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Study Of Social Media Marketing And Purchase Intention Of Apparels Through Machine Learning Algorithms

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Abstract:
Aim/purpose – Consumers are showing interest in digital marketing tools that augment purchase intention (PI). Among several products, apparels are well-known for its own creativity and fashionable brands and the increasing rate of purchase also augments economic condition of the country. The present investigation aimed to predict PI as per dataset of Social Media Marketing Activities (SMMA) viz. Facebook (FB) add (advertisement), other social media (SM) add, short message service (SMS) add and online add among consumers who visited organized apparel sector in eastern India.
Design/methodology/approach – The forecast of PI through machine learning algorithm modelling plays an important role in recent days. In the present study, 599 datasets of consumers as per categorization of Likert scale in which 14 algorithms were selected by using WEKA tool.
Findings – The better performance accuracy predicted that three models followed by other eight models as per training and testing dataset. The PI has cumulative effect when these four SMMA viz. FB add, other SM add, SMS add and online add are functioning at a time.
Research implications/limitations – As per the study methods, a limitation of the research attributes viz. FB add, other platform, adv., SMS adv. and online adv. are focused on SMMA, without consideration of each platform adv. being used as Twitter, YouTube, Instagram, etc. Each platform along with FB may provide better data accuracy on machine learning algorithms. Other limitation observed is small number of respondents (599 nos.) and the study was carried out only in one region of India.
Originality/value/contribution – The findings showed that performance accuracy of PI of apparel products through the influence of SMMA was much better as per ML algorithms in the Eastern part of India.

Keywords: social media marketing activities, digital marketing, apparel products, purchase intention prediction; machine learning modelling
JEL Classification: C1, C6, C8.

1. Introduction

In a revolutionized way, e-commerce can be done through internet especially for marketing and several organizations such as “google.com”, “yahoo.com”, “amazon.com”, “alibaba.com”, and “youtube.com”, etc. are supporting the selling and buying of the products (Bala & Verma, 2018). In a review, Bala & Verma (2018) mentioned that trade and commerce may be benefited from “Digital Marketing” through several attributes like optimization of “search engine”, “promotional tools”, “marketing contents and its automation”, “marketing influencers”, “marketing of e-commerce”, “marketing strategy”, and “marketing through social media” (SM). Moreover, the optimization of SM, it was established that e-mail, short message service (SMS), display of online advertisement, e-books, optical disks, games, etc. are more potent online contents in recent advanced technology for direct marketing (John et al., 2017; Yadav & Rahman, 2017). According to Suchacka & Chodak (2016), online-stores are replacing the physical stores through digital marketing approach. In another research by Kujur & Singh (2017) mentioned about YouTube, which is the most important social networking site (SNS) where buyers can be permitted to view, upload, put remarks, and connect to videos on the site related to brands. According to them, an emotional appeal is being made to buy the promotional products through YouTube advertisements and the promotional activities of big brands enriched the market in India. Kujur & Singh (2020) studied on a conceptual model, which was based on the "consumer-brand relationship" and this has potential impact of visual communications among buyers though SNS.

The apparel products have shorter life cycles and higher product turnover. In this context, the consumer's purchase intention (PI) is showing contrasting attitude on apparel products in SM (Prasad, 2014; Kunwar, 2017; Parsons, 2019). In national and international studies, it was reported that online marketing of products induces the PI among consumers (Bauer et al., 2005; Kujur & Singh, 2017; 2018; Enginkayaa & Cinarb, 2018; Seippel, 2018; Jaya Singh, 2019; Kujur & Singh, 2020). Seippel (2018) explained that the scope of on-line purchasing activities is higher than physical visit to stores for buying apparels. Few studies find the impact of digital marketing or SMMA on the apparel sectors related to PI among consumers (Stephenson, 2009; Ahmad et al., 2015; Seippel, 2018; Sarkar, 2019; Sharma et al., 2021).

Moreover, to predict the PI of products through on-line shopping among consumers for which researchers are showing interest to investigate through e-commerce or digital platform activities (Lo et al., 2014; Lee et al., 2015; Korpusik et al., 2016; Tan et al., 2016; Suchacka & Templewski, 2017; Lang & Rettenmeier, 2017; Seippel, 2018; Avudaiappan et al., 2020; Yoganarasimhan, 2020). The prediction of PI for apparels can easily be done through machine learning (ML) algorithm modelling (Seippel, 2018; Ebrahimi et al., 2022; Satu & Islam, 2023). The present study was attempted to predict PI through ML algorithm modelling as per dataset of SMMA viz. FB add, other SM add, SMS add and online add among consumers who visited organized apparel sector in eastern India.

2. Literature review based on theoretical framework

2.1 Social media marketing activities and purchase intention

Cultural aspects may influence buyers through the usage of SNS and an extraordinary effect on buying intentions through online mode (Pookulangaran & Koesler, 2011). The targeted brand interaction in SM is seen contrastingly by shoppers, which depends upon the message they communicate (Shin, 2008). The use of SM has become immensely popular related to the digital marketing and the communities who have digitally converted as buyers and retailers with wider access to information, better SNS, and increased correspondence skills (Kucuk & Krishnamurthy, 2007). While Kozinets et al. (2010) reported that SM websites provided a platform for the people in which easy access to product information facilitated buying decisions. From earlier research it was seen that online business or e-commerce should be possible through SM, and it empowers to arrive more purchasers. Because of the advantages of SM is associating organizations straightforwardly to end-buyers, in a short period and cost-effective manner (Kaplan & Haenlein, 2010). It is a great time for all kinds of businesses to adopt SM and take it seriously (Neti, 2011). SMMA plays as a marketing tool used by billions of people. According to Mangold & Faulds (2009), SM has helped biased consumers' behaviour from data securing to post-purchase behaviour viz. disappointment, explanations or behaviours about a product or an organization. It was known that the shopping has consistently been a euphoric encounter and SNS permits customers to interface with people through online mode. eMarketer (2018) has mentioned about worldwide communication through SM, the entire data of SM active people is projected to predict about 3.29 billion in 2022 that is supposed to be 42.3% of the global communities. The worth of SM for promotion, which is reported by Trusov et al. (2009) and Stephen & Galak (2012) and they established regarding specific types of social communications that affect significant marketing results to allure consumers and thereby increasing sale. However, the importance of advertising on SM endures to be recently discovered (Gordon et al., 2019), and the way it communicates with another form of media like television (Fossen & Schweidel, 2017; 2019) that helps in the acceptance of product through the dispersal of info mechanisms (Hennig-Thurau et al., 2015). Old-style SM has amplified their platforms to deliver a wider collection of purposes and amenities (Cheng, 2017; Chowdry, 2018). Haenlein (2017) and Haenlein & Libai (2017) defined invisible customer relation management (CRM) as upcoming events that will enhance consumer commitment simple and easily reachable. Kujur & Singh (2020) suggested a conceptual model based on the "consumer-brand relationship" via visual communications of customers on corporate SNS. This was concerned about SEM, which authenticated the visual effect concerning the content related to information, entertainment, and price for consumer engagement to regulate the consumer-brand relationship (Reinartz et al., 2019).

