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THE IMPACT OF ARTIFICIAL INTELLIGENCE ON SUSTAINABLE CORPORATE BRAND: A NETNOGRAPHY STUDY OF TESLA

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ABSTRACT OF THE MASTER'S THESIS

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Abstract

The global market has become ever more turbulent due to digitalisation and digital transformation. Artificial Intelligence (AI) plays a central role in moving forward the advance of technology. AI has become an important research field in marketing while various companies have successfully implemented AI technologies to meet customers' needs. However, the impacts of AI on brands have not been widely explored in both scientific and managerial aspects. Brands generate values for businesses by providing functional and non-functional benefits that can be contributed by implementing AI technologies. Mainly, developing sustainability is crucial to address stakeholders' concerns for today's brands. The sustainable corporate brand can be a solution to this market demand as its promise has sustainability as a core value.

Through exploring this phenomenon, the thesis answers the research question: *to what extent does AI contribute positive impacts on sustainable corporate brands in the electric autonomous vehicle (EAVs) sector?* The EAVs industry, represented by the case company, Tesla, is chosen for conducting this research because it integrates the variants of electric vehicles that provide environmental benefits and the autonomous cars that use AI technologies. The study is performed using the qualitative research method of netnography. The data are collected from the publicly available information on Twitter and Youtube based on their relevance to the research question. One hundred sixty tweets and thirteen Youtube videos are extracted in textual form and analysed following the guidelines of thematic analysis and triangulated with multiple sources of data.

The key results of the research suggest the unique characteristics of the three AI features, machine learning, natural language processing (NLP) and Big Data analytics, help create the normative emotions and efficacy in the mind of stakeholders. These norms of emotions and efficacy further motivate stakeholders' normative actions that, in return, enhance the normative emotions and efficacy in a loop. Five elements represent the values AI technologies contribute to brand promise through creating a unique experience for the stakeholders that differentiate the brand from its competitors. The refreshed excitements and trust are brought by machine learning technologies. The fun and human characteristics and safety are brought by NLP technologies. Technology superiority is made possible through Big Data analytics. Four elements act for the values conveyed by AI technologies that enrich and expand the brand identity. NLP features can effectively enhance the connections between the focal brand and the other brand associations: the CEO, the affiliate brands and meaningful cultural references. The shared ownership of the brand is intensified through the co-creation of Big Data analytics. By contributing to brand promise and brand identity, AI implementation helps foster positive impacts in building an authentic, emotionally charged, and behaviourally based sustainable corporate brand.

Keywords
Sustainable corporate brands, brand promise, brand identity, artificial intelligence, EAVs

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1 INTRODUCTION

1.1 Rationale of the study

This research investigates the positive impacts of Artificial intelligence (AI) on sustainable corporate brands through the case study of the electric autonomous vehicle (EAVs) brand, Tesla. Electric vehicles (EVs) have been widely adopted in the transport system due to their environmental benefits. Autonomous vehicles (AVs) provide businesses with great potential in increasing traffic safety and saving operational costs. In scientific fields, researchers also become interested in AVs for their safer driving and lower noise pollution (Monios & Bergqvist, 2020; Rafael, Correia, Lopes, Bandeira, Coelho, Andrade, Borrego & Miranda, 2020). Therefore, the industry of EAVs serves as an excellent example for studying this research. The case company, Tesla, is chosen for the wide range of variants it provides, combining the implementation AI technologies and the environmental benefits through its use of green energy. In addition, the vast research interests in both EVs and AVs industry contribute to the rich academic resources. As the existing literature related to the impact of AI on sustainable corporate brands is sparse, the resourceful studies of EAVs provide vastly available materials for carrying out this cross-disciplinary research.

The global market has become ever more turbulent due to digitalisation and digital transformation. AI, the epitome of the digital revolution, plays a central role in moving forward digitalisation and digital transformation, which can potentially impact the global market scene on the internet scale. AI, i.e. deep learning, has helped companies become agile and innovate, drastically boosting global organisational spending on AI (International Data Corporation, 2019, West, Clifford & Atkinson, 2018). According to International Data Corporation, Global spending on AI forecast, growing 44% over the amount spent in 2018 to reach $35.8 billion in 2019 (International Data Corporation, 2019), continues to double, rising from $50.1 billion in 2020 to more than $110 billion in 2024 (International Data Corporation, 2020). Through observing these long-term trends that are rapidly reshaping the market, researchers argue AI will revolutionise marketing as the advance in technology has profound impacts on marketing. For example, the rise of the internet has led to the declined of big media, deepening customer relationships, and expanding the service economy (Rust, 2019, West et al., 2018). It is not difficult to argue that AI has become an important research field in marketing. At the same time, companies, i.e. Amazon, have successfully implemented various AI technologies to meet customers' functional needs. However, AI's impact on brands has not been widely explored in both scientific and managerial aspects (Thiraviyam, 2018, West et al., 2018). As the value of brand is acknowledged by marketing researchers (Aaker, 2007), it can be beneficial to study this research gap.

The value of a brand is to differentiate. Pioneering brand management researcher, Aaker (1991, p 15), defines brand's purpose as to "signals to the customers the source of the product, and protects both the customer and the producer from competitors who would attempt to provide products that appear to be identical". Existing literature suggests that the non-functional benefits brands provide are considered the most effective sources of brand differentiation as they cannot be easily imitated (West et al., 2018). As the brand-building model offers the opportunity to investigate AI's impact on brand functional benefits and non-functional benefits, this theory selection is justified. Mainly this research focuses on studying AI's relationship with sustainable corporate brands. A sustainable corporate brand is defined as a corporate brand whose promise has sustainability as a core value (Stuart, 2011, p139). To elaborate, sustainability represents a new approach to integrating researchers' previous efforts on mapping the relationship between corporate social responsibility (CSR), ethical issues, and branding, aiming to address the interlinked problems of modern economic development. In today's market, most companies understand that developing sustainability in business is required to address stakeholders' concerns. From corporate citizenship to green initiative, the topic of sustainability has evolved for more than a century, resulting in increasing consumer awareness on sustainability (Gond & Moon, 2010, Schultz & Block, 2013). Furthermore, companies can be motivated by the belief that business should be sustainable. To acknowledge and address the phenomenon, the sustainable corporate brand can be the solution to align sustainability with the brand's value (Stuart, 2011).

Exploring the duality of the two subjects that do not have rich existing literature can be expected to be challenging. AI experts point out that although AI enables brands to improve the consistency of fulfilling the brand promise, the technology is absent from many industries. The status quo is because most companies are technologically naïve, and marketers do not come from a technical background (West et al., 2018). Moreover, the sustainable corporate brand is still a developing concept that is newly formulated to synthesise CSR and corporate branding. Nevertheless, understanding the impact AI has on sustainable brands is significant as it enables marketing to become even more efficient, human, and sustainable (Nedergaard & Gyrd-Jones, 2013). This research attempts to provide theoretical gain by assessing AI's positive impacts on sustainable corporate brands in the context of the EAVs sector, bridging the two elements that can potentially benefit one another. In addition, this research seeks to contribute to the managerial implication of AI in its implementation on sustainable brands by deepening the connection of these two elements, attracting more businesses' interests in using AI in the marketing sector.

1.2 Goal of the study

This study aims to explore the positive impacts AI has on sustainable corporate brands in the EAVs industry through the case study of Tesla. To better understand this study's subject, we first visit the definition of AI, which is a subject of much discussion. The term is not precisely defined as the measure of intelligence is not universally agreed upon in the field of AI. A definition that is closer to the modern perspective defines AI as a science that makes machines capable of imitating intelligent human behaviour. However, we should note that the definition will change over time due to the rapid development of the industry (Kok, 2009, p2, Minsky, 1988, p5).

On the investigation of AI's impact on branding, West et al. (2018) suggest that researchers should try to identify the implementation of AI as a source to brand success. AI expert claims that some AI allows brands to consistently fulfil their promise, which aligns the role of AI as a risk reducer for brand performance. In addition, AI sub-categories, i.e. machine learning, improve brands' performance on personalisation. As a result, the relationship between brand and customer is strengthened. A brand-customer strong relationship can be characterised as a source of brand success. Through reading the existing literature that discusses the connection between AI and branding, three relevant sub-components of AI can be identified: machine learning, Natural Language Processing (NLP), and Big Data analytics (Carah & Angus, 2018, Gigli, Pantano, Bilotta & Melewar, 2019, West et al., 2018). These three AI elements are underlined in this research when discussing the current AI applied to branding.

Stuart's (2011) conceptualisation of sustainable corporate brand is selected for this study as it outlines the synthesis of sustainability and corporate branding. According to Stuart (2011), the several drivers that motivate companies to implement sustainability as their brand value can be divided into external drivers and internal drivers. External drivers are utilitarian, which perceives sustainability as an instrument to achieve performance goals and a duty to conform to consumers' expectations. On the other hand, internal drivers approach sustainability with the normative belief that organisations should be sustainable. This model aligns with our previous discussion on AI's impact on the brand's functional and non-functional benefits; hence the connection of the two subjects is appropriate.

Tesla claims its goal is to provide zero-emission electric power generation options (Musk, 2012c; Tesla, n.d.-a). Hence, Tesla can be seen as a sustainable corporate brand following Stuart's (2011) definition. Tesla uses all the three AI methods mentioned above for its product. Machine learning is utilised to build and optimise its autopilot feature (Morando, Gershon, Mehler & Reimer, 2020). NLP is used to deliver its digital assistant voice commands (Tesla, 2021b). The use of Big Data analytics is best represented by a company-owned data platform that all self-driving features train on (Tesla, 2019b). Therefore, Tesla is a suitable case company for exploring this research goal.

Stuart (2011) argues organisations must have a normative approach towards sustainability that tackles the real, sustainable problems that occur in business operation. The normative approach proposed by Stuart (2011) is based on "the normative alignment model" developed by Thomas, MacGarty and Mayor (2009), as Figure 1, and Balmer, Stuart and Greyser 's (2009) AC^{3}ID test, as Table 1. Under this framework, the sustainable corporate brand is part of an organisation's identity, which is also the promise the brand stands for. The alignment of other organisation identities with the sustainable corporate brand is crucial for building an authentic brand. It is expected that the application of this framework will support the sustainable corporate brand to achieve an emotionally charged, authentic, and behaviorally based identity (Stuart, 2011).

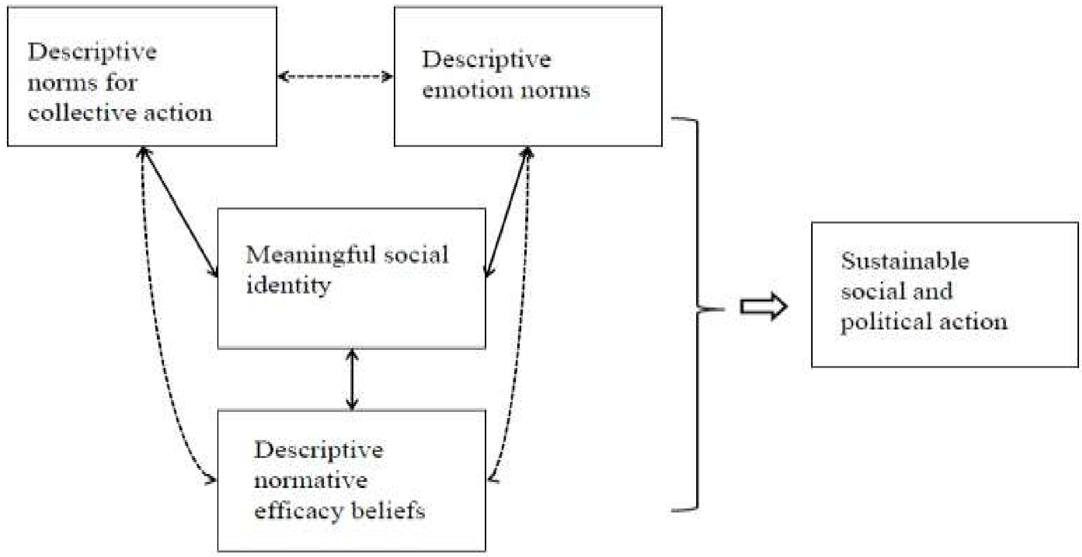

Figure 1, Conceptual normative alignment model (Adapted from Thomas et al., 2009, p 196)

Marketing researchers advocate the significance of business operations to develop a suitable branding approach. Urde, Baumgarth, and Merrilees (2013) suggest the market-oriented approach is the default option for most organisations since it reflects the domain marketing disciplines of being customer-centric in the last few decades. However, the evolution from market orientation to market and brand orientation will become essential when the market share of the organisations increases. Nedergaard & Gyrd-Jones (2013) also suggest that traditional market-oriented strategies should be complemented with innovation and investment around the brand. To create and maintain sustainable corporate brands, companies should develop a cultural foundation with the organisation that involves the brand's whole ecosystem.

Lastly, we should note the differentiation between sustainable corporate brand (Stuart, 2011), which this research focuses on, from brand sustainability. As a business term, sustainability carries a different meaning. Brand sustainability concerns finding the means of developing, growing, and maintaining brands for avoiding brands to decline or fail due to not being appropriately managed (Schultz &

Block, 2013). While brand sustainability underlines the measure of brand preference and market share, the sustainable corporate brand communicates sustainability as part of its brand promise that combines CSR and other ethical issues (Stuart, 2011).

Table 1, Balmer's AC^{3}ID Test (Adapted from Balmer et al., 2009, p 7)

Critical Concern	Identity Type	Concept	Time Frame
What we really are	Actual	Corporate Identity	Present
What we say we are	Communicated	Corporate Communications	Past/Present
What we are seen to be	Conceived	Corporate Image	Past/Present
What the brand stands for	Covenanted	Corporate Brand	Past/Present
What we ought to be	Ideal	Corporate Strategy	Future
What we wish to be	Desired	CEO Vision	Future

1.3 Research questions and limitations

The subject of this study, the impact of AI on the sustainable corporate brand, is investigated through the following main research question: *To what extent does AI contribute positive impacts on sustainable corporate brands in the EAVs sector?*

For answering the main research question, the following three additional sub-questions are used:

1) *To what extent does machine learning contribute positive impacts on building sustainable corporate brands in the EAVs sector?*
2) *To what extent does NLP contribute positive impacts on building sustainable corporate brands in the EAVs sector?*
3) *To what extent does Big Data analytics contribute positive impacts on building sustainable corporate brands in the EAVs sector?*

The research is conducted through netnography, focusing on collecting the qualitative data relevant to the research question. As this research applies a qualitative research method, it does not shed light on the research subject from a quantitative aspect, i.e. directly proving a standardised prediction (Yilmaz, 2013). The research is designed as a single-case study that provides in-depth insights into the case company (Yin, 2009, p. 47), limiting the possibility of generalising the findings to other cases (Moeyaert, Ugille, Ferron, Beretvas, den Noortgate, 2013). However, the limitations are compensated with the justification of the focal brands containing a wide range of variants typical for other cases and the data triangulation using multiples references to strengthen the validity of the research findings (Jack & Raturi, 2006). Lastly, the results do not generalise across sectors as it focuses on studying the EAVs sector.

By examining the relationship between sustainable corporate brands and AI, this study seeks to bridge the two subjects that lack cross-field academic studies. It should be noted that this research is exploratory. It aims to observe and explore the phenomenon, to which I attempt to offer new ways of perceiving the phenomenon by applying new concepts (Reiter, 2017). It is expected to gain more theoretical insight into how AI contributes to the value creation of sustainable corporate brands in the EAVs industry. In the practical aspect, this research aims to benefit the efficiency of sustainable branding by taking advantage of AI innovation, providing marketing managers more options in their toolbox for achieving brand success.

1.4 Research methodology

The research data will consist of qualitative data, which will be elicited by netnogrpahy from publicly available information in online communities. Netnography allows the researcher to observe stakeholders unobtrusively and collect data without decontextualisation (Kozinets, 2002). The data are extracted following both the guideline of purposive sampling and netnography. Purposive sampling indicates the researcher intentionally choose informants based on the virtue of their knowledge using a non-random technique. At the same time, sampling in netnography requires collecting data from the online communities that provide information that is most relevant to the research question, have a high traffic of posting, rich text of posts and high engagement rates (Kozinets, 2002; Etikan, 2016).

Following the qualitative research methodology, this study is based on constructivist epistemology, which explores a socially constructed dynamic reality through a holistic and context-sensitive framework, developing an in-depth description of the phenomenon to reveal the meaning people attach to their experience of the world (Yilmaz, 2013). The qualitative approach is selected because it preserves the chronological flow of the data with minimal distortion from the subjective view of observers and offers a precise way to assess causality in organisational affairs (Miles, 1979). The qualitative approach also provides insight into the participants' individual experiences, which is suitable for this research, requiring extracting rich data from participants' thoughts and feelings (Yilmaz, 2013).

The data will be collected inductively, which is compatible with the exploratory nature of this research. The method poses an open-ended question that helps the study discover the underlying pattern of the data (Thomas, 2006). Two public online communities, Twitter and Youtube, are selected as they best fulfil the criteria of the sampling guidelines mentioned above. The data are collected without logging into a personal account to ensure only public data are used. The data are extracted in textual form and stored in the excel sheets. After the data collection is finalised, the data are saved as PDF file for importing to NVIVO for analysis. Further, resources from various resorts are collected for data triangulation.

The inductive approach is chosen to condense the textual data, establish links between the research objectives and the findings, and develop a framework that is evident in the data (Thomas, 2006, p237). The data is analysed through thematic analysis, which is compatible with the constructivist epistemology because it acknowledges the researcher's active role in identifying patterns and themes (Braun & Clarke, 2006). The thematic analysis is performed following Braun and Clarke's (2006) 6-phase guide.

