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What is the Market Value of Artificial Intelligence and Machine Learning? The Role of Innovativeness and Collaboration for Performance

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A R T I C L E I N F O

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A B S T R A C T

As AI and ML technologies are increasingly incorporated into products, there is a need to understand the role of these incorporations in enhancing performance. This study uses new types of methodology related to textual data analysis to explore the question of whether there is a difference between market sentiments—and consequently marketing and business performance—when it comes to communicating either AI or ML. We test and confirm the hypothesis that AI rather than ML attracts more positive sentiments in the marketplace. Additionally, we find that AI is mostly used when the discussion centers on innovativeness, and that discussions concerning collaboration in these technologies attract more positive sentiments. We further contribute methodologically by leveraging textual data available online on the titles of web-page contents and the results of the Vader sentiment analysis to test our hypothesis. We conclude that, to enhance business performance, firms should communicate using AI-related vocabulary especially when the topic is innovativeness and collaboration.

1. Introduction

The proliferation of artificial intelligence (AI) and machine learning (ML) technologies holds out the prospect of enabling radical changes in products, services, innovation processes, business models, and the very nature of business activities in industrial ecosystems (Iansiti and Lakhani, 2020; Sjödin et al., 2020). In particular, due to their ability to respond to complex customer demands faced by companies today, AI and ML have become popular in creating new products and advanced services to improve customer outcomes. Indeed, an increasingly growing body of science has endorsed the value of incorporating AI and ML to develop products that effectively address deeper and more complex customer needs and customer satisfaction (Iansiti and Lakhani, 2020; Sjödin et al., 2020). Yet, customer sentiments towards such AI/ML services may be fickle and subject to influencing factors (e.g., biases) beyond the actual outcomes achieved. Thus, AI and ML may be perceived as both opportunities (e.g., innovation, optimization) and threats (e.g., security, privacy, loss of jobs), and the vocabulary of external communication that presents these offerings to the market may trigger such sentiments.

Although the literature currently places ample focus on AI and ML, scant attention has been paid to how much customers value the incorporation of AI and ML into products. The dialogue on AI and ML has mostly been driven by researchers in both technical fields, whilst managerial studies have only recently begun to look more closely at the phenomenon (Iansiti and Lakhani, 2020; Shrestha et al., 2019). Indeed, studies in the management literature on AI/ML are still in their nascent stages, and much greater effort could be devoted to researching these topics. Particularly on business performance, there has been no close examination of how the market values AI and ML differently, especially when the discussions center on innovativeness and/or collaboration. To achieve greater business performance, should a company use ML in its communication, or is AI more appropriate? Which of those most corresponds to innovativeness? And is there higher value in collaboration?

Understanding these issues is important because it has practical implications for marketing and firm performance. As scholars in elaboration likelihood theory argue (Douglas et al., 2008; Morris et al., 2005) the emotional weight of messages (in our research, on AI and ML)

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could lead to the enhanced engagement of customers. Choice of words in communication corresponds to positivity of sentiments. As scholars such as Chen (2003) note, this in turn affects the likelihood of recommending and purchasing, which in turn improves business performance. Indeed, the difference in public perceptions of AI and ML is an undeveloped area of inquiry for future management research. Additionally, the literature has rarely investigated sentiments towards AI and ML in the marketplace, which is a drawback because different sentiments and overall feelings in the market could lead to discrete levels of marketing and business performance.

To address these shortcomings, one aim of the present study is to investigate how the communication of AI or ML influences performance. In addition, we explore the use of AI and ML in communicating innovativeness. Finally, we examine the effects of discussing collaboration on market sentiments, which enhance performance.

