that can be drawn from the dataset can be made with higher confidence.

Different Distinctive Asset types may be processed differently in memory and impact the effectiveness of suggestiveness. Therefore, the third research question is posed:

RQ3: *What, if any, are the differences in suggestive and non-suggestive asset performance across Distinctive Asset types?*

5.4 Data and Method

We examined 1,162 Distinctive Assets from 21 product categories (e.g., salty snacks and cars), four industries (consumer goods, durables, services, and retailers), and three countries (Australia, the United Kingdom, and the United States). The data came from 12 questionnaires administered by a commercial research provider over seven years (2016 to 2022). The sample size of respondents in each questionnaire ranged from 229 to 1500; the average sample of a survey was 583, all representative of the population, a specification provided to the survey provider. Respondents are shown six Distinctive Assets, all of which are de-branded, and asked to name the brands each asset belongs to within a given category.

To address our first research question, we calculated the Fame and Uniqueness by benchmarking the performance of Distinctive Assets. First, Fame reflects how many people can link the Distinctive Asset to the target brand (Romaniuk & Nenycz-Thiel, 2014). Using a de-branded example from our sample, *Brand A* in the lip care category, Equation 3 outlines that Fame of 32% stems from 132 people who linked Brand A to the element (i.e., Distinctive Asset) divided by the 412 category buyers (i.e., sample).

Equation 3: Distinctive Asset Fame

$$fame = \frac{people\ who\ linked\ the\ target\ brand\ to\ element}{sample}$$

Continuing, Uniqueness is the share of responses the target brand attains versus competitor brands (Romaniuk & Nenycz-Thiel, 2014). Once again, using Equation 4, the Uniqueness of 63% is calculated from 189 times the target brand (i.e., Brand A) is linked to the element (i.e., Distinctive Assets) divided by the 300 times any brand is linked to the element. Overall, Brand A's Distinctive Asset has 32% Fame and 63% Uniqueness. We systematically calculate all Fame and Uniqueness scores to provide a benchmark.

Equation 4: Distinctive Asset Uniqueness

$$uniqueness = \frac{times\ the\ target\ brand\ is\ linked\ to\ element}{times\ any\ brand\ is\ linked\ to\ element}$$

To answer our second research question, determining if the Picture Superiority Effect is present for Distinctive Asset types, we compare the Fame and Uniqueness scores across asset types. In line with prior classifications (Romaniuk, 2018; Ward et al., 2020), Table 5 outlines how the six Distinctive Asset Types were classified into three umbrella categories – Auditory (i.e., Audio), Word (i.e., Word), and Visual (i.e., Color, Story, Face, Shape, and Design). To precisely compare visual assets against word and audio-based assets, an independent t-test (Student, 1908) was run on each Distinctive Asset type, and for the significant types, their effect size was calculated through Cohen's D (Cohen, 1977).

The Fame and Uniqueness scores that are used to determine results were calculated by a commercial research provider.

Table 5: Distinctive Asset Type Breakdown

Auditory		Word	Visual				
Audio (n=52)		Word (n=262)	Story (n=129)	Face (n=85)	Shape (n=299)	Design (n=201)	Color (n=134)
Background instrumental	Non-vocal	Taglines	Style	Spokespeople	Symbolic images	Pack images	Single Colors
Jingles	Vocal	Fonts	Components	Celebrity	Pack	Product	Color Combinations
Popular songs	Styles	Words	Moments	Characters	Logos	Store	

Adapted from Romaniuk (2018) and Ward et al. (2020)

We compare the Fame and Uniqueness scores to answer the third and final research question, the influence of suggestiveness on Distinctive Asset performance. To classify non-brand name suggestiveness, three field experts adopted the Keller et al. (1998) definition of brand suggestiveness, *'code as suggestive if the Distinctive Asset conveys relevant attribute or benefit information in a particular product or category context.'* All assets were classified independently with an inter-coder reliability of 67% (calculated by percentage agreement), a moderate agreement (McHugh, 2012). Where differences occurred, short discussions emerged until the classification was finalized. This approach replicates previous research for suggestiveness coding (Bali et al., 2024).

Following this, GPT-4o was employed to undertake the same task. The exact instructions provided to GPT-4o are displayed in the Appendix. The final benchmark classifications established by the three human coders and the list established by GPT-4o scored an inter-coder reliability of 69%; this agreement is moderate (McHugh, 2012). The 31% differences were then analyzed by the primary researcher, and any inconsistencies across results were resolved; for example, the Burger King logo is shaped like a hamburger, which is suggestive, as Burger King primarily sells hamburgers. If GPT-4o or the human coders have coded this as non-suggestive, the primary researcher will change this to suggestive. The process allows for creating the most accurate final coded list via Human-In-The-Loop. The double-layering to this coding process allows for the data and results to be more precise than if produced by humans or AI alone (Shah, 2024; Wu et al., 2022), as it eliminates various types of errors (e.g., human error from fatigue). Overall, 41% of the 1,028 assets were deemed to be suggestive. Please note that the 134 Color asset types (e.g., single colors and color combinations) were excluded from the suggestive vs. non-suggestive analysis, as all colors are non-suggestive. For instance, a purple color, part of Cadbury's Distinctive Asset palette, cannot be considered suggestive of the category or the product.

5.5 Results

To provide benchmarks for Fame and Uniqueness scores, we examined the mean average scores for 1,162 Distinctive Assets across 21 categories. Figure 5 demonstrates that the average Fame score is 26%, and the average Uniqueness score is 54%. Fame and Uniqueness: the distributions have a slight positive skew, with 57% and 52% of the data falling beneath their respective averages. The indication is that often, the Fame and Uniqueness of an asset will drop beneath 26% and 54%.

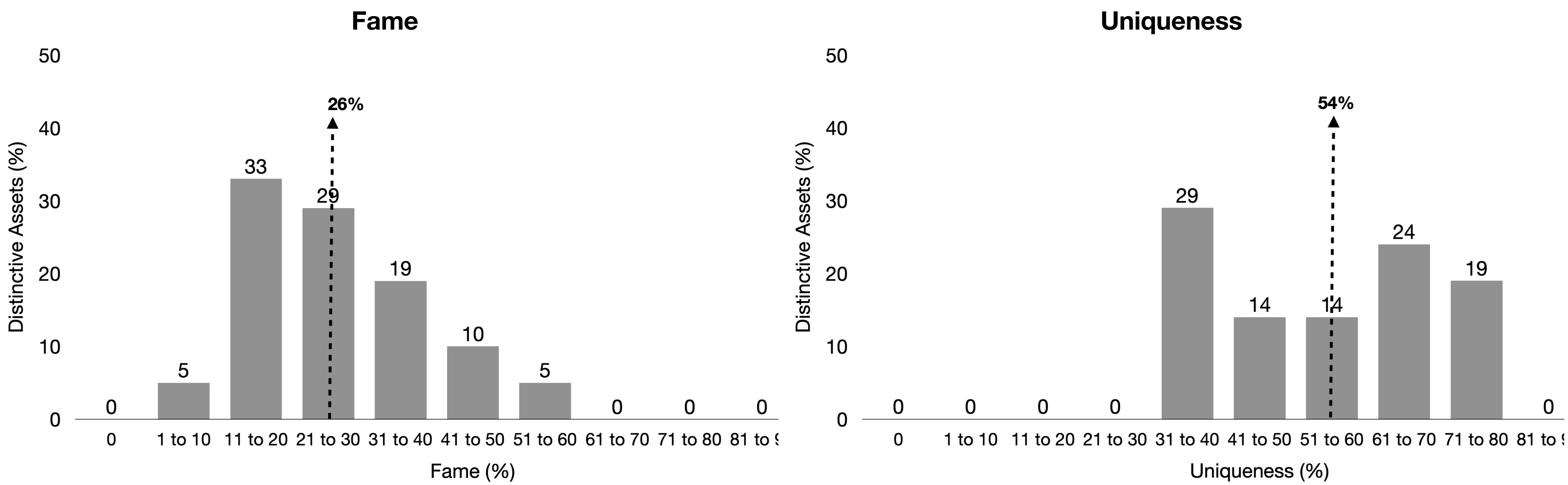

Figure 5: Fame and Uniqueness for 1,162 Distinctive Assets in 21 diverse categories in three countries