The data are encoded and analysed systematically by Nvivo, collecting and interpreting the examples of the phenomena to find patterns and structures (Basit, 2003). The relationships between each theme are analysed, adopting the methodology used by West et al. (2018), comparing the latent meanings shared by the theories in two different fields. Therefore, coding will be characterised based on the commodities of concepts instead of the commodities of technical terms. The choice of analysing data based on the commodities of ideas ensures the findings can relate the data about AI to the data about sustainable corporate brands.

1.5 Key concepts

Branding

A brand is used by businesses to differentiate their products from competitors meaningfully and appropriately. Branding consists of a set of tangible and intangible values that serve the stakeholders. In the early stage of branding, the intangible results of branding are viewed as difficult to measure. Therefore, brands should recognise the intangibility of a brand is not deemed to be successful (Murphy, 1992, pp. 1-2). In modern branding, however, researchers assume the financial value of brands to be established in the heart of the stakeholders and can be evaluated through brand associations and loyalty (Anselmsson & Bondesson, 2015). Organisational values, core values, and added values are the core values of brand building, which summarise the identity of the corporate brand and orchestrate the process of brand building (Urde, 2003).

CSR

CSR can be loosely defined as three aspects: firstly, the expectation that business is responsible to society. In other words, companies are accountable to compensate for the negative impact their business operation brings to society and contribute to social welfare; secondly, the expectation for companies to trade responsibly; lastly, the corporate-society interface of business management for strengthening stakeholder relationships (Gond & Moon, 2010).

Sustainable corporate brand

A sustainable corporate brand is a corporate brand that includes sustainability as part of the core values of its brand promise, comprising CSR, ethical issues, and branding. Its goal is to address the sustainable problems in business operations through adopting a normative approach that motivates organisations to be sustainable. In addition, a sustainable corporate brand is part of the brand identity that can be aligned with the other parts to create an emotionally charged, authentic, and behaviorally based brand identity (Stuart, 2011).

Brand value creation

The valuable intangible assets of companies are represented by their brands. It is crucial to managing brands strategically for optimising their value. A classical model of the brand value chain can be used to explain how brand value is created and the financial impact of marketing investment, which can be broken down to four value stages: firstly, marketing program investment; secondly, customer mindset; thirdly, brand performance, and lastly, shareholder value (Keller & Lehmann, 2003).

AC^{3}ID test

The AC^{3}ID test addresses and resolves the problem of brand identity misalignment commonly seen in organisations. The framework of the AC^{3}ID test is based on six critical identity types that senior managements have to orchestrate harmoniously with each other, which are actual, communicated, conceived, covenanted, ideal, and desired identities. The goal of the framework is never absolute alignment between the identities but to assure dynamic congruence.

Normative alignment model

The normative alignment model suggests that promoting the commitment to collective action can be achieved by crafting a social identity with a relevant pattern of norms for emotion, efficacy, and action, conceptualised as contributing to a dynamic system of meaning. This dynamic system helps shape the collective identity as people who identify with a specific group will behave according to its norms. Arguably, a strong identity of sustainable social and political action can be created when the three types of norms are enacted in the context of meaningful social identity (Thomas et al., 2009).

AI

AI is a subset of computer science. The term can be loosely defined as a science that makes machines capable of imitating intelligent human behaviour (Kok, 2009, p2), which can be examined through its task-specific skill and generality. The aspect of task-specific skills looks into if machines can perform tasks that would require intelligence if done by humans (Minsky, 1988, p5). On the other hand, the aspect of generality emphasises if machines can solve the task they have not prepared for beforehand (Chollet, 2019).

Machine learning

Machine learning is a subset of AI, inspired by the idea of programming computers to learn from experience and then automatically improve the efficiency of their programs during execution (Michie, 1968, p 19). Besides its automation feature, another interrelated aspect machine learning focuses on is the fundamental statistical computational-information-theoretic laws that govern the learning system of computers (Jordan & Mitchell, 2015, p. 255).

NLP

NLP is a subset of AI intersected with the linguistic discipline. NLP is a theoretically motivated range of computational techniques for analysing and representing naturally occurring texts to achieve human-like language processing for various tasks or applications. The ultimate goal of NLP is for machines to truly understand both written and oral human language, which is not yet fulfilled (Liddy, 2001, Nadkarni et al., 2011).

Big Data Analytics

Big Data is a subset of AI that processes large volumes of scientific data for visualisation. It can be characterised by volumes, variety, and velocity. Volume refers to the amount of data generated from a range of sources. The sources can be the Internet of Things (IoT), which indicates the data is gathered from a range of devices and sensors connected through the internet. Variety refers to using multiple kinds of data from devices, sensors, the internet, or the web browser to analyse the situation or event. Velocity refers to the data is increasing rapidly in the Big Data warehouse, which will be utilised to make decisions (O'Leary, 2013, p96).

1.6 Structure of the research

The thesis begins with the introduction that provides the rationale and goal of the study, research questions and limitations, a brief description of research methodology, and the key concepts.

The following two chapters introduce the theoretical background of the research. The second chapter provides a theoretical review of the elements that comprise the sustainable corporate brand, including brand value, brand promise, brand identity, and CSR. The third chapter provides the definition of AI and the overview of the AI sub-categories the study focuses on, which are machine learning, NLP, and Big Data analytics. At the end of the third chapter, a theoretical framework is proposed for conducting the research.

The fourth chapter details the methodology for this research, including the literature review, research design and strategies, data collection, and data analysis. The empirical results and analysis are provided in the fifth chapter, including the supplementary background knowledge, the impact of machine learning, NLP, Big Data analytics on brand promise, brand identity, and sustainable corporate brand.

The sixth chapter is the conclusion and discussion, which presents the key findings. The answers to the main research question and the three sub-questions are provided. The discussion includes the theoretical contribution, managerial implications of the research. Lastly, the thesis ended with evaluating the limitation, validity of the study, and suggestions for future research.

2 SUSTAINABLE CORPORATE BRAND

This chapter provides a theoretical review of the elements that comprise the sustainable corporate brand. The chapter begins by analysing the formation of brand values and their value to businesses, following by discussing the significance of brand promise, brand identity in generating brand values. Subsequently, these brand elements are linked to the sustainable corporate brand for illustrating a comprehensive view of the theoretical model. Lastly, we examine the aspect of CSR in sustainable corporate brands.

2.1 Brand value creation in sustainable corporate brand

This section visits the essential branding elements for understanding how to promote a sustainable corporate brand by creating brand value. The section begins with discussing the definition of brand value, exploring how brand value benefits businesses. Subsequently, we focused on capturing the comprehensive view of brand identity and brand promise, which are part of the sources that contribute to creating brand value. Lastly, we conclude by connecting these brand elements underlined in the model of sustainable corporate brand proposed by Stuart (2011).

2.1.1 Brand value

To understand how the brand value is created, Keller & Lehmann (2003) conceptualised the model of the brand value chain, which is one of the domain frameworks that capture the essential elements of brand value. Based on the model, brand value is built up in customers' minds and then converted to market performance and cash flow. It also indicates that building brand equity is a long-term process that leads to consistent sales and marketing performance (Anselmsson & Bondesson, 2015, p 58; Keller & Brexendorf, 2019).

Here we explain the four stages of the brand value chain in detail, as Figure 2. The first stage, the marketing programme, deals with the actions companies take to influence their brand and the products under the brand name. The examples of these efforts can be the 4 Ps of the marketing mix, i.e. pricing or promotions. In the second stage, the customer mindset indicates the associations linked to the brand in a customer's mind. Everything that customers can connect to the brand in their memory is included in this stage, i.e. feelings, experience, attitudes. These associations are what the brand mindset concepts are built upon, i.e. brand preference and brand satisfaction. The third stage, the market performance, entails how customers react or respond to the brand, which can manifest in market performance data differently, i.e. market share, and market penetration. These performance data show the tangible result converted from the intangible values of the brand by providing evidence for the cash flows that the brand brings to the company (Keller & Lehmann, 2003; Anselmsson & Bondesson, 2015).

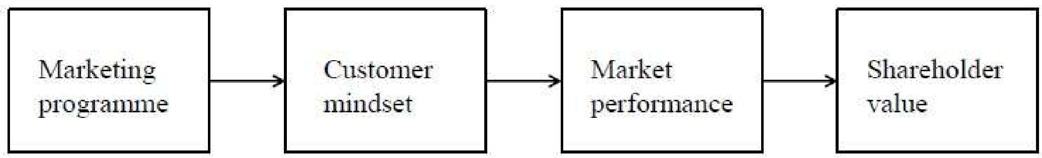

Figure 2, Model of the brand value chain (Adapted from Keller & Brexendorf, 2019, p 1429)

It should be noted that, besides the brand, many factors, i.e. relations to the channel partner, can influence customers' mindset. Hence, the connection between customer mindset and the brand market performance at this stage is not very clear. The fourth stage, shareholder value, acknowledges that a brand's objectives are to create values for brand equity owners (Keller & Lehmann, 2003; Anselmsson & Bondesson, 2015).

2.1.2 Brand promise

Brand promise is the brand as a cluster of functional and emotional values that enable stakeholders to recognise a promise about a unique experience (Chernatony & Christodoulides, 2004, p238). From the philosophical perspective, brand promise is a promise to the stakeholders it addresses and stems from the view that the brand is a service or a collection of activities.

The product attributes of the brand are not emphasised by brand promise because physical products can be easily standardised and imitated. On the contrary, services are a promise that can shape the brand in customers' minds through their past experience with the brand and an expectation of what will follow (Furey, Springer & Parsons, 2014).

In the early work of Balmer (1998), the corporate marketing vortex that describes the corporate level construct also involves the concept of corporate branding in the covenant element, of which the critical concern is "what is promised and expected". The brand promise in corporate branding is delivered to the external stakeholders relying on the employees' attitude and behaviour. Therefore, internal branding can align employees' behaviour with brand value to deliver brand promise. Helping employees internalising brand value will be the management's efforts to make (Punjaisri & Wilson, 2007, p. 62).

2.1.3 Brand identity

According to Aaker (2002), brand identity is a unique set of associations representing what the brand stands for and implies a promise to customers from the organisation, which is crucial for building strong brands to create brand value. Aaker's brand identity concept, as in Figure 3, consists of twelve elements categorised into four groups: the brand-as-product, brand-as-organisation, brand-as-person, and brand-as-symbol.

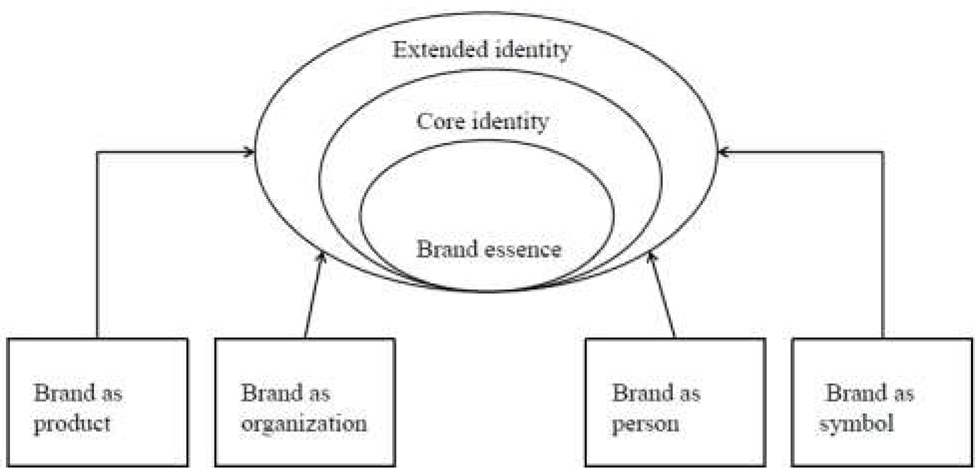

Figure 3, Brand identity model (Adapted from Aaker, 2002, p 68)

The structure of brand identity is divided into a core identity and an extended identity wherein the twelve elements are grouped in a cohesive and meaningful way. By maintaining the meaningful associations of brand identity, the brand aims to establish a relationship with the customers by creating a value proposition that includes functional, emotional, or self-expressive benefits. To generate brand values, the balance of these four groups needs to be adjusted based on brand strategic analysis (Aaker, 2002, p 68).

Törmälä & Gyrd-Jones (2017) challenge the traditional perspective on the formation and dynamics of corporate brand identity, which is considered stable and endogenous to the organisation based on the reputational capital of the organisation or the founder and concerns the organisational identity. Traditionally the corporate brand identity is presented as a managerial tool to differentiate and position the brand based on its core and distinctive character. From this perspective, corporate brand identity is regarded as a fixed and stable entity. In addition, brand identity is seen as unilaterally defined and communicated by the firm to its stakeholders through the groups of brand associations we discussed above (Aaker, 2002; Urde et al., 2013).

In contrast to the traditional managerial approach, Törmälä and Gyrd-Jones (2017) propose that brand identity formation sees corporate brand identity as developing over time through inputs from managers and other social constituents. According to this view, corporate brand identity is essentially co-created through the ongoing process of dialogue between a company and its stakeholders. It evolves in response to both internal and external contextual changes. Brand identity as a socially shared reality exists in the actors' minds within a company's context. It can only be accessed through the different meanings to which the actors relate.

2.1.4 The implementation of sustainable corporate brand

For implementing the sustainable corporate brand, which is the focus of this study, Stuart (2011) suggests internal drivers that are self-motivated by the normative belief in the organisations can help build an authentic brand. The normative alignment model is utilised for the implementation, aiming at a long-term goal to make the brand identity with the brand-related norms for emotions, efficacy, and actions. In other words, the long-term support required to build a sustainable corporate brand lies in an authentic brand identity that is emotionally charged and behaviourally based. Both "inside-out" and "outside-in" approaches effectively place CSR in the centre of brand value. It requires an integrated framework that synthesises both internal building and development of values and the external expression designed from stakeholders' viewpoint.

Thomas et al. (2009) proposed the normative alignment model to capture "one solution to promoting ongoing commitment to collective action lies in crafting a social identity with a relevant pattern of norms for emotion, efficacy, and action" (p 194). From the perspective of social identity, norms can be explained as to how the members of the groups should ideally do in a specific situation based on subjective notions shared by the members. The normative emotions can be established within a group based on the shared social identity of the members. In other words, group-based normative emotions mean the shared understanding of the world between group members. The normative emotions greatly influence nurturing collective actions as they build connections between people by informing them of their shared position in an environment. The normative efficacy can be established within a group when group members believe in their collective actions to achieve a shared goal. Notably, normative efficacy is vital when the shared belief is linked to the possibility to change. The norms of emotions and efficacy relevant to the group empower collective actions, which three elements contribute to a dynamic system that promotes sustainable social identities, conceptually interlinking the collective identity and subjective meaning shared by individuals (Thomas et al., 2009).

Combined with the normative alignment model, the AC^3ID test entails that the corporate brand is seen as part of the identity system of an organisation. Here the model of the AC^3ID test aligns with Balmer's corporate marketing vortex we previously mentioned. The corporate brand is characterised as covenanted identity (what the brand stands for), which is the brand promise the managements are aspired to orchestrate with the other identities. The ideal identity (what we ought to be) optimises sustainability in the organisational context. The desired identity (what we wish to be) is developed by the management and represents the CEO's vision of sustainability. As a result of this, the commitment of the CEO is the key that maintains a sustainable corporate brand. The actual identity (what we really are) is where the implementation of the sustainable corporate brand begins (Balmer et al., 2009).

From the perspective of corporate communication (what we say we are), it is essential for organisation members to use the sustainability language for integrating the identity of sustainability into the corporate story. As many different voices exist in an organisation, there is a need to prioritise sustainability as the key feature. Through communicating with the sustainability language, the authenticity of sustainability claims is demonstrated and communicated to employees. Therefore, the norms are set for employees to follow, and guidelines are provided for the external aspirations (Balmer et al., 2009; Stuart, 2011; Schmeltz & Kjeldsen, 2018).

2.2 CSR in sustainable corporate brand

In this section, we discuss the concept of CSR in detail for understanding its definition, scope, and domain theories. To do so, we begin with reviewing the conceptual development of CSR and, followed by introducing Carroll's Pyramid of CSR, which is a critical theory that serves as an integrated foundation for modern CSR. Lastly, we examine the triple bottom line model (TBL), which is the widely applied CSR theory in businesses today.

2.2.1 The conceptual development of CSR

Gond & Moon use the metaphor of Chameleon to describe the constantly changing of the conceptual change of CSR in both academic field and managerial implications. Especially in the twenty-first century, the conceptual development of CSR underwent more remarkable changes compared to the last century. The volatile conceptual change of CSR is influenced by the related social phenomena and the cycle of managerial fashions, which explains CSR's quality of being dynamic, overlapping, and contextual (Gond & Moon, 2010).

The managerial viewpoint of social responsibility emerged in the late 1800s in the U.S. The ideology stemmed from the religious beliefs of business leaders and the movement of managerial professionalisation. Social responsibility as an ideology aims to enhance the legitimacy of large corporations and their management, whose rise in history was considered a threat to American democracy at that time. Therefore, the management of corporations started to pay attention to how the general public perceived their business activity. Subsequently, the idea of the corporation's duty of serving the public emerged (Gond & Moon, 2010).

In the 1920s, two main managerial concepts of CSR were stewardship and trusteeship, carrying on the religious influence on the foundation of CSR. The two concepts underline business owners' duty of serving and being responsible to God and society. The impact of the two concepts on CSR continued to grow until the 1960s. From the 1950s to the 1960s, the academic field became interested in social responsibility, and CSR became a theoretical concept. Howard R. Bowen defined social responsibility as businessmen's obligation to pursue policies or actions in terms of the objectives and values of our society (Gond & Moon, 2010).

Bowen's definition of CSR has led to the following academic refinements and redefinitions. The conceptual changes have been abundant since then. To name a few, Friedman (1970) proposed the idea of the only business social responsibility being to use its resources to engage in open competition without deception; Carroll (1979), nonetheless, considered CSR to encompass the economic, legal, ethical, and discretionary expectations that society has of organisations. Campbell (2007) viewed CSR as acting in socially responsible ways on the premises of not knowingly harming their stakeholders and rectifying it if it is discovered that they harm the stakeholders (Gond & Moon, 2010).