To investigate these questions, we build on a data set of more than 1,300 observations of AI and ML that are available online and modern text-based analysis techniques. More specifically, we utilize the Valence Aware Dictionary and the sEntiment Reasoner (Vader) algorithm (Hutto and Gilbert, 2014) for two sets of search item titles related to AI and ML, and we compare their average sentiment scores using a t-test. The research evidence presented in this paper sheds light on a core question about the value of incorporating and communicating AI and ML in product offerings. The findings suggest caution in labeling products with either AI or ML. Moreover, the results partly challenge traditional views that do not acknowledge value differences between AI and ML. Our findings show that AI attracts more positive sentiments than ML. Specifically, we find a significant difference in Vader compound scores from more than 650 observations each on AI and ML. In addition, by looking into the contents of the texts, we found that 5% of the topics related to AI concern innovation and new products and services, in comparison to ML where the figure is 1%, a difference that is statistically significant. Finally, we find that, in texts related to both ML and AI when the topic is about collaboration and partnership, the emotional response of the market is slightly higher. This suggests that the context in when AI or ML is mentioned matters.

Our study offers several contributions to research on AI and ML in marketing. First, AI is associated with more positive sentiments. Considering this emotional feedback from potential customers, we suggest that AI is better than ML in marketing communication. The higher sentiment scores associated with the incorporation of AI implies higher levels of marketing and business performance. Second, we show that, when online discussion topics center on new products and services and innovations, AI is used more often than ML. This again points to the practice of discussing AI rather than ML when the public (producers and customers alike) discusses new products and services. Third, we present evidence that collaboration and partnership in AI and ML technologies heightens sentiments in the market leading to heightened business performance. Fourth, in line with recent research (e.g., De Silva et al., 2021; Piñeiro-Chousa et al., 2021), our paper proposes modern-AI and text-analysis techniques that could be utilized by future researchers. In this regard, we find that the Vader algorithm is a modern tool that could be utilized more fully in future research. That is because our results from the Vader sentiment analysis accord with the practice of communicating AI, more often than ML, in discussing new products and services. Consequently, this could open up an academic discussion on whether Vader sentiment scores—as a theory—explain the presence of certain concepts in communications regarding new products and services.

2. Theoretical background and hypothesis development

2.1. Sentiments and Performance

Elaboration likelihood theory posits that messages have the potential to change the attitudes of recipients (Cacioppo and Petty, 1984). Morris et al. (2005) state that emotions are key factors that can increase the likelihood of elaboration by the recipients of messages. Marketplace sentiments are closely related to emotions, when they are defined as “collectively shared emotional dispositions” (Gopaldas, 2014, p. 995). Sentiments are, in other words, the general feeling in the marketplace for a specific concept. There is a large body of literature investigating consumer emotion at the individual level (e.g., Holbrook and Hirschman, 1982; Jun et al., 2014). Sentiments, as feelings at the market level, have been discussed in more recent research, as the computational tools to gauge feelings in the marketplace have been undergoing development (e.g., De Silva et al., 2021; Piñeiro-Chousa et al., 2021). Previous methods—for example, Gaski and Etzel (1986)—measure the sentiments of consumers towards only one concept (in this case, marketing) using questionnaires. In comparison, more recent studies apply modern sentiment analyses to textual data to measure sentiments and the general feeling in the marketplace (e.g., Kauffmann et al., 2020)

Sentiments, as they correspond to emotions, can enhance the elaboration likelihood (Douglas et al., 2008; Morris et al., 2005) and, hence, lead to superior marketing performance. Moreover, since previous decades, researchers in marketing have known the importance of word of mouth in explaining marketing and firm performance (e.g., Liu et al., 2019; Organ, 1977; Perez et al., 2020). Others have explored the notion that positivity of sentiments towards a concept relate to customer satisfaction with that concept (e.g., Choi et al., 2020; Ferreira and Lee, 2014; Swain and Cao, 2019; Yu et al., 2013). For example, scholars such as Chen (2003), Xiang et al. (2015), and Kim and Park (2017) find that sentiments positively corelate with customer satisfaction, which in turn leads to enhanced firm performance. In other words, if the sentiment measures for a product are high, that also means that, on average, customers have greater satisfaction with the products. This is consistent with the view in the marketing discipline, suggesting that greater customer satisfaction is at the core of value creation and firm performance (Kim and Park, 2017).