We quantified the Fame and Uniqueness scores across the Distinctive Asset types to answer the second research question about visual superiority. We compared the average Fame and Uniqueness scores across the groups. Although the asset types were sorted in Figure 6 by Fame, we note a strong positive correlation with Uniqueness (r=0.97). The results show that three of the five visual assets (**bolded**) primarily perform better than audio (underlined) and word-based (*italicized*) assets. Figure 6 shows that shape, story, and design have the highest levels of Fame; however, the two other visual-based assets (i.e., face and color) have the lowest levels of Fame, subsequently going against the Picture Superiority Effect (Childers & Houston, 1984). Further, in contrast to previous findings (Crutcher & Beer, 2011), we find that *word*-based assets outperform audio assets; however, there are few audio assets in the sample.

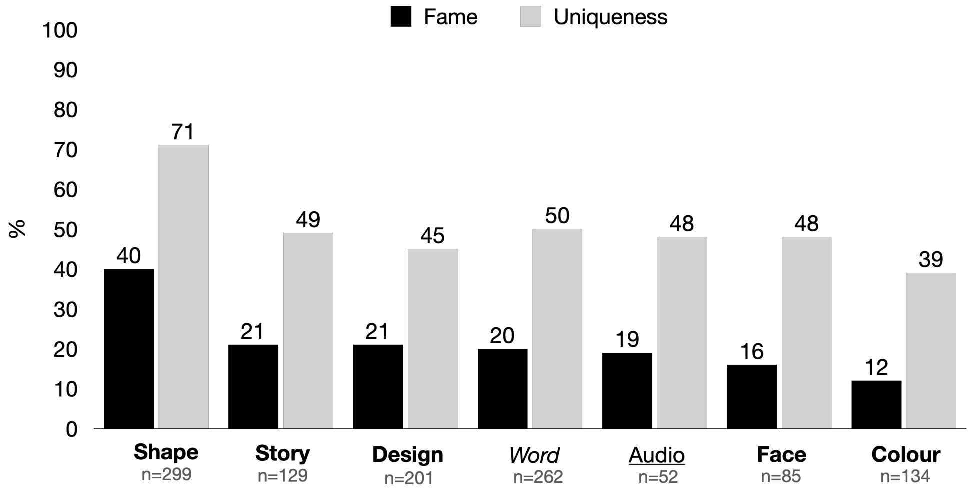

Figure 6: Overall Strength of Distinctive Asset Types
Visual Assets are **bold**, *Words are italicized, and Auditory are* underlined.

We compared their strength to answer our third research question, that is, the performance differences between suggestive and non-suggestive Distinctive Asset types. Figure 7 depicts the performance of suggestive (black) vs. non-suggestive (grey) across asset types, sorted by their Fame and/or Uniqueness scores. Asset types that were stronger when suggestive are depicted to the left of the first dotted line (audio and design for Fame, audio for Uniqueness); in the middle of the two dotted lines are assets that score the same or have minor differences (story and face for Fame, face, story, and design for Uniqueness), and asset types stronger as non-suggestive are shown to the right of the last dotted line (shape and word for Fame and Uniqueness).

Our results show that non-suggestive word-based and shape assets outperformed their suggestive counterparts. T-tests and effect size testing enabled us to determine that non-suggestive word-based assets significantly outperformed suggestive ones in both Fame (25% vs. 14%) and Uniqueness (59% vs. 39%), with small and medium effect sizes, respectively (Fame: d=0.48 Uniqueness: d=0.66). The same was seen for shape-based assets with Fame (45% vs. 27%) and Uniqueness (77% vs. 55%), with medium and large effect sizes, respectively (Fame: d=0.62 Uniqueness: d=0.84).

The differences in scores between suggestive and non-suggestive execution for other asset types were less pronounced. While the average Fame and Uniqueness were higher for suggestive audio (Fame=29% vs. 17%, Uniqueness=55% vs. 47%) compared to non-suggestive ones, the differences were not statistically significant (p= 0.22 and 0.47 for audio Fame and Uniqueness, respectively). Design, story, and face had minimal differences in Fame and Uniqueness scores between suggestive and non-suggestive groups (differences were less than five percentage points). These differences were not statistically significant (p=0.11 and 0.84 for design, p=0.86 and 0.87 for story, and p= 0.97 and 0.96 for face, for Fame and Uniqueness).

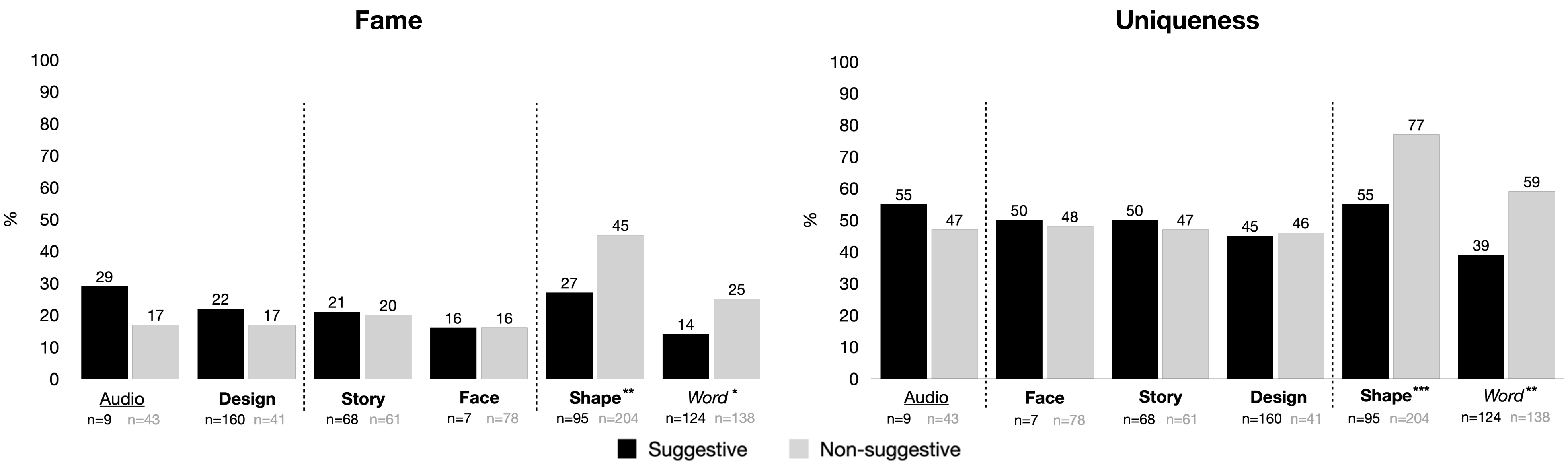

Figure 7: Performance of Suggestive and Non-suggestive Distinctive Assets

** signifies medium effect sizes (Cohen's d ≤ 0.5), *** signifies large effect sizes (Cohen's d ≥ 0.8)

5.6 Discussion

Results demonstrated that the average Fame and Uniqueness of a Distinctive Asset are 26% and 54%. This indicates that most Distinctive Assets have investment potential, as Uniqueness is the metric that tends to be more challenging to build over Fame, so the average asset operating above 50% Uniqueness already has a head start; thus, further efforts to develop these assets may be a wise investment (Romaniuk, 2018). For the likes of Gap, Tropicana, and JC Penney, perhaps instead of completely changing an asset already in their palette (Andrivet, 2015; Olenski, 2012; Williams, 2021), our results indicate they should invest in building the links with the brand rather than throwing it out altogether, which had led to multi-million dollar losses (Williams, 2021).