CSR has been a highly contested concept due to multiple borrowing from different disciplines, i.e. economics and sociology, which results in challenges. As the fields represent the worldviews of scholars from different schools of thought, the same subject can be defined in distinct ways, which evolved to intellectual disagreements. Another factor can be the impacts of the megatrends, i.e. globalisation, urbanisation, and the internet. The influences from the Macro level create a turbulent and ever-changing market. In this context, the concept of CSR has to evolve with the change of the markets (Gond & Moon, 2010).

2.2.2 Carroll's Pyramid of CSR

According to Carroll, "CSR has typically been understood as policies and practices that business people employ to be sure that society, or stakeholders, other than business owners, are considered and protected in their strategies and operations (Carroll, 2016, p. 2)". A firm's four responsibilities for society and the stakeholders are divided into Economic responsibility, Legal responsibility, Ethical responsibility, and Philanthropic responsibility (Carroll, 2016).

Economic responsibility is a social responsibility that society requires a firm to have. Business organisations must sustain themselves by being profitable and able to incentivise owners or shareholders. When businesses create profits, they add value to the ecosystem, bringing benefits to all the shareholders (Carroll, 2016). Economic responsibility is considered a baseline requirement because firms that cannot sustain themselves economically will simply go out of business. With that said, it will not be possible for firms to fulfil any other responsibility if they do not succeed financially (Carroll, 2016).

Legal responsibility is established by society as the minimal ground rules for businesses, including law and regulations. Companies are required to comply with these laws and regulations as a condition of operating. In the long run, society requires businesses to conduct themselves as law-abiding corporate citizens, providing goods and services that meet minimal legal requirements (Carroll, 2016).

Besides society's essential requirement for businesses to abide by the law, it also expects firms to act on the "spirit" of the law. In other words, society expects firms to operate the business ethically. Ethical responsibility can be explained as companies are expected to conduct themselves fairly and objectively when there is no guidance of law or regulation. To be good corporate citizens, firms have to do what is morally and ethically adopted by society (Carroll, 2016).

Philanthropic responsibility includes all forms of business giving, which is not a responsibility in the literal sense but normally expected by society today. The business-giving can be gifts of monetary resources, product and service donations, and any other voluntary contribution to the community or stakeholder groups. Most companies carry out their philanthropic responsibility to demonstrate their good citizenship, enhancing firms' reputation (Carroll, 2016).

Though Carroll separates a firm's social responsibilities into four categories, Ethical Responsibility should be perceived as a factor that permeates the entire pyramid, presenting itself in each category. In the Economic responsibility category, the pyramid assumes a capitalist society. Capitalism considers owners or shareholders benefits from the return on their investment to be ethical. Hence the firms that obligate their economic responsibility are ethical. In the Legal responsibility category, we can acknowledge that most laws and regulations were created based on ethical rationale, i.e. protecting customers' safety or the natural environment. Therefore, law and regulation can be regarded as the code of ethics formalised by society. The component of ethics in ethical responsibility is self-evident. While the law can be perceived as passive minimal compliance, ethics suggest a level of conduct that strives to do what is above most laws. Philanthropic responsibilities, as mentioned earlier, are sometimes done for practical purposes, i.e. to be seen as good corporate citizens. Sometimes companies can also engage in charitable activities because they are ethically motivated. Therefore, ethical motivations assume a vital role in Carroll's CSR pyramid (Carroll, 2016).

Carroll also pointed out the pyramid is an integrated, unified whole. The Pyramid of CSR should be considered on the whole, not the different parts. The four categories of the pyramid should not be interpreted to mean that businesses should fulfil their social responsibilities from the base sequentially. Instead, companies should engage with all responsibilities simultaneously as the four responsibilities are portrayed to represent the total social responsibility of business. In the managerial aspect of Carroll's pyramid, a CSR-driven firm should strive to make a profit, obey the law, engage in ethical practices, and be a good corporate citizen at the same time (Carroll, 2016).

2.2.3 Triple Bottom Line

TBL stands for economic prosperity, environmental quality, and social justice. The three bottom lines are interrelated, interdependent, and partly in conflict (Jeurissen, 2000, p 231). The TBL framework gained popularity with the emergence of the term "sustainable development" from the Brundtland Report in 1987(Alhaddi, 2015). In the report, "sustainable development" is defined as the "development that meets the needs of the present generations without compromising the ability of the future generations to meet their own needs", which goal TBL strives to achieve (Brundtland, 1987, p 43).

The economic line of TBL refers to the impact of the organisation's business practices on the economic system. It regards the economy's capability as one of the subsystems of sustainability to support future generations. As the economic line ties the organisation's growth to the economy's growth, it focuses on the economic value provided by business organisations for its capability to support future generations (Alhaddi, 2015). The social line of TBL refers to conducting beneficial and fair business practices to the labour, human capital, and the community. Social performance focuses on the interaction between the community and the organisation. The idea is that these practices provide value to the society and "give back" to the community (Alhaddi, 2015, p8). The environmental line of TBL refers to engaging in practices that do not compromise the environmental resources for future generations, i.e. the efficient use of energy resources. According to scientific analysis, organisations that protect the environment have outperformed their industry peers financially during an economic downturn. In other words, environmental practices benefit the business sustainability of the organisations (Alhaddi, 2015).

TBL model plays an essential role in CSR as it is adapted by NGOs to produce sustainability reporting standards, i.e. the Global Reporting Initiative (GRI), widely used by big corporations and smaller businesses (Hahn & Lülfs, 2013). This research acknowledges researchers' critical view towards the TBL model. Norman and MacDonald (2004) point out vagueness and controversy can be found in the promise of the TBL model to quantify the social and environmental impact of a firm and make transparent the data of the company to stakeholders. Advocates of 3BL claim the sustainable reporting of the TBL model responds to all stakeholders' demands and serves as a valuable management tool that allows you to react faster to stakeholders, incorporating the change in their behaviours into business strategies.

This critical view does not go against the fact that some companies that aim to make fundamental changes in their corporate culture and improve social and environmental issues can benefit from implementing the TBL model. However, it points out the propagation of using TBL is possible because issuing TBL-based reports does not require companies to commit to TBL principles. There is no meaningful methodology established to calculate social and environmental bottom lines to enable these two additional bottom lines to become comparable to the economic bottom line. Companies' freedom on changing the indicators over time in TBL-based reporting also makes comparing companies' long-term performance in these two aspects difficult. Norman and MacDonald’s (2004) viewpoint entails that the TBL model is not developed enough to meet its claim.

3 ARTIFICIAL INTELLIGENCE

This chapter provides the definition of AI and the overview of the AI sub-categories the study focuses on, which are machine learning, NLP, and Big Data analytics. At the end of the third chapter, a theoretical framework is proposed for conducting the study.

3.1 The importance and research fields of AI

This section discusses the basic concepts and features of AI, attempting to lay a foundation for further discussion on the AI application in sustainable corporate branding. We begin by exploring the definition of AI through explaining some crucial principles relevant to its business applications. Three sub-areas of AI, machine learning, NLP, and Big Data analytics connected to branding are introduced following the same structure.

3.1.1 The definition of AI

The intelligence in the AI domain primarily refers to human intelligence because human intelligence is the prototype that mainstream artificial intelligence tries to imitate. From a psychological point of view, Gardner's Multiple Intelligence theory (MI theory) asserts that human intelligence to be a combination of heritable potentials and skills that can be developed in diverse ways, stemming from multiple abilities to problem-solve (Davis, Christodoulou, and Seider, 2011, p486). In other words, human intelligence is pluralistic and can be developed through learning. As mentioned in section 1.2, currently, there is no universally agreed definition of intelligence. MI theory, for example, is one of the developed theories that attempt to capture the forms of human cognitive activities.

From the perspective of neuroscience, human intelligence is a biological algorithm. AI Researchers study how brains function to understand how the same intelligence can be duplicated on machines. According to the Astonishing Hypothesis proposed by British biologist Francis Crick, such a goal is possible as the hypothesis assumes that "all intelligence is machine intelligence. What distinguishes natural from artificial intelligence is not what it is, but only how it is made (Wilczek, 2019, p 64)." Crick argues that both human and artificial intelligence capabilities emerge from physical processes (Wilczek, 2019, p 69). His hypothesis takes the same claim as computationalism does. This domain theory in cognitive science explains that intelligent behaviour is performed through the computation of the agent's cognitive system (Piccinini, 2009, p515).

In the context of AI, to compute is to execute an algorithm. A device that computes means that a modelling relationship exists between the device and an algorithm and supporting architecture. An algorithm, in this case, is a mechanical procedure for achieving a specified result (Copeland, 1996). Another critical feature of machine intelligence is its ability to learn. For researchers that think machine intelligence lies in the general ability to acquire new skills, learning can direct machines to solve problems they have not previously encountered. Recently, the success of Deep Learning has triggered interest in generalisation theory in the context of machine learning, aiming to develop the ability of machines to handle tasks that differ from previously encountered tasks.

The generalisation of AI can be qualitatively defined into four categories. Firstly, there is an absence of generalisation, in which AI systems cannot generalise to novel information that is unknown to its system or its creator. An example can be a sorting algorithm that can only put all lists in order. Secondly, local generalisation, in which the AI system possesses the ability to handle new points from a well-scoped set of known tasks when given sufficient sampling. An example can be the image classifier. The generalisation of this category is what machine learning focuses on since the 1950s till today. Thirdly, broad generalisation, in which AI system can handle a wide variety of tasks and environment without human engineer stepping in. In this case, AI systems can reflect human-level capability restricted a broad activity domain, i.e. driving. Level 5 self-driving car of SAE model that is fully automated belongs to this category.

State-of-art AI systems have not reached this level of generalisation, but they are developing quite close to this goal. Lastly, extreme generalisation, in which AI systems can handle entirely new tasks that only share common abstract attributes with previously encountered tasks in a broad scope. Biological intelligence, including human intelligence, is an example of this category. State of the art AI systems are far from the strong AI that belongs to this category. Most AI research focuses on studying narrow AI that aims at achieving more specific sub-goals (Chollet, 2019, pp 9-10; Adams, Arel, Bach, Coop, Furlan, Goertzel, Hall, Samsonovich, Scheutz, Schlesinger, Shapiro & Sowa, 2012; Zhan, Wan & Huang, 2020).

3.1.2 Machine learning

Machine learning is a branch of AI, which is intensively researched and growing rapidly due to the cost reduction brought by the digital revolution. The origin of machine learning took place soon after with the commercial production of electronic computers. The algorithms were developed to enable modelling and analysing large sets of data.

As mentioned in section 1.5, machine learning aims to enable the computer to automatically extract the algorithm from the designated tasks or past experience. This goal is reached through programming computers to optimise a performance criterion using example data (Alpaydin, 2014, p2). The founding AI researchers established three main branches of machine learning: symbolic learning, statistical method, and artificial neural networks (ANN). Among them, ANN is the model on which deep learning algorithm trains and is an important research area in machine learning (Kononenko, 2001).

Three sub-areas of machine learning are categorised according to the problems they are trying to solve: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is often used to solve binary classification problems. AI uses the input to carry out the task of predicting the correct output or label. An example can be AI is given a photo and is asked to answer whether the image contains a speed limit traffic sign. In this case, AI will output the label in the form of yes/no. Supervised learning is the most commonly used machine learning approach in business, i.e. analysing customer lifetime value.

Unsupervised learning does not label the outputs. Its task is to discover the data structure and output the results as the clusters of similar items or reduce the data to a small number of dimensions, i.e. data visualisation. Reinforcement learning is utilised when AI agents must operate in an environment, i.e. self-driving car runs on the road. It comprises incremental planning algorithms that provide feedback on a small set of important choice with some delay (Thrun & Schwartz, 1995; Goodfellow et al., 2016, pp. 98-99).

3.1.3 Natural Language Processing

NLP is a mix of multiple disciplines, which influences the research of one another in the field. The three key disciplines of NLP are computer science, linguistics, and cognitive psychology. Computer science contributes to NLP by developing internal representations of data and processing the structures efficiently. Linguistics contributes by providing formal and structural models of language and the universal language pattern. Cognitive psychology contributes through perceiving language as a window to human cognitive processes and setting the goal of modelling language in a way that is reasonable to psychology (Liddy, 2001).

Natural language means the language human speak, read, write or listen to for expressing their thoughts or feelings. Hence, natural languages can come in different forms, i.e. a written text or a dialogue. As mentioned in section 1.5, NLP is inspired by the concept of building a machine that is capable of interacting with humans in the form of natural language. To build NLP systems that process languages like human, computational technologies and computational linguistics are required. NLP can be defined as the semi-automatic or automatic processing of natural human language. In addition, NLP is trained using machine learning technology, i.e. supervised learning (Thanaki, 2017, p 9).

The concept of NLP is applied to expert systems, which are computer systems that simulate the decision-making ability of a human expert (O’Keefe & O’Leary, 1993). In practice, the critical NLP applications include speech recognition system, question answering system, language translation, text summarisation and classification, topic segmentation, sentiment analysis, and template-based chatbots. These basic NLP systems can be trained on deep learning to become advanced applications. For instance, the basic NLP system for language translation can translate from one specific language to another. With the help of deep learning, NLP advanced application is closed to develop a universal machine translation system. Advanced NLP systems can generate a topic for a document or an image through text summarisation and topic segmentation applications (Thanaki, 2017, pp 14 -15).

3.1.4 Big Data analytics

Big Data indicates massive data sets with a large, varied, and complex structure and are difficult for storing, analysing, and visualising for further process. The process of research into Big Data for discovering hidden patterns and correlations is called Big Data analytics. Big data analytics provides helpful information for organisations to gain rich and deep insights into the ecosystem they compete in (Sagiroglu and Sinanc, 2013)

In the early 2000s, data volumes escalated drastically since the World Wide Web entered general use. Big Data caused data scalability problems at that time, overwhelming the storage and CPUs (central processing units). The crisis led to the development of CPUs of better capacity, speed, and intelligence. Companies begin to use a large volume of detailed data to discover facts that are unknown before and study the reason behind the change of market using advanced analytics. As briefly mentioned in section 1.5, volumes, variety, and velocity can characterise Big Data. Therefore, Big Data is concerned with a large volume of data and related to diverse types of data delivered at various speeds and frequencies. Among these three components, variety makes Big Data incredibly complex and massive. Different sources of data, i.e. social media, are generally divided into structured, semi-structured, and unstructured. Structured data is easily stored in a data warehouse that is tagged. Unstructured data is random and hard to analyse. Semi-structured data are not stored in fixed fields but contain tags to separate data elements (Russom, 2011; O'Leary, 2013, p96, Sagiroglu and Sinanc, 2013).

Many examples of Big Data in diverse industries can be found in the literature. The internet provides opportunities for Big Data to understand user intelligence. In the

EAVs sector, Big Data insights help brands with specifying market aim, capacity planning and benefit from analysing user behaviour and battery security.

Companies can customise actions for suitable products and services. Researchers point out that Big Data analytics benefits organisations because of its optimisation of marketing aim. Business insights lead to better opportunities in sales and the market. However, technical, financial, and ethical issues can become the barriers to using Big Data (Sagiroglu and Sinanc, 2013; Li, Kisacikoglu, Liu, Singh & Erol-Kantarci, 2017). Particularly in the ethical aspect, Big Data analytics is criticised for breaching the privacy of individuals, potential discrimination, encouraging consumerism, which is the problems organisations need to address while benefited from Big Data analytics (Kirsten, 2015).

3.2 AI in branding

In this section, we review the study of West et al. (2018) that sheds light on how AI technologies influence branding and discuss the social and emotive association of the three AI branches to analyse the relationship between AI and branding.

Brands create value through emotive and social associations. West et al. (2018) propose establishing AI as a source of brand success for three reasons: firstly, AI can improve operational efficiency by optimising the consistency of delivering the brand promise. Machine learning allows personalised recommendations and offers. NLP can better the quality of customer service. To successfully implement machine learning and NLP technologies, Big Data plays a crucial role as NLP and machine learning require data of good quantity and quality and the knowledge of data manipulation.

On the other hand, the advance of machine learning also leads to Big Data analytics as machine learning methods train the NLP model. The three AI categories are interrelated, and the lines that divide the three in AI applications can be fuzzy and blurry. As brands are multifaceted and highly complex, it is impossible to claim that specific AI applications can determine the success of brands. Instead, it is more appropriate to research the impact of AI applications on the components of brands and subsequently explore these components' impact on a strong brand (West et al., 2018).

On the relationship between AI and branding, West et al. (2018) suggest that AI has a significant impact on brands. Some of its contributions might be different from traditional branding literature. Firstly, full-stack AI, which includes the acquisition of data to training the AI applications, can help deliver brand promise by improving the consistency of business operation. Although the existing branding literature suggests the main contribution of the brand is its ability to differentiate, which is non-functional benefits (Furey et al., 2014). In contrast, West et al. (2018) find that AI fulfils the brand promise by providing functional benefits.

The argument for functional benefits in branding literature is that they can be replicated. However, AI experts point out AI applications that help to deliver brand promise is, in fact, difficult to duplicate due to the barrier of understanding and building complex AI system is high. Therefore, AI applications might present a novel and unique case of functional benefits to brands. In a sense, AI becomes the risk reducer that reduces operational performance risks for brands. On the other hand, it is essential to acknowledge that brand promise is more than consistency. AI applications shall be perceived solely as part of the elements that help deliver brand promise.

West et al. (2018) also point out that customers nowadays have higher expectations of the service they receive, which is labelled as the expected value in the literature. Businesses are finding the rising expectation of customer service hard to keep up. There are three areas companies need to tackle in respect of customer service: timeliness, accessibility, and proactiveness, which can be improved through using AI applications as AI can provide real-time interaction automatically that can be easily scaled. These AI solutions commonly apply NLP technology, i.e. voice assistant.