2.2. Market sentiments for AI and ML communication

How AI and ML are perceived in the marketplace may very well relate to how the technologies are defined. ML is defined as “the machine’s ability to keep improving its performance without humans having to explain exactly how to accomplish all the tasks it’s given” (Brynjolfsson and Mcafee, 2017, p. 2). ML is a term that has recently been used as the equivalent of AI because ML offers the methods for designing AI that are currently applicable (Marr, 2016). AI is nonetheless the general ability of a machine to “think” and has been the subject of discussion since Turing’s publication in 1950 (Turing, 1950). In recent years, AI has gained traction in the marketplace and among customers. There is research evidence that the sentiments towards AI are positive (Garvey and Maskal, 2020). However ML and AI are often used simultaneously and interchangeably (e.g., Brynjolfsson and Mcafee, 2017; Capatina et al., 2020; Liu et al., 2020), because ML is in fact the currently-manifested form of AI. But when it comes to sentiment and customer satisfaction, we argue that AI is more positive. That is because ML is mostly associated with complex and ambiguous technological developments where the conversion from inputs to outputs is a black box engendering low trust and transparency for users (e.g., Cui et al., 2006). On the other hand, AI is associated with technology, the future, and automation (e.g. Baum et al., 2011). Higher levels of sentiment, as discussed, translate into higher emotional engagement on the part of customers. That means greater likelihood of elaboration, which according to elaboration likelihood theory, is a cause of attitude change (Cacioppo and Petty, 1984). That change, assumed to be positive in this case, is about greater feelings of satisfaction. In addition, logically and based on prior research (Kim and Park, 2017) we expect customer engagement and satisfaction, as indicators of marketing performance, to lead to greater firm performance. Therefore, the following hypothesis, if true, implies that customer satisfaction related to the products using the technology (AI and ML) will be more positive if AI rather than ML is communicated.

H1: *The sentiments of the phrase "artificial intelligence" are more positive, leading to higher performance, than that of "machine learning".*

2.3. AI and ML communication in marketing innovations

Incorporation of AI and ML into products and services involve substantial innovation by firms. Yet, we still lack insight into how these innovations are communicated. Most recent marketing research on AI and ML has focused on the use of these tools for the purpose of marketing (e.g., Capatina et al., 2020; Huang and Rust, 2021), business model innovation (Burström et al., 2021; Sjödin et al., 2021) and innovation (Leverenz et al., 2021) . Hitherto, research attempts to investigate the marketing-related consequences of using AI and ML vocabulary in marketing communications have been minimal. Thus, there is a need to investigate the practice of communicating AI or ML when the topic is new products and services and innovation.

As discussed, we expect sentiments towards AI to be more positive than ML and, therefore, we expect in practice that AI will be more often used when the discussions are on new product and service innovations, for several reasons. First, we argue that marketing professionals are not naïve and are attuned to targeting the prevalent sentiments in the marketplace in their communication of innovations. This means that professionals are aware that AI is the better choice to communicate that a product or service is highly innovative. This underscores the idea of an important level of comprehensiveness in relation to market sentiment towards AI and innovativeness. Second, giving consideration to fewer and closely linked alternatives in the communication leads to quicker purchase decisions (Fredrickson and Mitchell, 1984). AI is more clearly linked to something innovative. Communicating ML may be viewed as overcomplicating market communication with customers. Third, simplifying communication slows down rational information processing and makes decision making faster (Mann and Janis, 1982).

H2: Compared to machine learning, artificial intelligence is more often used when the topic is about innovation and new products and services.

2.4. Sentiments towards AI/ML-related collaboration

The development of new technologies requires mutual action in the business ecosystem, and that is for the most part perceived positively by both the companies and the market (Penttilä et al., 2020). In other words, messages on collaboration trigger higher positive emotional responses in the marketplace. This indicates that, when AI or ML sentiments are mentioned in product or service offerings, collaboration may also be mentioned, and this is something that customers will value. In that regard, collaborative efforts often lead to more positive sentiments (Nidumolu et al., 2014). In terms of this research, collaboration in AI and ML technologies is perceived positively, and is mentioned when new products are introduced (Kolbjørnsrud et al., 2016), as a sign of improved performance. In this context, we expect the market to make a more positive, emotional response when collaborative efforts on AI and ML technologies are communicated, and we anticipate that this positive emotional engagement will lead in one way or another to enhanced performance.