Further, the research demonstrates that most visual assets (i.e., shape, story, and design) generally showed slight superiority over auditory and word-based assets, providing some confirmation of the Picture Superiority Effect (Paivio, 1971). However, visual-based assets of face and color went against the previous findings (Childers & Houston, 1984), performing worse than audio and word-based assets. Face assets essentially performed in line with story, design, word, and auditory assets, at most a 5pp difference; therefore, its lower performance is negligible. However, color assets performed substantially lower than all other asset types. The result aligns with existing research findings that colors are challenging to build for a brand (Hoek & Gendall, 2010; Piqueras-Fiszman & Spence, 2011). Further, our research replicates results in prior literature, finding that shape-based assets emerged as the most notable top performer and color(s) the worst performer (Ward et al., 2020).

Concerning suggestiveness, suggestive Distinctive Assets were inferior to non-suggestive. Notably, word and shape assets performed better as non-suggestive than suggestive, with small to large effect sizes indicating managerial significance (Kennedy et al., 2014). Audio performed slightly better as suggestive assets. However, the differences were statistically insignificant, indicating the suggestiveness of an audio asset had limited practical relevance. Finally, visual assets, including design, stories, and faces, showed minimal differences between suggestive and non-suggestive.

5.6.1 Implications for the body of academic knowledge

Our findings give academic researchers a better understanding of Distinctive Asset effectiveness by asset type and suggestiveness in two critical areas. First, the Picture Superiority Effect is once again confirmed as often visual-based assets such as shape (i.e., logos) and design (i.e., product form and pack) outperform word-based assets (i.e., taglines) (Childers & Houston, 1984). The visual effect has a stronger impact on memory, making the encoding and subsequent retrieval of images easier than words and audio (Crutcher & Beer, 2011). The visual-based assets that did not follow this effect were face and color. Face assets performed similarly to most other asset types, contrasting with previous findings on characters (a face asset) (Ward et al., 2020). Faces are said to be more accessible to process in memory (Bruce, 1982; Ellis, 1975; Samal & Iyengar, 1992), but this is not observed in a branding context compared to other elements. However, our finding for the color assets is not surprising. Since every brand must have a color palette (Hoek & Gendall, 2010), it is challenging to develop a strong color asset (Labrecque et al., 2013). As a result color assets often perform the worst among Distinctive Asset (Ward et al., 2020). Color is usually used to signal a particular category or variant/flavor, making it difficult to associate a color with a specific brand synonymously (Piqueras-Fiszman & Spence, 2011).

We demonstrated the viability of academics employing a novel Human-In-The-Loop approach (Gómez-Carmona et al., 2024) wherein humans and AI work together in data collection to assess suggestiveness. We adopted a previous suggestiveness coding application for brand names (Bali et al., 2024) and extended it to Distinctive Assets. Additionally, we applied two measures to assess their success, Fame and Uniqueness, adding further evidence to prior research that used recall (Sen, 1999) and attitudinal data (Gunasti et al., 2020).

The benefits of suggestive assets can be observed with audio assets. This finding aligns with the notion that the suggestive element could overcome an audio asset's inherent disadvantage (Crutcher & Beer, 2011) – that being suggestive supports an audio asset required to be encoded and recalled better in memory (Romaniuk, 2009), resulting in the consistent display of higher Fame and Uniqueness as suggestive assets - arguably compensating for the lack of visual stimulation (Romaniuk, 2018). While the effect sizes were small, we note the small sample of suggestive audio, potentially hinting at an untapped potential for suggestive audio.

5.6.2 Implications for marketing practitioners

Our research guides marketing practitioners on three fronts. First, advertisers should harness their shape-based assets and understand the improbable nature of owning color-based assets. Shape assets perform substantially better in Fame and Uniqueness, and while all brands must use colors, they should be used alongside stronger asset types to ensure an effective advertising strategy. Thus, advertisers should prioritize visual-based assets. These include symbolic images, packaging shapes, and logos. Regarding suggestiveness, considering the specific context of the industry and category the brand operates in is crucial (Hoffman & Liebman, 2018). For example, suggestive audio-based assets scored higher Fame and Uniqueness than non-suggestive assets; thus, advertisers may consider attaching some meaning to an audio asset because there is a chance that suggestive elements may aid recognizability and linkage to the brand that can compensate for the lack of any visuals in an audio asset (Simmonds et al., 2020; Wang & Muehling, 2010). With meaning embedded into audio assets, they may have a better chance of becoming linked to a brand via the mental shortcut suggestive branding can permit (Keller et al., 1998). For instance, the 'Zoom Zoom' sound commonly used in Mazda advertisements directly establishes the link between Mazda and being a vehicle. Suggestive audio may help cut through to the inattentive consumer without being overly intrusive (Ford & Campbell, 2022; Tripathi et al., 2022).

Second, the Fame and Uniqueness benchmarks can help brand managers prioritize assets, ensuring that finite resources are allocated effectively for consistent and quality execution of Distinctive Assets in all touchpoints (Phua, Hartnett, et al., 2023; WARC, 2020). Determining which, if any, Distinctive Assets should be suggestive of the category is a vital decision when implementing a branding strategy. Our results demonstrate that it is best to use non-suggestive shapes and word-based assets over suggestive ones, potentially as shape-based assets that look too similar to competitors face increasing difficulty in becoming famous or unique. Thus, a better strategy for brand managers is to build a unique synergy between a brand and its logo (shape asset) (Ward et al., 2020). In terms of adopting non-suggestive branding for word-based assets, it is crucial that a brand manager carefully selects their strategy. These asset types are some of the most ubiquitously used in branding along with shape (Romaniuk, 2018). Despite being commonly used, words do not perform as strongly as other asset types and have long been known to have a weaker memory effect (Ghosh et al., 2022; Paivio & Csapo, 1971). To combat this weakness, using a non-suggestive variety of word-based assets may establish Uniqueness that allows for a unique association to the brand due to low memory competition (Keller et al., 1998), whereas a suggestive word-based asset reflective of a commonly linked attribute of the category may increase memory competition.

Last, practitioners operating in a market research or consumer insights role can note the successful application of a Human-In-The-Loop approach (Wu et al., 2022) through the user-friendly interface of GPT-4o. Our approach, in conjunction with recent other marketing-related AI research (Campbell, 2023; Gupta et al., 2024) provides numerous valuable and practical insights derived through AI's help.

5.6.3 Limitations and Future Research

Due to our real-world data, the results may be affected by survivor bias (Brown et al., 1992). Some asset strategies perform so poorly that they tend to be weeded out by market competition or dropped by marketers. We could not assess this because our data is restricted to Distinctive Assets currently on the market.

Furthermore, the Human-In-The-Loop approach (Gómez-Carmona et al., 2024) allowed greater accuracy in the final benchmark. Yet, AI is making great strides in its image-processing capabilities; thus, a replication and extension of our approach would be worthwhile when AI can analyze and code audio and video-based Distinctive Assets.

5.7 Appendix

Prompt to GPT-4o (used between 5/14/24 – 5/24/24)

1. *I am doing a study on suggestive Distinctive Assets.*
2. *I want to know how common they are as opposed to non-suggestive Distinctive Assets in many different categories.*
3. *I will use your help to determine these results.*
4. *I define suggestive Distinctive Assets as "a non-name branding element that conveys relevant attribute or benefit information in a particular product or category context"*
5. *Could you please classify the new pictures I am about to send to you as suggestive or non-suggestive into a table format, with suggestive as 1 and non-suggestive as 2.*
6. *The category is X.*
7. **Insert Distinctive Asset images*.*

Chapter 6
Conclusion

Chapter overview

Chapter 6 concludes this thesis. The academic and industry contributions are first discussed, followed by the limitations of the studies and how these can be resolved through further research.

