"Alexa, build me a brand"
An Investigation into the impact of Artificial Intelligence on Branding

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Abstract

Brands are built by "wrapping mediocre products in emotive and social associations" (Galloway, 2016). Nike and Coca-Cola differentiate through the emotional benefits associated with their brand, not their products functional benefit - with the latter long considered the worlds' most valuable brand (Interbrand, 2016). This brand-building model has not been scrutinised in an environment where technology is a primary driver of organisational success, not merely a support function (E&Y, 2011). Artificial Intelligence (AI) has made "giant leaps" (Hosea, 2016) - algorithms fly our planes and beat us at chess. Organisational spending on AI is set to reach $47 billion by 2020 (Ismail, 2017) with many (32%) claiming its biggest impact will be in marketing. Marketing communities conject that AI will 'revolutionise' marketing (John, 2015) and while companies like Amazon appear to use a different model - utilising AI to fulfil customer's functional needs (commerce) - AI's impact on brand has seldom been explored in an academic context. This paper aims to establish the implementation of AI as a source of brand success - recommending to marketing professionals how to allocate resources to sustain brand effectiveness. Grounded theory research was used; semi-structured interviews were conducted and data collection/analysis was done concurrently. There were three major findings: AI can improve operational efficiency - improving the consistency in which a brand delivers their promise. Natural Language Processing (NLP) can improve elements of customer service. And Machine Learning enables personalised offerings, but organisations are limited by data quality/quantity and knowledge of the technologies applications.

Introduction

Whilst exact definitions differ, academics and industry have largely agreed that brands represent *'something more than a product'* (Ries, 2014) and that brand value is created when organisations invest, as Coca-Cola have done, in emotive and social advertising (emotional benefits) over product innovation and R&D (functional benefits). Recent years however, has seen the likes of Amazon, Google and Facebook overtake Coca-Cola to become the world's most valuable brands (Interbrand, 2016); all of whom are product-centric companies that are either investing significantly in, or centering their strategy around AI - *"We're moving from a mobile first, to an AI first company* (Google CEO) (Zerega, 2017). This paper explores this AI focused brand-building model in detail, establishing which AI technologies impact branding and how marketing professional can utilise AI to create brand value.

Literature Review

De Chernatony & Dall'Olmo Riley's (1998) systematic review of brand definitions, which analysed over 100 brand papers and interviewed twenty brand experts, has proven valuable to this paper and the work of six hundred others. The definitions most frequently cited by brand experts were *brand as a value system* (Thrift, 1997; Beckett, 1996); *as a personality* (Griggs & Alt, 1988) and *as a logo* (American Marketing Association, 1960). This review will discuss theory from a wider range of authors, not just the popular ones, ensuring a "*relatively complete consensus of the existing literature*" (Webster and Watson, 2002).

Brand as a logo

The American Marketing Association (1960) formally defined a brand as a "name, term, design, symbol, or a combination of them, intended to identify the goods or services of one seller and to differentiate them from competitors". Inspired scholars built on this, defining brand as an identifier (Wood, 2000) and a signal of a product's source (Kotler *et al.*, 1999) and of a resolver of the problem of product indistinguishability (Park *et al.*, 2011). Scholars argued this definition was too product focused (Crainer, 1995) and that it failed to account for the intangible elements of brand theory (Gardner and Levy, 1955). Riley (2009) criticised the literal wording of the definition, claiming that it was almost a replica of the US Federal Trademark Act's definition of 'trademark'. (Economides, 1988). Whilst AI experts have not directly criticised this theory, the progressive nature of their industry poses questions over the relevance of these definitions. Recent developments in machine learning has changed the way we search for products, using keywords or voice (Yoganarasimhan, 2014). This improved search functionality more accurately and more efficiently matches consumer needs with the brands that fulfil those needs – limiting the effectiveness of the brand as an identifier.

