Exploring the Uniqueness of Distinctive Brand Assets within the UK Automotive Industry

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Abstract

Distinctive brand assets, such as logos, fonts, and jingles, help strengthen the link between a brand and its marketing communications, which is pivotal to anchoring any message to the right mental structures of category buyers. However, budget and time constraints mean that brand managers can only effectively build and own a limited number of assets, heightening the need for guidance on selecting the most valuable ones to invest in. The only exhaustive paper on the topic revealed that logos, logotypes, and characters offer the best opportunities for ownership in FMCG categories. We extend these findings to the automotive industry, a first in a high-involvement product category, and replicate the Competitive Intensity formula used in this contribution to enable comparison. Results of testing 44, in-market and de-branded assets show that logo is the most uniquely ownable asset type. Fonts, slogans, and colours all emerge as having Low Uniqueness Concentration. The dispersion of competitive intensity within asset types varies in line with their uniqueness concentration, raising the importance of creative execution and consistent usage to develop a sufficiently high level of unique ownership. Finally, we observed neither gender nor generational differences in the uniqueness scores, nor in the dispersion of competitive intensity.

Keywords:

Branding – Brand Identity – Identity Elements – Distinctive Brand Assets – Uniqueness Concentration

1.0 Introduction

When it comes to defining a brand's identity and artistic direction, the disconnect in thinking between designers and brand managers has become a trending topic in the brand management academia (Golob et al., 2020). This is ensued by the different educational institutions these professionals typically go to, Art School the former and Business School the latter, and the capacity of a brand's leadership team to enable a shared vision with their creative counterparts (Schroeder, 2005; Golob et al., 2020). Such a tension between the art and business worlds may help explain why brand communications are, to a large extent, indistinctive. As an example, a revealing study from the Ehrenberg-Bass Institute (EBI) – which examined 143 Tv ads in Australia – found that only 40% of respondents recognised the tested creatives, of which only 40% could correctly link them to the sponsoring brand, resulting in a 16% brand recognition share or, in other words, an 84% wastage (Sharp, 2010). Given that this is not an isolated case, as demonstrated by prior large-scale studies which had disappointingly similar ad recognition scores (Du Plessis, 1994; Franzen, 1994; Romaniuk, 2012), one wonders whether brand managers are properly equipping creative departments with the business knowledge they need to create more distinctive advertising executions. Fundamentally, this consists of prioritising the development of a unique brand identity and consistently using it across all communication activities to reinforce the brand-advertisement link in the memory of category buyers (Romaniuk 2018). In fairness to brand managers, however, the marketing academia has overlooked the importance of distinctiveness in equal parts. Indeed, notwithstanding a few marketing scholars who have acknowledged the necessity of making the brand stand out in advertising (Percy and Rossiter, 1992; Kapferer, 1995; Franzen, 1999), the wider marketing literature has largely overemphasised the concepts of brand associations and differentiation (e.g., Reeves, 1961; Trout and Rivkin, 2000; Aaker, 2005) over the more need to be easily recognisable (Ritson, 2018) – which is crucial to anchor any brand message to the right mental structures of consumers (Ehrenberg et al., 2002; Romaniuk et al., 2007).

This paradigm, however, is changing. The ascension of EBI, fuelled by compelling empirical evidence and solid neuroscience and behavioural economics foundations, has led to questioning the importance of brand differentiation in marketing, heightening the focus on creating a distinctive brand identity. Some of the biggest corporations in the world, including the likes of P&G, Unilever and Coca-Cola, now sponsor this institute and are heavily invested on developing strong brand identity elements to create more effective marketing communications (Ehrenberg-Bass Institute, 2022). Brand identity elements, henceforth referred to as Distinctive Brand Assets (DBAs), include logos, fonts, colours, taglines, and anything else that elicits the brand name in its absence (Romaniuk, 2018). Although such a great variety of assets offer limitless creative opportunities, as demonstrated by best-in-class examples such as McDonald's use of its Golden Arches, 'I'm Lovin' it' jingle and red and yellow colours, building easily recognisable DBAs is a costly endeavour, and brand managers need to commit to years of consistent use at every customer touchpoint to have a chance of being successful (Ward et al., 2020). Hence, given the ever-shorter reporting cycles allowed to marketers (Ritson, 2019a), and the current inflationary environment and recession, which are set to heavily downsize marketing budgets in the coming years (Houston, 2022), understanding which DBA types to focus on has become an increasingly important matter for practitioners.

To be truly distinctive, and establish the pivotal brand-advertisement link, brand assets must be uniquely owned by a single brand in the mind of consumers (Romaniuk and Nenycz-Thiel, 2014). Therefore, uniqueness, which refers to the propensity of DBAs to be exclusivity associated with a single brand, is key (Romaniuk, 2018). The current research explores this very topic. We build upon the only comprehensive academic paper in this research area (Ward et al., 2020), to extend its findings on packaged goods to the automotive industry, thus enabling a comparison between the ownability potential of different DBA types across low- (FMCG) and high-involvement (automotive) product categories. To make results directly comparable with Ward et al.'s (2020) findings, we employ the Herfindahl-Hirschman Index to calculate the competitive intensity of the four most-widely used DBA types by automotive brands – logo, font, slogan, and colour. Successively, we investigate differences in the uniqueness scores given by gender and generational groups, along with the dispersion of uniqueness concentration of each DBA type. The main conceptual contribution of this paper is concerned with differentiating the ownability potential of DBA types in product categories with vastly different involvement levels, and the subsequent implications for brand identity development (MacInnis, 2011). As later discussed, not only does this fill a gap in DBAs research, but it also adds to the literature by contrasting low- and high-involvement purchase decisions on a yet-unexplored dimension.

2.0 Literature Review

2.1 Differentiation in Marketing

Differentiation – as a field of academic studies – traces all the way back to the 1930s, when Chamberlin (1933) and Robinson (1933) produced the first pieces of research which deviated from the perfect competition model in economics (Chamberlain, 1971); their assertion being that to face less competition in any given industry, marketers had to find a way to differentiate their offering. Nevertheless, it was not until the second part of the twentieth century that the concept of brand differentiation started to pick up momentum in the marketing literature; most notably with the contribution of Ries and Trout (1986), who stressed the need for differentiation to be "perceived" by customers, and those of Reeves (1961), Carpenter et al. (1994) and Kotler et al. (1996) – which helped define differentiation as something that had to be truly valued by customers, albeit not necessarily for the extrinsic features of a product. Rather, these scholars pointed to symbols, emotions, and any other intangible association as equally qualified to successfully differentiate a brand's offering. This research stream's most polarised arguments possibly came from Trout and Rivkin (2000), who famously stated "differentiation or die", and the likes of Levitt (1980) and MacMillan and McGrath (1997), whose scholarly contributions clearly implicated marketers should be evaluated on their ability to differentiate their brands (see Appendix A for summary).

