Effectiveness of Hyper Localized Data Driven Advertisements in India

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Marketing in the modern era is becoming more quantitative, targeted, and linked to organisational goals. Advertisements are becoming more personalised in real time using artificial intelligence. Considering the strong research gap, the impact of AI-enabled, data-driven advertisement in India is examined. AMOS based Statistical analysis using CFA and SEM, indicates that AI Enabled data driven campaign leads to a favourable attitude and attitude leads to positive purchase intention. The study has a strong implication considering the fact that it will be useful to marketers, strategy makers, local retailers, and retail businesses as a whole.

Keywords: Data-Driven Advertisement, Attitude, Purchase Intention, Local Retailers, Retail Business

1. Introduction

Every year, new technologies emerge and alter our perspective on the world. There has been a major change in marketing approaches with the introduction of the Internet. Today's businesses use a wide variety of promotional strategies to get the competitive advantage. They are moving closer to a smart marketing mix that incorporates both traditional and digital tactics. Over half of the world's population is now regular users of social media, making it the most effective way to reach a wide audience. Therefore, marketers need to put an emphasis on digital tactics and make use of the vast opportunities presented by social media, which can be particularly transformative for start-ups (Parisini, A., 2022). New avenues of advertising and storytelling have emerged as a result of Artificial intelligence (AI) based advanced features. New marketing paradigms are emerging, with an emphasis on enhanced contextual personalization and targeting. Humans' interactions with gadgets, information, enterprises, and commodities have seen radical transformations in recent years. Artificial intelligence is responsible for everything (Chen et al. 2011). These first widespread commercial applications of AI have generated a lot of attention and debate because they have shown the marketing world what AI is capable of doing (Lieto, Bhatt, Oltramari, & Vernon, 2017). Engineers, IT specialists, and analysts have been the main audiences for AI, but it is increasingly gaining attraction in management and marketing, outside of its traditional areas of use (Mazurek, 2011a, 2011b, 2014). Artificial intelligence is a result of information technology. It can be defined as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages" (Oxford Dictionaries, 2019). AI goes a step further and creates new marketing opportunities like personalised customer service, quicker shopping periods, and automatic recommendations and relevant product ideas (Grewal, Roggeveena, & Nordfältba, 2017). As AI improves, it becomes increasingly important for organisations to provide solutions using AI (Parisini, A., 2022).

AI can be used in a variety of marketing contexts. It is used in commercial solutions for autonomous robots, automobiles, voice recognition, text recognition, decision making, picture recognition, and text recognition. While the other three are often employed in advertising campaigns, leading tech firms such as Amazon, Google, Apple, and Microsoft instead devote significant resources to studying speech recognition (Chartrand 2005). Since they are more strongly associated with Industry 4.0, robotics and autonomous cars have a harder time gaining attraction than the development of novel elements of the marketing mix. The vast majority of AI-powered marketing tools currently available are short-term, supporting only a single campaign. This could be because industry 4.0 is dealing with the first real-world uses of AI, which has businesses wary of using and experimenting with the technology, additionally industry 5.0 is focusing more on automation and manufacturing (Huang, M. H., & Rust, R. T., 2022).

2. Literature Review

2.1 Data Driven Campaign

Today's marketing strategies are data-driven, goal-oriented, and quantitative. There has been a rise in real-time, targeted advertising and incentives. There are several channels via which businesses can reach their customers, but the use of digital media is becoming widespread across the world (Coulter et al. 2005). The marketing departments of companies still work with agencies, many of which have built up their own in-house analytic resources. Data collection, market analysis, segmentation, targeting, and positioning, as well as the standardisation and personalization of the consumer experience, are all areas where marketers are making successful use of AI at present. The most revolutionary aspect of AI is the way it can substitute for and enhance human intelligence. Modern AI's ability to personalise campaigns by automatically analysing enormous quantities of data is one of its most exciting features (Treen, 2018). Big data is being used to gain insightful customer knowledge in order to provide a better experience. The most cutting-edge methods of message delivery to clients are being transformed by AI. AI will be the ultimate privacy test because it also threatens user data. With the use of machine learning, marketers may stealthily compile client data from many sources, merge it, and mine it for actionable consumer insights (Aral and Walker 2014; Katona et al. 2011).