H3: Artificial intelligence and machine learning are more positive, suggesting better performance, when mentioned in the context of collaboration.

3. 3.Methods

3.1. Data Source and Data Approach

We collected online texts using Google API services by searching machine learning (excluding artificial intelligence) and artificial intelligence (excluding machine learning). Google search items reflect the overall market's sentiment on specific topics, which can in turn reflect sentiments and feelings on the market level. We searched the two queries for different time ranges (every 6 months for the first 2 years, and every 3 months for the other 4 years) since the beginning of 2015 up to the end of 2020 because that provides a sufficiently large sample of recent data. The search was conducted using automated algorithms. We acquired 668 search items for the query on AI, and 693 items for the query on ML[1]. To show the overall content of the two sets, Table 1 presents the first twenty items, and Fig. 1 illustrates the most common words in the items for the two queries. These give an overview of the range of topics and discussions when either AI or ML is used in online discourse. This is in line with our theoretical assumptions that ML is mostly associated with technical issues often involving complexity, while AI is associated with technology and innovation. To collect and analyze the data, we utilized Python algorithms.

3.2. AI Methods and Algorithm

As discussed, market sentiments are collectively shared emotional dispositions, which can be measured by the Vader sentiment analysis. We employed, therefore, the Vader sentiment analysis to examine the first hypothesis (Hutto and Gilbert, 2014). Vader is an extension to

Table 1
Titles of the twenty search items related to two queries

+"Machine Learning" -"Artificial Intelligence"	+"Artificial Intelligence" -"Machine Learning"
Machine Learning	The Artificial Intelligence Revolution: Part 1 - Wait But Why
Machine Learning 10-601 Spring 2015	Our Fear of Artificial Intelligence | MIT Technology Review
Amazon Machine Learning Documentation	AIonAI: a humanitarian law of artificial intelligence and robotics
Machine Learning 10-601: Lectures	'Soft' Artificial Intelligence Is Suddenly Everywhere - WSJ
What is Amazon Machine Learning?	AAAI-16: Thirtieth AAAI Conference on Artificial Intelligence
Introducing Amazon Machine Learning	Regulating Artificial Intelligence Systems: Risks, Challenges ...
MarI/O - Machine Learning for Video Games	Clever computers - The dawn of artificial intelligence | Leaders | The ...
Matrix Methods in Data Analysis, Signal Processing, and Machine ...	Artificial intelligence - BBC Future
A Review of Relational Machine Learning for Knowledge Graphs	Journal of Experimental & Theoretical Artificial Intelligence
Machine learning in computational docking	Artificial intelligence
Convolutional LSTM Network: A Machine Learning Approach for ...	Bill Gates on dangers of artificial intelligence: 'I don't understand why ...
Intro to Machine Learning | ECE, Virginia Tech | Spring 2015: ECE ...	Open Letter on Artificial Intelligence - Wikipedia
Evaluation of machine learning algorithms for treatment outcome ...	Research areas | Department of Computer Science and Engineering ...
Model-Based Machine Learning (Early Access): an online book	Paradigms of Artificial Intelligence Programming: Case Studies in ...
Aerosolve: Machine learning for humans | by AirbnbEng | Airbnb ...	Welcome to IJCAI 2017!
Torch | Scientific computing for LuaJIT.	Human-Centered Artificial Intelligence (MSc) | Read your MSc at ...
Kaggle R Tutorial on Machine Learning – DataCamp	Stanford AI4ALL Landing Page | Stanford AI4ALL
Wekinator | Software for real-time, interactive machine learning	Table of Contents | Advances in Artificial Intelligence | Hindawi
aws-samples/machine-learning-samples: Sample ... – GitHub	Conference on Uncertainty in Artificial Intelligence (UAI 2015)
Machine Learning for Developers by Mike de Waard	Artificial Intelligence Laboratory