6 Conclusion

Overall, this thesis concludes that the effectiveness of a suggestive brand has various layers. While suggestive branding is generally less effective than non-suggestive branding at a broad level, there are specific circumstances where suggestive branding can be more effective. Study 1, using a human-in-the-loop approach, finds that the prevalence of suggestive branding is lower than non-suggestive branding despite marketing practitioners seeing greater value in the former. Moreover, regardless of the industry, suggestive Distinctive Assets were less effective than non-suggestive ones, exhibiting lower Fame and Uniqueness metrics; these findings lead to the assumption that suggestive assets should seldom be considered a branding strategy. Study 2 examines the effectiveness of Distinctive Assets based on their type, determining that most visual-based assets tend to outperform auditory and word-based assets. Building on the first study's findings by examining the intricacies of suggestive branding performance, again utilising a human-in-the-loop approach, this study demonstrates a place for both suggestive and non-suggestive Distinctive Assets - depending on the asset type.

6.1 Academic and practical contributions

6.1.1 Academic Contributions

Study 1 is the first to use the help of artificial intelligence to determine the prevalence of a suggestive brand name on a large scale. Furthermore, past research was restricted to brand names; however, this study expanded into suggestive Distinctive Assets, determining their prevalence and effectiveness. The exploratory nature of this thesis provides future researchers with a foundation to build on and many benchmarks to assess against.

Study 2 determines the effectiveness of Distinctive Assets, Distinctive Asset types, and the influence of suggestiveness on Distinctive Asset types using artificial intelligence, which has never been explored in literature. These intricacies were essential to explore, as results found that asset type did matter when deciding whether to use suggestive or non-suggestive branding. Like Study 1, this research contributes to the exploratory nature of this thesis, subsequently providing future researchers with solid foundations to build on.

6.1.2 Practical Contributions

Study 1 finds that although marketing practitioners see great value in a suggestive name, the usage of suggestive branding in the market does not reflect this, as its prevalence is low. Brand managers may wish to reconsider whether their beliefs are being adequately portrayed through their final branding strategy. Furthermore, the performance of a suggestive Distinctive Asset was inferior to non-suggestive elements irrespective of the industry a brand operates. Thus, regardless of the industry, non-suggestive branding elements should always be considered ahead of suggestive assets. However, these results were caused by aggregation of the dataset, found through study 2. The second study broke Distinctive Assets down into their types, discovering nuances not detected by the first study. Whether suggestive Distinctive Assets should or should not be used was circumstantial; for instance, suggestive assets for audio types and non-suggestive assets for word types were found to lead to higher effectiveness in asset performance.

Beyond suggestiveness, Study 2 provides other critical implications for managers, first on how their Distinctive Asset performance is tracking against the average and which Distinctive Asset types to prioritise in branding strategy. Knowing that visual assets are top performers guides brand managers in making branding decisions. However, differences in the performance of Distinctive Assets based on industry in Study 1 and between Distinctive Asset types in Study 2 (excluding shape and colour-based assets) were not substantial, so marketing practitioners should not hinge their branding decisions on these factors alone.

6.2 Limitations and future research

Studies 1 and 2 encounter similar limitations and subsequent pathways for future research. Both studies used a human-in-the-loop approach, wherein humans with Chat GPT-4 and Chat GPT-4o work together to produce results faster, cheaper, and more accurately than either could alone. However, once artificial intelligence reaches a point of mastery in tasks such as coding for suggestiveness, it could work entirely alone, allowing for the examination of larger datasets.

Both studies analysed Westernised markets; however, expansion of analysis into other countries would also be worthwhile. Specifically, Lee and Ang (2003) mention that Mandarin characters tend to contain a lot of meaning, which could indicate different results to Western countries for brand suggestiveness. Thus, investigating the usage of such naming practices, their cultural significance, and how these brands perform in the market would make for valuable future study.

Beyond the scope of suggestiveness, there are many other ways to classify names, as discussed in Arora et al. (2015). To name a few, promoter's names (e.g., Harley-Davidson), places of origin, compounding (e.g., White Claw), abbreviations, and blending (e.g., Photoshop). These ways of classification can also extend to Distinctive Assets. Suggestiveness is one of many other strategies; therefore, future research can investigate these branding decisions.

7 Statement of Authorship

University of South Australia

Statement of Authorship

Title of Paper	How prevalent are suggestive brand names and Distinctive Assets? An AI-human approach
Publication Status	☒ Published ☐ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
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PRINCIPAL AUTHOR	
Name of Principal Author (Candidate)	Larissa Mae Bali
Contribution to the Paper Brief description of your work in this publication	Contributed heavily to every section.
Overall Percentage (%)	90%
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature *Signatures will be redacted by the Library at the time of publication*	Date 09/07/2024
CO-AUTHOR CONTRIBUTIONS	

By signing the Statement of Authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);

II. permission is granted for the candidate in include the publication in the thesis; and

III. the sum of all co-author contribution is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper Brief description of your work in this publication	Contributed heavily to every section.
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Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature *Signatures will be redacted by the Library at the time of publication*	Date 09/07/24
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References

Aaker, D. A. (1991). *Managing brand equity: Capitalizing on the value of a brand name*. The Free Press.

Alba, J. W., & Marmorstein, H. (1987). The effects of frequency knowledge on consumer decision making. *Journal of Consumer Research*, *14*, 14-25.

Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior*, *22*, 261-295.

Anderson, J. R., & Bower, G. H. (1979). *Human Associative Memory*. Lawrence Erlbaum.

Anderson, J. R., & Bower, G. H. (1980). *Human Associative Memory: A Brief Edition*. Erlbaum Associates.

Andrivet, M. (2015). What to Learn From Tropicana's Packaging Redesign Failure? *The Branding Journal*. https://www.thebrandingjournal.com/2015/05/what-to-learn-from-tropicanas-packaging-redesign-failure/

Anesbury, Z., Nenycz-Thiel, M., Dawes, J., & Kennedy, R. (2016). How do shoppers behave online? An observational study of online grocery shopping. *Journal of Consumer Behaviour*, *15*(3), 261-270.

Arora, S., Kalro, A. D., & Sharma, D. (2015). A comprehensive framework of brand name classification. *Journal of Brand Management*, *22*(2), 79-116. https://doi.org/https://doi.org/10.1057/bm.2015.8

Ashour, M. L. (2018). Services Marketing is Different: The case of Telecom Services. *The International Journal of Business Management and Technology*, *2*(6), 6.

Atkinson, R. C., Shiffrin, R. M., Spence, K. W., & Spence, J. T. (1968). Human memory: A proposed system and its control processes. In *The psychology of learning and motivation: Advances in Research and Theory, vol. 2*. Academic Press. http://search.epnet.com/login.aspx?direct=true&db=psyh&an=1974-02719-003

Australian Bureau of Statistics. (2017). *Census reveals a fast changing, culturally diverse nation*. https://www.abs.gov.au/ausstats/abs@.nsf/lookup/media%20release3

Bali, L., Anesbury, Z., Phua, P., & Sharp, B. (2024). *How prevalent are suggestive brand names and Distinctive Assets? An AI-Human Approach*.

Barwise, P. (1995). Good Empirical Generalizations. *Marketing Science*, *14*(3), G29-G35.

Bass, F. M. (1995). Empirical Generalizations and Marketing Science: A Personal View. *Marketing Science*, *14*(3), G6-G18.