However, the concept of differentiation has come into increasing scrutiny both in the academic and professional spheres (Ritson, 2019b), with the marketing scientists at the EBI leading the charge. One of their first influential contributions came from Sharp and Dawes (2001) who, following a deep dive into the related literature across multiple disciplines, inferred that differentiation is specific to certain buying situations and fully dependent on a given market's characteristics, as opposed to something a brand can influence. This underscores that elements such as physical proximity to a store or general product-person fit – e.g., whether a size fits the body – are by far the key differentiating drivers, as opposed to brand associations and perceptions (ibid.). Corroborating evidence has since followed in several forms. To begin with, Romaniuk et al. (2007) and Romaniuk and Gaillard (2007) tackled head on the topic of brand associations and differentiation by researching it across multiple product categories – seven and eight respectively – with robust samples. Romaniuk et al. (2007) demonstrated that most category buyers do not perceive differences between the brands they consume and those they do not. Based on these findings, they questioned differentiation as a driver of buying behaviour and challenged widespread information processing models, such as Fishbein and Ajzen's (1975) Theory of Reasoned Action, due to their assertion that attitude (in this case, towards the differentiated brand) anticipates (consumer) behaviour. As for Romaniuk and Gaillard (2007), their empirical evidence proved how rare unique brand associations are, as well as their limited benefits, compared to associations shared by multiple brands, in terms of impact on brand usage and perceived brand performance. Sharp (2010), too, weighed in on this topic, most notably in reference to the widely-cited Dimensions of Brand Personality framework (Aaker, 1997). Alongside scoring too poorly to be managerially relevant, he argues, very few researchers have ever tried to test the same participants twice in the context of brand personality scores, as EBI led research shows that about 75% of the times respondents will provide two different answers, making these personality perceptions not only weakly-held at population level, but at an individual one too (Sharp, 2002; Rungie et al., 2005; Driesener and Romaniuk, 2006).

A second foundational pillar of differentiation would want differentiated brands to appeal to distinct customer segments who value a company's differentiating elements (e.g., Kotler and Armstrong, 2014). However, Kennedy et al. (2000) and Kennedy and Ehrenberg (2001) have demonstrated little perceivable difference in demographics, or any other identifying variables, within the customer base of any two brands in a product category. Indeed, except for predictable patterns such as luxury category buyers having a higher disposable income than non-buyers, there is virtually no demographic or attitudinal difference in the customer base of competing brands (Sharp, 2010). Additionally, Sharp et al. (2003) looked at brands similarly positioned on perceptual maps, and their likelihood to share a larger proportion of customers. This did not appear to find any empirical ground, underscoring that brand associations do not correlate well with brand buying patterns, and supporting the Duplication of Purchase Law (Ehrenberg, 1988; Ehrenberg et al., 2004) – that is, a brand shares its customer base with competitors in line with their respective market share, with partitioning being a rare and statistically-insignificant occurrence (see Appendix B for summary).

2.2 Behavioural Economics and Neuroscience Principles

The limited impact of brand-level differentiation – which assumes consumers effortfully and deliberately try to decode a brand's desired associations – could be explained and expanded through Kahneman's System Thinking Theory (2003). According to his research, the brain is compounded by two parallel systems which control our decision-making process (Mishra et al., 2007). System 1 is automatic, rapid and makes a heavy use of shortcuts, or heuristics, to save our limited cognitive capabilities; System 2, in contract, is slow, effortful and jumps in when rational decision-making is required (Stanovich and West, 2000; Stanovich, 2004; Kahneman, 2011). Whilst the two act jointly, it is the associative System 1 that we use in most of our decisions, so as to limit the energy we spend at any given time – particularly when we are exposed to marketing communications (Collins and Loftus, 1975; Shleifer, 2012; Bellman et al., 2019). Not only does this notion provide some context to what was uncovered in the previous paragraph, but it also helps explain why the marketing academia has churned out extensive literature on brand differentiation (e.g., Aaker, 1997; Keller, 2013), and comparatively little on the marketing implication of system 1 (Sharp, 2010; Kahneman, 2011; Lipovetsky, 2020). That is, due to the requirement of logic to be expressed, thought-through brand perceptions – belonging to System 2 – are inherently more tangible and, thus, easier to measure and theorise. By the same token, Kahneman's (2003) contribution has significantly elevated the role of heuristics, given their strong influence on System 1-led purchase decisions (Zhang et al., 2014; Tasgal, 2015; Chu et al., 2020; Tan et al., 2021). And this, together with the knowledge that brands are not perceived as differentiated even by their customers (Romaniuk et al., 2007), should arguably heighten the focus on being unmistakably recognisable and meaninglessly distinct; in essence, making heavy use of DBAs as heuristic devices to anchor all brand exposures to the desired mental structures of category buyers (Perry and Wisnom, 2003; Olson, 2004; Sharp and Romaniuk, 2004; Hoek and Gendall, 2010; Sharp, 2010; Kennedy et al., 2013).

On the topic of mental structures, it is now pivotal to dig deeper into how they work, by drawing on the Associative Network Theory developed in Anderson and Bower's (1979) and Anderson's (1983) seminal contributions. According to these academics, any piece of information is stored as an individual node in memory which is linked to other related nodes by means of associative networks (Wyer and Srull, 1989;

Tulving et al., 1994). Further, these nodes have varying levels of strength, and a spreading activation process determines whether they will be retrieved from long-term memory and how (Ratcliff and McKoon, 1988). Crucially, Keller (1993) argues that the success of this process is fully dependent on the strength of association between the activated node and the ones linked to it within an associative network.

In light of these foundational neuroscience principles, a brand can be considered a node in memory that is linked – with various degrees of strength – to other associations and attributes (including DBAs) which, in turn, are themselves loosely linked to other parts of our memory (Romaniuk, 2018). In addition, the aforementioned retrieval process can be thought of as a competitive exercise. Indeed, the link between a brand and an association does not guarantee that the former will be retrieved when the latter is used as marketing cue, as the proven limitations of the brain mean that other things, including competing brands, may be triggered instead (Romaniuk, 2006). This has two important implications: long-term memories can be subjected to contamination, particularly if the exposure to marketing communications activities – new nodes – of a given brand are not consistent overtime (Kitamura et al., 2017), and the subsequent necessity to develop, own and persistently use DBAs to help consumers successfully decode any brand's message (Romaniuk, 2018). Finally, using a variety of DBA types has been found to add a layer of sensory brand information in consumer memory, which can result in an expansion in the ways a brand is encoded, stored, and ultimately retrieved (e.g., Kanwisher et al., 1997; Bernard and Gage, 2007; Keller et al., 2008).