[1] The final search was carried out on Jan. 8th, 2021

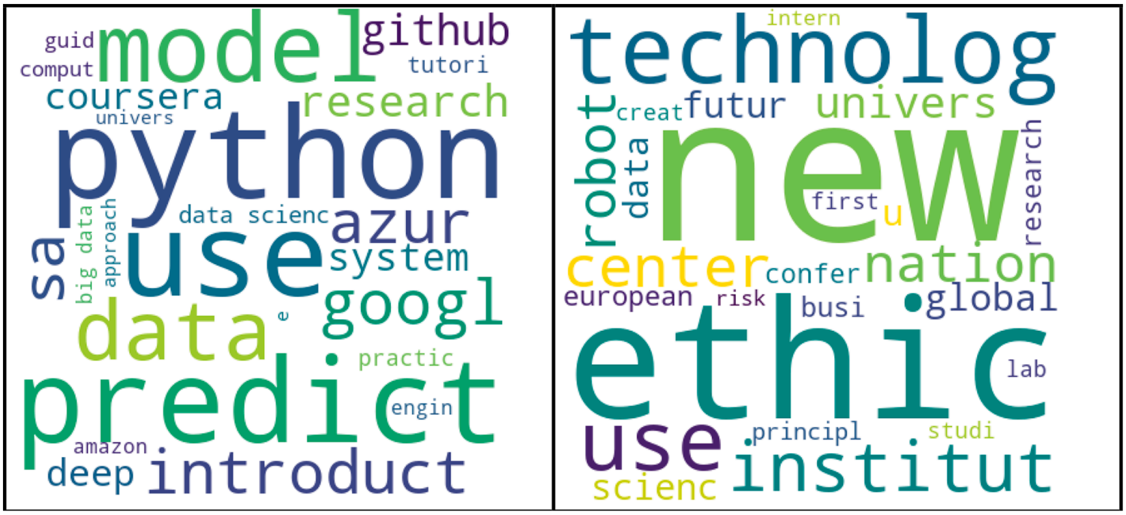

Fig. 1. Word clouds related to the two sets of titles

Linguistic Inquiry and Word Count (LIWC) methods. These methods are based on predefined dictionaries in which words are translated into different roles in speech and emotion (positive and negative) related to those measured by different human judges over time. Similarly, Vader is a polarity-based sentiment lexicon that, in addition to possessing the benefits of earlier methods of LIWC (Tausczik and Pennebaker, 2010), accounts for the intensity of words as well as expressions. Furthermore, it has been validated by humans (Hutto and Gilbert, 2014), and it has been used in research on customer satisfaction (Borg and Boldt, 2020).

We calculated the Vader compound score—which ranges from -1 to 1—for the titles of the search items in both queries. The higher the score, the more positive the sentiments on the concept. We then took an average for the scores related to the two sets of items. We saved the compound Vader score, based on the scores related to each text. Finally, we ran a t-test to determine the significance of the difference between the two groups of scores.

To examine the second hypothesis, we looked for the presence of words such as "new ","innova", "invent", "cutting edge", "breakthrough", "launch", "prototyp", "pilot", and "demo " in the content titles to determine whether they were related to innovation and new product and services. Then, we measured the percentages of such topics in the titles and conducted a t-test for the difference in the two sets (related to either AI or ML), considering the number of observations.

Finally, to examine the third hypothesis, we looked for the presence of words such as "collab ", "partner", "alianc", "together", "cooperat", "co-operat", "consort", "joint", and "exchang" in both content titles of the AI and ML searches to determine whether they were related to collaboration and partnership. Then, we measured the average Vader compound score for the titles and performed a t-test to obtain the difference in the two sets (related to either AI or ML, but different in indicating collaboration or not).