Brand as a Personality

Aaker (1997) defined 'brand personality' as the set of human characteristics associated with a brand. The concept has since seen significant contribution, with focus on the creation of value above and beyond a product's functional capability (Alt and Griggs, 1988; Blackston, 2000). Zinkhan *et al.* (1996) argued that consumers choose the brand whose personality best fits the personality they wish to project. Other scholars claim that functional brand benefits are 'easy to leapfrog' or 'emulate' (Lambin 1996; Chernatony, 2010), suggesting that creative communications and associations are better sources of brand differentiation (Lambin, 1996). AI experts argue that AI will drive product innovation (Domingos, 2015) and that because AI expertise is in short supply and high demand (Mizroch, 2015), that those who access the right talent can differentiate through AI-fueled product innovation (Woodward, 2017). Scholars also question the effective measurement of brand personality (Ehsan Malik and Naeem, 2013) and its effectiveness within different cultures with different personality traits (Garolera, 2001). Furthermore, this theory and much of its criticism was developed before the most recent developments in AI.

Brand as an Added Value

Like others, Jones (1986) defined brand as the non-functional benefits over and beyond a product's functional capabilities. Chernatony (2010) quantified the value of these benefits, theorising that whilst accounting for only 20% of a brand's costs, the non-functional brand elements contributed 80% of the impact on a customer's purchase decision. Chernatony (2010) claimed that non-functional benefits are often emotive values that are difficult to imitate. American Express for example, provide functional value (banking services) and an emotional value of 'prestige' - with the latter impacting purchase more. AI experts would argue that it's date (pre-1992) fails to account for recent AI milestones (Press, 2016) which would alter the 80/20 rule utilised in this theory.

Brand Themes and Synthesis Matrix

The above analysis of the literature indicates there are three major themes. One, brands contain a functional element, the purpose of which is to fulfil the functional needs of the customer. Two, brands contain a non-functional element, which is often the major source of brand differentiation. Three, the functional element of a brand is easily emulated or copied. However, although the literature establishes the importance of branding to businesses it generally fails to consider how these major themes are impacted by the emerging AI based technologies. This study pursued the following objectives:

Research Objectives
Identify which AI based technologies are impacting each of these brand themes.
Understand how the brand themes are impacted by the identified AI technologies.
Investigate how different organisations are using AI, and how this has impacted the strength of their brand.

Research Approach

An initial review of the literature highlighted the absence of any existing theory, hypothesis or models that directly addressed, or combined, the concepts of brand and AI, deeming an exploratory, inductive research approach - whereby concepts, insights and themes emerge from the collection and analysis of raw data (Taylor, *et al.,* 2015) - most suitable. It began with vaguely formulated questions and added data as and when it became useful. Thus, it was likely, due to the size and openness of the topic, that additional themes and sub-themes would emerge (Taylor, *et al*., 2015) and in turn, be investigated with further research.

Research Methodology

This study used a mixed-method research methodology, largely consisting of qualitative, semi-structured interviews with experts in the studies core fields – brands and AI; a data collection method Taylor *et al.* (2015) suggested is the most suitable to answer the broad, and technically complex questions posed in this study's first and second research objectives. The initial research findings informed, and directed the next phase of data collection and analysis (Saunders and Lewis, 2014) which in this case, due to the nature of the third research objective, used a mixture of qualitative and quantitative research techniques.

As a cross sectional study, critics may argue that the study's results may become less relevant over time, especially given the speed of technological development and more specifically, the fast rate of change within the field of AI. Whilst these critics are well founded, the time constraints imposed on this study do not allow for a comprehensive longitudinal study, which most critics would argue is more suitable. To increase its future applicability, interview questions were designed to gain an understanding of both the current and potential impact of AI on brands. Whilst these will be merely predictions, they will provide some insight into how AI's impact on branding may change over time.

This study's three research objectives were understood and answered chronologically as the understanding of one research objective was dependent on the findings from the previous objective. I.e. we first need to know *which AI technologies* will impact brand before we understand *how those AI technologies* will impact brand. This is deemed as a grounded theory approach with constant comparative analysis - a process of concurrent data collection and analysis whereby the findings from the first phase of analysis informs subsequent data collection (Glaser and Strauss, 1967) - a suitable strategy for this research. It was likely, given the complexity of the topics, that the authors, having analysed the initial interviews, had to return to the field to collect additional data on the themes that have emerged from prior analysis. This cyclical process continued until theoretical saturation were reached (Glaser and Strauss, 1967).

