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The Role of Machine Learning in Digital Marketing

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Abstract

Artificial Intelligence has been under researched. Machines with deep learning abilities can take digital marketing to new heights with their Artificial Intelligence making all the difference. This research aims to identify the outcomes from the study of Indian customer's responses across varying demographics to machines and their abilities to sell, which will well be the future of digital marketing. We find that software developers need to build the architecture is partnership with digital marketers who use machines with deep learning by taking attitude of the customers, behavior and choices into consideration. This will unlock huge benefits to the companies as accurate information about customers will be easily available to the marketers in future. How the machines are going to perform under various conditions are explained using a causal model using regression models. SPSS version 24 and R software were used for analysing the data and data regarding the customer's behaviors, their choices and emotions are collected and based on fuzzy-set qualitative comparative analysis (fsQCA) approach how they can be influenced to use the services of the machine, fsQCA is used to compare case oriented and variable oriented quantitative analysis.

Keywords

AI, deep learning, digital marketing, machine learning

Introduction

Machine learning is a game-changing technique in digital marketing which records, analyses, and reuses the clicks and the comments about brands learning the emotions relating to the brand. This analysis helps marketers to personalize the sales tools toward individuals empowering the marketers to customize their sales calls to each potential customer. The techniques backed by machine learning helps in enhancing customer's visits by categorizing the various reactions in the form of clicks toward brands engaging them at a much-customized level (Ashley & Tuten, 2015). The massive cache of data created every day is categorized into various sectors and analyzed to establish patterns by deep learning about digital customers helping understand him better (Cambria et al., 2012).

The research identified 1,250 digital customers based on judgmental sampling in India to determine the effectiveness of machine learning in digital marketing on multiple abilities of machines dealing with the customer's behaviors, their choices and emotions.

The distinction between digital and non-digital technologies is not clearly defined (Stefano, 2019). The human behavior is influenced by digital technologies (Williams & Edge, 1996). To transform firm's artificial intelligence and machines learning is extensively used (Nambisan et al., 2017). Input and output both influence the machines learning capacities, outputs which go through continuous improvements (Garud et al., 2008). Digital technologies today mainly are Artificial intelligence and machine learning (Bughin & Hazan, 2017) which transform human lives across the world. Machine learning has redefined the digital marketing changing the way value is created (Magistretti et al., 2019; Ullal et al., 2021). Customers today on digital platforms have options and in this thickly populated marketing where machine learning can help marketers provide customers the right product (Verganti, 2017). Machine learning is a general technology and impacts daily activities (Youtie et al., 2008).

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The existing literature considers machine learning in the field of digital marketing worthy of further research. Companies in digital marketing are seeing new opportunities because of advancements in machine learning (Buganza et al., 2020). This research opens opportunities for customers in services field specifically to digital marketing (Kastalli & Van Looy, 2013). Facebook and Amazon are excellent examples of how machine learning can take the digital marketing to the next level. Starting from connecting people to connecting group of players, from selling books to creating a platform were employers meet employees and vice versa (Trabucchi & Buganza, 2020).

Research Gap

But there exists a gap in literature on how this machine learning impacts the various types of marketing (Gambardella & McGahan, 2010). The research tries to find out how machine learning impacts the digital marketing scene in India. We aim to increase the existing knowledge on machine learning and its resourcefulness in digital marketing (Kaplan & Haenlein, 2019; Vinish et al., 2021) which served as the motivation and need for the study. We try and find the solutions for the questions:

Research Questions:

Questions 1: What are the variables explaining the understanding of the customers about machines in digital marketing.
Question 2: Out of customer's behaviors, their choices and emotions which is more powerful for machine learning backed marketing and sales.

The review of literature throws some crucial questions at us on behaviors of customers their choices and emotions. The research aims to provide answers to these questions. Based on the finding, we identify the needs and roles of a machine in sales and marketing.

Theoretical Background

Customer Attitude Analysis

The findings of the customer's psychology are the basis of any marketing research. The marketers who build strategies based on customers can customize offers and decide the numbers of exposures and timings of ads to close sales (Chen & Lin, 2019; Hawaldar et al., 2019; Pallikkara et al., 2021; Ullal & Hawaldar, 2018; Vinish et al., 2020). There are multiple digital platforms, with each having millions of unique customers, marketers need to identify the right digital platform to reach them with appropriate content and facts (Tsimonis & Dimitriadis, 2014). Understanding the customer's digital life and creating meaning for it is essential for the machines to deliver marketing presentations (Miller, 2018). Online brand communities are significant influencer about how customers spend their money (Kaplan & Haenlein, 2010). Machines can understand the behavior of these communities and classify them on multiple parameters into various clusters such as spending power and their interests. The machines provide information about such communities with deep learning which also analyses their personality, which is built by such communities (Farquhar & Rowley, 2006; Ullal et al., 2020). Machines have multiple analytical tools to analyze digital customers to customize digital ads to customers (Holsapple et al., 2018). The machines collect data on marketing mix, and the stage at which the prospective customers is customizes the ads accordingly (Lee, 2018).

Deep learning by machines goes through various layers of data on customers from being a prospect to an existing customer and this helps to recommend different products to individuals as per the needs of every customer (He et al., 2013). Machines in future can also go to the extent of creating the products assisted by customer's and suggesting decisions on what to buy and when to buy (Bhimani et al., 2019).

Behavior Analysis

Machines are analytical, human-like and personalized (Kaplan & Haenlein, 2019). The analytical aspect of the machine is logical and intelligence-driven decoding the behavior of the online customers, which is driven by big data of the past customer behavior. The current usages of machine learning in India is limited to analytics being used to identify the behavior of the customers. Machines in marketing have not explored beyond the customization of communication and improve upon targeting (Kosinski et al., 2013; Suwajanakorn et al., 2017). The customers in India are exposed to multiple brands daily, and machines backed by Artificial Intelligence work on analyzing the behavior of the customers concerning each brand on digital platforms. The social media is a strong reflection of the likes of the customers and machines crawl through them to identify the likes of the customers concerning brands. The social media serves as big data to the machines regarding the behavior of customers online toward various brands (Capatina et al., 2020). The description of the online behavior could be easily decoded by the machines and recorded for future analysis and usage (Garimella et al., 2016). Automatic tools employed by the machines in sales and marketing can describe the behavior of the customers based on his clicks, likes, and shares. This tells the humans behind the machines as to what are the expectations of the customers based on his online behavior. Tools analyzing the behavior of online customers have been increasingly used due to the machines deep learning abilities (Hinton et al., 2006). The shares and the likes on social media are recognized by the machines (Karpathy & Fei-Fei, 2015). The behavior of the customers concerning retail brands could be analyzed using this behavior online (Ullal & Hawaldar, 2018). The potential of machines with deep learning is much more than how it is used as these can dive deeper to analyze the patterns of clicks, the changes in the patterns and behaviors very well in the future (Bengio, 2009). The research recommends the software developers to build machines with abilities to differentiate between behaviors over time with the categorization of likes based on brands and products.