2.2 Retail Store Credibility

Since organised retail stores function as corporations, it is possible to conceptualise perceived corporate credibility as equivalent to perceived retail store credibility. The two aspects of retail shop competence and trustworthiness can be used to describe perceived retailer credibility on the scale. Trustworthiness and expertise are the most widely acknowledged kinds of credibility, despite the fact that credibility in other settings (such as brand and source credibility) is expressed in other ways. For instance, Malshe (2010) examined how the sales-marketing interaction affects marketers' reputations and defined credibility as expertise and dependability. This study defined competence as the capacity to add value and marketing experience, and trustworthiness as the ability to follow promises and commit resources.

2.3 Celebrity Endorsement

As such, studies have focused on how celebrity endorsement plays a role in determining how much people like the endorser, and how this might be exploited to boost the impact of endorsements (Friedman, 1979). Physical attractiveness only "fits" with the advertised product to have a significant impact on the endorsement's effectiveness. As a result, celebrity endorsement could help to close the sale of cosmetics but would be counterproductive in the computer industry. Attractiveness can be understood in a larger context as a positive outlook towards the endorser, despite the fact that traditional study on attractiveness has focused on physical attraction (Liang & Xianyu 2008). Adoration or perceived similarity can both contribute to the development of these emotions, but the admiration component is more likely to be used in successful advertising because celebrities' influence is so intrinsically linked to their reputation as role models (McGuire, 1985)

2.4 Awareness

Numerous studies show that a variety of rational consumer actions are significantly influenced by customers' awareness and knowledge (McEachern & Warnaby 2008). Hartlieb and Jones (2009), for example, emphasise the necessity of ethical labelling in order to improve perceptions. By prominently integrating moral qualities into product features, ethical labelling aims to make consumers aware of and educated about the critical factors that are predicted to influence their decisions or behaviours. Men and younger persons were found to have a greater understanding of privacy regulations and best practices. As a result, these societies have developed unique safeguards for the invading ring. Donoghue and de Klerk (2009) researched customer complaints to elucidate the nature of these complaints by examining the characteristics and attitudes of the target demographic. The significance of this work has thus been demonstrated. Chartrand argues that informing consumers is the first step toward influencing their (often subconscious) actions and choices (Chartrand, 2005). This is why being self-aware is essential to shape effective consumer behaviour (Hartlieb & Jones 2009).

2.5 Social Media Involvement

The opinion of a consumer can be heard by a much larger audience. Electronic "word of mouth" reaches a much wider audience and has more weight than traditional "word of mouth," which spreads through frequent human meetings. This encourages a substantial group of scholars to zero down on e-WOM-related issues (Hudson, 2015; Viglia, 2016). Importantly, 92% of studies discovered that the use of social media platforms boosts the prevalence and impact of positive word-of-mouth in comparison to conventional tactics. Consumers are increasingly free to share their unfiltered, broad-based opinions, whether favourable or negative (Priyanka, 2013). Coulter and Roggeveen (2012) also noted that a customer's response is significantly influenced by the size of the product community and the number of community members who are on their friends list. To predict customers' participation in electronic word of mouth, Chu and Kim (2011) sought important criteria (e-WOM). Their data offered substantial support for the significance of trust and normative influence in customers' interactions with e-WOM. It is more likely that visitors who join in online forums will promote local businesses to their friends (Casalo et al., 2010). social media influences people' perceptions of and participation (Hudson et al., 2015).

2.6 Consumer Preference

Consumers have a predisposition to choose one brand over another depending on their familiarity with the brand (Keller, 2003). It is common practise to ask consumers to name their favourite brands from among a set of options in order to get an idea of consumer preference. Majority of the studies consider Preference as it affects intention to purchase premium products (Truong, McColl, & Kitchen, 2010; Vigneron & Johnson, 2004).