Semi-structured, face-to-face interviews allowed for the collection of a richer set of data upon which themes could emerge, providing depth of meaning where experts are more likely to participate over an in-depth questionnaire (Fusch and Ness, 2015). The lack of rigidity in semi-structured interview structures allowed the discussions to lead into areas the authors had not previously considered – but areas that will likely be relevant in addressing the complex research objectives posed in this study (Schindler and Cooper, 2008). Moreover, semi-structured interviews allowed the authors to ask exploratory and explanatory probing questions (Schindler and Cooper,

2008) which, given the technicality of the two topics, and the current knowledge gap between the author and the experts, provided a deep understanding of the relevant phenomena.

Initial interviews were conducted with Daniel Hulme and John Garnett – experts in AI and Brand respectively, and whose combined insights helped address the research objectives. Additional themes emerged from the analysis of the initial interviews. Firstly, the impact of Natural Language Processing (NLP) on customer service and secondly, the impact of Machine Learning on personalisation. Both themes, which relate to two technologies that form part of the overall AI stack (a set of technologies) were explored in further detail by interviewing experts in their respective fields - Alex Lilburn (NLP) and Alistair Ferag (Machine Learning).

Since completing his doctorate in computational complexity (AI), Daniel has founded Satalia, an organisation that builds end-to-end AI solutions for clients. Daniel runs a Business Analytics Master's (MSc) in the Computer Science department at University College London (UCL); where he teaches Machine Learning, Data Science and AI. Daniel was selected for his deep technical knowledge and his experiences of how AI can be applied to create value for organisations and their customers. His insights provided an understanding into which AI technologies are most impactful, and how these technologies are affecting brand development in the organisations he works with.

John Garnett was selected for his vast experience in the brand-focused FMCG industry; with expertise in the development and management of brands using traditional brand theory, i.e. those discussed in the literature. Garnett was Managing Director for Heinz UK, worked at P&G for twelve years and now runs his own brand consultancy. Garnetts' insights helped assess the strength of current brands, and help the authors understand the relative importance of the elements of a brand that are most impacted by AI.

Alistair, a Senior Data Scientist at Satalia, has vast experience building machine learning systems across the retail, financial and technology sector. He has a background in Economics, and a MSc in Computer Science from University College London. He has recently developed a price optimisation system for a hospitality company, and a customer churn analysis system for a B2B hardware distributor. Ferag's insights, given his academic background and practical experience, provided a deep understanding of the applications and challenges that surround machine learning in industry.

Alex Lilburn is an expert in NLP - with qualifications in Psychology, Law and a MSc in Business Analytics from UCL. Lilburn has extensive experience in the development of systems that can be interacted with through natural language (text or voice.) He also has experience building applications using 3rd party NLP tools - and thus was able provide insights around the accessibility of NLP, it's limitations and its applications for a modern brand.

Data Analysis and Coding

Researchers are often confused when analysing qualitative data, and many use coding to quantify it in a way that allows it be statistically analysed (Miles and Huberman, 1986). A different approach is to use coding to decipher or interpret themes and categories in qualitative data (Böhm, 2004) – before naming and discussing them in more detail. Given that the aim of this study is to assess the underlying impact of AI on brand, and not quantitatively measure this impact, this non-mathematical approach to coding is more suitable.

Open coding is the initial stage of data analysis. Here, data is broken down analytically and basic concepts are derived from the text (Böhm, 2004). Strauss and Corbin (1998) advise the analysis of short textual passages (line-by-line) to achieve an extensive theoretical coverage. Böhm (2004) clarified that whilst open coding generates basic concepts, these concepts will likely be crude to begin with. Axial coding is the second stage of data analysis and involves clustering the *concepts* together to form more meaningful *categories* – upon which conclusions can be drawn (Böhm, 2004). This typically begins by analysing the concepts in more detail to establish how they relate to each other i.e. it may be found that two different AI technologies provide the same benefit to a brand, in which case the technologies would be *concepts* and the benefit to the brand would be the *category* that relates them. A multi-staged data analysis process was selected to ensure that the findings from one interview (AI) could be related, and assessed against the findings from the other interview (Brand) (Böhm, 2004). Given the differences in the interviewees expertise, and thus the language used by the brand and AI experts – it would not have been possible to find commonalities in the two topics had a single stage of data analysis been conducted.