2.2 Social media marketing activities through Facebook

SM always confirms a keeping relationship between the retailers and its customers in which customers often visit or communicate about the brands as per loyalty and they are showing interest on some advice by friends and family (Baird & Parasnis, 2011). An interesting part in SM is termed as "word of mouse" from "word of mouth" in which it is not always necessary to meet consumers and retailers physically (Stokes & Nelson, 2013). Bashar et al. (2012) reported that buyers are accepting SM especially more on Facebook as a suitable platform compared to other platforms, and engaged to know more and more about products, and related offers. Many investigators studied about brands through corporate Facebook page, and it was observed that consumers engagement related to the firms, which can be employed Facebook communities to boost satisfaction and loyalty by extending the right kinds of relationship benefits (Gummerus et al., 2012), factors are significantly affecting consumers' liking and commenting behaviour on Facebook brand pages (Kabadavi & Price, 2014), improved understanding of both experiences and facilitators of consumers' connections with companies and brands on Facebook (Bitter et al., 2014), customer brand engagement has significant impact on brand trust (Bagnied et al., 2016), distant Facebook friend influenced the consumer's visiting purpose and the Facebook post's identified diagnostic tool (Bitter & Grabner-Kräuter, 2016), and "customer engagement behaviours (CEB)" on social media like Facebook have the possible to boost relationships between organizations and consumers (Ajiboye et al., 2019).

H_1: SMMA through Facebook advertisement has a relationship on purchase intention.

2.3 Social media marketing activities by different web platforms

The "Blogs", "YouTube", "MySpace", "Facebook", etc. are instances of SM that are prevalent amongst all types of buyers (Sin et al., 2012). Hanna et al. (2011) reported that the exclusive features of SM related to popularity, which was found to be revolutionized through marketing strategies especially advertising and promotion of products. Based on a study in 2009, it showed that most of the successful organizations as per "Internet Retailer" had accounted on about 79%, 69% or 59% in the case of Facebook, Twitter or both types respectively (What's in a Retail email, 2009). A report by "Deloitte Touché", mentioned about US buyers in which about 62% read online reviews related to consumer-generated and majority of them (98%) observed these reviews appropriate. Whereas these consumers of about 80% explained that prior reading of these reviews had prejudiced their PI (Pookulangaran et al., 2011). SM, a commanding technique of digital marketing, plays a great role in enhancing brand acknowledgment and brand consciousness thereby augmenting brand visibility. Getting loyal customers is of utmost importance in current days as there are numerous players in the market. Kujur & Singh (2017) studied an empirical study on the activity of brandings, marketing, etc. by using SNS. They also studied structural equation modelling (SEM) and its impact on SM. Kujur & Singh (2018) emphasized that YouTube is the most informative SNS, where consumers are active on the site regarding brand activities. They explored that passionate appeals are utilized in SNS like YouTube publicity in which advancement of their items through large brands of various types in a developing business sector like India. Recently, SM platform such as Facebook, WhatsApp, Twitter, Instagram (Hellberg, 2015) as well as e-commerce platform viz. Amazon, Flipkart, etc. has attracted millions of consumers to purchase various products (Boyd & Ellison, 2007; Hellberg, 2015; Kati, 2018; Kujur & Singh, 2018; Satish Kumar, 2018; Kujur & Singh, 2020). Online gatherings applied an observable impact on the behaviour and customer purchasing intension as per buying choice (Ioanas & Stoica, 2014). Research carried out by Bashar et al. (2012) found that presently people are passionate about SM such as Facebook, YouTube, blogs, and Tweeter, etc. In the present scenario, the marketing through SM is showing more interest in purchasing the products through the process of better review, discounts, brands, visualization, etc. (Kujur & Singh, 2017; 2018; 2020).

H_2: SMMA through different platforms advertisement has a relationship on purchase intention.

2.4 Digital marketing through SMS

Digital marketing communication tools are less expensive and helps us to understand about our clientele's opponents as well as market scenario (Yamin, 2017). The online service in communication helps us by facilitating our business to communicate with the target audience through automated pertinent real-time communications combined across desktop, mobile, digital & conventional marketing networks (Bauer et al., 2005; Bhattacharjee, 2012; Enginkayaa & Cinarb, 2014; Kamal, 2016; Kanan & Li, 2017; Idrysheva et al., 2019). As described by Kamal (2016), there is possibility of business success as per the trend of digital marketing through new customer involvement. The major channels are SM and email marketing, all powered by content publicizing. While using these viable channels, number of free access, and paid tools are accessible for directing and improving the efficiency of online campaigns (Kamal, 2016; Zhang et al., 2017). The Brick-and-