2.7 Purchase Intention

Purchase intention is the possibility that a customer will purchase a particular product. Additionally, making an attempt when making a purchase could be viewed as a consumer's intent. The consumer's impression of the value and benefits affects their decision to buy (Wang and Tsai, 2014). Purchase intention can also be thought of as a consumer's preference to purchase products or services because they believe they are necessary (Madahi and Sukati, 2012). Jaafar and Laalp (2013) define "purchasing intention" as the use of technology to anticipate the purchasing process. Decisions made by customers to buy a product from a certain retailer are influenced by their objectives and are based on impulse. According to Rahman et al. (2012), it is possible to predict customers' purchase intentions by looking at their willingness to make purchases, desire to make purchases in the future, and desire to make repeat purchases. According to Shah et al. (2012), a consumer's purchase intention is determined by their attitude toward the brands of the things they want to acquire (attitude towards brands). People weigh several brands that meet their requirements and are believed to fulfil their needs and goals when choosing one (Thomas & Mills 2006).

2.8 Attitude

The definition of an attitude, according to Schiffman, is "learned propensity to behave favourably or negatively concerning a particular object." Due to its value in forecasting customer behaviour, research on the creation of consumer attitudes is important (Mitchell & Olson, 1981). An attitude is an ongoing assessment of an object, a person, or an event by an individual or group of individuals (Solomon, 2010). A constant positive or negative taught disposition towards an object is referred to as an attitude (Schiffman et al., 2010). Additionally, a mindset differs from particular behavioural intents (Fishbein &Ajzen, 1975). Such a behavioural purpose is the greatest and most direct predictor of the associated explicit behaviour (Ajzen & Madden, 1986). Additionally, an attitude, significance, knowledge, accessibility, etc. has a different effect on conduct intentions (Fazio & Olson, 2003). Consumer attitudes toward the product can be discovered through personal experience or the use of outside data. A person's attitude is simply defined as "their feelings or ideas about something." Additionally, when a specific subject is brought to the customers' attention, they become more interested in it (Berger et al., 1999).

2.9 Need for Study

Marketing is a battle for consumers' attention, according to Seth Godin. In the highly competitive climate of today, businesses are concentrating on differentiation, where they aim to obtain a competitive edge by doing something different. The retail industry, in particular, has undergone a huge paradigm shift as a result of AI enabled campaigns. Data-driven marketing is a cutting-edge strategy. There is less academic research about AI enabled Marketing Campaigns. This allows the firm a unique opportunity to identify and explore the model. This study aims to identify how consumers' perceptual constructs and attitude affects their purchase intention about their purchases from local retail stores. From the theoretical consideration, the proposed AI enabled marketing framework provides an integrated understanding about how consumers respond to data driven marketing strategies. The study provides strong practical and theoretical contributions.

2.10 Scope of the Study

The scope of the study is limited to Gujarat, Maharashtra, Madhya Pradesh, and Delhi with reference to India. Moreover, studies are limited to the retail industry only. Additionally, the study's conceptual focus is limited to the use of technology in marketing, data-driven marketing fuelled by Artificial Intelligence, attitude, and the purchase intention component of consumer buying behaviour. The study considers a wide range of demographic variables based on a literature review.

3. Methodology

The Research Objectives of the study is to a) identify important variables to measure AI enabled data driven campaign b) To investigate the impact of AI enabled data driven campaign on consumer attitude c) To investigate the impact of consumer's attitude on purchase intention with reference to AI enabled data driven campaign. A descriptive research design has been used for primary research. The snowball sampling technique was used for the study. The campaign was shown to the respondents (https://www.youtube.com/watch?v=5WECsbqAQSk) and prior consent was taken from respondents before the survey. Prior pre- testing was done with 7 marketing professionals associated with AI enabled data driven marketing campaigns and required changes were done. The time duration of the survey was four months (July-October 2022). The target population is the consumers of India who have seen and purchased a product after watching a campaign of Cadbury (Not just a Cadbury ad). Total data was collected from 942 respondents, and 897 sample size was finalized after data cleaning that met with the minimal sample size requirement for CFA. The response rate was 71%. Here researcher has used a five-point Likert scale ranging from 1= Strongly disagree, 5= strongly Agree. Researcher has also verified that Multicollinearity has not been found. The researcher has proposed following hypothesis:

H_{01}: There is no significant impact of AI enabled data driven campaign on consumer's attitude.