Bedford, E. (2023). *Market share of grocery stores in Great Britain from January 2017 to April 2023*. https://www-statista-com.eu1.proxy.openathens.net/statistics/280208/grocery-market-share-in-the-united-kingdom-uk/

Bellman, S., Nenycz-Thiel, M., Kennedy, R., Hartnett, N., & Varan, D. (2019). Best Measures of Attention To Creative Tactics in TV Advertising: When Do Attention-Getting Devices Capture or Reduce Attention? *Journal of Advertising Research*, *59*(3), 295-311. https://doi.org/10.2501/JAR-2019-002

Bien, N., Rajpurkar, P., Ball, R. L., Irvin, J., Park, A., Jones, E., Bereket, M., Patel, B. N., Yeom, K. W., & Shpanskaya, K. (2018). Deep-learning-assisted diagnosis for knee magnetic resonance imaging: development and retrospective validation of MRNet. *PLoS medicine*, *15*(11), e1002699. https://doi.org/https://doi.org/10.1371/journal.pmed.1002699

Blaess, N. (2023). Building Distinctive Brand Assets: The Key to a Strong Brand Identity. *Medium*. https://medium.com/@NineBlaess/building-distinctive-brand-assets-the-key-to-a-strong-brand-identity-59c09ec4ded3

Bound, J. A., & Ehrenberg, A. (1989). Significant sameness. *Journal of the Royal Statistical Society*, *152*, 241-247.

Brown, S. J., Goetzmann, W., Ibbotson, R. G., & Ross, S. A. (1992). Survivorship bias in performance studies. *The Review of Financial Studies*, *5*(4), 553-580. https://doi.org/https://doi.org/10.1093/rfs/5.4.553

Bruce, V. (1982). Changing faces: Visual and non-visual coding processes in face recognition. *British Journal of Psychology*, *73*(1), 105-116.

Bulmer, S., & Buchanan-Oliver, M. (2004). Meaningless or meaningful? Interpretation and intentionality in post-modern communication. *Journal of Marketing Communications*, *10*(March), 1-15.

Burke, R. R., & Srull, T. K. (1988). Competitive Interference and Consumer Memory for Advertising. *Journal of Consumer Research*, *15*, 55-68.

Campbell, C. (2023). Ready or Not, Generative AI Is Here to Stay: Advertisers Need More Research To Harness the Benefits of AI Technologies. *Journal of Advertising Research*, *63*, 202-204. https://doi.org/10.2501/JAR-2023-019

Campbell, C. (2024). Introducing 2024 JAR Research Priorities: An Advertising Industry-Informed List of Areas Where Research Is Needed Most. *63*, iv-vi. https://doi.org/10.2501/JAR-2024-006

Campbell, C., Plangger, K., Sands, S., Kietzmann, J., & Bates, K. (2022). How deepfakes and artificial intelligence could reshape the advertising industry: The coming reality of AI fakes and their potential impact on consumer behavior. *Journal of Advertising Research*, *62*(3), 241-251. https://doi.org/10.2501/JAR-2022-017

Carlston, D. E. (2007). Associative Networks. In R. F. Baumeister & K. D. Vohs (Eds.), *Encyclopedia of Social Psychology* (pp. 53). SAGE Publications. https://doi.org/http://dx.doi.org/10.4135/9781412956253.n30

Childers, T. L., Heckler, S. E., & Houston, M. J. (1986). Memory for the visual and verbal components of print advertisements. *Psychology & Marketing*, *3*(3), 137-149. http://ezlibproxy.unisa.edu.au/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=ufh&AN=11580091&site=ehost-live

Childers, T. L., & Houston, M. J. (1984). Conditions for a picture-superioritye effect on consumer memory. *Journal of Consumer Research*, *11*(September), 643-654.

Clift, J. (2016). *Better audio advertising: How radio can make campaigns more effective*. WARC.

Cohen, J. (1977). *Statistical power analysis for the behavioral sciences* (1st ed.). Academic Press.

Cohen, M. A., Horowitz, T. S., & Wolfe, J. M. (2009). Auditory recognition memory is inferior to visual recognition memory. Proceedings of the National Academy of Sciences, United States.

Collins, A. M., & Loftus, E. F. (1975). A spreading activation theory of semantic processing. *Psychological Review*, *82*(6), 407-428.

Collins, A. M., & Quillian, M. R. (1969). Retrieval time from semantic memory. *Journal of verbal learning and verbal behavior*, *8*(2), 240-247.

Costley, C. L., & De Wald, D. (1991). Cue modality: Video and audio effects on recall. *Advances in Consumer Research*, *18*, 819-825.

Craik, F. I. M., & Lockhart, R. S. (1972). Levels of processing: A framework for memory research. *Journal of Verbal Learning and Verbal Behavior*, *11*, 671-684.

Crutcher, R. J., & Beer, J. M. (2011). An auditory analog of the picture superiority effect. *Memory & Cognition*, *39*, 63-74. https://doi.org/https://doi.org/10.3758/s13421-010-0015-6

Degani, T., & Tokowicz, N. (2010). Semantic ambiguity within and across languages: An integrative review. *Quarterly Journal of Experimental Psychology*, *63*(7), 1266-1303. https://doi.org/https://doi.org/10.1080/17470210903377372

Djedi, S. (2018). The Effect of Brand Name Suggestiveness on Consumer Perception and Purchase Intentions.

Dogan, M. E., Goru Dogan, T., & Bozkurt, A. (2023). The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. *Applied Sciences*, *13*(5), 3056. https://doi.org/https://doi.org/10.3390/app13053056

du Plessis, E. (1994). Recognition Versus Recall. *Journal of Advertising Research*, *34*(3), 75-91.

Ebbinghaus, H. (1913). *Memory: A contribution to experimental psychology*. University Microfilms.

Ehrenberg, A. (1966). Regularities of Behaviour. *Applied Statistics*, *15*, 13-27.

Ehrenberg, A. (1990). A Hope for the Future of Statistics: MSOD. *The American Statistician*, *44*(3), 195-196.

Ellis, A. W., & Lambon Ralph, M. A. (2000). Age of acquisition effects in adult lexical processing reflect loss of plasticity in maturing systems: Insights from connectionist networks. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(5), 1103-1123. https://doi.org/10.1037W278-7393.26.5.I103

Ellis, H. D. (1975). Recognizing Faces. *British Journal of Psychology*, *66*(4), 409-426.

Enarsson, T., Enqvist, L., & Naarttijärvi, M. (2022). Approaching the human in the loop–legal perspectives on hybrid human/algorithmic decision-making in three contexts. *Information & Communications Technology Law*, *31*(1), 123-153. https://doi.org/https://doi.org/10.1080/13600834.2021.1958860

Espinosa, J. A., & Ortinau, D. J. (2016). Debunking legendary beliefs about student samples in marketing research. *Journal of Business Research*, *69*(8), 3149-3158. https://doi.org/https://doi.org/10.1016/j.jbusres.2015.12.003

Evans, J., & McKinven, J. (2024). Uncensored CMO In *Creativity driven performance, CPG lessons for SaaS and the power of distinctive assets*. https://uncensoredcmo.com/124#t=29m20s

Ferraro, C., Demsar, V., Sands, S., Restrepo, M., & Campbell, C. (2024). The paradoxes of generative AI-enabled customer service: A guide for managers. *Business Horizons*. https://doi.org/https://doi.org/10.1016/j.bushor.2024.04.013

Fiocchi, G., & Esfahani, M. S. (2023). Exploring the uniqueness of distinctive brand assets within the UK automotive industry. *Journal of Brand Management*, 1-15. https://doi.org/https://doi.org/10.1057/s41262-023-00329-6

Ford, J. B., & Campbell, C. (2022). The Quest for Consumers' Attention: Exploring Ad Tools, Tactics, and Devices. *62*, 197-198. https://doi.org/10.2501/JAR-2022-019

Gaillard, E. (2007). *How brand distinctiveness is communicated, from a consumer's perspective* University of South Australia]. Adelaide.