Mortar apparel stores are shifting online due to supremacy of e-retailers and e-commerce technology, which is the cause of various challenges for sellers. In the year 2017 amazon has been pushed towards the forefront as successful apparel retailer in the US due to adoption of online channels by the millennials (Keyes, 2018). The digital transformation of business has brought the use of robots and artificial intelligence (AI) even to stitch and cut cloth. AI will also contribute to forecast style and augment manufacture (Ramya & Kartheeswaran, 2019). Different SM platforms are immensely valued for fashionable and chic brands. On the other hand, digital marketing also involves marketing through short message service (SMS) in which consumers can receive mobile data for different advertisement related to apparels (Dickinger & Haghirian, 2004). According to Smutkupt et al. (2012), SMS marketing have potential impact on brand awareness and quality perception. Manappa (2012) reported that SMS can be provided a powerful tool for connecting with consumers for business development, marketing, and advertising. Tarcea (2020) mentioned that familiar SMS marketing is a prospecting tool for fashion brands to grow an efficient revenue-generating network, which not only helped the bottom line but also provided customer retention and boosting their brand experience.
H_3: SMMA through SMS advertisement has a relationship on purchase intention.

2.5 Different online mode

Shao (2009) reported that different modes like text, images, audio, and video influence the consumers on brand activities as well as other consumers' motivations. Pöyry et al. (2013) stated that the internet facilitates the exchange of easy information and communication without any limitation of time or space. In other work, Habibi et al. (2014) reported that brand community is a place where people visit physically or virtually those who love a certain brand. They also mentioned specialized and non-topographically bound community where the relation is based on an organized group of society as per brand followers. Gong et al. (2017) evaluated on the relationship between brand rights and consumer brand engagement behaviour through brand liability and self-development through the smartphone.
H_4: SMMA through online advertisement has a relationship with purchase intention.

2.6 Prediction of Purchase Intention

The prediction of any activities viz. buying behaviour in marketing management, web-based personalization, operational efficiency, profit achievement and credit risk assessment in banking sectors, disease diagnosis, biological data analysis, etc. can be determined by using AI, "machine learning (ML)" and "deep learning (DL)" based on performance accuracy of dataset (Chakraborty et al., 2017; Seippel, 2018; Ramya & Kartheeswaran, 2019; Appiahene et al., 2020; Avudaiappan et al., 2020; Mishra et al., 2020; Singh & Prasad, 2020; Yoganarasimhan, 2020). These three types are closely related and help in computational prediction of different model algorithms (Garbade, 2018). Moreover, ML defines based on statistical methods or algorithms simulated to identify the features of the dataset and forecast based on these features (Dzyabura & Yoganarasimhan, 2018). It was established that ML model algorithms are based on several methods viz. "binary classification", "neural networks", "logistic regression", "support vector machines", "k-nearest neighbour", different decision trees, etc. (Seippel, 2018; Avudaiappan et al., 2020; Ebrahimi et al., 2022; Satu and Islam, 2023). The performance prediction was conducted through ML modelling for buying or without buying categories for apparel products (Seippel, 2018). According to Seippel (2018), ML modelling algorithms help to predict dataset performance and algorithm performance and very few studies were predicted the PI related to apparel products. Shi (2021) evaluated the factors that may influence visitors' buying intention based on "online shoppers purchasing intention dataset" in which classical ML models (Logistic Regression, Decision Tree and Random Forest). Ebrahimi et al. (2022) examined the combination of structural equation modelling (SEM) and unsupervised ML approaches to know the effect of consumers' purchase behaviour (CPB) on social network marketing (SNM). Satu & Islam (2023) proposed a ML model, which employed multiple data analytics and ML techniques to manipulate customer records and predict their purchase intention. Bilal et al. (2024) used the social support theory to investigate consumer buying intentions by combining AI technology, engagement of consumer in SM, and consumer experience.
The conceptual model was developed related to PI of apparel products between four attributes of SMMA viz. FB adv., other SM adv, SMS adv. and online adv. in which the hypotheses have been established (Figure 1). It studied consumers' demographic profiles viz. gender (G), age (A), marital status (MS), education (E), financial independence (F. Ind) and family income (FI) that may influence PI in organized apparel sector.

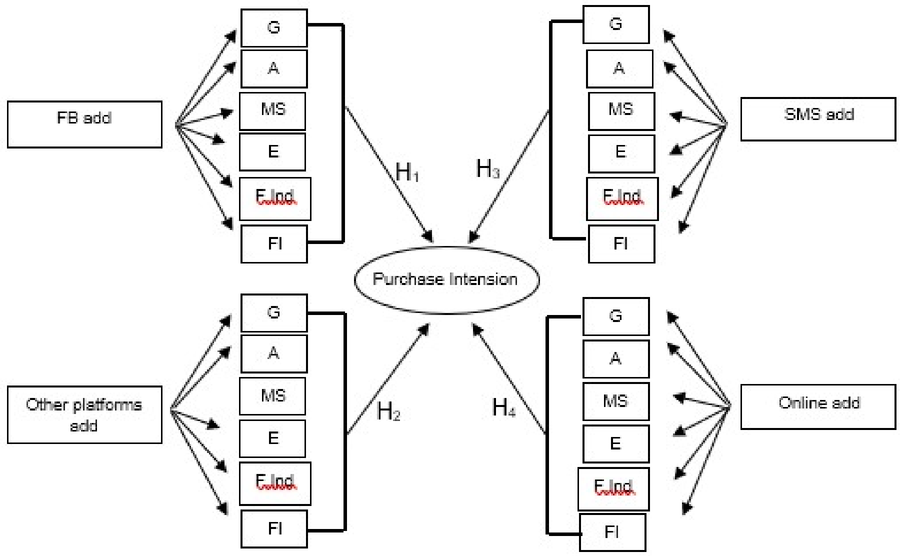


Fig 1. Theoretical framework for hypotheses testing (G = gender, A = age, MS = marital status, R = education, F. Ind = financial independence and FI = family income)

3. Research methods and procedures

3.1 Sample size

In the present study, sample size was selected 770 nos. Total 385 participants were selected from Patna and Ranchi while another 385 nos. from Kolkata, which combined as 770 nos. However, out of those 171 responses were rejected because they were not properly filled up whereas 599 nos. filled up questionnaire completely, recruited for the present study. The questionnaire with slight modification for 4 statements was administered to the respondents. The study was done to develop a dataset for finding the effective strategies through SMMA especially FB add, other SM platforms add, short message service (SMS) add and online add influencing consumer PI in apparel retail sector. In this study the target population who were visiting in shopping malls as it is easy to access and interact. The survey was carried in eastern part of India, covering three capital cities of India such as Kolkata, Ranchi, and Patna. The main reason behind the selection of study area because researcher is linked to all the cities, which made possible an easy admittance to the data source.