H_{02}: There is no significant impact of consumer's attitude on purchase intention with reference to AI enabled data driven campaign.

4. Data Specification

The researcher has analysed data in this chapter. It begins with a city-wise profile of the sample, demographic characteristics of respondents, and descriptive analysis, followed by calculation of Cronbach's alpha, hypothesis testing, CFA and Structural analysis.

State-wise Profile of the Sample

Samples were collected from the four major states of West India with reference to Gujarat, Maharashtra, Madhya Pradesh and Delhi. The no. of respondents from four states is mentioned below.

Sr. No.	States	No. of	Percentage
1	Gujarat	256	28.7
2	Maharashtra	223	24.8
3	Madhya Pradesh	205	22.8
4	Delhi	213	23.7
Total		**897**	**100**

4.1 Demographic Profile of Respondents

Variables	Category	Frequency	Percentage (%)
1. Gender	Male	493	54.96
	Female	404	45.04
	Total	**897**	**100.0**
2. Age	18-28	247	27.52
	29-38	267	29.77
	39-48	233	26.02
	49-58	100	11.13
	Above 58	50	5.56
	Total	**897**	**100.0**
3. Marital Status	Married	534	59.5
	Unmarried	363	40.5
	Total	**897**	**100.0**
4. Education	Up to higher Secondary	254	28.87
	Graduate	453	50.53
	Post graduate and above	190	21.20
	Total	**897**	**100.0**
5. Annual Family income	Less than 200000	175	19.5
	200001-400000	248	27.7
	400001-600000	346	38.6
	600001-800000	67	7.5
	Above 800000	59	6.6
	Total	**897**	**100.0**

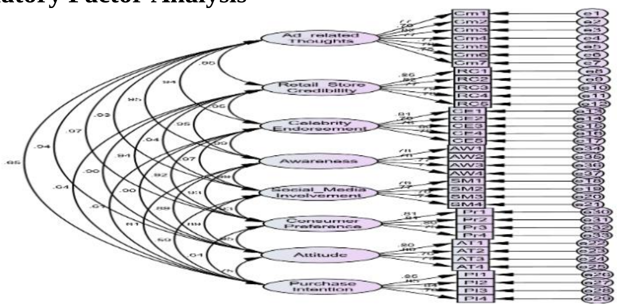
6. Number of Members in household (Including you)	1-3	391	43.6
	4-6	410	45.7
	7-9	72	8.0
	Above 9	24	2.7
	Total	**897**	**100.0**
7. Occupation	Student	101	11.26
	Home maker	252	28.09
	Self Employed	190	21.18
	Salaried	354	39.46
	Total	**897**	**100.0**

4.2 Reliability Analysis

Variable No.	Variable	Cronbach's Alpha	N of items
1	Data Driven (AI Enabled) Campaign	.900	5
2	Retail Store Credibility	.902	5
3	Celebrity Endorsement	.916	5
4	Awareness	.886	4
5	Social Media Involvement	.876	4
6	Consumer Preference	.805	4
7	Attitude	.867	4
8	Purchase Intention	.880	4

Here all the values are above 0.7, which indicates that data is reliable for further studies (Nunnally J, Bernstein L., 1994).

4.3 Confirmatory Factor Analysis



The usage of SEM broadly known as structural modelling has a variety of advantages over some conventional methods of analysis, such as performing numerous multiple regression analyses for a model's dependent variable (Kline 1998). A graphical depiction of the complete measurement model is shown in mentioned Figure 1. It has 29 indicators and 8 latent variables, and each relationship between a construct and an indicator is represented in the model and has been predetermined based on marketing theory. Overall, AI enabled marketing constituted 8 latent variables are constructed through latent variables namely AI advertisement, Brand image, retailers' perception, social media involvement, preference, customer engagement and attitude towards the campaign. Purchase Intention constitute of 4 indicators. An individual error term is associated with each signal, and independent variation among the many constructions is tolerated (Blunch, 2008).