The concepts proposed by West et al. laid a good foundation for understanding the relationship between AI technologies and building a strong brand, which serves as a good guideline for inductively exploring the impact of AI on the brand components of brand identity and brand promise in the context of the EAVs sector. As mentioned in section 1.2, this research aims to investigate the three AI features Tesla implemented, which are the machine learning features autopilots, the NLP features voice commands, and Big Data analytics used for the software platform (Tesla, 2019b; Tesla, 2021b; Morando et al., 2020,). The impact of these three AI features typically used in the EAVs sector on sustainable corporate brands are examined through their direct influence to brand promise and brand identity. West et al.'s (2018) perspectives are used as references during data collection and analysis. However, since this is exploratory research that attempts to discover answers for open-ended questions, it should be noted that West et al.'s viewpoints are not examined deductively but used as a-prior theorising to extract interesting data relevant to the research question.

3.3 AI ethical issues

This section discusses two crucial AI ethical issues in machine leanings. The trolley problem is applied to the ethics of autonomous driving. The Black box architecture is applied to the use of deep learning methods. The two ethical issues are relevant to the research question and the case company. Therefore, they should be reflected upon in the applications of AI technologies.

3.3.1 The trolley problem

For the machine learning technologies in the EAVs sector, the trolley problem is a hypothetical moral dilemma widely debated over the applied ethics of autonomous driving. The philosophical thought experiment of the trolley problem is used to test the variables in the context of the science experiment (Wu, 2019). The trolley problem depicts the condition that a trolley driving towards a group of five people that are tied to the track. As the trolley's brakes are broken, the driver is not able to stop the trolley. However, he can choose to turn the trolley to another track on the right. Regrettably, there is one individual tied to the right-hand path. Whether the driver should turn the trolley depends on his assessment between the positive duty to save life and the negative duty of refraining from killing. One may argue the driver should turn the trolley to save the five people; however, that means he kills the one person on the right track (Thomson, 1976).

Naturally, the right decision for the moral dilemma remains unclear due to the divided opinions. Wu (2019) points out the trolley problem is deployed to the ethics of autonomous driving because the decision-making of machines is programmed by the company beforehand. Companies' involvement leads to the liability problem once the accident occurs, questioning whether the company or the driver will be responsible for accidents that happen when self-driving features are engaged. The ambiguousness of the liability problem in terms of ethics and law can potentially cause harm to society, which will eventually prevent self-driving vehicles from being released on a mass scale. Therefore, the trolley problem should be addressed through the cooperation between companies and researchers with governmental policymakers overseeing its legal aspect.

As discussed in section 2.2.2, for companies to be sustainably responsible, operating their business based on legal grounds is only the minimum requirement. To be ethical, companies should adapt to what is considered morally and ethically acceptable by society (Carroll, 2016). To evaluate the ethics of autonomous driving beyond its legal responsibility, autonomous vehicle manufactures can look into the human elements through the hypothesis of the trolley problem. Danielson (2015) points out that the principle of human responsibility is an essential factor to consider. The mainstream opinion in the applied ethics of autonomous robots often sides with the intuitive principle determining only humans can be held morally responsible. In autonomous driving, the possibility of machines can make moral decisions is intuitively unsettling to humans. The rationale implies people will seek to shift blame to humans in an incident for emotional comforts. This phenomenon can lead to the negative consequence of blaming innocent passersby or victims for the accidents caused by autonomous vehicles.

Technological solutionism also provides a different angle to scrutinise the scope of technological interference in the trolley problem. Morozov (2013) argues that smart technology enables sensors and algorithms to be involved in our daily lives in real-time, inducing technological interference in the aspects of our lives we did not have to deal with before. To what technology companies perceive as problems to improve, they tend to pursue efficiency and perfection, disregard the context of human nature. With that said, complex social situations are reduced to neatly defined problems through computable solutions. The presumed problems are often defined subjectively. The attempt of solving a problem without thoroughly investigating the complex environment it is embedded in can lead to three negative consequences: 1) the technological interference worsens the problem; 2) the technological interference does not produce any result; 3) the technological interference undermines the previous accomplishment. Although technology can solve many problems in scale, technology companies can restrain human nature with their solutions if they do not acknowledge the ambiguity and opacity in our daily lives. The advance of technology used with empathy to human nature and understanding to the complex social environment every actor is embedded in can give us new visions and capabilities. Balancing between the elements of efficiency, optimization, human nature, and the complex social environment, the use of AI technologies can thus become prolific, humanistic, and responsible (p5, 6, 7, 13, 14).

3.3.2 Black box architecture in deep learning

Deep learning is an important sub-branch of machine learning due to its progress in recent studies (Chollet, 2019). As mentioned in section 3.1.2, there are three sub-categories of machine learning, supervised learning, unsupervised learning, and reinforcement learning, which categorizations also applied to deep learning. Deep learning relies on ANN, which is formed of layers aggregated of neurons that get input directly from the data. ANN also has hidden layers that use the other neurons' output as their input. Although ANN is made up of simple components like neurons, it is difficult to explain why the algorithm operates the way it is because each neuron reacts to stimuli following its own rules. Already knowing the architecture of ANN, explaining the logic behind ANN's operation is still very complicated, especially for unsupervised learning (Goodfellow et al., 2016, pp 1, 5, 6, 14, Adadi & Berrada, 2018). As ANN is a powerful tool that significantly impacts businesses, its black box architecture has caused some ethical and legal concerns.

The black-box nature of deep learning systems has become an impediment to the use of AI-based systems due to the lack of transparency. Researchers argue there is a crucial need for explaining AI outcomes as AI now makes decisions for users in their daily life from content recommendation to disease diagnosis. Hence, trusting important decisions to the black box system presents obvious danger (Adadi & Berrada, 2018). Some engineers and scientists also avoid the application of black box systems as they cannot interpret the results. In the legal aspects, the European Union General Data Protection Regulation (GDPR) requires subjects to provide meaningful information about the logic involved in automatic decision-making based on their data. The regulation entails the same distrust from governmental organizations (Holm, 2019, p26). To address the black box issue, the concept of explainable AI (XAI) is proposed to improve trust and transparency in the AI-based system. For instance, more active research is recommended for studying various levels of grey box systems to countermeasure the exploitation of the black box concept by technology companies (Adadi & Berrada, 2018).

3.4 Development of the theoretical model

Based on the theories discussed in the previous sections, an initial theoretical framework for examining the impact of AI on sustainable corporate brands in the EAVs sector is developed, as Figure 4. For investigating the research question inductively, the proposed theoretical model is examined following a bottom-up approach, beginning from understanding the functions and characteristics of the applied machine learning features, NLP features, and Big Data analytics in detail.

Adapted from Stuart's (2011) sustainable corporate brand model, the functions and characteristics of the three AI features are linked to the three elements of the normative alignment model: normative emotions, normative efficacy, and normative actions (Thomas et al., 2009). The hypothetical connections of AI features and the normative alignment model help the researcher examine how the applied AI technologies impact the norms of emotions, efficacy, and actions of the stakeholders of sustainable corporate brands.

As Thomas et al. (2009) point out, the norms of emotions, efficacy, and actions contribute to a dynamic system of meaning, based on which a robust social identity can be created. Stuart (2011) combines the normative alignment model with Balmer et al.'s (2009) AC^3ID test to illustrate the sustainable corporate brand representing the brand promise, which is the ideal brand identity the brand strives to become.

With that said, we connect the three elements of normative alignment to the brand promise and brand identity of the sustainable corporate brand, aiming to interpret the impact of AI features to brand promise and brand identity through the normative alignment model.

Lastly, we intend to discover the underlying pattern of this dynamic system that forms parts of the sustainable corporate brand by examining the relationship between the elements in the proposed theoretical model. West et al. (2018) have suggested it is implausible to determine whether the application of AI technologies leads to the success of a brand. Nevertheless, Stuart's (2011) sustainable corporate brand model demonstrates that orchestrating brand identity can help create an authentic brand. This conceptualization can capture the indirect values AI technologies create for sustainable corporate brands.

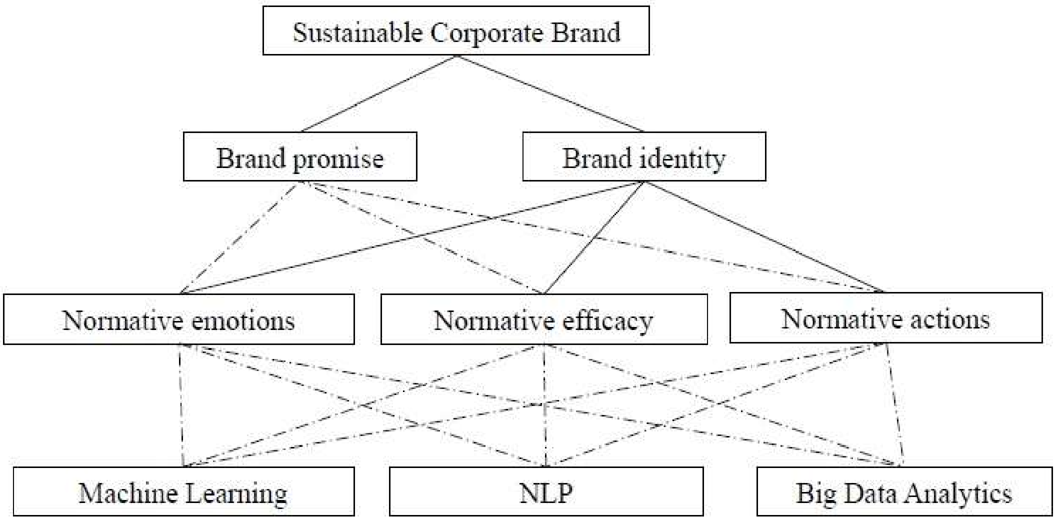

Figure 4, Proposed theoretical framework

4 RESEARCH METHODOLOGY

This chapter details this research methodology, consisting of a literature review, research design and strategies, data collection, and data analysis. The research process, as Figure 5, is conducted through the qualitative inductive approach based on constructivist epistemology and interpretivism in the theoretical aspect. The research is designed as a single-case study, and the data is collected by unobtrusive observation of netnography and triangulated with multiple sources of secondary data.

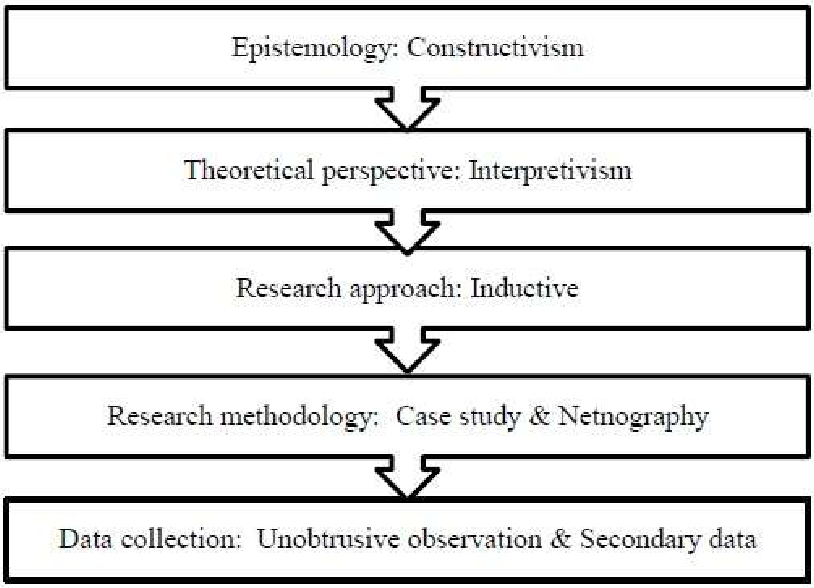

Figure 5, Research Process (Adapted from Gray, 2018, p 35)

4.1 Literature review

The literature review seeks to deepen the understanding of the methodology chosen for this research, which is the qualitative inductive approach based on constructivist epistemology. Qualitative research is selected for this research for producing rich textual data in the form of transcripts, which is the raw data of the study that provides descriptive records and can be interpreted by researchers. The analytical process begins during data collection as part of the collected data is analysed and influenced by ongoing data collection. It allows researchers to continuously refine the research questions during data collection, thinking deeper about the research topic (Pope, Ziebland, & Mays, 2000).

Using the inductive approach in the qualitative research method is appropriate for the study. The inductive approach can be used to develop a model for describing the underlying structure extracted from textual data (Thomas, 2006). Moreover, this research seeks to explore a research gap with little existing literature. Using the inductive approach enables the researcher to condense varied raw text data into a summary format and establish clear and transparent links between research objectives and findings derived from the analysis (Thomas, 2006).

The exploratory aspect of this study also plays a vital role in the research design. Exploratory research needs to be conducted in a transparent and self-reflexive manner to provide new perspectives to analyze reality. To be reliable, researchers should first recognize their own interests and limitations by articulating them at the beginning of the research. A-priori theorizing for formulating hypotheses is needed before conducting research. It is crucial to differentiate the a-priori theorizing in inductive, exploratory research from the hypotheses in confirmatory deductive research, which seeks to verify a theory. The a-priori theorizing in the inductive, exploratory study is based on the idea that no pure exploration is possible as researchers' ideologies and knowledge inevitably implicit theories, which need to be stated in the research to produce more objective arguments (Reiter, 2017).

Exploratory research underlines how well a theory explains something, providing a solid and robust connection between the variables and reality. Researchers can offer a new explanation for the subject researched through this process. In other words, exploratory research can be compared to a learning process, which iterates the steps of reformulating theories and adapting explanations inductively using empirical data. The goal of exploratory research is for the researched subject to make more sense to the researcher who can explain the reality in a scientific way (Reiter, 2017).

4.2 Research design and strategies

This research follows the guidelines for undertaking cross-disciplinary research. A distinction is made between the theoretical domain of knowledge represented by the general theories and the empirical domain of knowledge represented by the applied theories. The midrange theory is the intersection of the two domains (Lindgreen et al., 2020), as Figure 6. General theories are framed at the highest conceptual level and provide a perspective of explanation for a domain (Lindgreen et al., 2020, p A1). In this research, the general theory is Stuart's (2011)'s sustainable corporate brand model. The applied theory is embedded in context, empirical research, and theory-in-use, recognising that practitioners and other stakeholders use theories (Lindgreen et al., 2020, p A2). In this research, the applied theory is AI implementation in branding. Midrange theories are context-specific, which provide frameworks that can be used to undertake empirical observation and models to guide managerial practices (Lindgreen et al., 2020, p A2). In this research, the impact of AI on sustainable corporate brands serves as the midrange theory illustrated in Section 3.3.

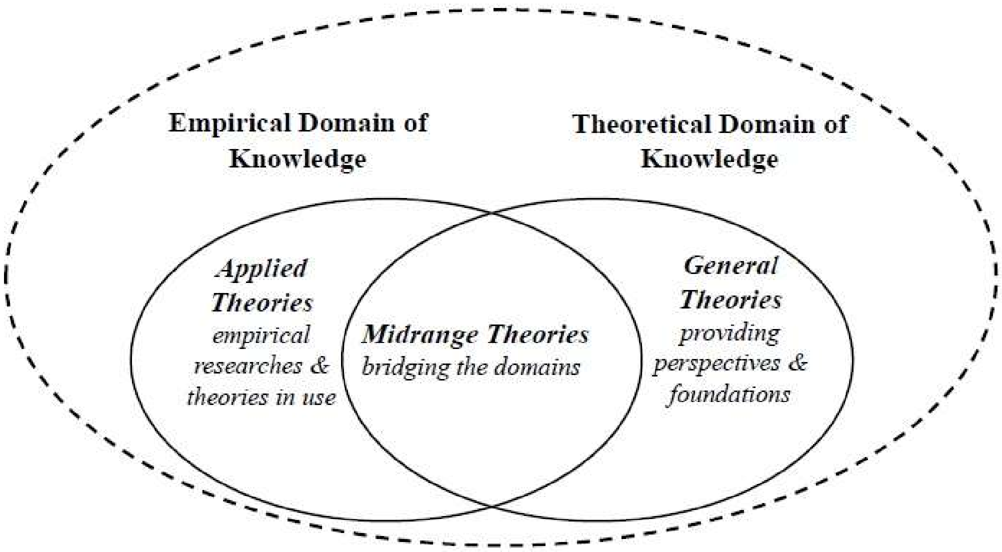

Figure 6, Domains of knowledge and levels of theory (Adapted from Lindgreen et al., 2020, p A2)

The research is conducted through the design of a single-case study, focusing on the electric automobile brand, Tesla. Tesla is selected as an "extreme or unique case (Yin, 2009, p. 47).” According to Seawright and Gerring (2008), the extreme case method is suitable for exploratory research in an open-ended manner; therefore, it is compatible with the research goal. The extreme case method selects a case because of its rareness of the value that provides a full range of variation and a representative picture of a large sample in the background. Tesla is chosen for studying the impact of AI on sustainable corporate brand for three reasons: 1) the brand claims sustainability as the purpose of its existence. Tesla 2019 impact report begins with the statement: “The very purpose of Tesla’s existence is to accelerate the world’s transition to sustainable energy (Tesla, 2020a).” 2) Tesla is an AI-centric brand that uses in-house built software on the vehicles' autopilot, which the brand claims to give customers more confidence and provides an enjoyable experience on the road (Ingle & Phute, 2016). 3) Tesla’s branded strategy aligns with the model of the sustainable corporate brand, which perceives the commitment of the CEO as the key to maintaining a sustainable corporate brand (Stuart, 2011). Besides having a strong presence in the market and customers’ mind (Loureiro et al., 2017; Interbrand, n.d.), Tesla states that their products are made to complete the CEO Elon Musk’s “Secret Master Plan”. The CEO’s plan for Tesla is to fulfil electric vehicles' popularisation for providing zero-emission electric power generation options (Musk, 2012c; Tesla, n.d.-a).