Further machines can predict the future needs before the customer can themselves identify their own needs, thus assisting the customer in decision making. The machines can also develop algorithms to match the exposure of a brand to the prospect and time the brand is purchased by the customers, thus cross-checking its predictions and matching with behaviors of the customers. The behavior of the customer and the consumption timing has been researched earlier by Vázquez et al. (2014). The exposure of ads, reactions of the customers to the advertisements, and forecasting the sales based on this has been explained by Lassen et al. (2017). The researcher analyzed the conversion percentage of brand exposure to sales. Machines not able to understand the behavior of the customer online based on the likes and shares on social media platforms cannot give the right product ads at the right time, thus not being efficient. The machines trained to catch up on the context and provide a textual description of the behavior is very useful for the brands to position and sell their ads appropriately (Karpathy and Fei-Fei (2015). The prospects are engaged at a higher level by machines which decodes the contexts, and they have to be developed with algorithms which understand the behavior well (Jaakonmäki et al., 2017).

Choice Analysis

Researchers have developed the theoretical framework for analyzing the choices of the customers (Verma et al., 2002). The decisions of the customers could well be categorized into dilemma choice where customers choose the less problematic options, Hobson's choice where the customer decides either one or nothing or Sophie's choice where you choose between two desirable options. Many researchers have combined all the types of choices for a better understanding of the customer. Options depend on sentiments of the customers and performances of the ads can be predicted by the sentimental model (Hawaldar et al., 2019; Liu et al., 2007). The products and the marketers also could be better explained by reviews sentiment analysis (McGlohon et al., 2010). Machines through deep learning are concentrated on choice-based analysis mainly using the social media platforms and the messengers trying to decode the likes, emoticons, etc. (Habernal et al., 2013). Brand equity decides the type of comments that the brands garner (De Vries et al., 2012). The data obtained in the form of comments and likes are categorized into various segments based on the sentiments depicted by the customers. The behavior exhibited by the customer online can be tracked concerning new and existing products (Garimella et al., 2016; Ullal & Hawaldar, 2018). The data provided on digital platforms are vital to foresee the brands' problems that may arise, and this data mined by the customer's choice is quite accurate as customers choose without being conscious of being judged (Mostafa, 2013). The choices the customer makes to like and share brands on social platforms reflecting their choices have had a social perspective (Wang & Li, 2015; Yang et al., 2014). The choices reflect the sentiments which are constantly changing, and marketers can mine the patterns and predict the future based on these patterns in choices.

The data thus mined can be used in digital marketing with precise ad placement and recommendations. Visual attribute paths at a high and low level have been studied previously (Borth et al., 2013; Jia et al., 2012; Ullal et al., 2020; Yang et al., 2014; Yuan et al., 2013). Deep learning has been used less to study the choices and underlying sentiments (You et al., 2015). To analyze the underlying sentiments of the choices made by the customers, some researchers have used cross-modality regression models (You et al., 2016).

Research Design

The Indian customers understanding of the machines backed by Artificial intelligence was researched based on a multi-method approach. India is a diverse country with many cultures and demographic changes. The research used interview methods and surveys to achieve their targets. The interviews tried to find the level of understanding of machine learning through digital marketers. Interview methods are the main source to collect qualitative data in social science, providing information from the participants (Brannen & Pattman, 2005). A total of 110 digital marketers were interviewed for the research coming from different IT hubs across India. The data thus obtained was used to develop questionnaires for the customers who buy online.

Surveys are a very efficient method of research to analyze consumer behavior (Engel & Schutt, 2012). The questions asked from the customers, and the practitioners were broadly divided into behavior and choices based on machine learning-driven by Artificial Intelligence. The respondents were categorized based on their education level and knowledge of machines in marketing. The questionnaire was constructed with a consultation with the experts who were engineers working on Artificial Intelligence in India and South Korea. After that, the questionnaire was sent to digital marketers and social media marketers and digital customers across three cities in India. Out of 1,297 customers and marketers (Figure 3), 47 did not respond.

Linear models were fit to data using iterated weighted least squares method (Dutang, 2017) to analyze the demographic variations about these respondents and to analyze their knowledge about machine learning. The software that will be developed was designed using fuzzy sets a qualitative

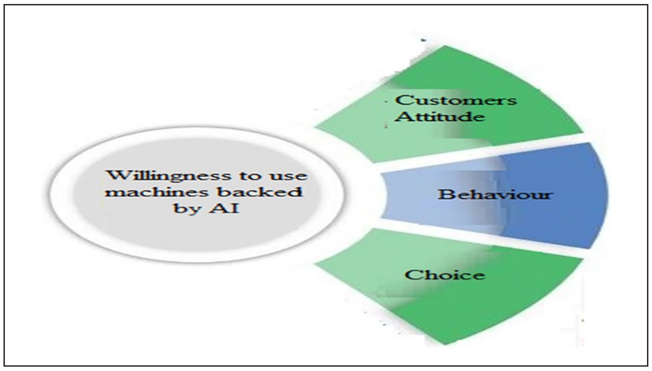

Figure 1. Group of antecedents conditions in machines used in retail affecting the results.
Note. Willing to use Machine backed by AI is driven by Attitude, Behavior, and Choice of the customers.

Table 1. Calibration of Measures.

Measure	Values		Belongingness
Strongly agree	5	1	Complete
Agree	4	0.80	Partially in
Neutral	3	0.60	Boundary
Disagree	2	0.40	Partially out
Strongly disagree	1	0.25	Out

comparative analysis method. The research examined how causal configurations of behavior, and choices lead to the results showing us the customers interest in using machine learning in buying. All the respondents were viewed as sets of causally relevant (Ragin & Fiss, 2008). The causal conditions fuzzy sets qualitative comparative analysis method is matched to identify groups within antecedent conditions (Khedhaouria & Thurik, 2017) based on which we design the capabilities of machines for the future. The machines backed by Artificial intelligence in retail outlets across the world is shown in Figure 1.

The customers were understood based on their shares and likes, their decision making, the ability of the machine to accurately recommend products, analyze the price variations, map previous purchases, identify repeat purchases, etc.

Behavior analysis understands the preferences of the customers concerning various offers, reactions to brands, discounts, etc. machines can identify the places where they buy and relate the shares to the comments and understand their behavior. The choice analysis is used to determine the purchase, the revisits to websites, reaction to new brands launched, and comments to the promotions.

The variables do not have a symmetric relation as India is a diverse country were culture varies every few kilometers. The scores ranged from 0.25 to 1.00 (Table 1) when alternative combinations of casual conditions were used. The calibration was done using one to explain the complete association, other no association and the exact boundary between the two.