2.3 Distinctive Brand Assets

According to Romaniuk (2018, p. xvi), pioneer of DBAs research, distinctive assets are "non-brand name elements that trigger the brand into the memory of category buyers". For an exhaustive list of all DBA types, divided by category, please refer to figure 1.

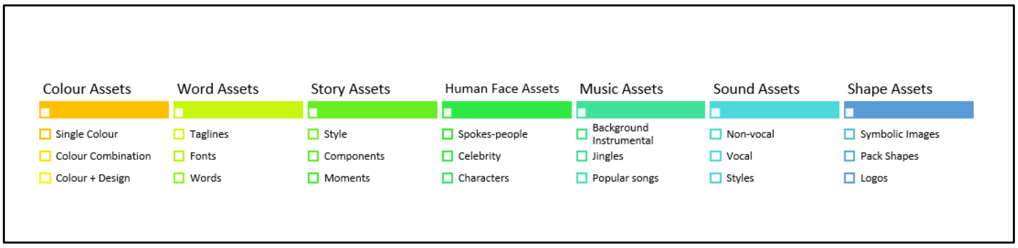

Figure 1: Distinctive Asset Types (Romaniuk 2018)

Before the EBI scholars started to research brand identifiers for their distinctive properties (Sharp and Romaniuk, 2004), with the subsequent development of DBAs as naming convention, the qualities of brand assets had already long been established and framed as a pivotal component of brand identity and the brand equity construct (Aaker, 1991; Kohli et al., 2002). DBAs have been studied under various names, such as identity elements (Zaichkowsky, 2010), brand elements (Keller, 2003) and trademarks (Hoek and Gendall, 2010), though despite this inconsistency in terminology the substance of what they are does not vary across research streams. Wider research on brand identifiers has demonstrated their positive impact on brand learning, recognition, and recall (e.g., Ogilvy and Raphaelson, 1982; Walker and Gonten, 1989; Perry and Wisnom, 2003; Romaniuk and Sharp, 2016), as well as their power in attracting consumer attention and breaking through the increasingly cluttered advertising environment (Van den Bosch et al., 2005; Major, 2014; Hartnett et al., 2016). Also, some traditional branding scholars have acknowledged brand assets' distinctive value as well, including Kapferer (2012) – who emphasises the importance of DBAs in delivering a unique look and feel which enables consistency across touchpoints.

It is perhaps the word 'unique' that more than anything else defines DBAs. In fact, what emerged from the discussion around mental structures does raise the need for these elements to be uniquely owned by a brand so that correct message anchoring occurs (Romaniuk and Hartnett, 2010; Romaniuk and Nenycz-Thiel, 2014). And this is where a clear fraction seems to appear in the body of research – whilst there have been scholarly contributions on DBAs outside the EBI, these have tended to focus on their semiotic meaning (e.g., Grimes and Doole, 1998; Aslam, 2006; Hynes, 2009) and impact on performance (e.g., Bellizzi and Hite, 1992; Kellaris et al., 1993; Mathur and Mathur, 1995; Bottomley and Doyle, 2004), as opposed to their uniqueness value (Romaniuk, 2018).

Furthermore, advertising executives have often challenged the EBI's emphasis on DBAs, maintaining that an excess of branding impacts negatively on creativity and brand perception (Romaniuk, 2018). As a result, several exploratory studies have been carried out, ultimately proving that there is no correlation between too much branding and negative sentiment, and when there have indeed been negative feelings towards the brand, these are heavily skewed toward lapsed customers (Winchester and Romaniuk, 2008; Nelson-Field and Romaniuk, 2013). In addition, Harrison (2013) and Hartnett et al. (2016) have shown that holding back on DBAs usage does not correlate well with improvements in advertising cut-through rate, while Newstead and Romaniuk (2009) have demonstrated that relatively lower branding identification from consumers does not have any demonstrable impact on advertisement likeability.

2.4 Durable vs Non-Durable Goods

Products can be categorised on manifold dimensions. One of which is durable vs non-durable goods (Kotler and Keller, 2012). Non-durable goods are normally consumed within a few uses, while durables survive longer time periods. Given the protracted negative consequences associated with buying a durable product that does not meet expectations, along with their typically higher price tag than non-durable goods, consumers are more likely to spend time researching the category and thoroughly evaluating alternatives (Zaichkowsky 1985; Morwitz et al., 2007). As such, involvement levels differ greatly in these two types of purchase decisions (Jourdan, 2001), with consumers displaying a higher involvement for durable goods than non-durable ones.

Several recent studies have researched differences between low- and high-involvement purchase decisions. For example, Kim and Chao (2019) explored the implications for the brand building process, examining elements such as brand experience, image, and trust to discern patterns between product categories with different involvement levels. While their findings highlighted a more hierarchical and layered consumer journey in high-involvement product categories, brand identity elements and their implications for involvement theory remained unexplored. Baumann et al. (2015) had previously carried out similar research, examining comparable variables in the context of ad recall and obtaining consistent results, but once again DBAs and their potential moderating effect were left out. To the best of our knowledge, the only two studies which have investigated brand assets within the involvement literature are Radder and Huang (2008) and Lotfizadeh and Lotfizadeh (2015). In a nutshell, both papers established the importance of DBAs in improving brand awareness across involvement levels, with the former research postulating that brand name is more effective in low-involvement categories whereas logo plays a bigger role in high-involvement ones. Although it represents a fair starting point in linking DBAs to involvement theory, neither study looked beyond logo and brand name, or brand assets as a consolidated variable, thereby neglecting the significance of every other DBA type identified by Romaniuk (2018).

Based on the discussion, durable and non-durable goods can also be framed through Petty and Cacioppo's (1986) Elaboration Likelihood Model (ELM). According to this model, there are two routes to persuasion: central and peripherical. The former is concerned with rational, attributes-focused messages which target highly involved consumers, while peripherical cues are often illogical, requiring less cognitive efforts, and are developed for an audience which is less involved in the purchase decision (Wang et al., 2019). Albeit there have been numerous contributions to the ELM (e.g., Park et al., 2014; Arora et al., 2019), the majority have focused on the impact of attitude, intention, loyalty, decision making and satisfaction on the central and peripherical routes (Shahab et al., 2021) – but hardly any touched upon DBAs. One could infer that consistently using a variety of brand assets may be more important for low-involvement purchases, as consumers are less interested in decoding the brand claims and peripherical cues should prevail. However, we argue that DBAs may be just as important for the central route to persuasion in high-involvement, durable categories. Indeed, as involved as a consumer may be in a purchase decision, and decoding a brand's messages, these will not have any positive effect unless the advertisement is firstly successfully attributed to the sponsoring brand, which can only happen by consistently using DBAs (Romaniuk, 2018).