4. Results

We found that sentiments on AI are generally higher than those on ML. In terms of marketing, that suggests that customers at the market level have more positive sentiments and higher levels of satisfaction with AI compared to ML. Consequently, if companies use technologies that can be categorized as both ML and AI, they should focus on communicating and delivering AI rather than ML. Moreover, we found that, compared to ML, most online discussions on AI are related to innovation and new products and services.

Table 2 includes the results of the t-test between the Vader compound scores related to the two sets of search results on AI and ML. The results in the top section of Table 2 show that the average compound score for over 600 observations on ML is only 0.03, which indicates that sentiments on the term “machine learning” is neutral. On the other hand, the average for roughly the same number of observations on AI is 0.44, pointing to a positive sentiment on AI. The t-test examining the significance of this difference shows that it is statistically significant ($p < 0.001$). This provides support for Hypothesis 1.

Table 2
T-test results for Hypotheses 1 to 3

T-test results comparing two different sets of text entries		
Sets that are the results of following queries	+"Machine Learning"-"Artificial Intelligence"	+"Artificial Intelligence"-"Machine Learning"
Number of items	693	668
Average Vader compound scores	0.0307	0.4419
t-stat	**-36.66*** **	
Sets that are the results of following queries	+"Machine Learning" -"Artificial Intelligence"	+"Artificial Intelligence" -"Machine Learning"
Number of items	693	668
Percentage of text entries on innovation and new products and services	1.15 %	5.69 %
t-stat	**-4.66*** **	
Sets based on the presence of terms suggesting collaboration	Suggesting collaboration	Not Suggesting collaboration
Number of items	11	1350
Average Vader compound scores	0.3832	0.2319
t-stat	**1.72†**	

*** $p < 0.001$; † $p < 0.1$

The middle part of Table 2 uses the same observations as the top section. Instead, it measures the percentage of topics related to innovation and new products and services. It shows that approximately 5.69% of AI-related topics are on innovation and new products and services, whereas the number for ML is 1.15%. The t-test shows that this difference is statistically significant ($p < 0.001$). Hypothesis 2 is therefore supported.

The bottom part of Table 2 shows that the number of items on collaboration and partnership in ML and AI has been minimal, only 11 out of a total of 1,358 items. That said, the higher score for items related to collaboration at least provides moderate support for Hypothesis 3 at the level of $p < 0.1$ significance.

5. Discussions

This study is dedicated to investigating the roles AI and ML, particularly when it comes to marketing, innovation, collaboration, and firm performance. The study offers a different perspective of looking at those roles. While previous managerial studies consider the use of AI and ML as managerial tools, this study looks at their roles in elaborating market level emotions and sentiments. As this study is part of a larger research agenda that seeks to understand the market value of AI and ML, offering different perspectives to the literature stimulates the discussions in order to understand these phenomena.

In particular, the present article explores market sentiments and the implications of differences in mentioning these terms when communicating with customers. This has been to some extent present in non-academic discussions (e.g. Marr, 2016) but lacking from the management research. Moreover, the context in which the terms as well as substance of AI and ML are used had remained unstudied. For that reason, the result showing that AI is used more often in context of innovation not only adds to our understanding these phenomena, but also could suggests to marketers how should they communicate AI and ML to customers. The results show, additionally, that collaboration in the fields of AI and ML are taken positively by the market. This means that the results of this study show that one benefit for collaboration is the positive market sentiment reaction, and that should be something for the managers to consider.

The results link AI and ML to alternative communication phrases, such as innovation and collaboration. From this research, a perspective is emerging that challenges the idea that it is unimportant when and where to mention AI and ML. This emergent perspective places crucial importance on related words that are communicated along with AI and ML. The view here is that, although the greater proportion of the value from AI and ML may arise from what they do with a product or service, there are nevertheless important aspects of value creation that are derived from communicating these concepts to customers. Furthermore, their mention through dialogue with the market exercises a profound influence on business performance. The emergent perspective holds that the emotion of customers is integral to understanding the value of AI and ML. Similarly, this article affirms that related words should be carefully selected in dialogue with the market.