Convergent validity can be estimated using the standardised factor loadings of each indicator included in the measurement model. The consensus among scholars is that a 0.70 threshold is best. (Hair et al. 2010). The Table below displays the standardised factor loadings for each particular scale.

4.4 Factor Loading

Indicator and latent variable			Factor Loading
Cm1	<---	Ad_related_Thoughts	.767
Cm2	<---	Ad_related_Thoughts	.759
Cm3	<---	Ad_related_Thoughts	.820
Cm4	<---	Ad_related_Thoughts	.771
Cm5	<---	Ad_related_Thoughts	.775
Cm6	<---	Ad_related_Thoughts	.788
Cm7	<---	Ad_related_Thoughts	.778
RC1	<---	Retail_Store_Credibility	.855
RC2	<---	Retail_Store_Credibility	.821
RC3	<---	Retail_Store_Credibility	.772
RC4	<---	Retail_Store_Credibility	.788
RC5	<---	Retail_Store_Credibility	.793
CE1	<---	Celebrity_Endorsement	.806
CE2	<---	Celebrity_Endorsement	.792
CE3	<---	Celebrity_Endorsement	.762
CE4	<---	Celebrity_Endorsement	.800
CE5	<---	Celebrity_Endorsement	.777
SM1	<---	Social_Media_Involvement	.759
SM2	<---	Social_Media_Involvement	.765
SM3	<---	Social_Media_Involvement	.762
SM4	<---	Social_Media_Involvement	.745
AT1	<---	Attitude	.800
AT2	<---	Attitude	.797
AT3	<---	Attitude	.764
AT4	<---	Attitude	.769
PI1	<---	Purchase_Intention	.852
PI2	<---	Purchase_Intention	.849
PI3	<---	Purchase_Intention	.839
PI4	<---	Purchase_Intention	.762
Pr1	<---	Consumer_Preference	.805
Pr2	<---	Consumer_Preference	.806
Pr3	<---	Consumer_Preference	.797
Pr4	<---	Consumer_Preference	.751
AW1	<---	Awareness	.783
AW2	<---	Awareness	.779
AW3	<---	Awareness	.772
AW4	<---	Awareness	.773

In the above Table above, factor loading for each scale is displayed. Here, all the factor loading values are above 0.7, which indicates strong convergent validity (Hair et al. 2010). The factor loading is reinforced by AVE and CR, two additional assessments.

Average Variance Extracted and Construct Reliability		
Construct	CR	AVE
Consumer_Preference	0.871	0.627
Ad_related_Thoughts	0.916	0.608
Celebrity_Endorsement	0.904	0.653
Retail_Store_Credibility	0.891	0.620
Awareness	0.843	0.674
Attitude	0.863	0.612
Purchase_Intention	0.895	0.680
Social_Media_Involvement	0.859	0.604

All constructs surpass the 0.70 threshold required for convergent validity analysis, hence showing considerable evidence of convergent validity. AVE is also less than the CR value for each structure.

4.5 Nomological Validity

The correlation between constructs should be based on existing theoretical research and should not change, according to nomological validity (Hair et al. 2010).

The covariance between latent variables is statistically shown in the above Table, which provides the evidence for nomological validity. Consistent application of this model can demonstrate acceptable levels of reliability and validity and performing route analyses using its validated constructs should yield statistically reliable results.