We compare our research with the studies across Europe. Initial research on machine learning has been limited to modernizing marketing by transforming businesses across Europe (Bardy et al., 1999). The knowledge discovered has been fed into decision making in marketing (Crone et al., 2006). Europe has been mainly limited to data mining algorithms but not much has been said about how machine learning impacts a specific type of marketing. Our study goes in detail to find how superior are machine backed with deep learning when compared to machines without deep learning and humans.

Demographic Profile

The variables associated with the model for the research question 1 is shown in Figures 2 and 4. Seventy-six percent of the respondents are men. Fifty percent of the participants are below 25 years of age going with the young population of India. Half of them work as digital marketers, and the rest half are regular buyers of digital platforms. The average experience of digital marketers was 5.12, and the standard deviation was 1.91.

Research Methodology

Two variables, attitude and behavior were selected to analyze machine learning:

Digital marketers and customers alike assessing their knowledge of machine learning in their areas which was analyzed through a rating scale from 1 to 5.

How they have used software's of machine learning in selling as a digital marketer and in buying as a customer again measured using rating scale on 1 to 5.

Over 50% of the respondents use machines backed by Artificial intelligence regularly, and 20% never used it. Rest said they use it but not regularly.

The knowledge about machines backed by artificial intelligence was measured through auto evaluation as variable X. X represents ordinal values. We use multiple linear regression to find the linear model between explanatory variables and response variables.

We then compare our findings with the outcomes across Europe on machine learning and do a comparison study.

The research tries to find the relation between X, which is the dependent variable and the other explanatory variables about the demography of variables. The questionnaire categorized these variables, and for other independent variables, a number system is adopted where m levels are changed to $m-1$ variables according to binary levels.

Variables after the numbering system are shown in Table 2. The variables with * are kept the same, and the

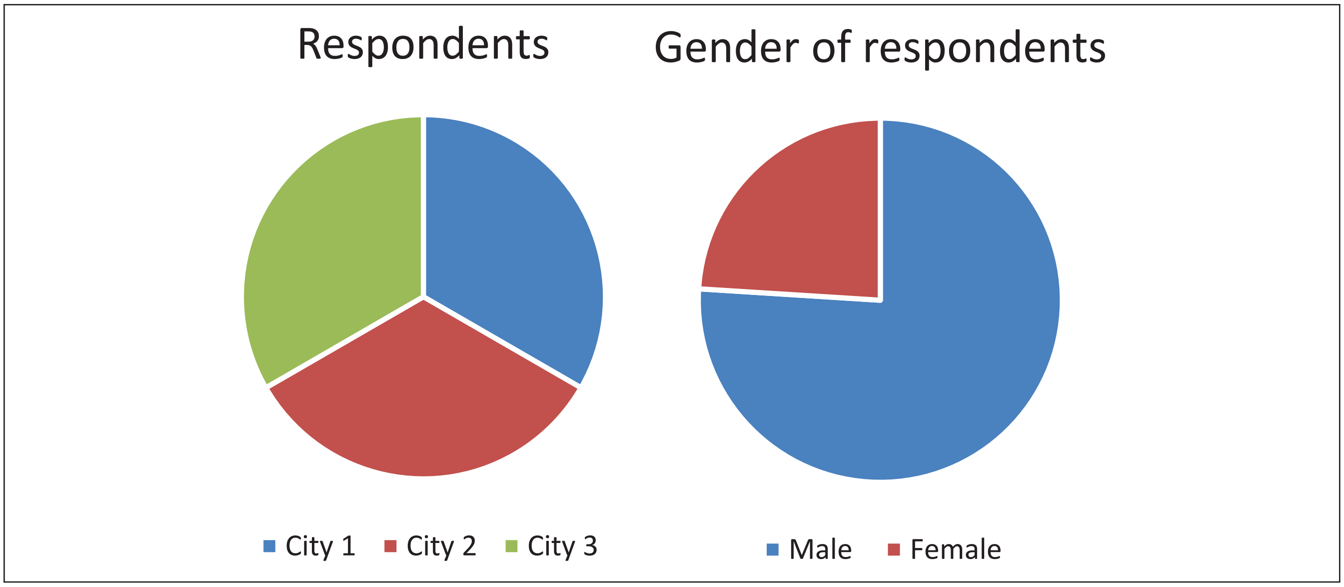

Figure 2. Showing demographic variables and number of the respondents.
Note. Number of respondents and gender split.
City1/City2/City3—33%.
Male/Female—50%.

Table 2. Showing Explanatory Variables After Coding.

Variable	Coding
*X**	Factor w/5 levels 1–5
Male*	Factor w/2 levels "0" "1"
Female**	Factor w/2 levels "0" "1"
Age*	Factor w/2 levels "0" "1"
Age**	Factor w/2 levels "0" "1"
City1*	Factor w/2 levels "0" "1"
City2**	Factor w/2 levels "0" "1"
City3**	Factor w/2 levels "0" "1"
Position*	Factor w/2 levels "0" "1"
Experience*	Factor w/2 levels "0" "1"
Usage*	Factor w/2 levels "0" "1"

variables with ** have been removed. There are 10 fixed explanatory variables which are represented by A_1 to A_{10}. The variable *X* can be denoted by one can say that

$$X = 1 \text{ when } X_* \Sigma_{do;d1,\ldots\ldots\ldots\ldots} X = 4 \text{ when } X_* \Sigma_{d3;d4},$$
$$\text{where } d0 = -\infty \text{ and } d4 = +\infty$$

${}^{d}1, {}^{d}2, {}^{d}3$ represents three unknown coefficients.

Multiple linear regression is used to model *X* where $X = \mu_0 + \mu_1 X_1 + \ldots + \mu_{10} X_{10} + \gamma_1$ where μ_0, μ_1 are unknown coefficients, γ is random variable is a symmetric that has symmetric distribution close to nil. Ordinal regression is used using the models presented by Winship and Mare (1984) and McCullagh (1980). Using the latent variable *X* and considering by knowing that $(A_1, \ldots, A_{10}) = (a_1, \ldots, a_{10}) = x$, we may accept that $X = k$ with $k \Sigma (1, \ldots, 4)$ is shown by

$$P_k(A) = P\Big((X = k)\big((A_1 A_{10}) \;= a\big)\Big)$$
$$= F\gamma\Big(d_k\big(\mu_0 + {}_1\mu x_{1+\ldots 10}\mu x_{10}\big)\Big)$$
$$F\gamma\Big(d_{k1}\big(\mu_0 + {}_1\mu x_{1+\ldots 10}\mu x_{10}\big)\Big)$$

The conditional probability is denoted by *P* and $F\gamma$ denotes the cumulative distribution function of the random variable γ. The γ is accepted to follow the logistic distribution. The unknown coefficients are $A_1 - \mu_0, \ldots A_{10} \ldots \mu_{10}$ by likelihood estimation method. R software is used to obtain numerical values.