2.5 Research Questions

One of the many under-researched yet promising areas of DBAs is comparing the uniqueness value of different asset types (e.g. is it a shape or a strapline which has more ownability potential?), as surfaced in a conversation with Romaniuk (2021) and in the only publicly-available academic paper written on the topic (Ward et al. 2020). This research analysed 1281 DBAs across 13 packaged goods categories. Characters, logos and logotypes emerged as the asset types with the highest uniqueness concentration, whilst colour and advertising style were the least unique identifiers. Except for this article, the limited research published so far has focused exclusively on one or two asset types per contribution (Kohli et al., 2007; Romaniuk and Nenycz-Thiel, 2014).

Exploring the uniqueness value of DBA types in a durable goods context, therefore, represents an unresearched area, and one recommended by Ward et al. (2020). And considering how heavily the automotive industry spend on marketing communications (Statista, 2022), extending the above research stream to this product category seems to be particularly valuable and managerially relevant. On top of this, as cars are high-involvement purchase decisions (Geva et al., 2013), and low-involvement FMCG have previously been studied by Ward et al. (2020), quantifying the ownability potential of DBAs within the automotive industry would enable a like-for-like comparison across products with vastly different involvement levels. As established in the Durable vs Non-durable Goods literature, this undertaking would thus also fill a gap both in the involvement theory and ELM research streams. Accordingly, we will tackle the following first research question:

RQ1: Which are the most unique DBA types in the automotive industry amongst UK category buyers?

Romaniuk (2018) argues that testing for segment differences within the sample could also evidence some interesting patterns, such as neglected DBA types or creative and media biases in the execution. Alongside these potential brand-induced outcomes, there are also the human ones – as wider research on information processing has showcased noticeable differences across age groups (e.g., Fung and Carstensen, 2003; Philipp and Stanton, 2004; Goodrich, 2013) and gender (e.g., Darley and Smith, 1995; Laroche et al., 2000; Cleveland et al., 2003; Chingching, 2007) in decoding marketing communications. Therefore, we will also be testing these demographic variables in the context of DBAs through two more research questions:

RQ2: Is there any significant difference in the mean uniqueness scores given by UK category buyers belonging to different age groups?

RQ3: Is there any significant difference in the mean uniqueness scores given by male and female UK category buyers?

3.0 Methodology

3.1 Research Design

Given our aim to replicate as closely as possible Ward et al.'s (2020) methodology, as an effort to extend their work to the high-involvement automotive industry, we employed the same online survey design to collect the data, along with their formula to calculate competitive intensity. This calculation consists of applying the normalised Herfindahl–Hirschman index (HHI*) which is the adaptation of an economics formula originally devised to calculate the intensity of competition of any industry – to assess the feasibility of corporate acquisitions (Hirschman, 1945). Considering the conversation around mental structures and the competitiveness of the retrieval process arisen in the literature review (see 2.2), the HHI* presents itself as a valuable proxy for calculating the uniqueness value of DBA types (Ward et al., 2020).

3.2 Data Collection Methodology

To ensure the accuracy and validity of the findings, we followed through Romaniuk and Neycz-Thiel's (2014) directions on running DBAs research. These researchers trialled four different methodologies to run DBAs questionnaires, as an effort to limit brand guessing and produce the most managerially relevant outcomes. They found that cuing assets without prompting the brand name is the best approach to reflect the aim of DBAs, which is to trigger the brand name in its absence. Furthermore, Romaniuk and Neycz-Thiel (2014) also flagged the need to account for participants' proneness to priming, which may occur when the previous survey question (e.g., on a BMW asset) can make the answer to the following more likely than otherwise (if this presents another BMW asset).

Based on these guidelines, our survey started with four questions aimed at categorising the sample on the following variables: UK residents, automotive category buyers, age of respondents and finally, gender. Successively, a selection of 44, in-market and de-branded assets belonging to the top twelve brands by market share in the UK automotive industry were shown to respondents in a randomised fashion. A content analysis of the key customer touchpoints used by automotive brands in the three months prior to this research highlighted four DBA types consistently used across channels: logo, font, strapline, and colour. Thus, these categories were chosen for the analysis (Appendix C). As for the accompanying question, we went for an adaptation of the one used by Romaniuk and Neycz-Thiel (2014); as follows, 'Please indicate which, if any, brands come to mind when you think about this *insert asset category* and the automotive industry, or leave the boxes empty if you don't think of any' (Appendix D).

3.3 Sample

In terms of sampling methodology, we deployed a mixture of snowball, quota and judgemental techniques. Due to time limitations, the data collection started by sharing the survey with people immediately close and available to the lead researcher, hoping that they would in turn share it with their family and friends. The quota of participants belonging to different gender and age groups was monitored throughout the month-long data collection, and judgemental sampling techniques were used to ensure an adequate demographic balance. All respondents were briefed ahead of the study and gave their consent.

A total of 239 respondents completed the survey, of which 206 conformed with the requirements of living in the UK and either owning or planning to purchase a car within the following 24 months. Thus, only these answers were used for the analysis. The gender split was 57% female versus 43% male, with 96 Gen Z, 79 Millennial and 30 Gen X participants. This resulted in a sample mean age just shy of 30 years old (29.34).

3.4 Data Analysis

As anticipated, to answer RQ1 we utilised the competitive intensity formula dictated by Ward et al. (2020). This involved two sequential stages: firstly, calculating the uniqueness expressed in percentage of each brand associated to an asset, which equals the number of times a brand is uniquely associated to the element divided by the sum of all associations with that element for any brand, ultimately multiplying by 100. At this point, only the scores of those brands that achieved at least 5% of uniqueness passed to the next phase of data analysis, as an effort to reduce sampling errors occasioned by very few respondents.

$$\text{Uniqueness} = \frac{\text{No. of times a given brand is linked to the element}}{\text{No. of times any brand is linked to the element}} \times 100$$

Then, we applied the HHI*, Ward et al.'s (2020) adaptation of Herfindahl's (1950) aforementioned index to gauge the intensity of competition, which is itself split out into two steps; to start with, the original index (HHI) is calculated by squaring the uniqueness scores (> 5%) of every brand associated to a given element, and then summing all them up to derive an index of competitive intensity expressed in decimals (e.g., to calculate the HHI of a strapline, we firstly squared the uniqueness scores of all brands associated with this asset, and then summed them up to derive this DBA's HHI).

$$\mathrm{HHI} = \sum_{i=1}^{N} U_i^2$$

Looking at Ward et al.'s (2020) formula, U stands for the uniqueness score of an individual brand's (i=1) and N refers to the numbers of brands linked to it.