To further justify why Tesla is an appropriate choice for the extreme case study, we can examine two categories of brands that offer products similar to Tesla for explaining these brands do not provide the wide range of variants for this research as Tesla does. The first category of brands is multinational automakers that produce electric vehicles, i.e. Ford Motor, BMW Group and Nissan. The difference between Tesla and these global automakers lies in the percentage of electric cars sales that account for the brands’ total sales. For BMW, the all-electric and hybrid-electric vehicle sales currently account for 8% of its total sales, while all Tesla built vehicles are electric (BMW Group, 2020). While Ford Motor has not disclosed the figure for electric vehicle sales, the company has only launched the first electric car in 2021 and have six hybrid electric vehicles among other diesel-fuelled cars. Ford Motor plans to transit all product lines to full electric in 2030 (Ford Motor, 2021). Sharing the same initiative as Ford Motor, Nissan also sets the goal of electrifying every all-new vehicle by the early 2030s (Nissan Motor Corporation, 2021). In addition, Tesla tops the ranking of total electric vehicle sales by automakers in 2019, double the number sold by the second-place automaker, General Motor (Edison Electric Institute, 2019).

The second category is the fast-growing electric vehicle start-ups that enter the market following the success of Tesla. Most electric vehicle start-ups that have started mass manufacture are based in China, i.e. Nio, Li Auto, and Youxia Motor. Although the three commercially successful start-ups share the same AI-centric brand element with Tesla, the brands' external communication shows less emphasis on sustainability. Although zero-emission is mentioned as one of the attractive features of their electric cars, neither the companies' sustainability reports are publicly available, nor sustainability is presented as the vision of the CEOs. From the display of their websites, these brands communicate the brand luxury and enjoyable customer experience as their unique selling points (Li Auto Inc., n.d.; NIO, n.d.; Youxia Motors, n.d.). As Tesla possesses the variants represented by these two categories combined, we argue it is an appropriate choice for the extreme case study method.

The methodology selected for carrying out this case study, netnography, is a qualitative technique for studying the cultures and communities emerging through online communications, collecting data from the online communities, which indicates the internet-based forums in which products and services are discussed. In online communications, one crucial factor that stakeholders join the discussion is to inform other stakeholders about brands, which significantly impacts brand equity. As netnography uses publicly available information in online communities, it is unobtrusive when observing naturally situated consumer behaviour, compared to traditional qualitative methods, i.e. interviews. It can be effectively carried out online without decontextualization caused by the obtrusiveness and artificiality of conventional qualitative methods. Furthermore, it allows continuing access to a specific online situation, which is beneficial for deepening the understanding of the researched case. On the other hand, the limitations of netnography mainly lie in its narrow focus on online communities. Careful evaluation of similarity and data triangulations are suggested when researchers attempt to generalize the findings (Kozinets, 2002).

As Kozinets (2002) points out, it is crucial for researchers to carefully consider the research ethics of netnography for being responsible and not damaging the medium. As netnography is distinct from traditional marketing research, two issues determine the design of the method in terms of research ethics: first, are the selected online communities public or private? Second, what fulfils informed consent in cyberspace in the selected online communities? This research follows the recommendation of Langer and Beckman (2005), which uses the access criteria for observation as the critical factor to distinguishing whether specific online communities are public or private, and thus different guidelines to follow. If the access to communities is restricted, i.e. using passwords, they would be considered private communications. If the access is not restricted, they can be seen as public communications. In terms of informed consent, Langer and Beckman (2005) suggest examining the issue from the ethnographic perspective of covert research. A pragmatic view is taken for the data collection of netnography, which acknowledges the need to protect the rights of informants and the researchers' obligation of not harming them, but still accepts covert studies.

To maintain the unobtrusiveness nature of netnogrpahy, this research is designed to be observational and only investigates the resources available in public online communities. As Langer and Beckman (2005) suggest, conducting observational netnography in public communities does not require researchers to follow the more rigorous guidelines for private online communities. In private communications, the researchers need to disclose their identity to community members, request permissions from members for quoting their online posts and present part of their analysis to the informants they studied for acquiring their comments (Kozinets, 2002). Following the guidelines, the user names of contributors and their eventual information, i.e. email address, will not be displayed. Instead, their user names are coded for anonymity. Langer and Beckman (2005) argue this data collection procedure is ethical as it meets the ethical standard for the content analysis of public media texts. On the other hand, disclosing the researcher's identity can weaken the main advantage of netnography, unobtrusiveness, leaving only articulate members engaging in conversation and hesitant users remaining in silence. Subsequently, the disclosure of the researcher identity results in the misrepresentation of online communities.

Purposive sampling is used for selecting the online communities. According to Etikan (2016), purposive sampling allows researchers to deliberately choosing informants based on the virtue of their knowledge and experience to elicit information-rich data that are the most appropriate within the resources available. The purposive sampling technique is a non-random technique through which the researcher selects informants based on their subjective view on what needs to be known, which does not require underlying theories or a specific number of participants. For this research, the sampling method follows purposive sampling and the sampling requirement of netnography. As Kozinets (2002) recommends, researchers should select the online communities based on their relevance to the research question, the traffic rate of postings, number of message posters, richer text of posts, and the engagement rate about research question related topics between community members.

4.3 Data Collection

As previously discussed, this research only collects data from public online communities for carrying out unobtrusive observation. Two public online communities, Twitter and Youtube, are selected due to the richness and relevance of their contents and the most community member activities and high engagements tied to the research question. To ensure all data collected are publicly available, data collection is carried out on these two platforms without logging into a personal account. The search of data begins with using the keyword, Tesla. Following the inductive method, new keywords are added following the information newly discovered in data collection. Although the researcher has familiarized with the language used by the community members as Kozinets (2002) suggests, more specialized languages and new technical terms will emerge along the process of data collection. Therefore, sources that provide in-depth explanations for the newly encountered specialized languages and technical terms will be collected for data triangulation, using multiple references to strengthen the research findings (Jack & Raturi, 2006). Lastly, the following aspects are also considered during the data collection:

1) The textual contents are relevant to the machine learning, NLP and Big Data analytics technologies used by the brand (West et al., 2018).
2) The textual contents are relevant to stakeholders' emotion, action, and efficacy towards the brand (Stuart, 2011).
3) The textual contents are relevant to the functional and emotional values that enable stakeholders to recognize the brand promise and the unique associations representing what the brand stands for (Aaker, 2002; Chernatony & Christodoulides, 2004).
4) The textual contents are relevant to the sustainability of the brand.
5) Both positive and negative comments about the brand will be collected.
6) Information overload is expected when conducting netnography. The researcher attempted to find information-laden sources guided by the research question (Kozinets, 2002). While many online sources found through the keywords are reviewed, the irrelevant materials are abandoned (Rageh et al., 2013).

In Twitters, data was retrieved by searching keywords using the two categories of the search filter, top and latest, for capturing the most dynamic and up-to-date content. The keyword, #Tesla, was firstly used for grasping the big picture of community members' discussion on the brand. However, the results show most of the contents surrounded the brand's stock price. A new keyword, #model X, the name of Tesla's well known sport-utility vehicle equipped with advanced technology features (Eisler, 2016; Tenhundfeld et al., 2019), is used searching product-focused contents. Subsequently, the returned results and the replies to the parent tweets are examined, and the suitable contents are collected in textual form. As the data collected inductively, more new keywords are generated through reading the Twitter users posts. The keyword, #Tesla autopilot, is used for searching machine learning related contents, and the keyword, #Tesla voice command, for NLP. Finally, we investigate two highly engaged tweets posted on the official Twitter accounts of Elon Musk recruiting Tesla owners to apply to participate in testing the full self-driving Beta program for extracting contents relevant to Big Data Analytics.

In Youtube, the textual data are extracted from the auto-generated subtitle of the selected videos. Modifications on the transcription are made if the auto-generated script does not match with the original audio. In addition, the comment sections of the videos chosen are reviewed. Comments that are interesting to the researcher or can deepen the researcher's understanding of the context of the videos are extracted as part of data. Similarly, Tesla is the first keyword used for searching for the most viewed and recent user-generated contents about the brand. The keyword, Model X, is also used for Youtube search after its use is proven to be effective in Twitter, surfacing massive contents of Tesla owners showing and driving their cars while discussing their user experience. Other AI feature related keywords, Tesla smart summon, Tesla autopilot and Tesla autopilot 2, are searched on Youtube for contents featuring the semi-autonomous driving feature of Tesla vehicles. Talk to Tesla and Tesla voice command are used for searching contents that show community members' talking about their experience with Tesla's NLP feature. As the data collection in Youtube is conducted after the data collection in Twitter, the keyword, Beta FSD (full self-driving), added from Elon Musk's tweets, is used for searching Youtube videos regarding community members' experience on participating in the Beta FSD programme.

As previously mentioned, to achieve an in-depth understanding of the newly encountered specialized languages and technical terms used by the stakeholders of Tesla, we will use publicly available information to triangulate the data. After careful selection, three presentations and one interview given by Tesla's director of artificial intelligence, Andrej Karpathy, are extracted from Youtube. Karpathy's insights provide more extensive technical knowledge behind Tesla's smart summon, autopilot and the Beta FSD program and cross-validate the information provided by the community members.

The data collected from Twitter and Youtube are stored in Excel as four parts for differentiating the context: 1) 100 tweets are extracted from Twitter users' posts and the replies; 2) 13 videos and 51 comments are extracted from Youtube users' videos and the comments; 3) 2 tweets are extracted from Elon Musk's Twitter account, and 58 tweets are extracted from the replies he receives; 4) 4 videos featuring the AI technologies of Tesla presented by the director of AI are extracted from Youtube, as Table 2. At this stage, all user names, except the Twitter account name of Elon Musk and the videos featuring Andrej Karpathy, are coded for anonymity. The excel files are output as four PDF files for importing to QSR Nvivo. Nvivo is Computer-Aided

Qualitative Data Analysis (CAQDAS) software that helps make content analysis manageable and organized. Using CAQDAS software allows more flexibility in coding data and organizing themes, easing the time constraint of analysis, which is beneficial for evaluating the rich data to answer the research question (Fenton & Procter, 2019).

Table 2, List of empirical data

Data source	Types of data source	Number of data source	Informants
1) Twitter	Tweets posted by the stakeholders of Tesla and the replies they receive	100	Twitter community members/the stakeholders of Tesla
2) Youtube	Videos posted by the stakeholder of Tesla and the comments they receive	13	Youtube community members/the stakeholders of Tesla
	the comments of the selected videos	51	Youtube community members/the stakeholders of Tesla
3) Twitter	Tweets posted by the CEO of Tesla	2	CEO of Tesla, Elon Musk
	Replies(tweets) to the post of CEO	58	Twitter community members/the stakeholders of Tesla
4)Youtube*	Videos featuring the AI technologies of Tesla	4	Director of Artificial intelligence at Tesla, Andrej Karpathy

*Data collected for data triangulation

4.4 Data Analysis

As qualitative research does not seek to quantify data, this analysis does not aim to identify a representative set from the gathered data statistically. Pope et al. (2000) suggest that qualitative analysis data remain in their textual form during analysis, developed to categories based on themes or theoretical explanations. Being inclusive is crucial for identifying data for each category. Constant comparison is utilized to examine the data coherently and systematically, aiming to reflect as many nuances as possible by adding categories. Most importantly, qualitative research requires researchers to use their analytical skills to discover the link between data and theory, interpreting findings beyond being descriptive.

The collected data is analyzed through thematic analysis, a process for encoding qualitative information that requires a model consisting of related themes, indicators, and qualifications (Boyatzis, 1998, pp. vi-vii). To further provide a clear definition, Boyatzis (1998) defines a theme as “a pattern found in the information that the minimum describes and organizes possible observations or at the maximum interprets aspects of the phenomenon” (p. vii).

Thematic analysis is a suitable choice because it is compatible with the constructivist epistemology of this research. In addition, it acknowledges the researcher as an active role in identifying patterns and themes by perceiving the analysis as the decisions made by the researchers (Braun & Clarke, 2006), which aligns with Reiter’s (2017) argument that researchers should recognize their own interests and limitations to be reliable by articulating them in the exploratory research as we previously discussed.

Braun and Clarke (2006) 6-phase guide is chosen to perform the analysis. Phase 1 is familiarizing yourself with your data, in which the researcher immerses herself in reading the entire data back and forth until they grasp the depth and breadth of the content. During the first reading process, the researcher forms the basic ideas for themes and patterns taken in a note for more detailed coding. Phase 2 is generating initial codes from the data. After familiarizing themselves with the data, the researcher read the whole data set systematically for identifying the parts of the content that draw their interests. Using Nvivo, the data is tagged and collated to codes by naming each data item. Equal attention is given to every data item for discovering the repeated patterns. Multiple categories can exist in one section of data. At this phase, the researcher attempts to code as many data items as possible to keep all relevant data for providing clear context.

Phase 3 is searching for themes, in which the researcher focuses on collating the relevant codes to the broader level of themes. More attention is given to how different codes may combine to form a theme. Particularly, the codes are analyzed at the latent level, examining the underlying ideas and assumptions that inform the semantic content of the data. A thematic map is produced using the initial codes to conceptualize the candidate themes, connecting all data items to the main themes or sub-themes, as Figure 7. Phase 4 is reviewing themes. At this stage, the candidate themes are refined on two levels. In level 1, the researcher examines the coded extracts' internal homogeneity and external heterogeneity to each of them appear coherent within the themes. In level 2, the researcher examines the relation between individual themes and the entire data set to refine the initial thematic map until it becomes an accurate representation of the analysis (Braun & Clarke, 2006). In practice, the researcher uses the matrix coding query feature of Nvivo further screen the common section labelled for different codes and themes.

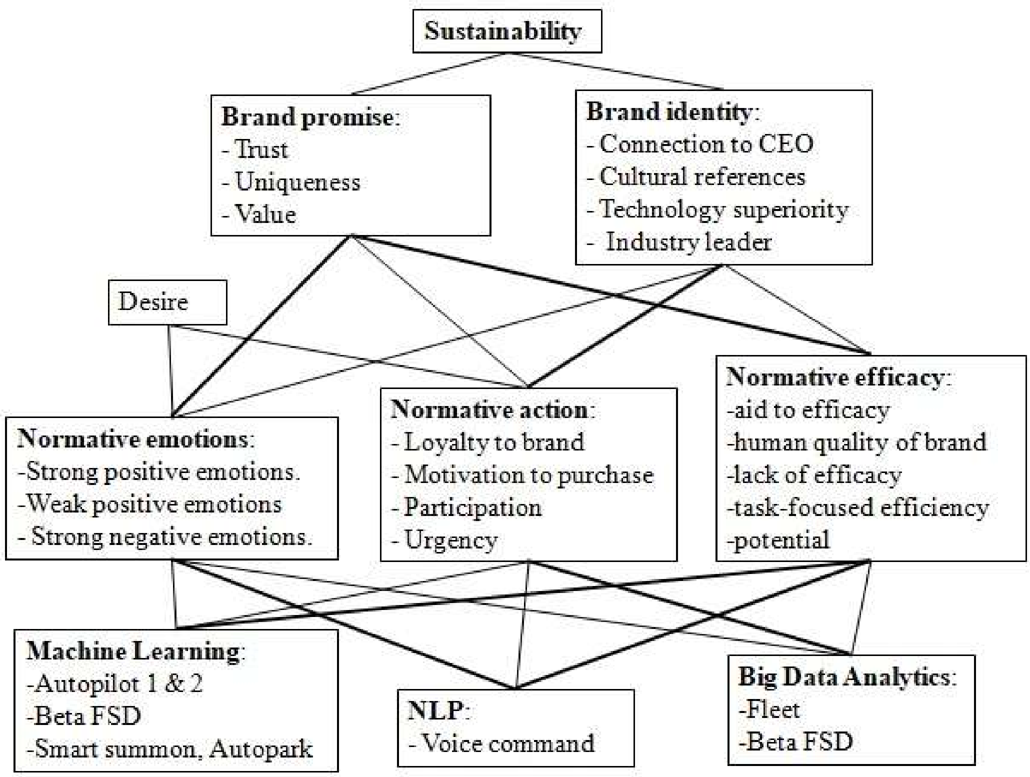

Figure 7, Thematic map of initial themes

Phase 5 is defining and naming themes. Each theme is refined and given clear definitions and names, generated by identifying the themes' essence. The researcher writes a detailed analysis of each theme's story, which should fit the overall level of the entire data set while remaining relevant to the research question. Phase 6 is producing the report. Some examples are selected for illustrating the scholarly analysis related to the research question and literature (Braun & Clarke, 2006).

5 EMPIRICAL RESULTS AND ANALYSIS

This chapter details the empirical results and analysis. The report begins with a summary of background knowledge, followed by the interpretation of each thematic segment following the proposed theoretical framework. The report is supported with the evidence within the data to demonstrate the validity of the analysis.

5.1 Background knowledge

Before discussing the empirical results, it is necessary to provide an overview of the AI features of Tesla mentioned in the collected data. Autopilot, Autopark and smart summon are frequently discussed machine learning features based on the collected data. Tesla Autopilot is the combination of lane steering assistance (Autosteer), which helps keep the car in the lane, and trafficware cruise control (T-ACC), which helps keep the vehicle a safe distance from other traffic (Dikmen & Burns, 2017, Morando et al., 2020). Both autopark and smart summon are part of Tesla self-driving features. Auotpark helps the vehicle detect the parking space and park itself. Smart summon helps the car navigate complex parking space environments and manoeuvre toward the user through a smartphone app (Dikmen & Burns, 2017; Tesla, 2021c).

Tesla states that all of their new cars "come standard with advanced hardware capable of providing Autopilot features today, and full self-driving capabilities in the future—through software updates designed to improve functionality over time (Tesla, n.d.-b)." Following J3016™ "Levels of Driving Automation" defined by the Society of Automotive Engineers (SAE), as Table 3, Tesla Autopilot is currently classified as an SAE Level 2 driver support features including steering and brake/acceleration support. At the same time, the full driving automation it promises to achieve in the future is an SAE Level 5 system.