The prediction is explained in Table 3, along with Wald tests that test the significance of the explanatory of the variables *X* are performed. Statistical tests are shown by *t*-value, and *p*-value shows the following *p*-values. Residual deviance and AIC are 192.113 and 203.114. The next rows show the predictions for $d_1 - \mu_0$, $d_2 - \mu_0$, and $d_3 - \mu_0$. The most significant variables are the frequency of use of machine learning, the number of years as a digital marketer, and number of years since they are buying online. The outcomes-based on predictions are fixed variables, as shown in Table 2. Fisher test shows the dependency among *X* and fixed variables.

Tables 4 to 6 shows the crossed results showing the *p*-value is $<.0001$ proving dependency between *X* and fixed variables. Spearman's rank correlation test proves *x* and frequency of usage. Digital marketers with knowledge on machine learning along with online buyers who know machine learning are those who frequently use it as a digital marketer and digital buyer.

Table 3. Showing the Predicted Outcomes of Parameters for the Model.

Variable	Value	Std. error	*t*-Value	*p*-Value
Male	−0.2937	0.3974	−0.6875	4.132-01
Age	−0.4112	0.4895	−0.7629	4.1456e-01
City 2	−0.3019	0.4165	−0.6756	4.1567e-01
City 3	1.0172	0.4765	2.1278	7.8453e-03
Position	−0.1925	0.3986	−0.3956	7.4329e-01
Experience	−1.0276	0.5976	−2.0125	1.8356e-02
Usage	−4.8346	0.6875	−6.9879	2.8564e-13
1/2	−5.6274	0.8745	−5.9856	1.7886e-10
2/3	−3.1897	0.7186	−4.0137	3.1504e-06
3/4	0.3678	0.6845	0.5170	5.1243e-01

Table 4. Contingency Matrix for *X* and Cities.

	City 1	City 2	City 3
1	11	16	5
2	7	6	6
3	17	15	19
4	8	5	16

Table 5. Contingency Matrix for *X* and Experience.

	0–2	2–5	>5
1	102	110	86
2	116	117	76
3	84	116	111
4	115	141	76

Experience in years.

Table 6. Contingency Matrix for *X* and Usage Frequency.

	1	2	3	4	5
1	5	28	6	5	5
2	3	5	5	10	1
3	1	1	4	21	21
4	1	2	1	4	30

Proportions to solve the research question no. 2.

P1. The patterns of originator circumstances which are situation, choice, and behavior in our research demonstrate similarity with future machines backed by Artificial intelligence features.

P2. The causal relationship that represents the testing of machine learning is varying greatly across all different cities within India. AIS obtained by Fuzzy set values of antecedent conditions in the conceptual model obtained by the fuzzy sets qualitative comparative analysis software. On testing the consistency on the AX graph in Figures 5 to 7 showing samples across Indian cities.

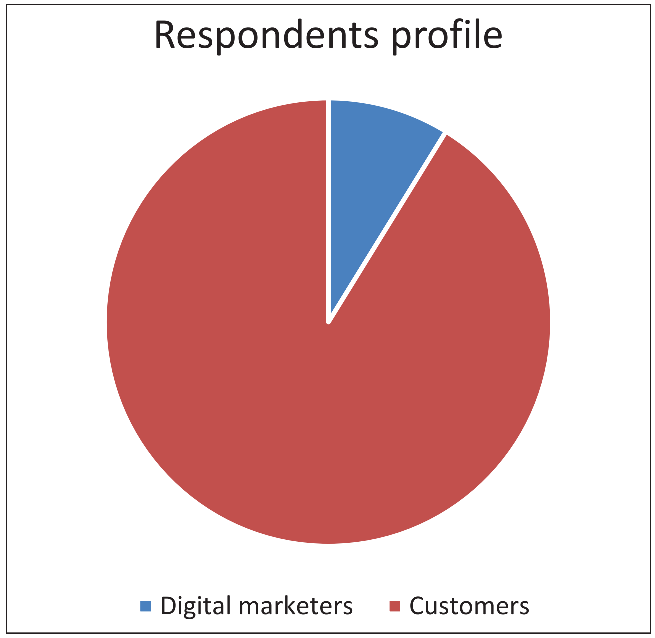

Figure 3. Professional profile of respondents.
Note. Number of respondents by occupation.
Digital marketers—90%.
Customers—10%.

The outcomes of the graphs of the samples across first city show that originator circumstances achieve the results in all cities across India as the bulk of the cases are above the diagonal in AX graph however some exceptions are there. The scores represent that the points on the figures are consistent with the assertions of our study, which says the respondents' perceptions are the same at a part of our outcome. Originator circumstance *s* coverage is 19.28%.

The second city represented in Figure 6 has a consistency score of 0.98, and the coverage score is 0.132. This indicates that the scattering of fuzzy sets is the same as the initial assertion in our study. The thirds Indian city the consistency score was 0.891 and the coverage score was at 0.148. The scores show that the fuzzy sets are consistent with the studies

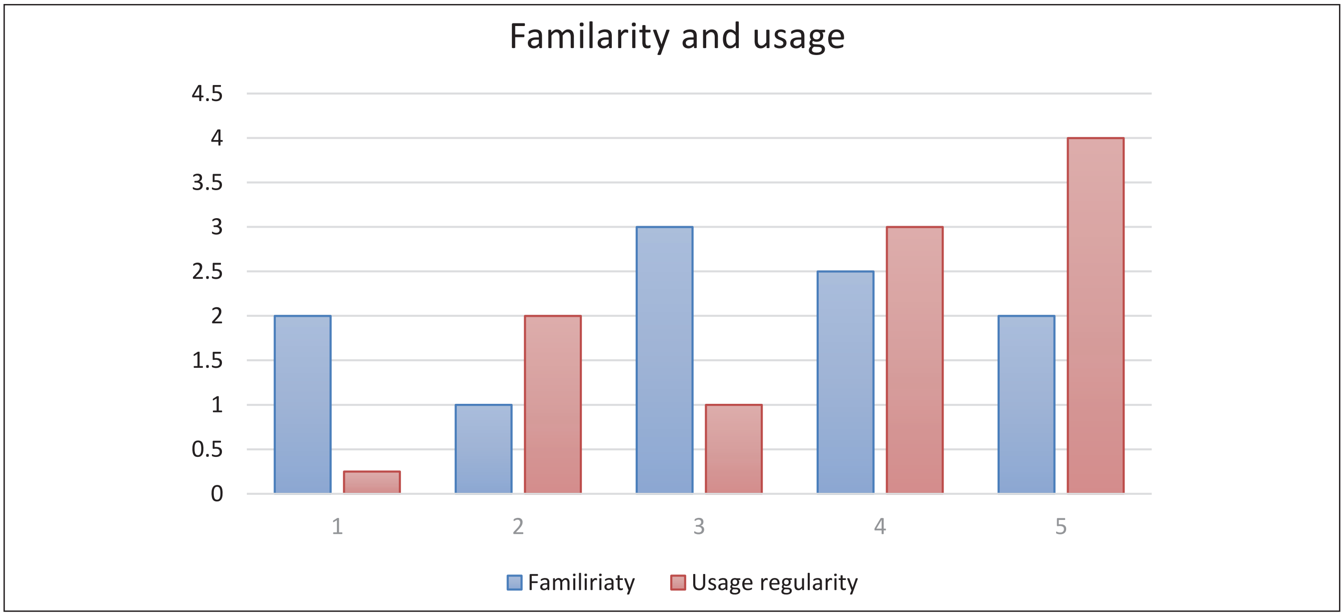

Figure 4. Showing the familiarity toward machine learning and usage regularity among respondents.