3.2 Sample collection

Primary data was gathered through questionnaire survey. The researcher visited various shopping malls at different hours of the day and approached the respondents with the questionnaire. The target respondents were those who were visiting the malls or leaving after shopping. According to the "Likert scale" (Likert, 1932), a "five-point Likert scale" is provided for research from "5 = strongly agree", " 4 = agree", " 3 = neutral", " 2 = disagree" and "1 = strongly disagree" and was used widely (Davino & Fabbris, 2012).

3.3 Empirical study

Analysis of variance (ANOVA) was done to know the relationship between purchase intention through four SMMA viz. FB add, other SM platforms add, SMS add and online add as dependent variable and demographic profiles such as age, gender, MS, education, financial independence, and family income as independent variables by using SPSS tool (version 21). The correlation coefficient of each data viz. FB add, other SM platforms add, SMS add and online add was calculated by using PAST (PAleontological STatistics) software (version 3.26) developed by Hammer et al. (2001).

3.4 Prediction of purchase intention through machine learning modelling

In the present study, data mining through ML modelling algorithm was performed by using WEKA (Waikato Environment for Knowledge Analysis) tool (version, 3.8.5) developed by Frank et al. (2016). The WEKA explorer was developed with data pre-processing, classification, regression, and association rules. The predictive performance accuracy of dataset categorized on eight attributes of different parameters viz. FB add, other SM platforms add, SMS add and online add and their classes as per Yes (Likert scale of 4 and 5) and No (Likert scale of 1, 2 and 3) on apparels through ML modelling algorithms such as Bayes Network (BN), Naïve

Bayes (NB), Logistic Regression (LR), Stochastic Gradient Descent (SGD), Sequential minimal optimization of Support Vector Machine (SMO), Simple Linear Regression (SL), Classification via Regression (CR); K-Nearest Neighbour (IBK), AdaBoost (AB), LogitBoost (LB); Pruned and unpruned decision tree C4 (J48), Random Forest (RF), Random tree (RT), and Simple Cart as class implementing minimal cost-complexity pruning (SC) from dataset to predict the overall performance accuracy on PI. The performance of model accuracy of above-mentioned ML algorithm classifications as per correctly and incorrectly classified instances, Kappa (K) statistics, mean absolute error (MAE) and root mean squared error (RMSE) were studied. As per Bouckaert et al. (2020), the summary of results of model algorithms were retrieved from WEKA tool. The prediction accuracy of studied ML models was analysed as per training and test set and result of each category was retrieved from summary results and the statistical parameters are "true positive (TP) rate", "false positive (FP) rate", "Precision value", "Recall value", "F-measures value", "Matthews correlation coefficient curve (MCC)", "receiver operating characteristic (ROC)" and "Precision-recall curve (PRC)", respectively were also retrieved and presented after validation of normal probability plot with respective correlation coefficient value.

4. Research findings and discussion

4.1 Frequency distribution and SMMA among and purchase intention among studied participants

Table 1 describes the frequency distribution of SMMA among participants. It was observed that three fourth (70.8%) of the respondents gave favourable perception when they were asked whether they follow add on FB. About 13.5% were neutral about it and 15.7% gave unfavourable opinion about the same. In the case of SM add, it was found three fourth (70.8%) of the respondents gave favourable perception when they were asked that whether they follow others SM platform add, about 12.7% were neutral about it and 16.6% gave unfavourable opinion about the same. About 65.1% of respondents were influenced by the promotional tool of SMS add to make their purchase decision, 18.7% did not have favourable perception about this and 16.2% were neutral about the fact. When the respondents were asked whether they are influenced by online add regarding recent fashion trends, the majority of about 85.6% had a very favourable response on this while 5.7% did not agree and 8.7% were neutral about the fact.

Table 1. Frequency distribution of social media marketing activities and purchase intention among participants

Parameters	Frequency	Percentage	Parameters	Frequency	Percentage
FB add			**Others SM platforms add**		
1	9	1.5	1	10	1.7
2	85	14.2	2	89	14.9
3	81	13.5	3	76	12.7
4	235	39.2	4	238	39.7
5	189	31.6	5	186	31.1
Total	599	100.0	Total	599	100.0
SMS add			**Online add**		
1	15	2.5	1	1	0.2
2	97	16.2	2	33	5.5
3	97	16.2	3	52	8.7
4	222	37.1	4	274	45.7
5	168	28.0	5	239	39.9
Total	599	100.0	Total	599	100.0

1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree, FB = Facebook, SM = Social media, SMS = short message service, add = Advertisement

4.2 Analysis of variance on SMMA and purchase intension among studied participants

The result on ANOVA obtains highly significant values for gender ($F = 15.604$, $p<0.00$), age ($F = 16.262$, $p<0.00$), and family income ($F = 24.345$, $p<0.00$) related to FB add. For others SM platforms add, highly significant value for family income ($F = 31.444$, $p<0.00$) age and ($F = 11.865$, $p<0.001$) followed by MS ($F = 7.351$, $p<0.01$) were observed. For SMS add, it was also observed highly significant value in family income ($F = 32.133$, $p<0.00$) followed by MS ($F = 12.867$; $p<0.01$), age ($F = 7.103$, $p<0.01$) and gender ($F = 6.787$, $p<0.01$), respectively while online add obtained highly significant value in family income ($F = 16.530$, $p<0.00$) followed by age ($F = 6.477$, $p<0.05$), respectively.