What sets apart the driver support features of SAE Level 0 – 2 and the automated driving features of SAE Level 3 -5 is the responsibility of the human in the driver's seat. For driver support features, the person in the driver's seat has to drive the car when the driving support features are engaged. On the other hand, the automated driving features are driving instead of the person in the driver's seat when engaged. Since Tesla Autopilot is only a Level 2 system – partial driving automation, the person in the driver's seat must carefully and constantly supervise the support features and take over driving whenever human interference is needed (SAE International, 2018; Morando et al., 2020).

Table 3, Taxonomy for Terms Related to Driving Automation Systems for On-Road Motor Vehicles (Adapted from SAE International, 2018)

	SAE Level 0	SAE Level 1	SAE Level 2	SAE Level 3	SAE Level 4	SAE Level 5
What does the human in the driver's seat have to do	You are driving whenever these driver support features are engaged –even if your feet are off the pedals and you are not steering.			You are not driving when these automated driving features are engaged –even if you are seated in "the driver's seat".		
	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety.			When the features request, you must drive.	These automated driving features will not require you to takeover driving.	
	These are driver support features			These are automated driving features		
What do these features do	These features are limited to providing warnings and momentary assistance.	These features provide steering or brake/ acceleration support to the driver.	These features provide steering **and** brake/ acceleration support to the driver.	The features can drive the vehicle under limited conditions and will not operate unless required conditions are met.		This feature can drive all vehicles under all conditions
Example features	Automatic emergency braking/ Blind spot warning/ Lane departure warning	Lance centering or adaptive cruise control	Lance centering and adaptive cruise control at the same time	Traffic jam chauffeur	Pedals/steeri ng wheel may or may not be installed.	Same as level 4 but the features can drive everywhere in all conditions.

For the NLP features, Tesla voice commands are supported by a natural language processor that helps the users interpret their requests into actions for the cars, emphasizing its adaption to the natural language instead of being limited by using specific words or phrases. Most features managed by the in-car touch screen can be controlled through voice commands, which include apps and settings, car controls, climate controls, navigation, phone and media (Tesla, 2021b).

Fleet and FSD Beta are the two Big Data Analytics subjects that surface among stakeholders' discussion about drivers' data contribution. Tesla fleet is a software platform that connects Tesla autonomous vehicles to allow Tesla AI algorithms, i.e. autopilot, to learn from the massive data gathered from other vehicles' experience. Therefore, by simply driving the cars, Tesla users contribute to data collection and machine learning in real-time (Tesla, 2019b). FSD Beta is the test version of full self-driving software that expands the existing driver assistance system. Tesla released the Beta programme to selected Tesla owners for testing on public roads. Even though FSD Beta is promoted as a component of the full self-driving system, it requires active driver supervision, which means it is an SAE Level 2 system like the Tesla autopilot (Reuters, 2020; Tesla, 2021c).

5.2 The impact of machine learning

Based on the collected data, repeated patterns show diverse feelings evoked in stakeholders' minds by using and experiencing autopilot and full self-driving features. The efficacy of norms lies in Tesla owners' belief that using autopilot can optimize self-driving features through data sharing, leading to their consistent use of autopilot. Two types of normative emotion and normative efficacy are discovered from the analysis: the refreshed excitements resulting from the changeability of software and the trust developed over time in using automation.

5.2.1 Changeability of software

Stakeholders expressed strong positive emotions toward using Tesla machine learning features within a different context. New Tesla owners or potential customers who test drive using autopilot often express excitement and amazement due to a unique driving experience distinct from their past experience with other vehicles. These positive emotional expressions are often coupled with the desire to purchase, intending to duplicate and incorporate their joyful experience with autonomous driving features in the future and the daily life.

Youtube content creator [Y01] talks about his thoughts while test driving a Tesla Model Y: “Now this thing is insane. It knows everything. We're just taking Model Y on a test drive to see if we're going to get rid of the Lamborghini here. …I do not know how to explain this. It feels right, dude. It feels so weird. Yeah, I honestly don't know how I feel about this thing. I'm buying one now.”

For Tesla owners who have been using autopilot, new excitement and amazement still arise when receiving software updates. Tesla provides over-the-air-updates that can be installed through the in-car touch screen. Without bringing their vehicles to a physical maintenance service point, Tesla owners expect the software updates to add new machine learning features and enhance the existing oneS regularly (Tesla, 2021a). If the updates meet or exceed the customers' expectations, they rejoice in the constant optimization of machine learning features.

Twitter user [T015] posted on his Twitter account: "I've owned my @Tesla Model3 for 3 years now and driving it is still a thrill. The acceleration, handling, lack of maintenance, and autopilot never gets old. Do yourself a favor, try driving a #Tesla. You won't regret it. "

Given the context of the data being collected from the posts shared on social media, the customers' endorsement of the vehicles also positions itself as positive Word-of-Mouth for the brand. Hence, the refreshed excitements are experienced by the Tesla owners and other stakeholders that watch and discuss the reviews.

Researchers argue the over-the-air updates that continue to modify the vehicles in use challenges the traditional model of the product life cycle. In the conventional product life cycle, customers do not expect any refreshment other than the finished products after the purchase. While the material characteristics of a physical object are considered resistant to change, the digital components are seen as lacking resistance to change due to the re-programmability of computers and the homogenisation of data. The digital features integrated into tangible products add open-endedness to how the products are perceived by the customers (Lyyra & Koskinen, 2016).

However, the changeability of software also leads to blurring the control of product traditionally possessed by the product owners (Lyyra & Koskinen, 2016). In the case of Tesla, the autonomous vehicles are connected through Wi-Fi to the manufacturer capable of altering the functionality of autopilot and other self-driving features without asking for the owners' permission.

Youtube user [Y05-C05] commented on a video uploaded by Youtube content creator, [Y05], in which he tests the new software update about the inconsistent performance of autopark feature: "Good video. My S is absolutely useless at autopark. It fails to recognize valid spaces at least 75% of the time but brings up the "P" when there's a gap in the shrubbery more often! Then it's so slow that I can't use it in most cases unless I want a road rage fight with someone behind me."

When the updated machine learning features fail at what it claims or perform below the users' expectations, the users show their concerns about the product's ability and frustration over the pain points during engaging with autonomous driving.

5.2.2 Trust in automation

Besides the heightened emotions, stakeholders also communicate weak positive emotions towards using autopilot and other self-driving features. Weak positive emotions, i.e. trust and satisfaction, are often achieved under the premise of Tesla owners' acknowledgement that the self-driving features are not entirely autonomous. Therefore, they anticipate the need for active supervision when autopilot is engaged and tolerate occasional malfunction of autopilot. Some negative emotions, i.e. concerns, are expressed in this context when the drivers experience erratic autopilot behaviour and have to take over driving promptly. However, these negative emotions are tolerated and accepted by the users who see the assistant quality of self-driving features as supports that make the driving experience more safe and drivers more confident.

Youtube content creator [Y12] describes his thoughts on using Tesla autopilot for a road trip the moment right after minor autopilot malfunction occurred: "This has been actually a really nice experience so far. Let's be honest, like when we're driving, we get distracted whether it is like in a conversation or my phone is ringing right now, but now there's another entity making sure I'm safe… It feels like I'm a passenger in an airplane."

Researchers argue that drivers' trust in self-driving features will increase over time despite the automation errors if there is no major accident. Performance, process and purpose are identified as the three components of trust. Performance indicates the user's observation of results. Process means the user's judgement on how the system functions. Purpose shows the aims of the system. When the three components align with each other in the user's mind, trust can be established. With that said, the driver's prior knowledge of the autopilot process explains why the malfunction occurred. In addition, they are capable of intervening and controlling the erratic autopilot behaviour. Under this circumstance, the drivers' negative emotions caused by automation errors are compensated, and their positive emotions towards the self-driving features still increase (Lee & See, 2004; Dikmen & Burns, 2017).

From this point of view, it is clear that the brands should strive to communicate the real purpose of the AI system for increasing trust and inspire other positive emotions. Tesla has long been criticised for its promotion approaches on its semi self-driving features, i.e. autopilot and FSD Beta, which can be easily mistaken as proper autonomous driving by the public. Researchers and regulator have warned Tesla that their promotion approach can be misleadingly dangerous (Reuters, 2020). This claim remains consistent with the findings of the analysis.

Youtube content creator [Y014] discusses his thoughts on FSD Beta during the test drive: "I think it's the worst part of this drive and probably one of the worst things I've experienced since I got the beta. It was messing up during that left turn. Because we were almost done with the left turn, I had fully expected the system to complete the left turn."

Twitter user [T117] also questioned Tesla's choice of naming a driver support feature "Full self-driving" in their reply to Musk's call for application to enter FSD Beta program on Twitter (Musk, 2021a): "It's not FSD, is it. It's still just Level 2 Driver Assist for $TSLA, isn't it. You're behind Honda now. Please fix."

While such negative emotional backlash toward Tesla's misleading promotion are not uncommon in social media, strong positive emotions, i.e. endorsement, and weak positive emotions, i.e. satisfaction and trust, accompanied with the tolerance to the negative emotions, i.e. concerns, caused by occasional malfunction are more typical of stakeholders' feelings toward using autopilot and other self-driving features. Especially Tesla owners have a more prominent voice on addressing how they feel about Tesla machine learning features continuously with each software update. Their exchange on social media creates the normative emotions and efficacy within the brand's stakeholders, which stems from a shared understanding of the world. Therefore, we can identify that the norms of emotions and efficacy exist within the group of Tesla owners based on their knowledge of the unique characteristics of Tesla machine learning features.

5.3 The impact of Natural Language Processing

Two types of normative emotions and efficacy are discovered in the analysis of NLP's impact, which are stakeholders' personification toward the vehicle and the hedonic value brought by the use of meaningful cultural references. These two types of norms lead to the broader technology acceptance of NLP features.

5.3.1 Personification of machine

Tesla's NLP features, voice commands, are not promoted as much as their machine learning features by the brand. Neither the CEO nor the director of AI shares the same amount of insight about their NLP technologies as they do about autopilots on various occasions of public discourse. Nevertheless, features of voice commands are frequently discussed by Tesla owners due to their convenience, interactiveness and fun. In addition, the emotions stakeholders expressed about voice commands are noticeably more positive than autopilot and other self-driving features. Efficacies wise, Tesla owners tend to narrate the malfunction of voice commands more objectively and addressing their audience about how the voice commands can fail without expressing negative emotions.

Youtube content creator [Y08] describes he is satisfied with the update of voice commands even though the new features do not function perfectly: "We got a new software update. This one is amazing! We've been asking for ever: give us texting capabilities. Lots of cars have that. Why don't we have it? Tesla finally delivered texting capabilities in the car as well as some really improved voice commands…It's not perfect yet. It still needs a little bit of work, but, hey, it's just a software update, and they can fix that as they go."

To which video another Youtube user [Y08-C06] replied, sharing the same outlook of the erratic behaviour of voice commands:" We have 2 model 3s, one the voice commands don't work at all; the other works somewhat. One of them keeps butt dialing the same number over and over. Both cars receive texts fine but neither will reply to texts nor can you initiate texts. Not uncommon to have bugs with new updates so look forward to the fix."

Possibly this phenomenon is related to users perceiving Tesla voice commands as an optional alternative to operating the features directly from the in-car touch screen. The NLP feature is not viewed as a critical feature determining the brand's values as the self-driving features. In addition, the brand's comparatively moderate promotion about its NLP function can be a reason that they do not overpromise but under-deliver as they do about machine learning features in the eyes of some stakeholders. Nevertheless, this does not mean voice commands do not provide significant values for the stakeholders. For the Tesla owners who adapt to using voice commands, the voice assistant offers quick access to activate various features, allowing them the flexibility to use these features simultaneously during the drive. Safety is considered an essential value offered by voice commands.

Youtube content creator [Y07] thinks voice commands solve the inconvenience of driving on a snowy day: "Over the weekend we actually got about 20 inches of snow…Now with everything being on the tablet you kind of have to take your eyes off the road and touch stuff on the tablet. That's fine when you're on the autopilot, or the weather's crappy, the roads are icy, or people are driving like crazy. It's a little bit of an inconvenience, but something I found out was using the voice commands and how they can actually help you a lot when you're in a driving situation that is not so good.

The ability of voice commands to adapt to the natural language spoken by the users is one of its qualities that evoke positive emotions in Tesla owners. Being able to communicate with the vehicles through natural language adds a human touch to the machine in operators' minds. Voice commands are designed to recognize a status described by the operator and act on the solutions for making the interaction between humans and machine resemble interpersonal interactions. For instance, saying "I am cold" or "I am hot" when engaged with voice commands will activate climate control; saying "my butt is cold" will start the seat heaters.

Youtube content creator [Y11] has expressed the same view on using voice commands:" When we need something we are programmed to then go to the screen to get what we need, and we are just not programmed to think: hey! Maybe I should just ask for it, so that's why I think these voice commands are just a little bit ahead of its time in the Tesla. I think that they will evolve over time, and we will start to use them more and more as we become more acclimated with asking for what we want instead of touching a screen for what we want."

Researchers point out conversational agents like voice commands are designed to provide naturalness and convenience to achieve comfortability. As conversational agents can simulate intelligent behaviours, users will personify them over time because humans are social beings who always pursue interaction with other societal members. The categorization of other subjects enables humans to understand and control them. In other words, the human characteristics presented in the machine's output can trigger users' positive emotions and perception towards the conversational agents, which increases users' intentions to use NLP technologies. Subsequently, users become more accustomed to using voice assistant, fostering broader users' acceptance of using the new technology (Wagner et al., 2019).

5.3.2 Hedonic values of meaningful cultural reference

Besides personification, the hedonic value of voice commands also leads to stakeholders' positive emotions, i.e. excitement and enjoyment. Several digital Easter eggs, which mean the undocumented features of a technological product, can be activated by specific voice commands. One of the well-known Tesla Easter eggs is the Santa mode that can be started by saying the voice command "Ho-Ho-Ho", which makes the car plays holiday songs (Pogue, 2019). Using voice commands to activate entertainment features connects using the device to a fun experience. Such experience has a positive effect on users' intent to the NLP features, which means the more users enjoy using voice commands, the more frequent they will use them (Wagner et al., 2019).

Twitter user [T088] talks about his thoughts on Tesla's comedy inspired Easter egg: "One of the many reasons why a Telsa is the best car money can buy: "More recently, voice command activation was also provided via an over-the-air update that allows Sentry Mode to be set using the phrase "Keep Summer Safe" from the Rick and Morty cartoon."

The voice command of the Sentry mode is one of the examples that Tesla stakeholders take a liking of the resonance between the cultural reference used in the voice command and the brand's external communication. Sentry mode can add protection to the vehicle by monitoring the environment when it is left unattended (Tesla, 2019a). The voice command for activating the Sentry mode, "keep Summer safe, " refers to the science fiction situational comedy Rick and Morty. In one episode of the sitcom, a space ship equipped with a voice assistant is given the command using the phrase, "keep Summer safe", by its operators to safeguard a passenger that remains in the unattended vehicle (Adult Swim, 2017). These two scenarios are embedded in the same context of using an intelligent voice assistant to activate the safety feature of the car. The pop-cultural reference associates Tesla with another product brand, Space X, which is housed under the umbrella of the Chief Executive, Elon Musk. Furthermore, Musk claims that the profit returned from his many ventures, including Tesla, will be invested in SpaceX for "making life multi-planetary", which he perceives to be a solution for human civilization to become sustainable beyond Earth (Musk, 2012c, SpaceX, 2017). By telling the brand story using cultural reference, the objectives of SpaceX is turned into the brand associations of Tesla, enriching their brand meanings shared by the stakeholders.

5.4 The impact of Big Data analytics

Stakeholders' attitude toward Tesla's use of Big Data analysis is examined through the Twitter users' responses to the two following tweets from the CEO urging Tesla owners to apply for participating in an early access programme of the unreleased self-driving features.

Musk (2021a) firstly announced the opportunity for entering the FSD Beta programme without giving explicit instruction on how to apply: "If you want the Tesla Full Self-Driving Beta downloaded to your car, let us know. Doubling beta program size now with 8.2 & probably 10X size with 8.3. Still be careful, but it's getting mature."

Musk posted the following tweet the next day after the first tweet received abundant replies: "Due to high levels of demand for FSD Beta, adding "Download Beta" button to Service section of car display in ~10 days (Musk, 2021b)."

It should be noted that we take the context of a call for action into consideration, which possibly attracts the responses from stakeholders that are most enthusiastic about Tesla's self-driving features. Nevertheless, these responses compensate the normality that Tesla owners who contribute to data sharing tend to focus on the self-driving features without putting much thought into data-sharing itself. Two norms of emotions and efficacy are discovered: the sense of participation stakeholders develop through sharing data and their expectation of receiving exclusivity as a reward.

5.4.1 Sense of participation

Tesla owners are aware that their driving activities are collected through WIFI connections and forwarded to the company to optimise autonomous driving features. At the least, the features of reporting the technical issues of autopilot and other self-driving features are frequently discussed by Tesla owners, which show their knowledge of the conduit connecting the real-time status of their vehicles to the service provider. Besides operational and diagnostic data, customers can voluntarily opt to share the videos recorded by the eight cameras equipped on the car that provide 360 degrees of visibility (Tesla, n.d.-b). The massive amount of data provided by Tesla owners is stored in the software platform, Fleet, which connects to more than 500,000 Tesla vehicles (Tesla, 2019b).

While the discussion on privacy concerns continues to surround the use of Big Data, many Tesla owners chose to share their data, including short video recording captured by the eight cameras, as they perceive their participation as contributions to developing the objectives of the brand.

Twitter user [T120] responds to the CEO's recruitment for the FSD Beta programme: "I drive about 300-600+ miles a day so I'm sure [that I] could offer a great deal of real world input to assist in the fine tuning. I'd enjoy being part of the data pool and contribution...playing a part in the progression, however minor."