Discussion

Brands are multifaceted and highly complex. There is no singular, proven recipe for brand growth and no universal agreement of how brands succeed. Thus, it would be implausible to attempt to directly attribute AI, and the benefits it provides, to the success of brands. It cannot be said for certain that brands who adopt AI will win, and those who do not will lose, and this research makes no such claim. This research adds value by providing insight into how AI will possibly impact the individual components of brand (service, product etc.) and through discussion with experts, and an analysis of the literature, attempts to identify the impact of these components on a brand's success. The findings indicated that whilst AI will undoubtedly impact all components of brand, its effects are currently the most profound on three brand components*; fulfilling on brand promise, customer service and personalisation.*

Fulfilling on brand promise with AI

The findings suggest that 'end-to-end' or 'full stack' AI - *"The acquisition of data, the extraction of insights and decision-making that adapts and improves over time" (Hulme, 2017)* - has the potential to vastly improve an organisation's operational efficiency which in turn, can improve the consistency in which they deliver their brand promise. Both AI and brand experts agreed that an organisation delivers on their promise when '*they do what they say they are going to do'* (Garnett, 2017). Hulme (2017) argues that this is largely due to the operational efficiency that AI enables - *"You make better use of your resources; you can improve customer satisfaction"* (Hulme, 2017).

The existing literature suggests that the success of brands is largely dependent on its ability to differentiate (Chernatony, 2010). The clear majority of literature shares the view that the most effective source of brand differentiation is through the non-functional benefits it provides (Kapferer, 1992; Alt and Griggs, 1988) - not the functional benefits that are '*easily replicated' or 'easily imitated'* (Lambin, 1996). This suggests that the impact of brand promise, and thus the indirect impact of end-to-end AI on a brand's success is dependent on whether that promise is functional or non-functional.

Functional Benefits Can Provide Differentiation

Whilst there are likely to be some examples of brands that promise non-functional benefits, such as luxury (Silverstein and Fiske, 2003), the findings suggest that brand promises typically provide functional benefits. Hulme (2017) gives examples of *'delivering packages on time'* (Retailer) and '*providing better phone signal'* (Telecommunications) – both of which are functional and provide no non-functional benefits to its customers. The findings of this paper differ from those found in the literature, specifically in regards to the effectiveness of a functional benefit as a brand differentiator. Given that most brand promises are functional, the literature would suggest that improving its consistency is not an effective way to differentiate a brand. However, the findings of this research suggest differently, with Garnett (2017) arguing that *"brand promise is the key thing that differentiates you"*; claiming that "*very few people can argue that they always deliver on their brand promise, all the time"* – a statement which directly opposes the argument, made in the literature, that functional benefits are easily copied. Hulme (2017) claimed that the AI that enables brands to consistently fulfil their promise is also difficult to replicate – *"understanding how to architect these complex systems and include all of the complex business nuances is very difficult to do"*. These findings are more aligned with the literature that argues a brand is a *'risk reducer'* (Assael, 1995) with the improved consistency of brand promise reducing the *'functional performance risks'* that are often associated with a brand (Bauer, 1960).

Consistency is Not Enough

Whilst these findings suggest that AI can improve the consistency of a brand promise, and that a brand promise is a strong source of differentiation, it was also found that the consistent fulfilment of a promise is not the only requirement needed for a promise to be effective. Garnett (2017) argued that a brand promise is made up of three elements – "*clarity, consistency and organisational alignment.*" This research explored the impact of AI only on the *consistency* in which it can be delivered, and it can only be conjected that its impact is less profound on the other two elements needed to differentiate on a brand promise. Thereby it is recommended that further research should build on where this research was limited, evaluating the impact of AI on the other elements of a brand promise (clarity, alignment). Only then can it be said that AI, in solidarity, can lead to a brand promise that acts as a source of brand differentiation.