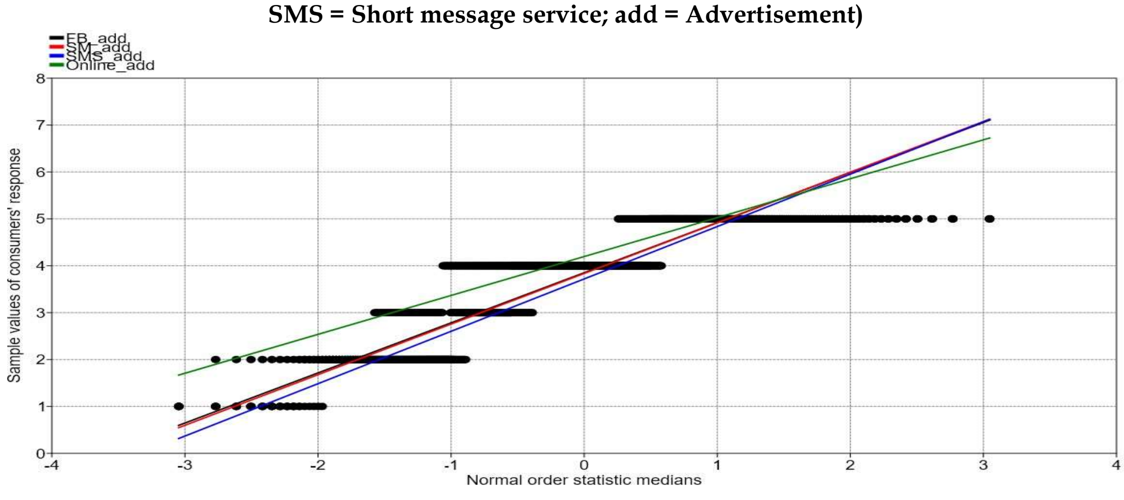
Table 2. ANOVA test on social media marketing activities and purchase intention among participants

Covariate	Type III Sum of Squares	df	Mean Square	F	Sig.
FB add					
Gender	.363	1	.363	.345	.557
Age	16.420	1	16.420	15.604	.000*
MS	17.112	1	17.112	16.262	.000*
Education	.164	1	.164	.156	.693
F_Indepe	.160	1	.160	.152	.697
Family_I	25.618	1	25.618	24.345	.000*
Others SM platforms add					
Gender	.303	1	.303	.280	.597
Age	7.972	1	7.972	7.351	.007**
MS	12.867	1	12.867	11.865	.001*
Education	.119	1	.119	.110	.740
F_Indepe	.047	1	.047	.043	.836
Family_I	34.099	1	34.099	31.444	.000*
SMS add					
Gender	7.804	1	7.804	6.787	.009**
Age	8.167	1	8.167	7.103	.008**
MS	5.055	1	5.055	4.397	.036***
Education	4.301	1	4.301	3.741	.054
F_Indepe	3.844E-07	1	3.844E-07	.000	1.000
Family_I	36.946	1	36.946	32.133	.000*
Online add					
Gender	.085	1	.085	.128	.721
Age	4.287	1	4.287	6.477	.011***
MS	1.045	1	1.045	1.579	.209
Education	1.975	1	1.975	2.984	.085
F_Indepe	.271	1	.271	.410	.522
Family_I	10.940	1	10.940	16.530	.000*

FB = Facebook; SM = Social media; SMS = short message service; add = Advertisement; MS = Marital status; F_Indene = Financial independence; Family_I = Family income; *p<0.01; **p<0.01 and ***p<0.05

Figure 1 exhibits normal probability plot in which SMS add was obtained highest correlation coefficient value (93%) followed by FB add and other SM platforms add (92%) while comparatively lower value was obtained in the case of online add (89%), respectively.

Figure 1. Normal probability plot on SMMA among consumers (FB = Facebook; SM = Other social media; SMS = Short message service; add = Advertisement)



4.3 Prediction of purchase intention through machine learning modelling

Figure 2 depicts the graphical representation of eight attributes of SMMA in which the categorisation was made for FB add, other SM add, SMS add and online add as well as their classes as per Yes and No in each case. The value of sum of weight is 599 for all numeric attributes. In the case of FB add, the mean ± SD value was obtained 3.851 ± 1.06 with minimum and maximum values of 1-5 in which the higher 235 instances with a range of 3.67-4.11, followed by 189 instances (4.56-5.00), and lower value of 9 instances (1.00-1.44), respectively. For other SM add, the mean ± SD value was obtained 3.856 ± 1.08 with minimum and maximum values of 1-5 in which the higher 238 instances with a range of 3.67-4.11, followed by 186 instances (4.56-5.00), and lower value of 10 instances (1.00-1.44), respectively. For SMS add, the mean ± SD value was obtained 3.72 ± 1.11 with minimum and maximum values of 1-5 in which the higher 222 instances with a range of 3.67-4.11, followed by 168 instances (4.56-5.00), and lower value of 15 instances (1.00-1.44), respectively. For online add, the mean ± SD value was obtained 3.72 ± 1.11 with minimum and maximum values of 1-5 in which the higher 274 instances with a range of 3.67-4.11, followed by 239 instances (4.56-5.00), and lower value of 1 instance (1.00-1.44), respectively. For class attributes (nominal) values were obtained for FB class (Yes = 421 and No = 178 instances), SM class (Yes = 426 and No = 173 instances), SMS class (Yes = 426 and No = 173 instances), SM class (Yes = 403 and No = 196 instances) and online class (Yes = 515 and No = 84 instances), respectively.