Another Twitter user [T119] also responds by claiming the potential values he can create for the brand by joining the programme: "I am a US Navy Veteran (Advanced Electronics Specialist). [I] drive a Model3 SR+ and I believe I can assist in providing great corner case scenarios."

Tesla owners who sign up to participate in the FSD Beta programme are motivated by developing the brand's technological superiority and understanding that using their know-how on testing can help the new self-driving features into broader release. The shared understanding of the brand's goals can be related to the brand's proactive communication on the technical process of achieving full-self driving. Tesla's director of AI, Andrej Karpathy, has continued to communicate about how the significance of data can help push the breakthrough on autonomous driving in public discourse (Karpathy, 2017; PyTorch, 2019; Tesla. 2019b; CVPR'20 WSAD, 2020).

Due to the success of the brand's external communication, many Tesla owners believe that data sharing can effectively improve the self-driving features, strengthening the normative efficacy in the minds of stakeholders.

According to Karpathy (Tesla. 2019b), the key for the autopilot to constantly improve is for the dataset that Tesla's multiple ANNs train on to cover all scenarios that can possibly happen on the road. Karpathy (2017) further stressed a concept he proposed as Software 2.0, which perceives the data-hungry neural network beyond an AI classifier. Software 1.0 means the classical stacks written by human engineers with computer languages that command the machine to perform specific desirable behaviour. In reverse, for Software 2.0, engineers only set the goal of desired behaviour for the machines and a rough neural net architecture that will search for the functional program in Big Data itself. The algorithm fills in the position of human because the data is too big more human to programme.

Since Tesla owners provide the data, the data contributors are highly involved in creating tangible value for the company. The data that consist of Tesla owners' driving patterns influence the driving decision of autopilot that is widely distributed to more customers. In a sense, using Big Data analytics enables the proliferation of the brand, people and devices. The hyper-connectivity of brand leads to the shift from the single ownership of the brand to the shared ownership, allowing stakeholders to co-create brand meanings and brand experiences (Swaminathan, Sorescu & Steenkamp, 2020). Having the feeling of shared brand ownership encourages the stakeholders to participate in co-creating the brand consistently and integrating their ideologies in co-creating an emotionally charged brand (Stuart, H.J. 2011; Veloutsou & Black, 2020).

5.4.2 Exclusivity as a reward to participation

Participating in the FSD Beta programme is perceived as exclusive by the stakeholders because only selected applicants will gain access to the programme without knowing the selection criteria. Some Tesla owners believe they are qualified for being part of the early access programme for both emotional and utilitarian reasons, regarding receiving the exclusivity from the brand as a reward for their loyalty to the brand. The possibility of accessing exclusive rewards leads them to refrain from inconsistent actions, i.e. paying extra fees for full self-driving capacity, frequently using autopilot, and drive with hypervigilance.

Twitter user [T097] responds to Musk's tweet for recruiting FSD Beta tester: "It would be amazing if you'd give FSD Beta to my Dad. It's his 77th birthday today. He's not on social media. He understands the tech more than anyone I know other than you. He's a pilot. He loves Tesla. He hand-washes his S every Sunday."

Twitter user [T100] is one of the many that argue customers that who invested in the brand at the early stage should be rewarded with exclusive access: "Obviously I want in, but how about a super simple and fair method of just sending it to the people who paid for FSD longest ago? And for people who initially bought with FSD, sort by time of deposit. I lined up in person for FSD 5 years ago - why does anyone have it before us?"

The sense of urgency Tesla owners have for owning the new features can be detected from these responses, which can result from emotionally and financially investing in the goal of creating true full driving automation shared between the brand and stakeholders.

5.5 The impact of AI on Brand promise

To understand what impact AI technologies have on brand promise, we can examine the relationship between brand promise and the norms of actions, emotions and efficacy created in the minds of stakeholders from their engagement with AI. As discussed in section 2.1.2, brand promise can be seen as an extension of brand position aiming at internal stakeholders delivered to external stakeholders as a promise from the brand that differentiates itself from the other competitors through providing a unique experience (Chernatony & Christodoulides, 2004; Punjaisri & Wilson, 2007; Munteanu, 2014). Taking the bottom-up approach of inductive analysis, we analyze the unique functional and emotional values provided by the machine learning, NLP, and Big Data analytics features, which consist of the brand promise of Tesla.

Both the personification and hedonic value of NLP features contribute to the norms of emotions and efficacy, which optimize Tesla owners' technology acceptance towards NLP features. As a result, Tesla owners use voice commands more intensely. The natural interaction with a digital voice assistant of fun and human characteristics they experience from using NLP features construct their expectation of what will follow when they continue to engage with the brand in the future.

Twitter user [T077] talks about the successful localization of voice commands: "#Tesla voice commands works really well in #Chinese. This #Model3 owner demos most of the common commands in Mandarin. The previous tweet I posted shows voice command recognizes various Chinese dialects as well. Congrats to Tesla China Team & @elonmusk."

Youtube content creator [Y11] talks about the possibility of controlling most touch screen features through voice commands: "If you want to control the windshield wipers, you can say put the windshield wipers on low, so you can actually control it with your voice…so instead of us fumbling around with the screen, all you have to do is hit the button and then control it with your voice. You can actually control both the climate and the heated seats with a voice command as well, so this makes it a lot more seamless and a touch-free experience."

Comfortability is the emotional values provided to the users through the ability of voice commands to interpret users' commands in natural languages successfully. Such emotional value results from the personification of machine made possible by the advance of NLP technology. The successful execution of commands increases the safety of drivers. Safety can be seen as both functional and emotional values as it reduces distractions by allowing more flexibility in multitasking when driving and making drivers feel safer by giving drivers more control through an option of verbal commands.

Twitter user [T022] posted a video of her grandma dancing to the holiday song played by the Tesla set in Santa mode and commented: "Hey @elonmusk! Thanks for creating my grandma's new dance partner."

Hedonic values of entertaining features delivered through voice commands provide emotional value to Tesla owners. The interactive brand experience can deepen the engagement between the brand and customers, strengthening the brand relationship (Nobre & Ferreira, 2017). The hedonic aspect of the brand can effectively attract stakeholders to engage with the brand and enrich their expectation to the brand, helping to differentiate the brand from the competitors in the market place.

The changeability of software and trust in automation provide Tesla owners with the unique experience of owning the finished product that can be refreshed regularly. Furey et al. (2014) suggest the product attributes of the brand does not effectively differentiate the brand because products can be easily imitated. On the contrary, employees' service is emphasized for brand promise as it makes actual distinctions for the customers. However, the empirical result shows that the product attributes of advanced AI product might not be easy to imitate due to the difficulty of programming.

Youtube content creator [Y013] documented his pleasant surprise by the sophistication of FSD Beta during his test drive: "What's totally blown me away about this FSD beta is watching it go through an unprotected left-hand turn. No lane markings like when we exit this neighbourhood here and come up to the stop sign. It'll even tell me when we can't see far enough. It'll say, creeping forward to observe. It'll creep forward. It'll look at what's going on around, and then when it's safe, it'll take off. "

While trust in automation can quickly meet the criteria of differentiation as part of brand promise because Tesla has one of the most capable autopilots in the market (Morando et al., 2020), the brand values changeability of software helps create might not be so straight forward. Instead of service provided directly from the employees, i.e. bringing the car to the maintenance point, the regular refreshments are carried by the AI features to the users in real-time with less geographical limits through over-the-air updates. It should be noted here that the technology of internet-of-things (IoT) that connected the vehicles and the software platform might appear to be the most important for the over-the-air updates. However, we should not overlook the fact that the production of the updates relies heavily on machine learning and Big Data analytics, which means the technological superiority of Tesla is the product of the two.

As West et al. (2019) point out, advanced AI technology is difficult to duplicate, which condition fulfils brand promise by providing functional benefits. With that said, Tesla's leadership in autonomous driving in terms of advanced AI technologies can be seen as the brand's strength that stakeholders highly value. It makes sense for customers to expect a unique experience from the brand based on their past engagements with the AI features of Tesla. Furthermore, emotional values are also created in customers' minds when engaging with the product's advanced technology. To conclude, these four elements contribute to brand promise through both functional and emotional values: changeability of software and trust in automation of machine learning features, and hedonic value and personification of NLP features.

5.6 The impact of AI on brand identity

To explore the impact of AI technologies on brand identity, we examine the relationship between brand identity and the norms of actions, emotions and efficacy related to using AI feature. As discussed in section 2.1.3, brand identity consists of a unique set of associations representing what the brand stands for, which also implies a promise to the customers. When all brand elements are grouped together in a meaningful and cohesive way, functional, emotional and self-expressive benefits are created to help the brand establish a relationship with customers (Aaker, 2002, p68). Furthermore, the brand identity is formed through an ongoing dialogue between the brand and the stakeholders, which constituted a socially shared reality in stakeholders' mind (Törmälä & Gyrd-Jones, 2017). Hence, we will investigate which norms of emotions, efficacy and actions contribute to providing meaningful and cohesive associations with the brand through creating multi-dimensional benefits.

The NLP features embedded in the context of cultural references provide the means for stakeholders to create meaningful emotional and self-expressive values that align cohesively with the brand proposition of Tesla. As previously discussed, the brand meanings of Tesla is enriched by its bold and clear objectives to popularize electric vehicles for distributing green energy (Musk, 2012c; Tesla, n.d.-a). This brand objective is one link in the chain of the CEO's agenda to make human civilization sustainable beyond Earth (Musk, 2012c, SpaceX, 2017). Tesla's own brand stories are meaningfully associated with the other brands founded by the CEO because they shared the same ultimate goal.

Youtube user [Y09-C02] commented on a video demonstrating new features of voice commands: "Honestly!!! This car feels like the future when in it." To which the content creator [Y09] replies: "It's my very own spaceship!"

By having a discussion online about how they perceive the brand, Tesla stakeholders further expand and enrich the brand associations, mediating the brand meanings to other stakeholders that see their discussion. The stakeholders deem the brand as futuristic not only because the brand uses advanced AI but also because the brand identity is strengthened by its affiliated brands, i.e. SpaceX, and the cultural references the brand meaningfully related to. While Tesla stakeholders have fun discovering the nuances hidden in the design of voice command, they also develop a stronger and more personal relationship with the brand through emotional and behavioural response. Especially for stakeholders who share self-identification with the brand, they can create a preference for the focal brand due to brand engagement (Nobre & Ferreira, 2017).

The sense of participation plays a crucial role in encouraging stakeholders' involvement in co-creating the brand identity with Tesla. Sharing data with the service provider involves the risk of leaking personal privacy, to which stakeholders need to have a strong motivation and trust to participate. In practice, the data shared by the stakeholders become a massive pool of examples within which the algorithms can search solutions for optimizing Tesla's self-driving capabilities. To some extent, the self-driving features represent a collective reality of the driving behaviours and the driving experience shared by Tesla owners.

Twitter user [T146] explained why he signed up for the testing of the FSD Beta programme: "Interested in FSD. My 8-year old asks me every day if "full autonomous is available." I always answer him he should ask @elonmusk ... so we are in!"

Twitter user [T150] expresses his interests in participating in the FSD Beta programme for better localization of self-driving in his region: "I live in British Columbia Canada and would do my best to be responsible for giving accurate and relevant feedback."

Arguably, the reliance on Big Data of self-driving optimization gives more control of brand ownership to the stakeholders because their inputs are internalized in the products, i.e. autopilot. Following the concept of Software 2.0, which suggests the machine learning algorithm and Big Data is replacing human engineers in some programming tasks, it implies that more control of the brand is naturally transferred to the stakeholders and the machine from the management. The data-sharing programme also becomes a means for stakeholders to create brand values in their rights. Therefore, the sense of participation leads to a strong sense of shared ownership for the stakeholders, who will continue to influence and negotiate the brand identity with the corporate brand.

Exclusivity as a reward to participation is an example of brand values created and negotiated by stakeholders. Although the company determines the limited spaces of the programme, the opportunity to participate will not be considered as a reward if stakeholders have not created the norms of emotions and efficacy in their minds after a long process of engaging with the brand. As the stakeholders can relate to the corporate brand identity on a functional, emotional and self-expressive level, a robust brand-customer relationship is established between Tesla and its stakeholders.

5.7 The impact of AI on sustainable corporate brand

As discussed in section 3.3, West et al. (2018) suggest that brands are highly complex, and branding experts have no universal agreement on how brand succeed. Therefore, it will be challenging to analyze the direct impact AI technologies have on building a sustainable corporate brand. A suitable way will be examining the relationships between AI methods and the brand components, brand promise and brand identity, through the interpretation of the normative alignment model.

Based on the empirical analysis, we argue that: 1) the machine learning features can regularly evoke refreshed excitements in stakeholders' minds due to software changeability. In addition, drivers' engagement with self-driving features can build trust over time. 2) The NLP features can increase users' technology acceptance through the personification of voice commands and create hedonic values through meaningful cultural references. 3) The use of Big Data analytics creates a context for stakeholder to gain a sense of participation and expect exclusivity as a functional and emotional reward in return.

The refreshed excitements and trust are brought by machine learning technologies. The fun and human characteristics and safety are brought by NLP technologies. Technology superiority is made possible through Big Data analytics. These five elements represent the values AI technologies of Tesla contribute to brand promise. For brand identity, the focal brand's connections to the CEO, the affiliate brands and meaningful cultural references are enhanced by NLP features; and the shared ownership of the brand is intensified through the co-creation of Big Data analytics. These four elements created through stakeholders' engagements with AI technologies enrich and expand the brand identity, helping establish a strong brand-customer relationship. Therefore, AI technologies provide both functional and non-functional benefits that help the stakeholders generate brand values for brand promise and brand identity. Although the direct impact of AI technologies on succeeding in branding cannot be determined due to the complexity of a brand, AI technologies help foster a successful sustainable corporate brand by contributing positive impacts to brand promise and brand identity.

Based on the TBL model, sustainability for a brand indicates maintaining economic growth from conducting fair business while not compromising the environmental resources of future generations (Alhaddi, 2015). Tesla has profited from its investment in green energy on a corporate level. Based on Tesla's impact report in 2019, which is the latest sustainability report available, Tesla generated around 600 million USD through selling emission credits to other car manufactures (Tesla, 2020a), which accounts for roughly 2.4% of their annual revenue of 24,578 million USD (Tesla, 2020b). Based on the results returned from searching the keyword, Tesla, the brand is well associated with sustainability.

Twitter user [T001] stated the feeling of guilt is why she wants to buy an electric car: "Is there a syndrome for feeling guilty about driving an ICE (internal combustion engine vehicle)? If there is I have it. When I see a Tesla or other #EV I breathe a little deeper and focus on my goals to get one."

Twitter user [T045] discussed the objectives of the band: "Majority of Tesla's patents are open sourced, they want the entire industry to transition to electrification as per their mission statement, besides Tesla innovates so quick they're thinking what to build in 3-5 years down the track."

This phenomenon entails the stakeholders of Tesla are aware of the company's goal, so they can associate sustainability with the brand, which can be one of the motivations for stakeholders to engage with the brand. However, from the stakeholders' online discourse about the AI technologies used in Tesla vehicles, sustainability is rarely mentioned, which implies the connections between the AI features and the sustainable objectives of Tesla are weak in stakeholders' minds. The phenomenon also supports the claim that AI technologies do not directly impact building a sustainable corporate brand. However, AI features serve as a unique asset that fosters positive impacts on the sustainable corporate brand, which will ultimately help the brand in progressing toward sustainability.

6 CONCLUSION AND DISCUSSION

This chapter concludes this research, starting with summarizing the study's key results and answering the research questions. A theoretical framework adapted based on the empirical work is provided by discussing the study's theoretical contribution and managerial implications. The limitations and validity of the research are also examined. Lastly, the chapter ends with suggestions for future research.

6.1 Key results

This research investigates the positive impacts AI features have on sustainable corporate brands by conducting cross-disciplinary research. The research is designed as a case study on the EAVs manufacturer, Tesla, as it provides a wide range of variants that cover both the applied AI technologies and sustainability as its brand objective. The research narrows down to the three AI sub-categories that are most relevant to branding: machine learning, NLP, and Big Data analytics, which are applied to the EVAs sector for building and optimizing the autonomous driving features and digital assistant.

The two elements of the sustainable corporate brand model, brand identity and brand promise, are highlighted as they provide the brand structure for exploring how brand values creation can be orchestrated through the brand proposition and are later created in stakeholders' minds. The brand structure captures how the brand and stakeholders negotiate and co-create the brand identity.

In the efforts of connecting brand identity and brand promise to the impact of the three AI technologies, the normative alignment model is used to interpret the relationship between the two subjects. By researching the norms of actions, emotions, and efficacy created in stakeholders' minds from their engagement with the three AI features, the results contribute to depict the impact of AI technologies on creating values for brand identity and brand promise. As brand identity and brand promise are the components of building an authentic, emotionally charged and behaviorally based brand, the research also attempts to descript the indirect impact AI technologies have on building a sustainable corporate brand. A proposed theoretical framework is provided to present the research rationale.

For answering the main research question, *to what extent does AI contribute positive impacts on sustainable corporate brands in the EAVs sector?* The answers to the three sub-questions are first provided based on the findings of empirical analysis.

1) *To what extent does machine learning contribute positive impacts on sustainable corporate brands in the EAVs sector?*

The machine learning technologies are utilized on self-driving features, i.e. autopilot. Two types of normative emotions are created in stakeholders' minds by engaging with machine learning features. The first one is the refreshed excitements due to the changeability of software. In contrast to the traditional model of the product life cycle, customers experienced strong positive emotions repeatedly following the optimized and new machine learning features delivered to the customers periodically through over-the-air updates. The refreshment of machine learning features is made possible due to the re-programmability of computers and the homogenisation of data.