Successively, we used this measure to work out the HHI*, which normalises the data to account for the influence of volume of brands recalled for every asset, making the results comparable across them (ibid.). It is calculated as follows:

$$\mathrm{HHI}^* = \frac{(H - 1/N)}{1 - 1/N}$$

Where N represents the number of brands mentioned for an element, and H is the decimal output of the usual HHI calculation (Ward et al., 2020). The result ranges from 0, where the intensity of competition is highest, meaning that there is no ownership of the asset, to 1, where an element is uniquely owned by a single brand (Figure 2). Having obtained the HHI* for every asset, we then performed an ANOVA to detect whether there were statistically significant differences in the mean uniqueness concentration of the four DBA types in analysis, thereby answering RQ1.

HHI* range	Concentration level
0	Intense Competition: the element is shared amongst competing brands. No brand mentally "owns" the element
0–0.5	Low Uniqueness Concentration: there is a high degree of sharing, but uniqueness is not divided amongst competing brands equally
0.5–0.8	Medium Uniqueness Concentration: one brand has the majority share of uniqueness although other brands are still sharing the element
0.8–1	High Uniqueness Concentration: the element is primarily unique to one brand, but minor competitor links still exist
1	Total Ownership: the identity element is entirely unique to one brand. The brand owns that element in the mind of consumers and does not compete with other brands

Figure 2: Interpretation of HHI Scores (Ward et al. 2020)*

Finally, we also investigated the dispersion of competitive intensity within DBA types, to delve into the breadth of scores given to individual assets and enable a comparison across categories. We derived it by calculating the Relative Standard Deviation (RSD) – also known as Coefficient of Variation – on SPSS, as it facilitates the measurement of variations on the same relative scale, thereby making results (expressed in %) comparable across DBA types.

When it comes to RQ2 and RQ3, concerned with age and gender differences respectively, we borrowed Ward et al.'s (2020) formula once again but this time the data was firstly sliced as follows: starting from RQ2 about age differences, we calculated individual asset-level scores separately for the following three generational categories: Generation Z (18-25 years old), Millennials (26-41) and Generation X (42-57) (Dimock 2019), effectively creating three groups. Furthermore, rather than testing for differences in the mean HHI* of DBA types, we aggregated all scores for the 44 assets and performed an ANOVA with the three generational groups, thus tackling RQ2. The same approach was employed for RQ3, but with a key difference: we used the gender variable to split the dataset before calculating the individual element HHI*, leading to two groups for the analysis – male and female. Then, we performed an ANOVA to gauge the difference in means between them. Once again, both for RQ2 and RQ3 we calculated and discussed the RSD, to add depth to the analysis.

4.0 Results

4.1 RQ1

As detailed in the methodology section, once we calculated the HHI* of each DBA, we performed a one-way ANOVA to identify differences in the mean uniqueness scores across the four asset categories in examination. These were coded as follows: logo (1, n=12), slogan (2, n=10), font (3, n=11) and colour (4, n=11). The results, in table 1, provide evidence of significant differences between the four groups: $F(3, 40) = 37.813$, $p < .001$, $\eta^2 = .739$ (table 2).

ANOVA

Uniqueness Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.369	3	1.123	37.813	<.001
Within Groups	1.188	40	.030		
Total	4.556	43			

Table 1: one-way ANOVA Output for RQ1

ANOVA Effect Sizes[a]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Uniqueness Score	Eta-squared	.739	.558	.808
	Epsilon-squared	.720	.525	.793
	Omega-squared Fixed-effect	.715	.519	.789
	Omega-squared Random-effect	.456	.265	.555

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

Table 2: Eta-squared of one-way ANOVA for RQ1

We then undertook a Tukey post-hoc test to reveal differences in the multiple comparisons between groups (Appendix E). The results, summarised in table 3, reveal that logo (HHI* = 0.76) had a significantly higher uniqueness concentration than the other three DBA types ($p < .001$ in each comparison). It follows that this element presents lower competitive intensity, and thus more opportunity for unique ownership.

Element Type	Number Tested	Mean HHI*	Relative Stdev % of HHI*	Min	Max
Logo	12	.76	34	.158	.955
Slogan	10	.21	41	.117	.401
Font	11	.08	116	.013	.272
Colour	11	.17	99	.029	.552

Table 3: Mean Competitive Intensity (HHI) of RQ1*

As for the other three DBA types, although font demonstrated the lowest mean uniqueness concentration, thus the highest competition for ownership (HHI* = 0.08), we observed no statistically significant differences between the groups, with p = .305 (> .05) between slogan and font, p = .943 (> .05) between slogan and colour and finally, p = .610 (> .05) between font and colour (Appendix E).

The RSDs range from 34% to 116% across DBA types, with an average deviation from the mean value of 72.5%. Interestingly, it appears that the dispersion of competitive intensity varies in line with the mean HHI*, indicating that less competitive elements (such as logos) are consistently less competitive. Comparatively, more competitive DBA types like font have greater variation (116%), making their success more occasional.

Finally, except for 10 logo assets – and an instance with a colour one – no other element achieved a 0.5 HHI*, which is considered the minimum threshold to be classified as Medium Uniqueness Concentration. In other words, 33 assets out of 44 had Low Uniqueness Concentration (Appendix F). This means that all font, colour (except one) and slogan elements in analysis have failed to gain an acceptable level of unique ownership (> 0.05 HHI*).

4.2 RQ2

Moving to RQ2, we firstly sliced the survey data into the three generational categories, and then calculated the HHI* for each brand asset. Next, considering the focus was on identifying differences in the mean uniqueness scores of different age groups, we aggregated the results for all 44 DBAs, and carried out a one-way ANOVA to answer RQ2. The three generational categories were labelled as follows: Gen Z (1), Millennials (2) and Gen X (3). The results, in table 4, demonstrate no significant difference between the three groups, with p = .925 (> .05).