Figure 2. Studied attributes on SMMA among consumers (FB = Facebook; SM = Other social media; SMS = Short message service; add = Advertisement)

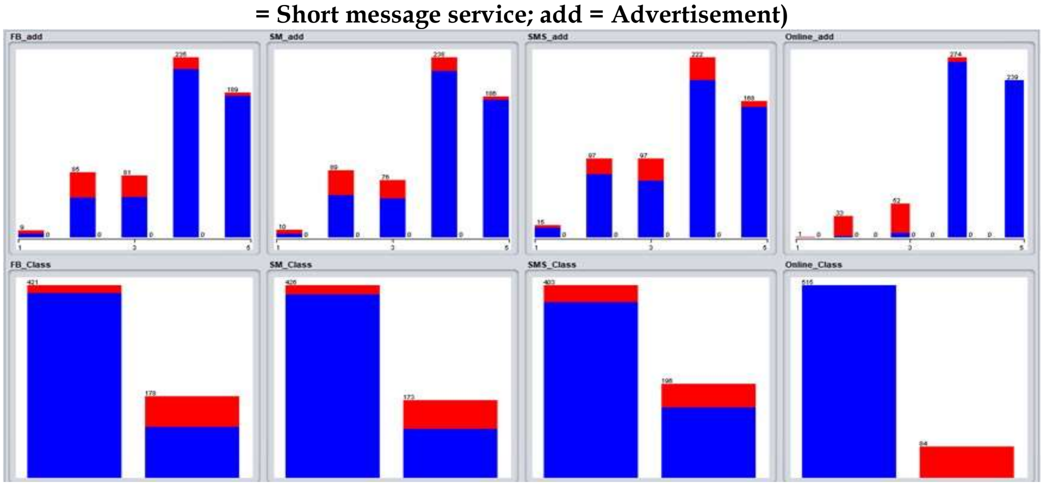


Table 3 describes the summary results of studied ML algorithm models such as Bayes Network (BN), Naïve Bayes (NB), Logistic Regression (LR), Stochastic Gradient Descent (SGD), Sequential minimal optimization of Support Vector Machine (SMO), Simple Linear Regression (SL), Classification via Regression (CR); K-Nearest Neighbour (IBK), AdaBoost (AB), LogitBoost (LB); Pruned and unpruned decision tree C4 (J48), Random Forest (RF), Random tree (RT), and Simple Cart as class implementing minimal cost-complexity pruning (SC) related to 8 attributes viz. FB add, other SM add, SMS add and online add as numeric as well as class like Yes and No for all of these four as nominal data to predict the overall performance accuracy. Overall prediction of algorithm model classification, the correctly classified models were observed with the highest values in IBK, RF and RT (98.5 and 97.5) followed by eight classifiers viz. SGD, SMOReg, SL, CR, AB, LB, J48 and SC (97.33 and 96.67) and LR (96.66 and 96.67) while the lowest values in NB (85.81 and 82.50) and BN (83.64 and 80.00), respectively as per training and testing dataset.

The performance of model accuracy of above-mentioned ML algorithm classifications as per "classified correctly and incorrectly instances", "Kappa (K) statistics", "mean absolute error (MAE)" and "root mean squared error (RMSE)" were studied separately for training dataset and testing dataset (Table 2).

Figure 3 (A-N) evaluates the graphical representation of the detailed accuracy of studied algorithm models as per training set and testing set. In case of the accuracy of a class of values for "TP rate, FP rate, precision, Recall, F-measure, MCC, ROC and PRC area" were estimated by using this tool. The better performance accuracy was obtained for IBK, RF and RT followed by SGD, SMOR e.g., SL, CR, AB, LB, J48 and SC and LR while comparatively lower performance in NB and BN as per training and testing dataset.

Table 3: Summary results of different classifier models (correctly and incorrectly classified instances) and Kappa statistic, mean absolute error and root mean squared error

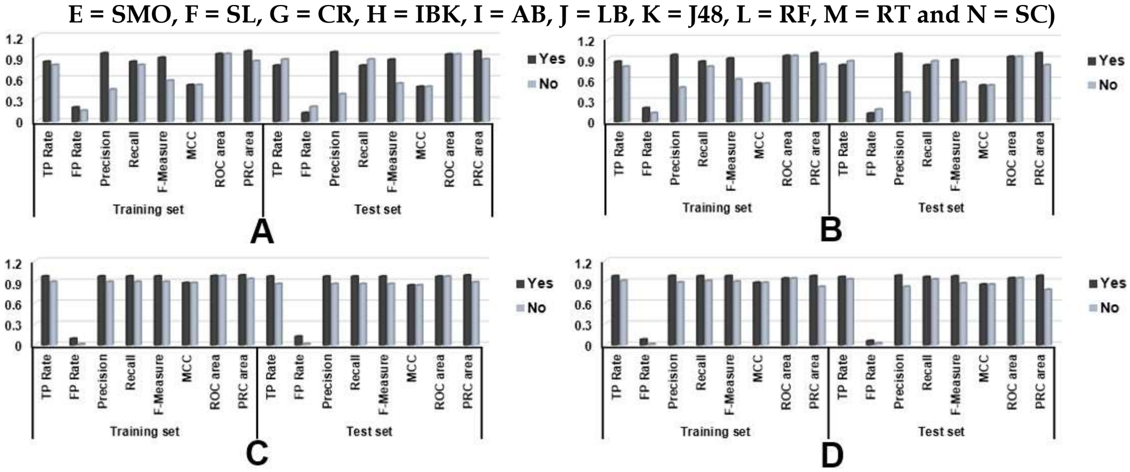
Classifier model	Correctly classified instances		Incorrectly classified instances	
	TrnS (%)	TS (%)	TrS (%)	TS (%)
BN	83.64	80.00	16.36	20.00