The second one is trust in automation. The findings show stakeholders experienced positive and negative emotions when regularly engaging with machine learning features. However, the negative emotions are often tolerated due to their knowledge of the current self-driving features not being entirely autonomous, which lead them to acceptant to the malfunctions of machine learning features and the need for human interference. Therefore, their trust in using automation as a driver assist feature still increase along with the time they engage with the machine learning features.

The changeability of software and trust in automation can provide Tesla stakeholders with the unique experience that differentiating Tesla from the competitors. Arguably, the capabilities of these machine learning features are difficult to imitate due to the technological superiority of the brand. Hence, the machine learning features contribute to creating values for the brand promise upon which customers build their future expectations.

2) *To what extent does NLP contribute positive impacts on sustainable corporate brands in the EAVs sector?*

NLP technologies are utilized in the voice commands that help to interpret natural languages to the actions of vehicles. The normative emotions and efficacy of safety are created in customers' minds due to the machine's personification and the hedonic values of meaningful cultural references connecting to the voice commands.

The capability of voice commands to quickly adapt to natural languages brings the users comfortability and demonstrates the human characteristics of the digital assistant. The well-functioned voice commands allow the users to multi-task when driving. From the touch-free experience, the users create safety feelings in their minds as they believe using voice commands makes driving safer. When engaging with a conversational agent that simulates intelligent behaviours, users will personify the machine over time. The personification of the NLP features evokes positive emotions within the users, which leads them to use the voice assistant more intensely. Eventually, the users will become accustomed to using voice commands, which further enhance their feelings of safety.

Using the voice commands to activate entertaining features provide both hedonic values through meaningful cultural references, which associate the focal brands with the CEO, the affiliate brands. The positive emotional values are strengthened through the users' engagement over time, and the brand meanings are enriched and expanded. Same as machine learning features, the personification and hedonic value of NLP features are the results of the technology superiority of the brand. Hence, interacting with a digital voice assistant of fun and human characteristics is a unique experience the brand creates through the NLP features, which contributes to the brand promise.

The NLP features embedded in the context of cultural references provide the means for stakeholders to create meaningful emotional and self-expressive values that align cohesively with the brand proposition of Tesla. Through the careful orchestration of brand identity, the goal of the focal brand is integrated for the shared objective with the other brand associations. The enrichment and expansion of brand meanings provide stakeholders with tools to co-create brand identity by creating emotional and self-expressive values.

3) *To what extent does Big Data Analytics contribute positive impacts on sustainable corporate brands in the EAVs sector?*

Big Data analytics are utilized for the optimization of machine learning features. The customers choose to share data with the brand because they believe doing so help the brand achieve a shared goal. Sense of participation and exclusivity of participation are the two norms of emotions, and efficacy stakeholders create in their mind when engaging with Big Data analytics.

The customers share data with the brand because they wish to support the brand in developing technological superiority and help the new machine learning features into broader release. As the data provided by the customers are essential for the brand to improve its machine learning features, customers contribute to creating tangible values for the brand. Customers' driving patterns are also deeply integrated into the machine learning features. Knowing this, customers who share data develop a strong sense of participation.

Partaking in a data-sharing programme with limited spaces that are only open to a selected group of customers is considered exclusivity in customers' minds. Such exclusivity is viewed as a reward to regularly participating in data sharing, indicating stakeholders' emotional and financial investment is in the hope of emotional and utilitarian return. With that said, the normative actions of data sharing are motivated by the normative emotions and efficacy of achieving the vision of truly autonomous driving.

The sense of participation effectively motivates stakeholders to co-create the brand identity. Through co-creation, stakeholders develop a sense of brand ownership, which allows them to have more control in co-creating the brand meaning. In return, a sense of shared brand ownership encourages the stakeholders to frequently engage with the brand, creating brand values in their own right. The exclusivity of participation is one example of brand values created and negotiated by the stakeholders as the stakeholders determine the values. Through co-creating brand identity, the brand-customer relationship is strengthened.

After answering the three sub-questions, I will answer the main research question along with the conceptualized model of the key empirical findings, which is adapted to the proposed theoretical framework, as Figure 8.

To what extent does AI contribute positive impacts on sustainable corporate brands in the EAVs sector?

The main research question can be answered by summarizing the empirical findings bottom-up. The unique characteristics of the three AI features lead to the normative emotions and efficacy of stakeholders, which further motivate their normative actions that, in return, enhance the norms of emotions and efficacy in a loop. Stakeholders create refreshed excitement and trust in their mind because of the changeability and automation of machine learning features, which increase their use of self-driving features.

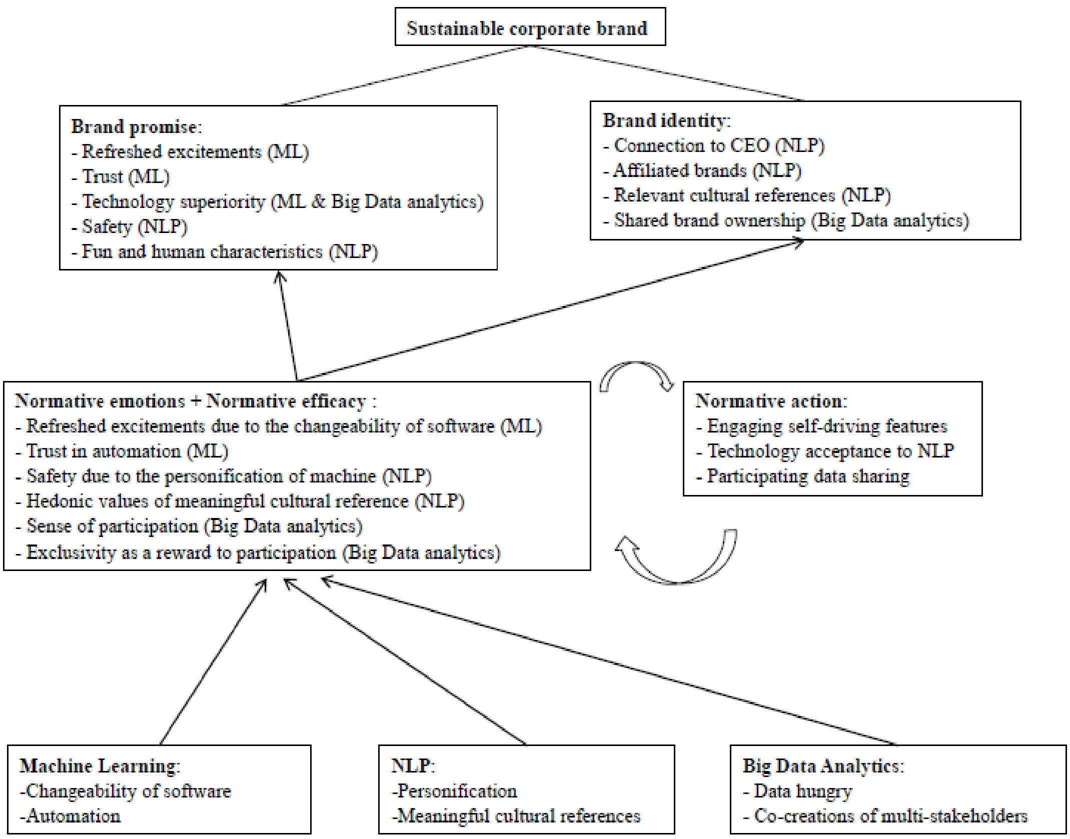

Figure 8, Conceptual model of the impact of AI on building sustainable corporate brand

Stakeholders create the fun and human characteristics and the feelings of safety towards the vehicle because of the personification of NLP features and the meaningful cultural references embedded in the use of NLP features. Thus the stakeholders' technology acceptance of using NLP features increases. Stakeholders create a sense of participation and expect receiving exclusivity as a reward for sharing data because Big Data analytics relies on users' data and serves as a platform for the co-creation of multi-stakeholders. As a result of building the emotional and utilitarian values in their mind, stakeholders are motivated to share data.

Five elements represent the values AI technologies contribute to brand promise through creating a unique experience for the stakeholders that will differentiate the brand from its competitors in the market place. The refreshed excitements and trust are brought by machine learning technologies. The fun and human characteristics and safety are brought by NLP technologies. Technology superiority is made possible through Big Data analytics. Four elements embody the values conveyed by AI technologies that enrich and expand the brand identity, helping establish a strong brand-customer relationship. NLP features can effectively enhance the connections between the focal brand and the other brand associations: the CEO, the affiliate brands and meaningful cultural references. The shared ownership of the brand is intensified through the co-creation of Big Data analytics.

Based on the findings, I argue the unique characteristics of the three applied AI features help customers create brand values for both brand promise and brand identity by providing both functional and non-functional benefits in the EAVs sector. However, it does not determine whether the uniqueness of AI features directly impact the success of building a sustainable corporate brand. As West et al. (2018) suggest, brands are so complex that it is implausible to determine how brand succeed. In addition, this research focus on only two components of the sustainable corporate brand Stuart (2011) proposes instead of examining the model as a whole. It will be more reasonable to say that AI technologies positively impact generating brand values for brand promise and brand identity, fostering the benefits of building an authentic, emotionally charged and behaviorally based sustainable corporate brand.

6.2 Contribution of the study

6.2.1 Theoretical contribution

In the theoretical aspect, this research contributes to identifying the factors of implementing machine learning, NLP and Big Data analytics in the EAVs sector that positively impact the brand value creations in brand promise and brand identity of the sustainable corporate brand (Stuart, 2011).

This study supports West et al.’s (2018) claim that AI technologies provide functional benefits that contribute to brand promise and build a strong brand, which differs from the traditional perspective that promotes only non-functional effectively generate brand values. Researchers consider the functional benefits of products easy to duplicate (Aaker, 1991, p 15). Nevertheless, the functional benefits of AI features are difficult to imitate because the resources required for building advanced AI for complex business models are rare (West et al., 2018).

While West et al.’s (2018) study focuses on the functional benefits of AI technologies in the broader use of branding, i.e. recommendation systems and chatbots, the thesis focuses on implementing AI in the EAVs sector, which provides not only functional benefits but also non-functional benefits to stakeholders. In the case of Tesla, NLP features provide hedonic value. It creates meaningful connections between the focal brand and other brand associations, which serves as an example that AI provides non-functional benefits. In the theoretical discussion regarding the components of brands, West et al. (2018) centre their study on how AI impacts brand promise and building a strong brand. This research also examines the impacts AI technologies contribute to brand identity through discussing the significance of brand identity for building strong brands (Aaker, 2002), demonstrating customers’ engagement with AI technologies help to strengthen the brand-customer relationship.

In addition, this research extends the discussion of brand identity to the brand co-creation perspective, arguing the brand identity is co-created through the ongoing process of dialogues between a company and its stakeholders (Törmälä & Gyrd-Jones, 2017). The case study of Tesla illustrates the co-creation of brand identity through customers' engagement with Big Data analytics. The findings contribute a new perspective to brand co-creation in the context of AI implementation that point out more control of the brand is transferred to the customers because the optimization of AI features relies heavily on data shared by the customers. Taking part in optimizing the AI features gives stakeholders a strong sense of brand ownership which effectively motivates them to engage with brands.

Stuart's (2011) sustainable corporate brand model combines the normative alignment model (Thomas et al., 2009) and AC^3ID test (Balmer et al., 2009). However, this thesis does not examine all the sustainable corporate model elements. For the AC^3ID test (Balmer et al., 2009), only the elements of brand promise and brand identity are studied in connection with stakeholders' engagement with AI features, while the other elements are not included in building the theoretical framework for this research. Those elements are excluded because brand promise and brand identity are connected to the theories of the impact of AI on branding proposed by West et al. (2018). In addition, including all elements will make the range of research too broad, causing difficulty for extracting in-depth knowledge from the phenomenon. This research bridges the selected aspects of sustainable corporate brands to AI, which is a trend that influences branding and marketing on a profound level.

6.2.2 Managerial implication

In the managerial aspect, utilizing the research result that AI implementation in sustainable corporate brands helps motivate stakeholders to engage with the brand, managers can consider using AI technologies as a tool to provide customers with a unique experience with border geographical outreach and in real-time. Due to AI's capability to reach customers with less geographical limits in real-time, it presents a possibility for managers to create exponential growth for the brand, establishing a more personal brand-customer relationship. The use of AI features also provides the opportunity to create a sophisticated product that helps generate values for the brand at a lower cost. The service can be provided by machines consistently, which indicates the brand's scalability. On the other hand, the capability for AI to create exponential growth also means it can potentially cause significant damage. Hence, managers should prioritise the ethical issues when considering the implementations of AI technologies.

In the existing literature, service is seen as the most effective brand differentiator of brand promise. AI as a product feature can provide a new opportunity to create brand value consistently and effectively, helping human employees to manage the brand experience in an integrated and efficient way. With that said, managers should understand that the opportunity of using AI in the mix of brand strategies does not indicate to replace the work of human employees but to automate the tasks that are repeated and laborious. In the case of Tesla, the use of machine learning method and Big Data analytics helps the brand solve the problem of processing massive data, which would be very difficult for human employees to handle. While human employees are in charge of deciding the goal of the tasks, AI technologies are beneficial in assisting humans in complementing the goal the brand attempts to achieve.

As AI features inspire customers to create a unique experience in their mind, brand co-creation is integrated into customers' direct contact with the products. In the EAVs sector, customers' engagement with AI features tends to be accustomed and continuous, providing managers ample opportunities to orchestrate brand value creation in designing this process. In the case of Tesla, hedonic values and cultural references of the brand are integrated with the NLP features that customers engage with regularly. This design allows the brand to communicate with customers naturally, simply through their use with the products. Managers can also alter the external communications of the brand freely with low cost because of the changeability of software, creating meaningful and timely brand associations using AI applications as a platform.

Managers can also consider AI implementation as a strategy to tackle the challenges of stakeholder engagements. Brands face challenges in increasing the engagement rate with the stakeholders through different platforms, i.e. social media. AI features provide an alternative channel that customers proactively engage with and, most importantly, leave digital footprints for rich customer insights. It is common for technology companies to accumulate massive data; however, the ethical issue of protecting customers' privacy is a crucial concern. In the case of Tesla, a shared goal between the brand and the stakeholders is well communicated, which increases stakeholders' willingness to share data with the brand. Taking from this example, managers can think about encouraging stakeholders to participate in co-creation with the brand through motives that are valuable to them.

To conclude, managers should see AI technologies as a tool that can help reach the brand objective when used together with other branding strategies. AI technologies are beneficial in optimizing brand performance, creating scalability and adding fun human characteristics to the customer-brand interaction. This thesis suggests the AI technologies help foster positive impacts on sustainable corporate brands when implemented appropriately and relevant ethical issues are considered.

6.3 Limitation and validity assessments

Distinct from the purpose of quantitative research, which seeks to provide simplistic and accurate results that can be generalized to other subjects, qualitative research emphasizes exploring the depth of one specific phenomenon. Its primary purpose is to gain a deep understanding and a holistic and close-up view of the particular experience (Thomas & Magilvy, 2011). Following this rationale, this research provides in-depth insights into Tesla's use of AI technologies and its positive impacts on building the sustainable corporate brand. Tesla as a brand offers a wide range of variants that can be found in the EAVs, EVs and AVs sector. Therefore, the result of the study can be generalized to other EAVs companies and for some overlapping aspects in EVs and AVs sectors. However, this research does not generate across industries for all the sustainable corporate brands that are AI-centric.

Thomas and Magilvy (2011) argue that the trustworthiness of qualitative research can be examined from four aspects: credibility, applicability, dependability, and confirmability. Credibility can be established on the accurate interpretation of the informants' experience. As this research is observational only, no member checking is conducted to involve informants in reviewing the report. However, this method is compensated by following Braun and Clarke's (2006) 6-phase guideline rigorously in data analysis to ensure the researcher is familiarized with the transcripts and produce the report following the informants' words as closely as possible.

Transferability refers to the extent to which the research can be transferred within different groups of informants of the study, which can be established by providing the informants' description in terms of demographics and geographic boundaries (Thomas and Magilvy, 2011). The transferability of this research is limited as the demographic and geographic information of the informants cannot be acquired through an observational study. Dependability refers to the extent to which the research can be duplicated by a peer researcher (Thomas and Magilvy, 2011). I argue the methodology of this research can be easily followed by others as the purpose of the study, details of the selection of informants, data collection and data analysis are clearly described in the methodology chapter.

Lastly, confirmability is built on the establishment of credibility, transferability and dependability for examining whether the research is reflective (Thomas and Magilvy, 2011). As discussed in section 4.1, the researcher is conscious about researching in a reflective manner as the subjective view researchers bring to qualitative research is acknowledged in designing the research method. Multiple secondary data sources are used for following the direction of data as truthfully as possible, ensuring the researcher correctly interprets the specific languages used by informants and the technical terms used in the AI sector. To conclude, the research is conducted with a sense of openness to reduce the researcher’s bias to a minimum.

6.4 Suggestions for future research

As this research is exploratory, it focuses on identifying the unique characteristics of AI that positively impact the sustainable corporate brand in the EAVs sector. Further research can be conducted on what negative impacts these identified characteristics of AI might lead to the sustainable corporate brand. Understanding the negative effects of AI technologies will provide a more comprehensive and strategic perspective for the implementation of AI in sustainable corporate brands. As previously mentioned, big automakers plan to electrify all of their new vehicles following the success of Tesla. Hence, the research on the negative impacts can be particularly beneficial as the use of the EAVs begins to popularize in the market, indicating the negative side of AI implementation will face scrutinization by the general public.

This research found the stakeholders of Tesla are aware of the brand's objective in achieving sustainability, which motivates some stakeholders to engage with the brand. However, the research also finds the connections between the AI features and the sustainable objectives of Tesla are weak in the minds of stakeholders attracted by the AI-centric characteristics of the brand. This phenomenon entails that this group of stakeholders contributing to the sustainable corporate brand is not motivated by sustainability, although their contributions to the brand are significant. Therefore, further research can be conducted on how sustainable corporate brands attract and maintain stakeholders that are not motivated by sustainability through AI implementation.

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