ANOVA

Uniqueness Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.019	2	.009	.078	.925
Within Groups	15.412	129	.119		
Total	15.430	131			

Table 4: one-way ANOVA Output for RQ2

Looking at the overview in table 5, Gen Z (HHI* = 0.32) and Gen X (HHI* = 0.32) had a marginally higher mean uniqueness score than Millennials (HHI* = 0.29), but not high enough to be statistically significant as revealed in the Tukey post-hoc test (Appendix G). It returned p = .937 (> .05) between Millennials and Gen Z and p = .938 (> .05) between Millennials and Gen X. As for the RSDs of the three groups, these range from 100% to 121%, with Gen X demonstrating the greatest variation. This, however, may be due to the sample size of this cohort being sensibly smaller than the other two, which made it more susceptible to larger deviations from the mean scores. Otherwise, the dispersion of uniqueness intensity between the groups does not reveal any significant difference, meaning that DBAs are equally successful across the generational cohorts in analysis.

Generation	Number Tested	Mean HHI*	Relative Stdev % of HHI*	Min	Max
Gen Z	96	.32	100	.004	.977
Millennials	79	.29	112	.004	.956
Gen X	30	.32	121	.001	1.0

Table 5: Mean Competitive Intensity (HHI) for RQ2*

4.3 RQ3

Concluding with RQ3, once again we split the survey data before calculating the individual element HHI* scores, with male (1) and female (2) being the two groups in examination. Successively, we aggregated the uniqueness scores for all 44 elements and carried out another one-way ANOVA. The results, in table 6, show no significant difference between the two groups, with p = .866 (> .05).

ANOVA

Uniqueness Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.003	1	.003	.029	.866
Within Groups	9.289	86	.108		
Total	9.293	87			

Table 6: one-way ANOVA Output for RQ3

Moving to the scores overview (table 7), the mean HHI* of male (0.32) and female (0.31) are not only very close between each other, but also in relation to those of the generational cohorts previously discussed. The RSDs of the two groups are both above 100%, but narrower between them in comparison to RQ2, indicating that there is virtually no difference in the dispersion of competitive intensity of male and female respondents.

Gender	Number Tested	Mean HHI*	Relative Stdev % of HHI*	Min	Max
Male	88	.32	106	.011	.973
Female	116	.31	104	.001	.972

Table 7: Mean Competitive Intensity (HHI) for RQ3*

5.0 Discussion

The current study expands on Ward et al.'s (2020) research across 13 FMCG categories by exploring the ownability potential of logo, font, colour, and slogan assets within the automotive industry, marking the first contribution of this kind within the context of durable goods and high-involvement purchase decisions (Geva et al., 2013). Also, we endeavoured to closely replicate Ward et al.'s (2020) methodology, to enable a like-for-like comparison with their research. In doing so, we contribute to the literature by comparing low- and high-involvement product categories on the yet-unexplored dimension of DBAs uniqueness.

5.1 DBA Types

Starting from the main finding of this research, logo has the highest mean uniqueness concentration of the four asset types analysed. Font, slogan, and colour elements, by contrast, are significantly more likely to be shared by multiple brands and have all been categorised as having Low Uniqueness Concentration, with no statistically significant differences between them. In comparing these findings with those of Ward et al.'s (2020) in low-involvement FMCG categories, they too observed a high uniqueness concentration in logo elements, which is supported by our study (although automotive DBAs have a higher mean HHI* for this asset type – 0.76 versus 0.61). This result also underpins broader academic contributions within the branding literature, which have portrayed logo as the basis of competitive differentiation (Watkins, 1986), alongside offering an effective means of building brand associations (Major et al., 2014). Unsurprisingly, brands invest heavily on the development of their logos, and there have been numerous cases of corporations starting fierce lawsuits to protect this asset type, such as Apple with its famous bitten apple (Tatiana et al., 2016). As for the stark difference in uniqueness concentration between logo and the other DBA types, compared with the much narrower in Ward et al.'s (2020) results, we argue that this is caused by the peculiarity of car brands, which are mostly exposed to consumers in the form of vehicles in the road where the logo is the only DBA in display. Conversely, packaged goods include multiple DBA types simultaneously within the product itself, which consumers are exposed to (e.g., a chocolate bar will invariably present a logo, font, pack, strapline and colour/s). Thus, we maintain that such a dissimilarity is the main reason why the HHI* scores for colour, strapline, and font assets are higher for packaged goods than automotive brands.

This paper's second important contribution concerns the RSD. Just as in FMCG (Ward et al., 2020), this metric – concerned with the dispersion of uniqueness scores within each DBA type – varies in line with the HHI* mean scores. That is, the higher the uniqueness intensity of an element, the lower its RSD. This corroboration is particularly important as it underscores two important implications: more unique elements are consistently more unique as they have less variation from the mean score – and vice versa – and the pivotal role of creative executions in determining the ownability of an asset. Albeit not to the extent of Ward et al.'s (2020) findings, the increasingly large variation from the mean HHI* of less successful DBA types mean that even they have the potential to achieve an acceptable level of ownership, when supported with an appropriate investment by brand managers. That said, whilst the HHI* mean difference between slogan and colour assets was relatively small in our paper, as it was in Ward et al.'s (2020), the RSD difference between these two DBA types was rather large for automotive brands (41% for slogan vs 99% for colour), differing notably from FMCG categories where slogan and colour had the exact same variance – 86% (Ward et al. 2020). Therefore, we posit that, when it comes to the high-involvement automotive industry, creative execution seems to matter more for colour and font (116%) than it does for slogan.

Another contrast with Ward et al. (2020) paper surfaces with font assets, although these researchers explored typefaces within a wider category which included logo, colours and pictograms, called logotype, thus diverging from the analysis of de-branded fonts undertaken in our contribution. With this caveat in mind, logotype had a 0.60 HHI* in Ward et al.'s (2020) study and was the third to best scoring asset out of eight analysed, nearly equalling the mean score of logo assets (0.61 HHI*). By contrast, in the UK automotive category font was the poorest scoring DBA type, with a mere 0.08 HHI*. Although we acknowledge that methodological differences in cuing this DBA type do make this comparison somewhat stretched, the poor ownability of font observed in our research finds corroboration in Sherman and Moran's (2011) study, who noted that fonts have no impact on the recall of the correct brand.