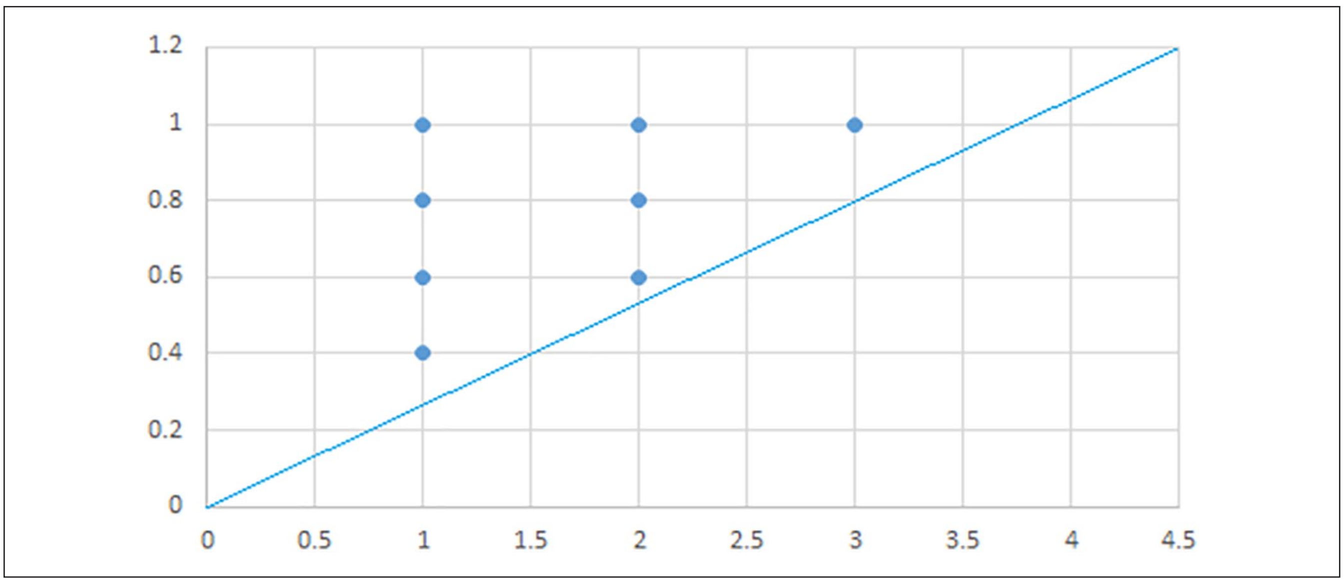

Figure 5. Showing City 1 fuzzy sets.

assertions with originator circumstances lead to the results, as shown in Figure 7.

The third city had multiple outlines affecting the results. The outcomes show the characteristics of the machines for the future as to how they should be. In the first Indian city, the machines identifying the patterns of the behaviors of the customers are found to be more capable than choice and attitude identifying capabilities. All the paths of antecedent conditions lead us toward the outcome proving the similarity principle, as shown in Table 7. The antecedent conditions are represented by α, and no antecedent's conditions are represented by α_1 (Fiss, 2007; Pappas et al., 2016). Blank spaces show irrelevance. All the consistency achieved are higher than the inception score of 0.60. The scores of consistencies in case of invalid outcomes are below the inception score of 0.60.

The second Indian city the choices analysis capabilities of the machines were more influential than the abilities of the machines to predict behavior and analyze attitudes. The similarity is shown by the multiple combinations leading to the outcome, as shown in Table 8.

The third Indian city shows that attitude analyzing aspect of the machines is more important than behavior and choice analysis, as shown in Table 9. The quine-McCluskey

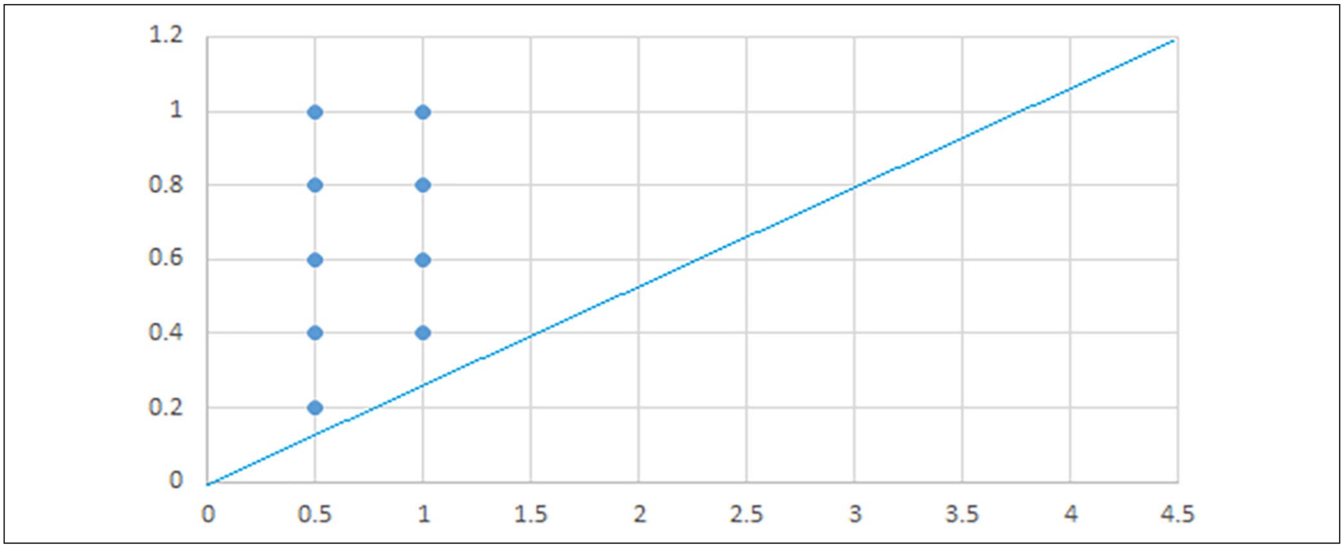

Figure 6. Showing City 2 fuzzy sets.