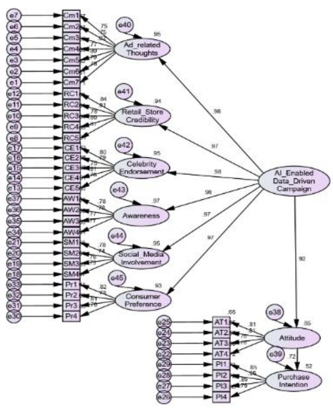
Nomological Validity				
	Estimate	S.E.	C.R.	P
Ad_related_Thoughts	.512	.039	13.063	***
Retail_Store_Credibility	.491	.032	15.535	***
Celebrity_Endorsement	.582	.041	14.282	***
Social_Media_Involvement	.650	.047	13.914	***
Attitude	.650	.046	14.264	***
Purchase_Intention	.918	.060	15.292	***
Consumer_Preference	.585	.040	14.570	***
Awareness	.548	.040	13.648	***

4.6 Goodness of Fit Analysis

The Table summarises the important model fit metrics. In addition to the 2 (Chi-Square) values, researchers must also submit a minimum of one "Absolute Fit Index" and one "Incremental Fit Index." Three to four fit indices are sufficient to demonstrate model fit. In accordance with these writers' recommendations, the able offers numerous fit statistics as below.

Measure	Estimate	Threshold	Interpretation
Chi-square	2011.115	…	…
CMIN/DF	3.346	<5	Excellent
RMSEA	.051	<.08	Good fit
NFI	.927	>.7	Excellent
CFI	.948	>.7	Excellent
TLI	.942	>.7	Excellent
IFI	.948	>.7	Excellent

4.7 Structural Analysis



The two-step SEM approach suggested by (Gerbing, 1998) enables numerous researchers to employ both a measurement model and a structural model simultaneously. This decision is justified by the CFA model's acceptable goodness-of-fit metrics and the positive findings of numerous construct reliability and validity tests.

The effect of endogenous constructs is shown in the above Figure (structural diagram), which gives information about the AI enabled marketing campaign on attitude and the effect of attitude on purchase intention. The two main hypotheses can be analysed by the two-path coefficient which is shown in the model and can be used to relate the objective of the study.

The structural model analysis can demonstrate the connection between the path relationship and the study's theoretical recommendation. The standardized beta weight of 0.92 and R square 0.85 was calculated which means that there is a positive and strong effect of AI enabled marketing campaign. Purchase intention is also affected due to this as there is a positive impact, which can be seen from beta weight 0.72 and R square 0.52. Attitude is highly affected by the effect of AI enabled marketing, but there is a moderate effect of attitude on the purchase intention.

5. Results and Discussions

5.1 Key Findings

From the total 897 respondents, 28.7 % of respondent were from Gujarat, 24.8% were from Maharashtra, 22.8 % were from Madhya Pradesh and 23.7% were from Delhi so almost equal proportion of samples has been taken from all 4 states. Male and Female ratio of the sample of the respondent was 54.96 % and 45.04% respectively. There are five categories of age, which ranges from the age group of 18-28 (27.52% Respondents), age group of 29-38 (29.77% Respondents), age group of 39-48 (26.02% respondents), 49-58 (11.13% respondents) and Above 58 (5.56% respondents). Majority of the respondents have an annual family income below Rs. 600000 (85.8%) and have less than 6 members in the household (89.3%).

Cronbach’s Alpha can be defined as the reliability measurement tool, for the selected construct, it should be above acceptance standard 0.7. The lowest Cronbach’s alpha was 0.805 for the customer engagement construct. It provides good reliability of all the constructs.

The measurement model includes eight latent variables and twenty-nine indicators. All the factor loadings were above the acceptance standard (0.70), lowest factor loading was 0.724 so it can be said that indicators are well loaded on their latent variables. AVE can be defined as the proportion of a variation recorded by a construct relative to the proportion of variance attributable to a certain measurement error. All the indicators explain the bulk of the variance, which is an encouraging sign for the model. The average variance extracted (AVE) has the lowest value 0.604 which is above the acceptance level of 0.5. The composite reliability of the model is excellent.

Factor loading, AVE and CR all three standards conclude that the model possesses a high level of convergent validity. In this context, convergent validity might be characterised as the measuring of theoretically related constructs. Additionally, it is observed that they are connected.

The fact that the square root of all AVE is greater than the correlation between a single item and other components gives more evidence of discriminant validity. Here, Discriminant validity can be defined as a measure of construct that should not theoretically be related to each other. It is also observed that the said constructs are not related to each other. All the covariance of the constructs was statistically significant, so it can also be argued that the nomological validity is acceptable.