Concluding the assets discussion with colour and slogan, both DBA types had a significantly lower uniqueness concentration than logo in the UK automotive industry and compared with their counterparts in low-involvement FMCG categories (Ward et al. 2020). Wider research on colour assets had already established the challenges of uniquely owning a colour (Hoek and Gendall, 2010; Zaichkowsky, 2010), and the limited memorability of this DBA type when used as a stand-alone cue (Henderson and Cote, 1998) – corroborated by our contribution. As for slogan, prior research had demonstrated the power of this DBA type in improving the memorability of an advertisement in different conditions, particularly when this takes the form of audio cues (Yalch, 1991). Furthermore, Dahlen and Rosenberg (2005) found the effectiveness of a slogan to be moderated by the brand equity of its brand, inferring that this element works better for older brands that have a long-established equity and consistently used their slogans over time (Cheema et al., 2016). However, while we did not test audio cues in the current study, no slogan was able to reach a 0.5 HHI* – minimum score to be categorised as Medium Uniqueness Concentration – despite featuring arguably popular and long-standing straplines such as BMW's "Sheer Driving Pleasure" and Audi's "Vorsprung Durch Technik". Therefore, based on these findings, we reject the notion that older brands and straplines have a discernible advantage when it comes to the ownability potential of this DBA type. Nonetheless, we recognise the need of additional research to test the differential impact of audio straplines over written ones.

5.2 Gender and Generational Differences

Finally, we discuss the generational and gender comparisons in the uniqueness concentration of DBAs. Differences in advertising processing between said groups had surfaced in the literature review (e.g., Fung and Carstensen, 2003; Cleveland et al., 2003), seemingly providing an interesting ground for testing in this research. However, we did not observe any statistically significant differences in the mean HHI* scores of either male and female or between the generational cohorts. What this means is that, within the UK automotive industry, DBAs have equal ownership potential with these demographic variables. Further, the RSD had little fluctuation between the groups in analysis, making differences in dispersion for individual elements also very limited.

Overall, these results are interesting. Considering that typically men buy more cars than women during their lifetime, and therefore invest more heavily in this product category (Maynard, 2012), one may have speculated that this segment would perform better in the identification of automotive DBAs. Equally, the information processing of older adults, which tend to be slower than younger demographics (Salthouse, 1994; Salthouse, 1996), could have made their abilities to recognise DBAs less effective, impacting on the mean score of Gen X. Nevertheless, the gender results obtained in the current research corroborate a study from McKelvie et al. (1993), which found no difference in recognising car brands from the vehicle shapes between male and female interviewees. We therefore argue that most category buyers generally pay little attention to marketing stimuli from car brands and the inherently associative nature of this research design – which draws on Kahneman's (2011) System 1 thinking – nullified any potential difference between the groups. As for the results by generation, similarly, Peters et al. (2007) observed that while older adults do not perform as well as younger ones when it comes to explicit tasks which require System 2 thinking – subjective awareness and effortful deliberation – there is no age difference whatsoever with implicit tasks such as the one performed within our survey. Hence, once again, we maintain that the System 1 thinking nature of our study nullified any potential disadvantage, offering a reasonable explanation to contextualise the results concerning both demographical variables in analysis.

6.0 Conclusion

To summarise, logo assets had a significantly higher uniqueness concentration than fonts, colours and slogans; no significant differences emerged in the mean HHI* of the other three DBA types. This both corroborates and contrasts Ward et al.'s (2020) results across low-involvement FMCG categories, where logo had a high uniqueness concentration too, although not as high as automotive brands, but colour and slogan performed significantly better. As previously mentioned, differences in the ways FMCG and cars are experienced by category buyers help explain the above finding – with cars only displaying the logo on the product itself, while packaged goods feature multiple DBAs simultaneously, including colour and slogan. In terms of generational and gender variables, neither test yielded any statistically significant difference. This means that, within the UK automotive industry, DBAs are equally ownable by a single brand with these two demographic variables.

6.1 Managerial Implications

In terms of contribution to the industry, the poor ownability of fonts, colours and slogans belonging to the top twelve car brands by market share in the UK is the most notable take away of our research. This underscores that carmakers are heavily reliant on logos to link their marketing communications to the right mental structures (i.e. brand-related nodes) of category buyers. Additionally, we have noted an industry-wide lack of consistency in building and using DBAs. Whilst one could consider this insight as worrying and somewhat disappointing, we argue that such a scenario unleashes interesting opportunities for automotive brands. That is, those corporations willing to commit their creative agencies to consistent and relentless usage of the brand's colours, font and slogan over time, and across all consumer-facing touch points, have the potential to reap benefits in the long-term – as supported by the RSD finding. In doing so, brand managers can help their creative production teams to develop advertising executions that leverage this industry-wide issue of indistinctiveness, setting themselves apart from the competition (Van den Bosch et al., 2005; Golob et al., 2020; Ward et al., 2020).

6.2 Limitations and Future Research

Our deliberate attempt to closely replicate Ward et al.'s (2020) study has enabled us to experiment their methodology within a new product category. However, this means that DBA types were considered in a static fashion and shown to respondents individually, which is hardly how consumers experience brand identifiers through exposures to marketing communications in the real world. Thus, this limitation suggests that there is value in exploring the ownability potential of brand assets through novel research designs, which could show category buyers partially branded advertisements (both static and video), or present multiple DBAs simultaneously in online survey – to observe how identity elements reinforce each other and impact consumers' memory (Ward et al., 2020).

Additionally, even though we have followed Ward et al.'s (2020) recommendation to expand their study to durable goods, though in a single category and country, more research is needed to assess the uniqueness concentration of DBA types in other industries too. This could highlight further differences and similarities between low- and high-involvement products, resulting in more refined guidelines for brand managers operating in yet-unexplored categories.

In conclusion, the survey tool used for our research, and peculiarities of the automotive industry, did not allow us to test other asset types, such as auditory elements. However, considering the compelling evidence recently brought up on the effectiveness of sound assets (Sheridan, 2020; Ritson, 2021; Williamson, 2021), and as an effort to enhance the validity of future DBA research, branding scholars should start to empirically test audio cues too. Equally, as Character assets were the most uniquely ownable DBAs within FMCG categories (Ward et al. 2020), and since no such element was found to be used in the automotive industry, future research should endeavour to validate Ward et al.'s (2020) finding in other product categories.

7.0 Declarations

7.1 Conflict of Interests Statement

The corresponding authors state that there is no conflict of interest.

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9.0 Appendix

9.1 A

Development of brand differentiation theory – visual summary.

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Authors	Synopsis
Chamberlin (1993); Robinson (1933)	First deviation from perfect competition model; differentiate offerings through product features to face less competition.
Reeves (1961); Carpenter et al. (1994); Kotler et al. (1996)	Differentiation needs to be valued by costumers; intangible benefits and associations are equally qualified to differentiate a brand's offering.
Levitt (1980); MacMillan and McGrath (1997)	Implicate that marketers should be judged on how well they differentiate their brands from competitors.
Trout and Rivkin (2000)	Publish «differentiation or die» book; one of the most extreme take on differentiation theory.