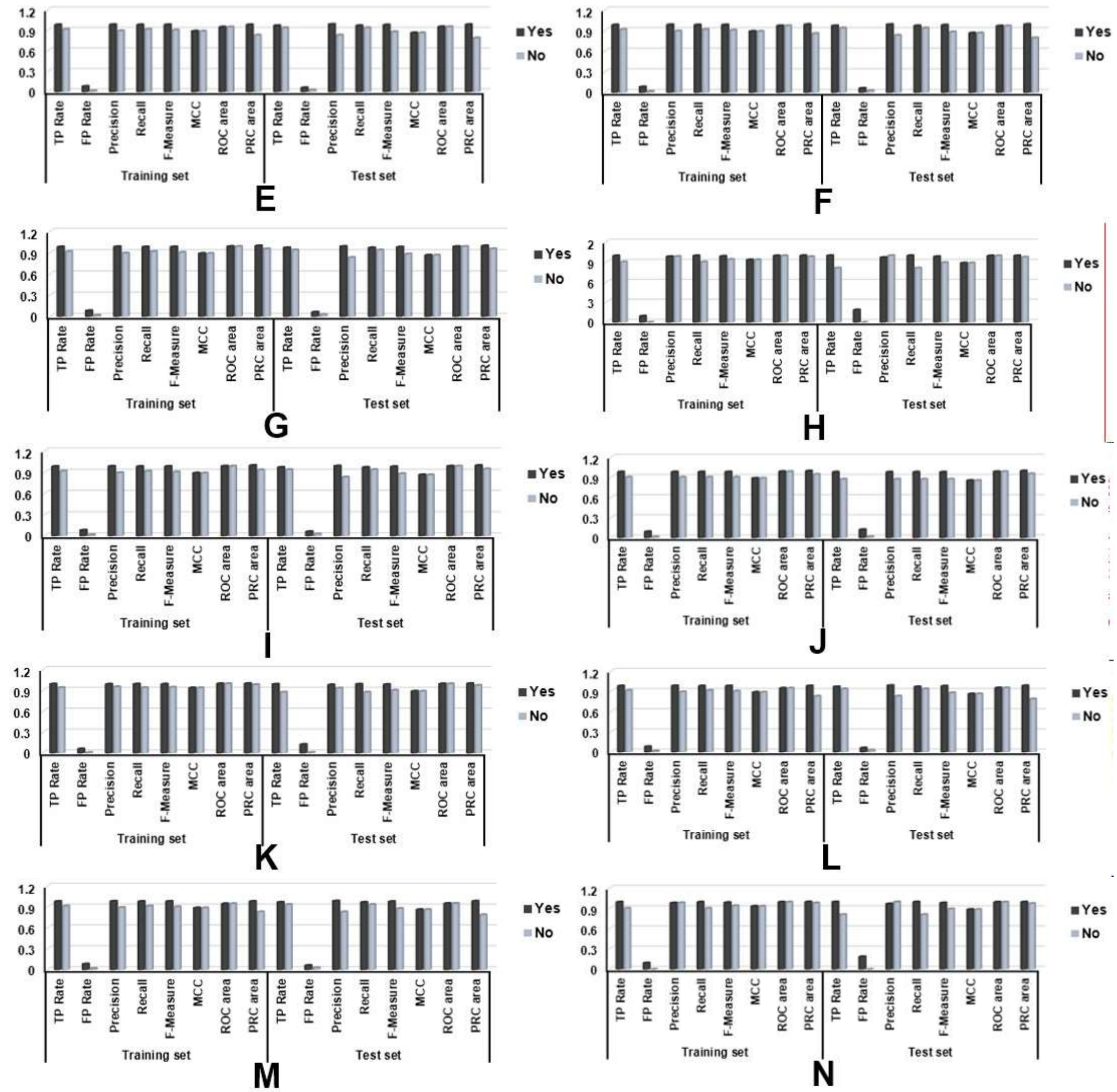
NB	85.81	82.50	14.19	17.50
LR	96.66	96.67	3.34	3.33
SGD	97.33	96.67	2.67	3.33
SMOreg	97.33	96.67	2.67	3.33
SL	97.33	96.67	2.67	3.33
CR	97.33	96.67	2.67	3.33
IBK	98.50	97.50	1.50	2.50
AB	97.33	96.67	2.67	3.33
LB	97.33	96.67	2.67	3.33
J48	97.33	96.67	2.67	3.33
RF	98.50	97.50	1.50	2.50
RT	98.50	97.50	1.50	2.50
SC	97.33	96.67	2.67	3.33

Classifier model	**TrnS**	**TS**	**TrnS**	**TS**	**TrnS**	**TS**
	KS		**MAE**		**RMSE**	
BN	0.48	0.43	0.14	0.17	0.34	0.37
NB	0.53	0.48	0.14	0.16	0.34	0.36
LR	0.86	0.85	0.05	0.05	0.15	0.16
SGD	0.89	0.86	0.03	0.03	0.16	0.18
SMO	0.89	0.86	0.03	0.03	0.16	0.18
SL	0.89	0.86	0.20	0.20	0.24	0.25
CR	0.89	0.86	0.05	0.05	0.15	0.15
IBK	0.93	0.88	0.02	0.03	0.10	0.13
AB	0.89	0.86	0.04	0.04	0.15	0.15
LB	0.89	0.85	0.04	0.04	0.14	0.14
J48	0.89	0.93	0.05	0.06	0.16	0.18
RF	0.98	0.89	0.03	0.03	0.11	0.13
RT	0.93	0.88	0.02	0.03	0.10	0.13
SC	0.89	0.86	0.05	0.05	0.16	0.17

BN = Bayes Network; NB = NaiveBayes; LR = Logistic Regression; SGD = Stochastic Gradient Descent; SMO = Sequential minimal optimization of Support Vector Machine; SL = Simple Linear Regression; CR = Classification via Regression; IBK = K-Nearest Neighbour; AB = AdaBoost; LB = LogitBoost; J48 = Pruned and unpruned decision tree C4; RF = Random Forest; RT = Random tree; SC = Simple Cart as class implementing minimal cost-complexity pruning; TrrS = Training set; TS = testing set; KS = Kappa Statistics; MAE = Mean Absolute Error; RMSE = Root Mean Squared Error