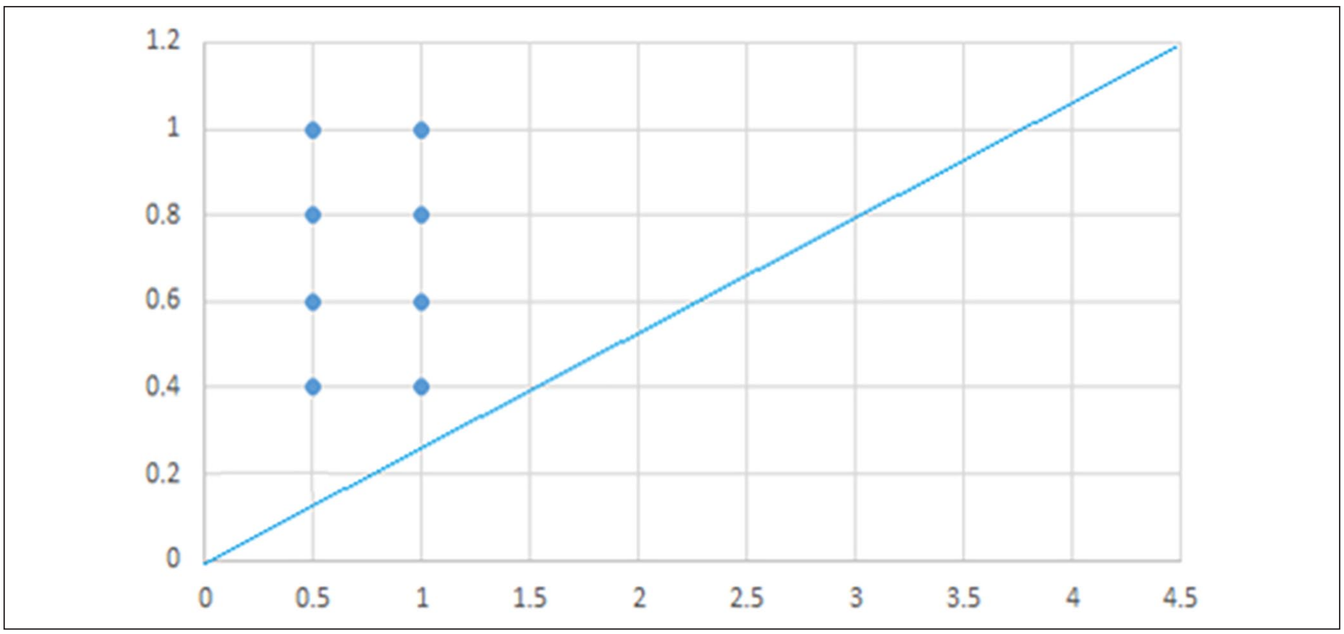

Figure 7. Showing City 3 fuzzy sets.

algorithm was used in all the three cities analysis by the research.

The similarity, however, is not proved as only one aspect of the machines is leading us to the outcome with scores above the inception. The first proposition is partially supported, as the configurations of the originator circumstances show similarity with curiosity to use machines backed by Artificial intelligence for the first and the second Indian cities. Still, the same does not hold good for the third Indian city. The second suggestion, however, is reinforced as the causal procedures to test the abilities of the machine are varying across the cities. To sum up, the behavior has more effect than attitude and choice has in the first Indian city. In comparison, choice analysis has more impact than attitude and behavior in second India city and attitude analysis by machines for the third city.

Findings, Implications, and Future Research

The result for machines with deep learning for digital marketing is its capabilities to sell based on its competences which are superior to other machines and humans. The outcomes from multiple Indian cities suggest that a deep

Table 7. Causal Procedures for Willingness to Use Machine Learning Software's in City 1.

	Willing		Non-willing	
Configurations	1	2	1	2
Behavior-based capabilities	A	A	α_1	α_1
Customer attitude-based capabilities		α_1		α_1
Choice-based capabilities	α_1		α_1	
Consistency	0.75	0.72	0.29	0.31
Coverage	0.71	0.67	0.82	0.87
Single coverage	0.02	0.01	0.01	0.01
Outcome consistency	0.74		0.26	
Outcome coverage	0.76		0.86	

Table 8. Causal Procedures for Willingness to Use Machine Learning Software's in City 2.

	Willing		Non-willing	
Configurations	1	2	1	2
Behaviour-based capabilities	α_1	α_1	α	
Customer attitude-based capabilities		α_1		A
Choice-based capabilities	α			A
Consistency	0.73	0.71	0.52	0.57
Coverage	0.76	0.74	0.34	0.21
Single coverage	0.02	0.01	0.1	0.01
Outcome consistency	0.73		0.62	
Outcome coverage	0.78		0.36	

Table 9. Causal Procedures for Willingness to Use Machine Learning Software's in City 3.

	Willing		Non-willing	
Configurations	1	2	1	2
Behavior-based capabilities	α_1		α	
Customer attitude-based capabilities	α			α
Choice-based capabilities			α_1	α_1
Consistency	0.74		0.61	0.60
Coverage	0.76		0.31	0.32
Single coverage	0.03		0.01	0.01
Outcome consistency	0.72		0.43	
Outcome coverage	0.71		0.45	

machine learning used for digital marketing will perform better than the existing practices in digital marketing.

Research in the field of machines with deep learning capabilities show that in the first city machines could accurately tell the places of future purchase with timings and also had the ability to correlate the sales with number of purchases that is frequency with which the advertisements were shown representing the causal procedures that help us construct the behavior analysis for the future in machines with deep learning that will be invented. The second city the capabilities of the machines to categorize customer likes and shares with their comments reflecting their sentiments while shopping online and the capabilities to analyze the reactions to new products launched on digital platforms show the causal procedures that help us construct the capabilities of the machines to analyze the customer's choices in the future. Similarly, in the third Indian city, the customer's attitude was analyzed, and it helps us build the capabilities in the machines to identify the attitude of the customers in the future. The demographic variations and the professions of the marketers do not significantly affect the awareness levels of machine learning in the jobs of the respondents. The cities the respondents reside in can explain how the usage of machine learning software's is affected in their professions. In comparison to existing, literature which only tells about how machine learning is important but does not tell how it impacts specific areas of marketing, our results clearly show the impact of machine learning on digital marketing. The previous literature does not give us inputs into areas as to how machine learning will affect digital marketing, our findings specifically show what capabilities should be built in the machines and the various dimensions on which it has to be developed. Our findings shows that the time and place of sales in future could be predicted which is not discussed in any of the literatures before.

The future researchers can compare digital marketing by machine learning with traditional forms of marketing and find new outcomes which will be beneficial to practitioners.

Conclusion

We can conclude that the cultural issue within the country is very crucial in the assessment of awareness of machine learning. The job of the customers affects the acceptance of machine learning among the respondents. All the respondents in the research can be customers of machine learning in the future. The study also guides the software engineers developing machine learning to develop models for cross-cultural and professional profiles.

The bottlenecks in developing machine learning could be avoided by beta testing collecting the user experience to refine the development process further. The developers, however, develop the software in consultation with the digital marketers focusing on assessing the customer's attitude, behavior, and choices (Capatina et al.). Making digital marketing more accurate and effective will bring huge benefits as researched by Phillips and Linstone (2016) and Paul (2018), Soriano (2010).