Gannon, D. (2023). *Supermarkets and Grocery Stores in Australia*. https://my.ibisworld.com/au/en/industry/g4111/about

Gemini. (2024). Release updates. *Gemini*. https://gemini.google.com/updates?hl=en-AU

Ghosh, T., Sreejesh, S., & Dwivedi, Y. K. (2022). Brand logos versus brand names: A comparison of the memory effects of textual and pictorial brand elements placed in computer games. *Journal of Business Research*, *147*, 222-235. https://doi.org/https://doi.org/10.1016/j.jbusres.2022.04.017

Gómez-Carmona, O., Casado-Mansilla, D., López-de-Ipiña, D., & García-Zubia, J. (2024). Human-in-the-loop machine learning: Reconceptualizing the role of the user in interactive approaches. *Internet of Things*, *25*, 101048. https://doi.org/https://doi.org/10.1016/j.iot.2023.101048

Gunasti, K., Kara, S., & Ross Jr, W. T. (2020). Effects of search, experience and credence attributes versus suggestive brand names on product evaluations. *European Journal of Marketing*, *54*(12), 2941-2963. https://doi.org/https://doi.org/10.1108/EJM-12-2017-0972

Gupta, R., Nair, K., Mishra, M., Ibrahim, B., & Bhardwaj, S. (2024). Adoption and impacts of generative artificial intelligence: Theoretical underpinnings and research agenda. *International Journal of Information Management Data Insights*, *4*(1), 100232. https://doi.org/https://doi.org/10.1016/j.jjimei.2024.100232

Hartnett, N., Kennedy, R., Sharp, B., & Greenacre, L. (2016). Marketers' intuitions about the sales effectiveness of advertisements. *Journal of Marketing Behavior*, *2*, 177-194. https://doi.org/http://dx.doi.org/10.1561/107.00000034

Hartnett, N., Romaniuk, J., & Kennedy, R. (2016). Comparing direct and indirect branding in advertising. *Australasian Marketing Journal*, *24*(1), 20-28. https://doi.org/https://doi.org/10.1016/j.ausmj.2015.12.002

Heath, R. (1999). The Low-Involvement Processing Theory. *Admap*, *34*(March), 14-17.

Heil, M., Rösler, F., & Hennighausen, E. (1994). Dynamics of Activation in Long-Term Memory: The Retrieval of Verbal, Pictorial, Spatial, and Color Information. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *20*(1), 185-200. https://doi.org/10.1037/0278-7393.20.1.185

Hirschman, A. O. (1964). The paternity of an index. *The American Economic Review*, *54*(5), 761-762.

Ho, Y. L., Lau, S. H., & Azman, A. (2022). Picture superiority effect in authentication systems for the blind and visually impaired on a smartphone platform. *Universal Access in the Information Society*, 1-11. https://doi.org/10.1007/s10209-022-00928-1

Hoek, J., & Gendall, P. (2010). Colors, brands, and trademarks: The marketing (and legal) problem of establishing distinctiveness. *Journal of Advertising Research*, *50*(3), 316-322.

Hoffman, A. B., & Liebman, G. (2018). *Context Matters: Emotions & Ad Effectiveness*.

Holzinger, A. (2016). Interactive machine learning for health informatics: when do we need the human-in-the-loop? *Brain Informatics*, *3*(2), 119-131. https://doi.org/https://doi.org/10.1007/s40708-016-0042-6

Hoyer, W. D. (1984). An examination of consumer decision making for a common repeat purchase product. *Journal of Consumer Research*, *11*(3), 822-829.

Hutchinson, J. W., & Alba, J. W. (1991). Ignoring irrelevant information: Situational determinants of consumer learning. *Journal of Consumer Research*, *18*(3), 325-345.

IBM. (2024). The new AI innovation equation. *IBM*. https://www.ibm.com/watson/advantage-reports/future-of-artificial-intelligence/ai-innovation-equation.html

Kara, S., Gunasti, K., & Ross, W. T. (2020). My brand identity lies in the brand name: Personified suggestive brand names. *Journal of Brand Management*, *27*(5), 607-621. https://doi.org/https://doi.org/10.1057/s41262-020-00201-x

Keller, K. L. (1987). Memory factors in advertising: The effect of advertising retrieval cues on brand evaluations. *Journal of Consumer Research*, *14*(3), 316-333.

Keller, K. L. (1991). Cue compatibility and framing in advertising. *Journal of Marketing Research*, *28*(February), 42-57.

Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. *Journal of Marketing*, *57*(1), 1-22. http://www.jstor.org/stable/1252054
Keller, K. L. (2005). Branding shortcuts. *Marketing Management*, *14*(5), 18-23.
Keller, K. L. (2012). *Strategic Brand Management* (4th ed.). Pearson.
Keller, K. L., Aperia, T., & Georgson, M. (2008). Choosing brand elements to build brand equity. In *Strategic brand management: a European perspective* (pp. 128-170). Prentice Hall Financial Times.
Keller, K. l., Heckler, S. E., & Houston, M. J. (1998). The effects of brand name suggestiveness on advertising recall. *Journal of Marketing*, *62*(January), 48-57.
Kennedy, R., Scriven, J., & Nenycz-Thiel, M. (2014). When 'significant' is not significant. *International Journal of Market Research*, *56*(5), 591-607. https://doi.org/10.2501/IJMR-2014-041
Kim, J., Kim, J. H., Kim, C., & Park, J. (2023). Decisions with ChatGPT: Reexamining choice overload in ChatGPT recommendations. *Journal of Retailing and Consumer Services*, *75*, 103494. https://doi.org/https://doi.org/10.1016/j.jretconser.2023.103494
Kohli, C. S., Harich, K. R., & Leuthesser, L. (2005). Creating brand identity: a study of evaluation of new brand names. *Journal of Business Research*, *58*(11), 1506-1515.
Krishnan, H. S. (1996). Characteristics of memory associations: A consumer-based brand equity perspective. *International Journal of research in Marketing*, *13*(4), 389-405.
Labrecque, L. I., Patrick, V. M., & Milne, G. R. (2013). The marketers' prismatic palette: A review of color research and future directions. *Psychology & Marketing*, *30*(2), 187-202. https://doi.org/10.1002/mar.20597
Lam, P. Y., Chan, A., Gopaoco, H., Oh, K., & So, T. H. (2013). Dual branding strategy for a successful new product launch in China. *Business horizons*, *56*(5), 583-589. https://doi.org/http://dx.doi.org/10.1016/j.bushor.2013.05.003
Learnship. (2023). ChatGPT is more efficient in English and you can B2! https://www.learnship.com/en/blog/chatgpt-is-more-efficient-in-english-and-you-can-b2/
Lee, Y. H., & Ang, K. S. (2003). Brand name suggestiveness: A Chinese language perspective. *International Journal of Research in Marketing*, *20*(4), 323-335. https://doi.org/https://doi.org/10.1016/j.ijresmar.2003.03.002
Lepitak, S. (2024). Why Doritos Is Evolving Its Long-Standing 'Bold' Brand Platform. *AdWeek*. https://www.adweek.com/brand-marketing/why-doritos-is-evolving-its-long-standing-bold-brand-platform/
Li, H., & Xu, Y. (2002). Survival bias and the equity premium puzzle. *The Journal of Finance*, *57*(5), 1981-1995. https://doi.org/https://doi.org/10.1111/0022-1082.00486
Livberber, T., & Ayvaz, S. (2023). The impact of Artificial Intelligence in academia: Views of Turkish academics on ChatGPT. *Heliyon*, *9*(9). https://doi.org/https://doi.org/10.1016/j.heliyon.2023.e19688

Lombard, M., Snyder-Duch, J., & Bracken, C. C. (2004). Interrater Reliability: Practical resources for assessing and reporting intercoder reliability in content analysis research projects. *Journal of Consumer Psychology*, *10*(1-2), 71-73.