NLP's Impact on Customer Service

"Customer service is fundamental to pretty much any brand" (Garnett, 2017). Primary sources and much of the existing literature agree that customer service is essential to the foundations of any brand in the modern world (Chernatony, 2010). The research found that Natural Language Programming (NLP) a sub component of AI, and described as *"taking unstructured data, text, speech, and generating structured data which has meaning" (*Lilburn, 2017) – has the potential to strengthen an organisation's customer service and overall brand experience. Expectations of customer service are rising in three areas - *"it's timeliness, it's accessibility and its proactiveness"* (Garnett, 2017). Further to this, Garnett (2017) highlighted how the partial or full automation of responses to customer enquiries can increase both the efficiency and accessibility of a brand's customer service. Garnett (2017) outlined how NLP technology was adopted by KLM (airline) - *"They programmed a chatbot to be able to deal with most queries*" (Garnett, 2017).

Chernatony (2010) argued that improved, or *enhanced* customer service, which can be obtained with NLP, is an *'expected benefit'*. One that, much like functional benefits, does not provide a sustained source of brand differentiation. This implies that good customer service is potentially just a threshold capability (Teece, et al., 1997) that organisations must have to stay competitive. Once again, the literature suggests that the impact of customer service, and thus the indirect impact of NLP on the overall success of a brand, is somewhat limited.

Whilst it cannot be said that customer service is an effective source of differentiation, findings from both primary and secondary research suggest its impact, and thus the impact of NLP on the overall success of a brand, is larger than the literature implies. Garnett (2017) claims that *"customer service is fundamental to the delivery of any product or service"*, whilst a recent report published by (American Express, 2011) highlighted that effective customer service, or lack of, can be the difference between winning and losing customers. Here it was found that 61% of customers will switch to a competitor when they experience bad customer service, and that 90% are happy to pay more to ensure a good customer service.

NLP Can Better Meet the Rising Expectations of Customers

Given that the literature labels customer service as an 'expected' value, it was surprising to discover that 62% of all customer service interacts fails to meet expectations (American Express, 2011). Garnett (2017) claims that expectations are rising in three key areas of customer service – its *"timeliness, accessibility and proactiveness*." The KLM chatbot has had a profound impact on the effectiveness of its customer service – improving response rate by 20% *(timeliness)*, increasing the number of customer queries by 40% *(accessibility)* and enabling the automated sending of boarding passes and flight updates *(proactiveness)* (Caffyn, 2016).

Data is Everything

Lilburn (2017) and other primary sources stated that NLP technology is starting to become commoditised - *"Wit is third party NLP engine…which makes it easy to setup NLP models."* (Lilburn, 2017), *"We're seeing the commoditisation of machine learning tools and data platforms."* (Hulme, 2017). However, experts warned that the quality and quantity of training and customer data the technology has access to is arguably more important than the technology itself – implying that these technologies need to be trained to become fully effective bots - *"You can't build a model with a small amount of data, or with bad data."* (Ferag, 2017). This indicates that despite increasing access to the same NLP technology, brands do not have immediate access to the enhanced customer service it has the potential to provide.

Speed is King

Lilburn (2017) elaborated on how brands can access the required mass of quality training data, and emphasised the importance of *"moving early"* to take full advantage of NLP – enabling it to become autonomous, effective and fit for purpose. This research highlights that the speed in which brands adopt these technologies is by far the largest determinant of their future effectiveness, and thus the effectiveness of the solutions they empower. Marc Benioff, Founder/CEO of Salesforce, regularly claims that *"speed is the new currency of business"* (Frain, 2016) – a claim highly applicable to NLP and one that suggests that the brands who are early to adopt NLP will be the ones that reap the most benefit from it.