This research, in addition, imply an opportunity for a methodological tool for theories such as elaboration likelihood theory. If emotions increase likelihood of elaboration, and that has indeed value for marketing purposes, as it is done in this research, one could in fact measure the emotional state in the marketplace. By collecting text, and calculating Vader scores related to different topics, studies that build upon elaboration likelihood theory could rigorously measure the emotional involvement at the market level.

5.1. Theoretical implications

AI and ML are fully researched in technical fields, whereas the managerial and marketing literature has just begun to explore what customers value in the technologies. In particular, there have been limited efforts to understand the technologies in relation to sentiment-related firm performance. When and what should marketers communicate to customers and what is the true value of communicating AI or ML in products and services? Marketing research has focused more on cases where these tools have been used in marketing, whereas the consequences for customer satisfaction of incorporating them have been neglected. The implications of this research for business performance are demonstrated by the fact that customers' more positive sentiments towards a concept lead to popularity and, consequently, enhanced marketing and firm performance. The results show a more positive sentiment towards AI in the marketplace compared to ML, and customers at the market level respond more positively to what is perceived as AI. In addition, this study shows that AI is more prevalent when discussions center on new products and innovation. We also found some evidence that collaboration in these technologies is being positively perceived in the marketplace. Accordingly, this study offers the following contributions to further research on AI in marketing.

First, while both AI and ML are used interchangeably in today's world to explain the same technologies, AI receives more positive emotional feedback from the market. The sentiments in the market lead to enhanced firm performance when AI is incorporated into new products and services. The primary implication is that the incorporation of new concepts generates emotional feedback from the marketplace and the public. The higher the sentiment scores on a concept, the greater the expectations of the public for incorporating the concept into new products and services, and the higher the levels of customer satisfaction.

Second, we observed that higher sentiment scores on a concept (AI, in this case) were related to a greater presence of that concept in discussions on innovation and new products and services. This indicates that incorporating what receives greater positive emotional feedback occurs in practice. In other words, sentiment analysis to measure feelings in the marketplace has the potential to explain the incorporation of certain concepts into new products and services.

Third, this research shows the relevance of sentiment analysis in ascertaining the terms that can be used in communicating new products in the marketplace. Although different terms may be closely related, that does not mean that they trigger the same feelings for future customers of new products and services. Different terms become associated with different topics in the public's minds. Therefore, companies are conscious of the need to use the right terms that are associated with more (emotionally) positive concepts when introducing new products. This research shows the relevance of sentiment analysis in this regard.

Fourth, we have built on elaboration likelihood theory by employing a tool that can measure emotional engagement. Previous literature (Douglas et al., 2008; Morris et al., 2005) suggests that emotional factors can contribute to elaboration likelihood. We demonstrate, at the very least, that these are correlated, because the highly elaborated topics (in this case, AI) show a higher Vader sentiment score, which is a measure of emotional engagement.

The article and the overall perspective developed in this paper suggest that messages (e.g., on AI and ML) carry a significant emotional weight. The setting in which this idea is tested offers a broad line of input for AI and ML into the marketing and management literature. If the ideas presented here survive in other contexts and can be extended in future theory development, we believe we have initiated a foundation on which researchers interested in this topic can build.

5.2. Managerial implications

This study has implications for businesses on how to improve their performance when dealing with products emerged from AI and ML technologies. In particular, we discussed performance that comes from market sentiment towards products. The managerial implication is that, when businesses introduce products that use ML and AI, they should communicate and deliver AI-related aspects of their products. The data point to an understanding that ML is more closely associated with technical complexity, while AI is mostly concerned with technology, innovativeness, and "the future". Additionally, companies can take into consideration that there tends to be positive market sentiments (which can lead to enhanced business performance) towards collaborative efforts in developing AI- and ML-related products. Finally, in practice, modern tools such as the Vader sentiment analysis and API services can be used by companies to gauge the feelings and satisfaction of their customers when new products and services are introduced to the market. These modern tools provide data-driven evidence on the terms and words that are associated with different positive and negative concepts by the public and the marketplace. Practitioners could make use of these tools to measure the emotional weight of different concepts in the entire marketplace. These measurements could, then, shed light on the extent to which these concepts should be used in products, and in the communications about them. As the results of this study show, AI in communication is associated with innovativeness and leads to greater emotional engagement.