Nomological validity can be characterised as a sort of validity in which a particular measure correlates positively with measurements of distinct but related constructs, as expected by theory. Absolute Fit Measures, that is Likelihood ratio - Chi-Square Statistics was Chi-Square/df = 3.346 and P= 0.000 which is acceptable, and it confirms the proposed model. RMSEA is 0.051, Lower value indicates a good fit for the model. Here it is very low which indicates a good fit for the model. Overall model has excellent reliability, validity and also has good score on CFA. NFI (0.927), CFI (0.948), TLI (0.942), and IFI (0.948) indicate excellent model fit. The effect of AI enabled marketing campaign is positive and strong on the overall attitude with the standardized beta weight of 0.93 and R square 0.85. It can be said that approximately 85 percent of the variance in overall attitude is due to AI enabled marketing.

5.2 Managerial Implications

As a result of this study's conclusion that these factors significantly contribute to the success of an AI enabled hyper-localized marketing campaign, marketers can put more emphasis on factors like AI enabled advertisement related thoughts, retail store credibility, celebrity endorsement, awareness, social media involvement, consumer preference that ultimately leads to a positive attitude and positive attitude leads to purchase intention. The conclusion about demographics is also highly helpful to strategy makers and marketers.

In this study, the researcher has used structural equation modelling and confirmatory factor analysis, two highly effective statistical procedures that increase the validity and reliability of results. This study is value addition to the available pool of literature considering a strong research gap, that will be helpful to academicians to conduct research on the effects of hyper-localization and artificial intelligence in marketing across other states and countries. It is critical that the campaign, intent, and company remain consistent since positive perceptions of retailers' AI-enabled marketing leads to positive attitude and attitude leads to purchase intention.

5.3 Conclusion

The study concludes that AI enabled marketing is measured through 8 different latent variables and 29 items. First portion of the study confirms the construct. Factor loading, AVE and CR conclude the convergent validity of the construct. Model is having discriminant validity and Nomological validity as well. The study concludes that there is a significant impact of AI enabled marketing on purchase intention which is channelized through attitude towards AI enabled marketing. Perception related to AI enabled marketing converges into a positive attitude, but it cannot convert in to purchase intention of customers in the same intensity.

The first objective was to identify important variables for measuring AI enabled marketing. The literature concludes major variables like AI enabled advertisement related thoughts, retail store credibility, celebrity endorsement, awareness, social media involvement, and consumer preference that ultimately leads to a positive attitude and positive attitude leads to purchase intention. This study is different from past research in such a way that the study has taken a holistic approach in the measurement of AI enabled marketing and it finds the effect of AI powered marketing on the attitude and purchase intention. The second and third hypotheses of the study principally focus on the impact of AI-enabled marketing on the perspective of the retailer with respect to the intention to buy. Past literature does not talk about how perception related to AI enabled marketing is formed and how it influences an attitude which leads to purchase imitation. Thus, this study rejects both the hypothesis and concludes that AI-enabled marketing has a positive as well as statistically significant impact on attitude and Attitude have a positive and statistically significant impact on purchase intention that will be beneficial to society as a whole along with small retailers and it solves a major challenge of customer acquisition for small retailers post Covid- 19.

5.4 Scope for Further Research

The present study has considered AI enabled campaign with reference to hyper-localization. This type of research can be performed for other than hyper-localization to investigate an effect of AI enabled data driven marketing on purchase intention. Here, the researcher has selected a limited number of demographic characteristics, but for future research, he or she can identify and include additional demographic data. In addition, the Target Population consists of retailers who participate in an AI-enabled campaign. Therefore, further research can be undertaken with a consumer population of a different age group. The current study has considered four major States of Gujarat, Maharashtra, Madhya Pradesh and Delhi; further study can be conducted at the international level. In the present method structural equation modelling, Confirmatory factor analysis is done using SPSS and AMOS to investigate the impact of AI Enabled campaigns on Small Retailers in India but for further study researchers can use different methods to generalize the findings.

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