Machine Learning and Personalisation

Machine learning involves *"predicting something about an entity that it has not been exposed to before"* (Hulme, 2017). Ferag (2017) gave practical examples of machine learning in industry, suggesting that the most common applications were "*Recommendation systems that show you what to buy* (Amazon) *or what to watch* (Netflix)." Secondary research into the effectiveness of these systems suggest that the level of personalisation machine learning enables has had a hugely positive impact on those brands that are investing in it. Latest figures estimate that 35% of all Amazon purchases (Krawiec, 2017) and 80% of all video watched on Netflix (Gomez-Uribe and Hunt, 2016) come from their recommendation engines. Unsurprisingly, Netflix continue to emphasise the importance of personalisation on their business - *"we develop and use our recommender system because we believe it is core to our business"* (Gomez-Uribe and Hunt, 2016).

Machine learning improves the level of personalisation that brands can achieve. This almost certainly has a positive impact on the success of the overall brand. A large, and well-established body of literature argues that successful brands are those that have personalities (Aaker, 1997). McKenna (1991) followed a similar line of thought, suggesting: *"a successful brand can be charecterised as having a strong relationship between a customer and a company."* – and it reasonable to assume that this relationship can be developed through personalised communications and product offerings. Given that scholars stress the importance of '*brand as a relationship*' (Aaker, 1997), it is appropriate to suggest that machine learning, and the personalisation that it enables, has a positive impact on the success of a brand. This impact is currently unquantifiable, and is recommended that further research should explore this.

Brand expert Garnett (2017) highlighted the rising demand for personalisation: *"people want greater and greater levels of personalisation"*. Secondary research implied that brands are starting to realise the importance of meeting this demand - with 79.3% of marketers saying it was either *"important" or "very important"* to their organisation (Saville, 2016). Despite rising demand and a clearly positive impact on brand – the latest data shows a mismatch between the number of brands that acknowledge the importance of personalisation (79.3%) and the number of brands who are actually implementing personalisation strategies (42%) (Saville, 2016).

This research becomes applicable when considering the reasons for this mismatch. Secondary research suggests that the top three barriers to the adoption of more sophisticated personalisation strategies are: *"lack of internal resource (45%), lack of technology (34%) and inaccurate data (32%)"* (Saville, 2016). Ferag (2017) claimed that machine learning was the *"next wave of standardisation"* – implying that the technology, and the level of personalisation it enables, is becoming commoditised and accessible to all brands.

Knowledge is the Limiting Factor for Brands

Whilst the commoditisation that Ferag (2017) describes is of interest, it is the source of the claim (Ferag) that arguably sheds more light on why machine learning is absent from much of industry, despite its increasing availability. Ferag (2017) is a practicing data scientist, making him a credible source to state what technology is available, and what it can be used for. Most marketers however, do not have a technical background and thus are not aware of how emerging technologies can be utilised to suit their organisational needs. This suggests that what is inhibiting brands from achieving greater levels of personalisation is not the lack of technology itself; but a lack of awareness that the technologies exist and a lack of understanding of how to utilise them to achieve greater levels of personalisation. Most brands, in simple terms, are technologically naïve and are not able to invest in, or implement technology they do not fully understand.

Research Limitations

It is likely that the findings found in this cross-sectional study, given the speed of technological development and the rate at which AI is improving, will be considerably less relevant in a year's time than they are today - limiting its longevity. Much hype, speculation and confusion surround the topic of AI, with numerous experts having differing opinions of what it is and what it can enable. This research drew its definition of AI from a highly regarded, yet small sample of AI experts - potentially limiting the study's generalisability. Finally, this study was constrained by time - and thus could only explore a small sample of AI technologies in the depth required to generate meaningful findings.

Further Research

This research took a sample of AI technologies (NLP, Machine Learning) and assessed their impact on a range of brand elements (customer service, personalisation). Future research should explore the impact of other AI technologies (machine vision, automation) and assess their impact on a wider range of brand elements (loyalty, communications, pricing) - establishing how else AI can be used to create brand value. This research focused on the impact of AI on functional brand benefits - *how can AI be used to build better products? and can those products act as sources of differentiation?* Future research should explore impact of AI on the emotive elements of a brand I.e. *Can an AI be creative? Can AI design emotional advertising?*

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