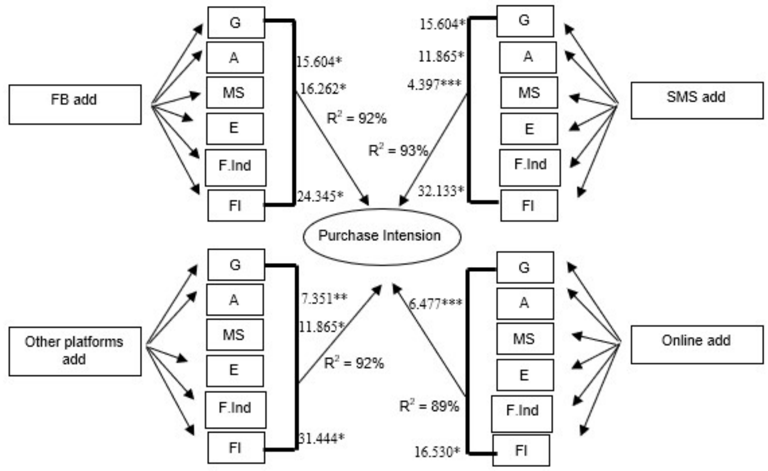
Figure 3. Performance accuracy of different studied algorithm models (A = BN, B = NB, C = LR, D = SGD, E = SMO, F = SL, G = CR, H = IBK, I = AB, J = LB, K = J48, L = RF, M = RT and N = SC)





The results clearly indicated that four attributes of SMMA viz. FB add, other SM add, SMS add and online add are closely related to PI. Moreover, different independent variables of demographic profiles such as gender, age, MS, and family income through SMS add followed by age, MS and family income through FB add and other platforms add while age and family income through online add were enhanced the PI among consumers of eastern India. Hence, hypotheses H_1, H_2, H_3 and H_4 were supported (Figure 4).

Figure 4. Results of hypotheses testing (G = gender, A = age, MS = marital status, R = education, F.Ind = financial independence and FI = family income)



The present study was attempted to predict PI as per dataset of SMMA viz. FB add, other SM add, SMS add and online add among 599 consumers who visited organized apparel sector in eastern India. The PI among consumers' is achieving higher growth of economic conditions through digital marketing of apparel products (Prasad, 2014; Kunwar, 2017; Parsons, 2019). Several studies have been reported that online marketing induces the intension on purchasing products among consumers' (Bauer et al., 2005; Kujur & Singh, 2017; 2018; Enginkayaa & Cinarb, 2018; Seippel, 2018; Jayasingh, 2019; Kujur & Singh, 2020). On the other hand, on-line apparel marketing is greatly influenced by different mode of advertisement. Seippel (2018) explained that the scope of on-line purchasing activities is higher than physical visit to stores for buying apparels. Few studies find the impact of digital marketing or SMMA on the apparel sectors related to PI among consumers' (Stephenson, 2009; Ahmad et al., 2015; Seippel, 2018; Sarkar, 2019; Sharma et al., 2021).
In general, the prediction of the PI of apparel products through on-line shopping among consumers through ML algorithm modelling is lacking while in other research sectors is well established by the investigators in the e-commerce or digital platform (Lo et al., 2014; Lee et al., 2015; Korpusik et al., 2016; Tan et al., 2016; Suchacka & Templewski, 2017; Lang & Rettenmeier, 2017; Avudaiappan et al., 2020; Yoganarasimhan, 2020). A close similarity with the present study of prediction of PI for apparels through ML algorithm modelling (Seippel, 2018). According to Seippel (2018), RF followed by LR algorithm models were performed better accuracy as 82% and 80%, while Shi (2021) observed RF model performed better for the prediction of online shoppers purchasing intention, with train accuracy 89.5% and test accuracy 87.5% respectively and Satu & Islam (2023) found similarity on RF model with the best accuracy of 92.39%, but in the present study the performance accuracy was higher as per correctly classified instances in which three models viz. IBK, RF and RT (98.5 and 97.5) followed by eight models viz. SGD, SMOReg, SL, CR, AB, LB, J48 and SC (97.33 and 96.67) and LR (96.66 and 96.67) while the lowest values in NB (85.81 and 82.50) and BN (83.64 and 80.00), respectively as per training and testing dataset were predicted.
Although, it was predicted among the consumers of abroad, however, the present study is a first-time endeavour to know PI of apparels by using ML modelling with the help of dataset gathered among consumers of eastern India. In other words, online add was predicted higher as per DT model but in cumulative effort of other three models of add performed a better accuracy in the case of 12 algorithm models.
It was observed that the significant relationship between SMS adv. and PI as per correlation coefficient value and predicted values. It was also noted that the cumulative effect of SMMA adds (FB, other SM and online adv.) has significant impact on PI validated by ML algorithm modelling.

5. Conclusion

The present study attempted to predict PI as per dataset of SMMA viz. FB adv., other SM add, SMS add and online adv. among consumers who provided their view on the SMMA about purchasing apparel products in eastern India. To predict the PI among consumers, the dataset of 599 participants was used through the WEKA tool for ML algorithm modelling. The best prediction accuracy was obtained for PI, which can easily be detected through the modelling results on SMMA that indicated the trend of buying of apparels within consumers. It is noted that SMS adv. is more potential for PI but the cumulative SMMA viz. FB adv, other platforms of SM adv, and online adv as per ANOVA analysis and correlation coefficient values of normal probability plot, which has been validated with ML model algorithm prediction and SMMA was observed to influence the PI among consumers of Eastern part of India. It is well known that digital marketing approaches influences PI which ultimately boosts economic condition. It is suggested to predict the PI with other SM platforms along with Big dataset that can be beneficial to marketing strategy and economic conditions of the country.

As per this study, a limitation of the research attributes viz. FB add, other platform, add, SMS add and online adv. are focused on SMMA, without consideration of each platform add being used as Twitter, YouTube, Instagram, etc. Each platform along with FB may provide better data analysis as per empirical study compared to machine learning algorithms modelling accuracy. Other limitations are also observed small number of respondents (599 nos.) and the study was carried out only in the small part of India.

Furthermore, future study is suggested with different web platforms adv. of SMMA along with demographic and socioeconomic profiles related to the other regions of India with larger sample size. Our predictive models can be used to validate with other countries across the globe to know about the growth of Indian economy in relation to apparel retails.

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