Therefore, practitioners should, due to the positive sentiments, consider expanding implementation of AI in their (collaborative) product developments and in their communications on those products. They can do this by asking the questions of whether there is a genuine way of implementing AI and ML in their products. If there is a need or opportunity for collaboration in such implementation, they should know that it would be positively received by market sentiments. As the AI and ML implementation in new products is done, it is important not to forget the importance of the words and terms that are used in communicating the technologies. AI and innovativeness are positively taken by the market sentiments. In addition, companies can employ tools such as Vader by their experts and marketers in order to be up to date about the sentiments of technologies as well as terms. Following that data could give them the opportunity to react in timely manner for implementation of technologies and terms in their products and services, which could benefit both their marketing and firm performance.

5.3. Limitations and outlook

Although this research has an objective that is essentially explorative, and it endeavors to shed light on something that is not covered adequately in the literature, there are certain limitations that could serve as the basis for future research. It is also possible to build on several of the findings presented in the study.

Most research on AI and ML has been dedicated to studying the technologies involved. Nevertheless, the questions of how they are perceived and valued by consumers and how that affects firm performance have received scant attention. As an initial effort, this paper has identified potential for future research by further examining these questions.

The interesting finding with theoretical implications is that sentiments towards ML are found to be neutral. In contrast to AI, ML does not trigger emotions among customers. An attempt to deal with this finding in future research could stimulate new discussions on the connections between AI, ML, sentiments, marketing, and business performance. In future studies, researchers could identify whether, when, and how to use these technological terms in marketing communications.

Collaboration and partnership in introducing new AI- (and ML-) related products are increasingly important topics as managerial studies on AI continue to develop (Penttilä et al., 2020). Although we found minimal support for the notion that such collaborative efforts receive more positive emotional feedback from the market, future studies could explore additional data to engage in a more in-depth investigation of this hypothesis. Collaboration may or may not be a powerful term to incorporate into AI or ML. However, it may also be the case that collaboration, for example, has limited value for customers when used together with AI.

This paper is also limited in its use of only those textual data that are publicly available. However, it is one of only a few studies that have examined, using AI algorithms and methods, how much customers value incorporation of AI and ML into products. Furthermore, the topic of this paper has been limited to measuring sentiment on AI and ML, not specifically the reasons for any difference. Future research could investigate the reasons for such difference and, hence, advice companies how better to deliver what customers expect of the technology.

Future research could also benefit from advances in AI-related methods when analyzing available textual data. Specifically, the wide range of lexicon-based algorithms including Vader and WordNet could contribute to the research on marketing, entrepreneurship, and management in general.

Additionally, as this paper has discussed sentiments and consumer satisfaction, the introduction of AI could impact other constructs in marketing research. The introduction of AI could, for example, impact loyalties, customer engagement, and employer branding. This suggests that more advanced models could be developed and tested. The ideas here should be considered preliminary and rudimentary elements of a new perspective that will uncover further research avenues.

This research has provided evidence of a greater presence of positive sentiments on AI when the discussions center on innovation and new product and services. This could denote that the public uses AI more often when it discusses new products and services. In an attempt to theorize, future research could investigate whether this is the case for all concepts. If the sentiment analysis shows higher scores for a particular term, that indicates that the term is more often the subject of new products and services.

CRediT authorship contribution statement

Ashkan Fredström: Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Vinit Parida:** Conceptualization, Supervision, Validation, Writing – review & editing. **Joakim Wincent:** Conceptualization, Supervision, Validation, Writing – review & editing. **David Sjödin:** Conceptualization, Writing – review & editing. **Pejvak Oghazi:** Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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