Implications

The implication of our research is that software engineers in future can develop machine learning software's must imbibe culture and profession of users into the algorithms. The marketers can use this to predict and analyze trends never seen before. The machine learning in digital marketing will definitely outperform machines without deep learning and humans. Practitioners can use the outcomes for behavior analysis, to predict future sales and customer attitude could be analyzed.

Limitations

The limitations are that the research was limited to 1,250 respondents from three metro cities of India which limits the generalizability of our findings. The study also limits itself to behavior, customer attitude, and choice analysis to test the machine learning capabilities.

Author Contributions

The research aims to find the impact of machine learning in digital marketing. It aims to provide an insight to marketers on how superior they are to humans and how this competency of machine could be leveraged. The research will help companies in the future to understand the importance of machine learning, which can accurately predict the time and place of purchase, thus help marketers in advertising the right product at the right time. Also, the paper gives the advantages of investing in AI.

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References

Ashley, C., & Tuten, T. (2015). Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement. *Psychology and Marketing*, *32*(1), 15–27.

Bardy, B. G., Marin, L., Stoffregen, T. A., & Bootsma, R. J. (1999). Postural coordination modes considered as emergent phenomena. *Journal of Experimental Psychology: Human Perception and Performance*, *25*(5), 1284.

Bengio, Y. (2009). Learning deep architectures for AI. Foundations and trends. *Machine Learning*, *2*(1), 1–127.

Bhimani, H., Mention, A. L., & Barlatier, P. J. (2019). Social media and innovation: A systematic literature review and future research directions. *Technological Forecasting and Social Change*, *144*, 251–269.

Borth, D., Ji, R., Chen, T., Breuel, T., & Chang, S. F. (2013, October). *Large-scale visual sentiment ontology and detectors using adjective-noun pairs* [Conference session]. Proceedings of the 21st ACM International Conference on Multimedia, Barcelona, Spain (pp. 223–232). ACM.

Brannen, J., & Pattman, R. (2005). Work-family matters in the workplace: The use of focus groups in a study of a UK social services department. *Qualitative Research*, *5*(4), 523–542.

Buganza, T., Trabucchi, D., & Pellizzoni, E. (2020). Limitless personalisation: The role of big data in unveiling service opportunities. *Technology Analysis and Strategic Management*, *32*(1), 58–70.

Bughin, J., & Hazan, E. (2017). *The new spring of artificial intelligence: A few early economies*. VoxEU.org.

Cambria, E., Grassi, M., Hussain, A., & Havasi, C. (2012). Sentic computing for social media marketing. *Multimedia Tools and Applications*, *59*(2), 557–577.

Capatina, A., Kachour, M., Lichy, J., Micu, A., Micu, A. E., & Codignola, F. (2020). Matching the future capabilities of an artificial intelligence-based software for social media marketing with potential users' expectations. *Technological Forecasting and Social Change*, *151*, 119794.

Chen, S. C., & Lin, C. P. (2019). Understanding the effect of social media marketing activities: The mediation of social identification, perceived value, and satisfaction. *Technological Forecasting and Social Change*, *140*, 22–32.

Crone, E. A., Wendelken, C., Donohue, S., van Leijenhorst, L., & Bunge, S. A. (2006). Neurocognitive development of the ability to manipulate information in working memory. *Proceedings of the National Academy of Sciences*, *103*(24), 9315–9320.

De Vries, L., Gensler, S., & Leeflang, P. S. (2012). The popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing*, *26*(2), 83–91.

Dutang, C. (2017). *Some explanations about the IWLS algorithm to fit generalized linear models*. https://hal.archives-ouvertes.fr/hal-01577698/document

Engel, R. J., & Schutt, R. K. (2012). *The practice of research in social work*. SAGE.

Farquhar, J., & Rowley, J. (2006). Relationships and online consumer communities. *Business Process Management Journal*, *12*(2), 162–177.

Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of Management Review*, *32*(4), 1180–1198.

Gambardella, A., & McGahan, A. M. (2010). Business-model innovation: General purpose technologies and their implications for industry structure. *Long Range Planning*, *43*(2–3), 262–271.

Garimella, V. R. K., Alfayad, A., & Weber, I. (2016, May). *Social media image analysis for public health* [Conference session]. Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San Jose, CA (pp. 5543–5547). ACM.

Garud, R., Jain, S., & Tuertscher, P. (2008). Incomplete by design and designing for incompleteness. *Organization Studies*, *29*(3), 351–371.

Habernal, I., Ptáček, T., & Steinberger, J. (2013). *Sentiment analysis in Czech social media using supervised machine learning* [Conference session]. Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, Atlanta, GA (pp. 65–74). Association for Computational Linguistics.

Hawaldar, I. T., Ullal, M. S., Birau, F. R., & Spulbar, C. M. (2019). Trapping fake discounts as drivers of real revenues and their impact on consumer's behavior in India: A case study. *Sustainability*, *11*(17), 4637. https://doi.org/10.3390/su11174637

He, W., Zha, S., & Li, L. (2013). Social media competitive analysis and text mining: A case study in the pizza industry. *International Journal of Information Management*, *33*(3), 464–472.

Hinton, G. E., Osindero, S., & Teh, Y. W. (2006). A fast learning algorithm for deep belief nets. *Neural Computation*, *18*(7), 1527–1554.

Holsapple, C. W., Hsiao, S. H., & Pakath, R. (2018). Business social media analytics: Characterization and conceptual framework. *Decision Support Systems*, *110*, 32–45.

Jaakonmäki, R., Müller, O., & Vom Brocke, J. (2017, January). *The impact of content, context, and creator on user engagement in social media marketing* [Conference session]. Proceedings of the 50th Hawaii International Conference on System Sciences, Hawaii.

Jia, J., Wu, S., Wang, X., Hu, P., Cai, L., & Tang, J. (2012, October). *Can we understand van Gogh's mood? Learning to infer effects from images in social networks* [Conference session]. Proceedings of the 20th ACM International Conference on Multimedia, Nara, Japan (pp. 857–860). ACM.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, *53*(1), 59–68.

Karpathy, A., & Fei-Fei, L. (2015). *Deep visual-semantic alignments for generating image descriptions* [Conference session]. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 3128–3137). IEEE.

Kastalli, I. V., & Van Looy, B. (2013). Servitization: Disentangling the impact of service business model innovation on manufacturing firm performance. *Journal of Operations Management*, *31*(4), 169–180.

Khedhaouria, A., & Thurik, R. (2017). Configurational conditions of national innovation capability: A fuzzy set analysis approach. *Technological Forecasting and Social Change*, *120*, 48–58.

Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, *110*(15), 5802–5805.

Lassen, N. B., la Cour, L., & Vatrapu, R. (2017). Predictive analytics with social media data. In L. Sloan & A. Quan-Haase (Eds.), *The SAGE handbook of social media research methods* (pp. 328–340). SAGE.