Lovelock, C., & Gummesson, E. (2004). Whither services marketing? In search of a new paradigm and fresh perspectives. *Journal of Service Research*, *7*(1), 20-41. https://doi.org/https://doi.org/10.1177/1094670504266131

Luffarelli, J., Mukesh, M., & Mahmood, A. (2019). A study of 597 Logos shows which kind is most effective. *Harvard Business Review*. https://hbr.org/2019/09/a-study-of-597-logos-shows-which-kind-is-most-effective?utm_medium=social&utm_campaign=hbr&utm_source=twitter&tpcc=orgsocial_edit

McHugh, M. L. (2012). Interrater reliability: the kappa statistic. *Biochemia medica*, *22*(3), 276-282.

McKinsey & Company. (2023). The state of AI in 2023: Generative AI's breakout year. *McKinsey*. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

Mecredy, P., Wright, M., Feetham, P., & Stern, P. (2023). Remembering less, or needing less? Age-related differences in the purchase funnel. *Marketing Letters*, 1-16. https://doi.org/https://doi.org/10.1007/s11002-023-09681-8

Mensink, G.-J., & Raaijmakers, J. G. (1988). A model for interference and forgetting. *Psychological Review*, *95*(4), 434. https://psycnet.apa.org/doi/10.1037/0033-295X.95.4.434

Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping Humans in the Loop: Pooling Knowledge through Artificial Swarm Intelligence to Improve Business Decision Making. *California Management Review*, *61*(4), 84-109. https://doi.org/https://doi.org/10.1177/0008125619862256

Michelon, A., Bellman, S., Faulkner, M., Cohen, J., & Bruwer, J. (2020). A New Benchmark for Mechanical Avoidance of Radio Advertising: Why Radio Advertising Is a Sound Investment. *Journal of Advertising Research*, *60*, 407-416. https://doi.org/10.2501/JAR-2020-007

Morin, C. (2011). Neuromarketing: The New Science of Consumer Behavior. *Society*, *48*(2), 131-135.

Murnane, K., & Shiffrin, R. M. (1991). Interference and the representation of events in memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *17*(5), 855-874.

Muzellec, L. (2006). What is in a name change? Re-joycing corporate names to create corporate brands. *Corporate Reputation Review*, *8*(4), 305-316. https://doi.org/https://doi.org/10.1057/palgrave.crr.1540257

Nguyen, C., Faulkner, M., Yang, S., Williams, J., & Tong, L. (2022). Mind the gap: Understanding the gap between intentions and behaviour in the charity context. *Journal of Business Research*, *148*, 216-224. https://doi.org/https://doi.org/10.1016/j.jbusres.2022.04.044

Office for National Statistics. (2021). *Language, England and Wales: Census 2021*. https://www.ons.gov.uk/peoplepopulationandcommunity/culturalidentity/language/bulletins/languageenglandandwales/census2021

Office for National Statistics. (2023). Understanding AI uptake and sentiment among people and businesses in the UK: June 2023. https://www.ons.gov.uk/businessindustryandtrade/itandinternetindustry/articles/understandingaiuptakeandsentimentamongpeopleandbusinessesintheuk/june2023
Olenski, S. (2012). JC Penney's Epic Rebranding Fail. *Forbes*. https://www.forbes.com/sites/marketshare/2012/06/15/jc-penneys-epic-rebranding-fail/?sh=21b091aa29e8
Olson, C. (2004). Maximizing brand recognition. *Information Outlook*, *8*(1), 43.
OpenAI. (2023a). GPT-4V(ision) system card. https://openai.com/research/gpt-4v-system-card
OpenAI. (2023b). *Research - GPT-4*. https://openai.com/research/gpt-4
OpenAI. (2024). ChatGPT — Release Notes. *OpenAI*. https://help.openai.com/en/articles/6825453-chatgpt-release-notes
Paivio, A. (1971). *Imagery and Verbal Processes*. Rineheart & Winston.
Paivio, A., & Csapo, K. (1971). Short-term sequential memory for pictures and words. *Psychonomic Science*, *24*(2), 50-51. https://doi.org/https://doi.org/10.3758/BF03337887
Paivio, A., & Csapo, K. (1973). Picture superiority in free recall: Imagery or dual coding? *Cognitive Psychology*, *5*(2), 176-206.
Paivio, A., Rogers, T. B., & Smythe, P. C. (1968). Why are pictures easier to recall than words. *Psychonomic Science*, *11*(4), 137-138.
Paul, J., Ueno, A., & Dennis, C. (2023). ChatGPT and consumers: Benefits, pitfalls and future research agenda. *International Journal of Consumer Studies*, *47*(4), 1213-1225. https://doi.org/https://doi.org/10.1111/ijcs.12928
Pecot, F., Merchant, A., & de Barnier, V. (2022). Why and when is older better? The role of brand heritage and of the product category in the evaluation of brand longevity. *Journal of Business Research*, *140*, 533-545. https://doi.org/https://doi.org/10.1016/j.jbusres.2021.11.021
Phua, P., & Hartnett, N. (2021). Maximise distinctive assets. *WARC*. Retrieved 1st September 2021, from https://www.warc.com/newsandopinion/opinion/maximise-distinctive-assets/4000
Phua, P., Hartnett, N., Beal, V., Trinh, G., & Kennedy, R. (2023). When brands go dark: A replication and extension. *Journal of Advertising Research*(June), 172-184. https://doi.org/https://doi.org/10.2501/JAR-2023-009
Phua, P., Kennedy, R., Trinh, G., Hartnett, N., & Page, B. (2018). *Are older consumers more loyal to older brands?* (83). https://sponsors.marketingscience.info/reports/are-older-consumers-more-loyal-to-older-brands/
Phua, P., Page, B., Trinh, G., Hartnett, N., & Kennedy, R. (2023). Does Childhood Exposure to a Brand Improve Brand Name Recognition?: Comparing Age-of-Acquisition Effects with Ongoing Brand Exposure and Experience. *Journal of Advertising Research*. https://doi.org/10.2501/JAR-2023-025
Piñero, M. A., Lockshin, L., Kennedy, R., & Corsi, A. (2010). *Distinctive elements in packaging (FMCG): An exploratory study* ANZMAC, Christchurch.