9.2 B

EBI-led empirical evidence challenging brand differentiation theory – visual summary.

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Authors	Synopsis
Sharp and Dowes (2001)	First, influential EBI-led contribution challenging brand differentiation; assert that differentiation is dependent on a given market's characteristics and cannot be influenced by brands.
Romaniuk et al. (2007)	Find that most category buyers do not perceive differences between the brands they consumer and those they do not.
Romaniuk and Gaillard (2007)	Prove how rare it is for brands to uniquely own associations, as well as their limited impact on brand usage and perceived performance.
Sharp (2010)	Challenges Aaker's (1997) Dimensions of Brand Personality with evidence on how low these associations score with category buyers. Also notes that 75% of times respondents give two different answers when tested twice on the same brand personality-related questions.
Kennedy et al. (2000); Kennedy and Ehrenberg (2001)	Demonstrate little to no differences in the user profiles of different brands across multiple product categories.
Sharp et al. (2003)	Look at brands similarly positioned in perceptual maps and find no correlation between perceptual closeness and degree to which customers are shared – thereby refuting the idea that brand associations lead to specific brand buying patterns.

9.3 C

Full Asset List for the top 12 Automotive brand by market share in the UK.

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Brand	Logo	Slogan	Font	Colour
Volkswagen	X		X	X
Ford	X	X	X	X
Audi	X	X	X	X
BMW	X	X	X	X
Mercedes-Benz	X		X	X
Vauxhall	X	X	X	X
Toyota	X	X		
Kia	X	X	X	X
Nissan	X	X	X	X
Land Rover	X	X	X	X
Peugeot	X	X	X	X
Skoda	x	X	X	X

9.4 D

Sample view of the questionnaire.

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Please indicate which, if any, brands come to mind when you think about this **logo** and the **automotive industry**, or leave the boxes empty if you don't think of any.

LOGO:

Brand 1

Brand 2

Brand 3

9.5 E

Tukey post-hoc analysis for multiple comparisons across the means of the four DBA types, along with the error bar plot. Key: Logo = 1, Slogan = 2, Font = 3, and Colour = 4.

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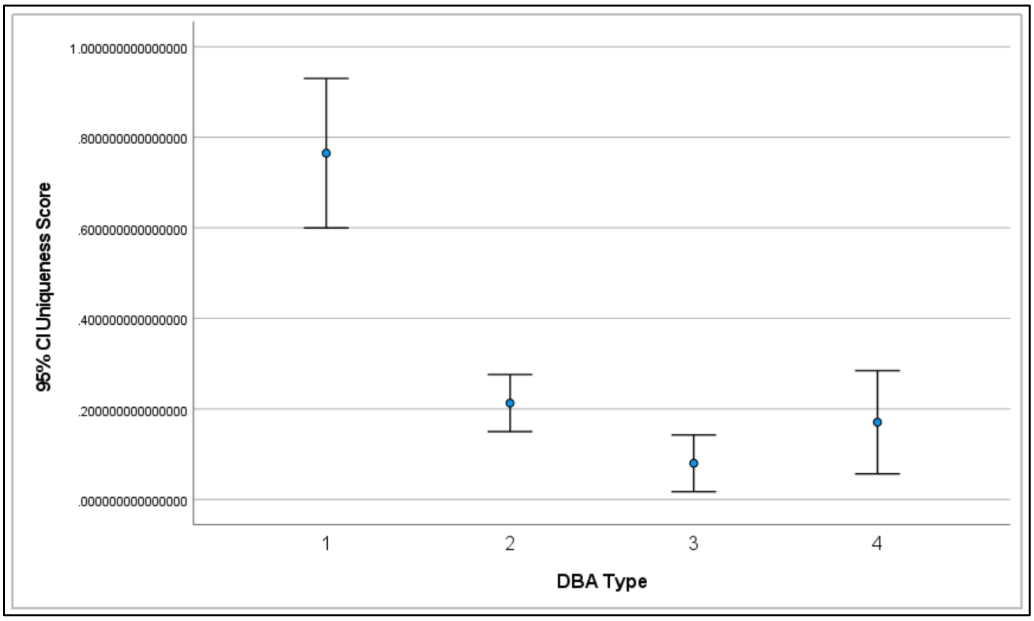
Multiple Comparisons

Dependent Variable: Uniqueness Score

Tukey HSD

(I) DBA Type	(J) DBA Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	2	.551964176*	.0737848040	<.001	.3541899612	.7497383908
	3	.684866250*	.0719321701	<.001	.4920578708	.8776746293
	4	.594250385*	.0719321701	<.001	.4014420057	.7870587642
2	1	-.551964176*	.0737848040	<.001	-.749738391	-.354189961
	3	.1329020741	.0752938518	.305	-.068917022	.3347211700
	4	.0422862089	.0752938518	.943	-.159532887	.2441053048
3	1	-.684866250*	.0719321701	<.001	-.877674629	-.492057871
	2	-.132902074	.0752938518	.305	-.334721170	.0689170218
	4	-.090615865	.0734792755	.610	-.287571136	.1063394053
4	1	-.594250385*	.0719321701	<.001	-.787058764	-.401442006
	2	-.042286209	.0752938518	.943	-.244105305	.1595328870
	3	.0906158651	.0734792755	.610	-.106339405	.2875711356

*. The mean difference is significant at the 0.05 level.



9.6 F

DBA types falling into the different intensity brackets.

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DBA Type	< 0.5 HHI*	0.5 – 0.8 HHI*	> 0.8 HHI*
Logo assets	2	2	8
Slogan assets	10	0	0
Font assets	11	0	0
Colour assets	10	1	0

9.7 G

Tukey post-hoc analysis for multiple comparisons across the means of the three generational categories, along with the error bar plot. Key: Gen Z = 1, Millennials = 2, and Gen X = 3.

[CLICK HERE TO GO BACK]

Multiple Comparisons

Dependent Variable: Uniqueness Score

Tukey HSD

(I) Generation Code	(J) Generation Code	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	2	.0252273918	.0736913580	.937	-.149500253	.1999550368
	3	.0000523596	.0736913580	1.000	-.174675285	.1747800046
2	1	-.025227392	.0736913580	.937	-.199955037	.1495002532
	3	-.025175032	.0736913580	.938	-.199902677	.1495526128
3	1	-.000052360	.0736913580	1.000	-.174780005	.1746752854
	2	.0251750322	.0736913580	.938	-.149552613	.1999026772