Lee, I. (2018). Social media analytics for enterprises: Typology, methods, and processes. *Business Horizons*, *61*(2), 199–210.

Liu, J., Cao, Y., Lin, C. Y., Huang, Y., & Zhou, M. (2007, June). *Low-quality product review detection in opinion summarization* [Conference session]. Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL), Prague (pp. 334–342). Association for Computational Linguistics.

Magistretti, P. J., Geisler, F. H., Schneider, J. S., Li, P. A., Fiumelli, H., & Sipione, S. (2019). Gangliosides: Treatment avenues in neurodegenerative disease. *Frontiers in Neurology*, *10*, 859.

McCullagh, P. (1980). Regression models for ordinal data. *Journal of the Royal Statistical Society*, *42*(2), 109–127.

McGlohon, M., Glance, N., & Reiter, Z. (2010, May). *Star quality: aggregating reviews to rank products and merchants* [Conference session]. Fourth International AAAI Conference on Weblogs and Social Media, Washington DC.

Miller, D. (2018). Digital anthropology. In F. Stein, S. Lazar, M. Candea, H. Diemberger, J. Robbins, A. Sanchez & R. Stasch (Eds.), *The Cambridge encyclopedia of anthropology*. University of Cambridge.

Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. *Expert Systems with Applications*, *40*(10), 4241–4251.

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. *MIS quarterly*, *41*(1), 223–238.

Pallikkara, V., Pinto, P., Hawaldar, I. T., & Pinto, S. (2021). Impulse buying behaviour at the retail checkout: An investigation of select antecedents. *Business: Theory and Practice*, *22*(1), 69–79. https://doi.org/10.3846/btp.2021.12711

Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2016). Explaining online shopping behavior with fsQCA: The role of cognitive and affective perceptions. *Journal of Business Research*, *69*(2), 794–803.

Paul, J. (2018). Toward a 'masstige' theory and strategy for marketing. *European Journal of International Management*, *12*(5–6), 722–745.

Phillips, F., & Linstone, H. (2016). Key ideas from a 25-year collaboration at technological forecasting & social change. *Technological Forecasting and Social Change*, *105*, 158–166.

Ragin, C. C., & Fiss, P. C. (2008). Net effects analysis versus configurational analysis: An empirical demonstration. *Redesigning Social Inquiry*, *240*, 190–212.

Soriano, D. R. (2010). Management factors affecting the performance of technology firms. *Journal of Business Research*, *63*(5), 463–470.

Di Stefano, C. (2019). *Configurations of masculinity*. Cornell University Press.

Suwajanakorn, S., Seitz, S. M., & Kemelmacher-Shlizerman, I. (2017). Synthesizing Obama: Learning lip sync from audio. *ACM Transactions on Graphics*, *36*(4), 1–13.

Trabucchi, D., & Buganza, T. (2020). Fostering digital platform innovation: From two to multi-sided platforms. *Creativity and Innovation Management*, *29*(2), 345–358.

Tsimonis, G., & Dimitriadis, S. (2014). Brand strategies in social media. *Marketing Intelligence & Planning*, *32*(3), 328–344.

Ullal, M. S., & Hawaldar, I. T. (2018). Influence of advertisement on customers based on AIDA model. *Problems and Perspectives in Management*, *16*(4), 285–298. https://doi.org/10.21511/ppm.16(4).2018.24

Ullal, M. S., Hawaldar, I. T., Mendon, S., & Joseph, N. R. (2020). The effect of artificial intelligence on the sales graph in Indian market. *Entrepreneurship and Sustainability Issues*, *7*(4), 2940–2954. https://doi.org/10.9770/jesi.2020.7.4(24)

Ullal, M. S., Spulbar, C., Hawaldar, I. T., Popescu, V., & Birau, R. (2021). The impact of online reviews on e-commerce sales in India: A case study. *Economic Research-Ekonomska Istraživanja*, *34*(1), 2408–2422. https://doi.org/10.1080/1331677X.2020.1865179

Vázquez, S., Muñoz-García, Ó., Campanella, I., Poch, M., Fisas, B., Bel, N., & Andreu, G. (2014). A classification of user-generated content into consumer decision journey stages. *Neural Networks*, *58*, 68–81.

Verganti, R. (2017). Design thinkers think like managers. *She Ji: The Journal of Design, Economics, and Innovation*, *3*(2), 100–102.

Verma, R., Plaschka, G., & Louviere, J. J. (2002). Understanding customer choices: A key to successful management of hospitality services. *Cornell Hotel and Restaurant Administration Quarterly*, *43*(6), 15–24.

Vinish, P., Pinto, P., Hawaldar, I. T., & Pinto, S. (2020). Impulse buying behavior among female shoppers: Exploring the effects of selected store environment elements. *Innovative Marketing*, *16*(2), 54–70. https://doi.org/10.21511/im.16(2).2020.05

Vinish, P., Pinto, P., Hawaldar, I. T., & Pinto, S. (2021). Antecedents of behavioral intention to use online food delivery services: An empirical investigation. *Innovative Marketing*, *17*(1), 1–15. https://doi.org/10.21511/im.17(1).2021.01

Wang, Y., & Li, B. (2015, November). *Sentiment analysis for social media images* [Conference session]. 2015 IEEE International Conference on Data Mining Workshop (ICDMW), Atlantic City, NJ (pp. 1584–1591). IEEE.

Williams, R., & Edge, D. (1996). The social shaping of technology. *Research Policy*, 25(6), 865–899.

Winship, C., & Mare, R. D. (1984). Regression models with ordinal variables. *American Sociological Review*, *49*, 512–525.

Yang, Y., Jia, J., Zhang, S., Wu, B., Chen, Q., Li, J., Xing, C., & Tang, J. (2014, June). *How do your friends on social media disclose your emotions?* [Conference session]. Twenty-Eighth AAAI Conference on Artificial Intelligence. AAAI-14 Quebec, Cananda.

You, Q., Luo, J., Jin, H., & Yang, J. (2015, February). Robust image sentiment analysis using progressively trained and domain transferred deep networks [Conference session]. *Twenty-ninth AAAI conference on artificial intelligence*. AAAI-15 Texas.

You, Q., Luo, J., Jin, H., & Yang, J. (2016, February). *Cross-modality consistent regression for joint visual-textual sentiment analysis of social multimedia* [Conference session]. Proceedings of the Ninth ACM International Conference on Web Search and Data Mining (pp. 13–22). ACM.

Youtie, J., Iacopetta, M., & Graham, S. (2008). Assessing the nature of nanotechnology: can we uncover an emerging general purpose technology? *The Journal of Technology Transfer*, *33*(3), 315–329.

Yuan, J., Mcdonough, S., You, Q., & Luo, J. (2013, August). *Sentribute: Image sentiment analysis from a mid-level perspective* [Conference session]. Proceedings of the Second International Workshop on Issues of Sentiment Discovery and Opinion Mining (p. 10). ACM.