Piqueras-Fiszman, B., & Spence, C. (2011). Crossmodal correspondences in product packaging: Assessing color-flavor correspondences for potato chips (crisps). *Appetite*, *57*(3), 753-757. https://doi.org/https://doi.org/10.1016/j.appet.2011.07.012
Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management*, *36*(1), 94-120. https://doi.org/10.1177/0149206309352110
Postman, L., & Underwood, B. J. (1973). Critical issues in interference theory. *Memory & Cognition*, *1*(1), 19-40.
Ray, P. P. (2023). ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet of Things and Cyber-Physical Systems*. https://doi.org/https://doi.org/10.1016/j.iotcps.2023.04.003
Reason, J. (2000). Education and debate: human error: models and management. *British Medical Journal*, *320*, 320.
Riebe, E., Driesener, C., & Beal, V. (2008). The Effect of Recency of Ad Exposure on Purchasing Across Categories and Media. (Part 4/Project Apollo), 202-209.
Rodgers, S., & Thorson, E. (2012). Brand Concepts and Advertising. In *Advertising Theory* (Vol. 514). Routledge New York. https://doi.org/https://doi.org/10.4324/9780203149546
Romaniuk, J. (2003). Brand attributes - 'distribution outlets' in the mind. *Journal of Marketing Communications*, *9*(June), 73-92.
Romaniuk, J. (2009). The efficacy of brand-execution tactics in TV advertising, brand placements and Internet advertising. *Journal of Advertising Research*, *49*(2), 143-150.
Romaniuk, J. (2013). Modeling mental market share. *Journal of Business Research*, *66*(2), 188-195.
Romaniuk, J. (2018). *Building Distinctive Brand Assets*. Oxford University Press.
Romaniuk, J. (2022). *Poll: To launch a new brand would you prefer a brand name with meaning related to what you sell (eg Airbnb) or one without (eg Spotify)?* LinkedIn. https://www.linkedin.com/feed/update/urn:li:activity:6994536234974937088/
Romaniuk, J., & Hartnett, N. (2010). *Understanding, identifying and building distinctive brand assets* (Report 52 for Ehrenberg-Bass Sponsors, Issue.
Romaniuk, J., & Nenycz-Thiel, M. (2014). Measuring the strength of color brand-name links: The comparative efficacy of measurement approaches. *Journal of Advertising Research*, *54*(3), 313-319.
Romaniuk, J., & Sharp, B. (2016). *How brands grow: Part 2*. Oxford University Press.
Romaniuk, J., & Sharp, B. (2021). *How Brands Grow: part 2* (J. Butler, Ed. 2nd ed.). Oxford University Press.
Saji, K. B., Jit Singh Mann, B., & Kaur, M. (2013). Exploring branding strategies of FMCG, services and durables brands: evidence from India. *Journal of Product & Brand Management*, *22*(1), 6-17. https://doi.org/https://doi.org/10.1108/10610421311298650

Samal, A., & Iyengar, P. A. (1992). Automatic recognition and analysis of human faces and facial expressions: A survey. *Pattern recognition*, *25*(1), 65-77. https://doi.org/10.1016/0031-3203(92)90007-6

Sands, S., Campbell, C., Ferraro, C., Demsar, V., Rosengren, S., & Farrell, J. (2024). Principles for Advertising Responsibly Using Generative AI. *Organizational Dynamics*, *4*, 1-9. https://doi.org/https://doi.org/10.1016/j.orgdyn.2024.101042

Sands, S., Demsar, V., Ferraro, C., Campbell, C., & Cohen, J. (2024). Inauthentic inclusion: Exploring how intention to use AI-generated diverse models can backfire. *Psychology & Marketing*. https://doi.org/https://doi.org/10.1002/mar.21987

Sen, S. (1999). The effects of brand name suggestiveness and decision goal on the development of brand knowledge. *Journal of Consumer Psychology*, *8*(4), 431-455.

Shah, C. (2024). From Prompt Engineering to Prompt Science With Human in the Loop. *arXiv preprint arXiv:2401.04122*. https://doi.org/https://doi.org/10.48550/arXiv.2401.04122

Shepard, R. N. (1967). Recognition memory for words, sentences and pictures. *Journal of Verbal Learning and Verbal Behavior*, *6*(1), 156-163.

Simmonds, L., Bogomolova, S., Kennedy, R., Nenycz-Thiel, M., & Bellman, S. (2020). A dual-process model of how incorporating audio-visual sensory cues in video advertising promotes active attention. *Psychology & Marketing*, *37*(8), 1057-1067. https://doi.org/10.1002/mar.21357

Stanford University. (2023). SQ2. What are the most important advances in AI? https://ai100.stanford.edu/gathering-strength-gathering-storms-one-hundred-year-study-artificial-intelligence-ai100-2021-1/sq2

Statista. (2023). *Grocery stores: Target shoppers in the United States*. https://www.statista.com/study/65608/grocery-stores-target-shoppers-in-the-united-states/

Stern, Y. (2002). What is cognitive reserve? Theory and research application of the reserve concept. *Journal of the international neuropsychological society*, *8*(3), 448-460. https://doi.org/https://doi.org/10.1017/S1355617702813248

Student. (1908). The probable error of a mean. *Biometrika*, *6*, 1-25. https://doi.org/https://doi.org/10.2307/2331554

Tripathi, S., Jain, V., Pandey, J., Merchant, A., & Ambika, A. (2022). When Consumers Tune Out Advertising Messages: Development and Validation of a Scale To Measure Advertising Disengagement. *Journal of Advertising Research*, *62*(1), 3-17. https://doi.org/10.2501/JAR-2021-020

Tucker, R. (2023). Barbie: A masterclass in strategic brand evolution. *Mumbrella*. https://doi.org/https://mumbrella.com.au/barbie-a-masterclass-in-strategic-brand-evolution-793621

Uncles, M. D., & Wright, M. (2004). Editorial: empirical generalisation in marketing [Editorial]. *Australasian Marketing Journal*, *12*(3), 5-12.

United States Census Bureau. (2022). *Language Use in the United States: 2019*. https://www.census.gov/library/publications/2022/acs/acs-50.html

Vaughan, K., Beal, V., Corsi, A. M., & Sharp, B. (2021). Measuring advertising's effect on Mental Availability. *International Journal of Market Research*, *63*(5), 665-681. https://doi.org/https://doi.org/10.1177/1470785320955095

Velykytė, G. (2023). Creativity in distinctive brand assets. *Creativity Studies*, *16*(2), 384-396. https://doi.org/https://doi.org/10.3846/cs.2023.19035

Viehoever, A. (1920). Popular names of crude drugs. *Journal of the American Pharmaceutical Association*, *9*(7), 671-676.

Wang, A., & Muehling, D. D. (2010). The effects of audio-visual and visual-only cues on consumers' responses to co-branded advertising. *Journal of Marketing Communications*, *16*(5), 307-324. https://doi.org/10.1080/13527260902970190

WARC. (2020). *What we know about brand and advertising awareness*.

Ward, E., Yang, S., Romaniuk, J., & Beal, V. (2020). Building a unique brand identity: measuring the relative ownership potential of brand identity element types. *Journal of Brand Management*, *27*(4), 393-407. https://doi.org/10.1057/s41262-020-00187-6

Watson. (2022). *IBM Global AI Adoption Index 2022*. https://www.ibm.com/downloads/cas/GVAGA3JP

Wilbur, K., & Farris, P. (2014). Distribution and market share. *Journal of Retailing*, *90*(2), 154-167.

Williams, A. (2021, 8 December). *Learning from the Gap Logo Redesign Fail*. The Branding Journal. https://www.thebrandingjournal.com/2021/04/learnings-gap-logo-redesign-fail/

Woolworths. (2023). *Pantry*. https://www.woolworths.com.au/shop/browse/pantry

Wu, L., & Wen, T. J. (2021). Understanding AI advertising from the consumer perspective: What factors determine consumer appreciation of AI-created advertisements? *Journal of Advertising Research*, *61*(2), 133-146. https://doi.org/10.2501/JAR-2021-004

Wu, X., Xiao, L., Sun, Y., Zhang, J., Ma, T., & He, L. (2022). A survey of human-in-the-loop for machine learning. *Future Generation Computer Systems*, *135*, 364-381. https://doi.org/https://doi.org/10.1016/j.future.2022.05.014

Yoon, S. J. (2013). Antecedents and consequences of in-store experiences based on an experiential typology. *European Journal of Marketing*, *47*(5/6), 693-714. https://doi.org/ https://doi.org/10.1108/03090561311306660

Young, M. R., DeSabro, W. S., & Morwitz, V. G. (1998). The stochastic modelling of purchase intentions and behavior. *Management Science*, *44*(2), 188-202.

Zaichkowsky, J. L. (2010). Strategies for distinctive brands. *Journal of Brand Management*, *17*(8), 548-560.