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Artificial Intelligence, Content Recommendation, Biases, and Consumer Behavior: An Analysis of the Impact of Artificial Intelligence on Consumer Behavior

[1]Dr. Sanghamitra Das, [2]Dr. Ankit Garg, [3]Dr. Neha Verma, [4]Dr. Deepak Jha ,[5]Dr. Ritesh Kumar Singhal, [6]Dr. Manupriya Gaur, [7]Rahul Singhal

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Abstract: Purpose: Information plays very important role in decision making. Awareness of brand, price, discounts, post sales activities like guarantee, warrantee, and maintenance must be advertised to influence the buying behaviour. But what if this information creates a bias. Does any type of bias generated by this information, in the form of advertisement, influence the buying behaviour? The present research is exploring the fact that how artificial intelligence-based advertisement suggestions and content recommendations create certain type of bias and how it affects the buying behaviour. This research is based upon a survey of consumers.

Design/methodology/approach: The methodology emphasised to eliminate the errors in measurement. Respondents were approached twice, in a gap of 30 days for collecting data. They were asked to retake the survey and data in both the attempts have been examined for any major deviation. The average of scores have been consolidated as final data of the research analysis.

Findings: The linear regression equation coefficients for the various model variables. The "B" values are the coefficients for each variable. In model 04 we could predict buying behaviour as BB (y) = 0.589 + .403 Anchoring bias + .284 Conformity Bias + .259 Heuristic Bias+ .233 FOMO.

Originality: Researchers have emphasis on exploring a new set of influencing factors for consumer behaviour rather following the key factors in systematic review of previous works. Thus, the work ensures the originality in research.

Key Words: *Artificial Intelligence, Content Recommendation, Biases, And Consumer Behaviour*

1. Introduction

It has been always a cause of concern for the marketer to understand the process of buying decision (Madhavan, M., & Kaliyaperumal, C., 2015). Marketers tried to understand the demand for goods and services with the help of 'need'. If a need is there, businesses make a product available to fill this need then the product will be sold (Osterwalder, A et al., 2015). But finding the exact product that meets an individual's needs is not too easy. In this commercialization era, a single need is catered to by multiple brands. In the red ocean of modern business, customers are flooded with advertisements (Ji, C., Mieiro, S., & Huang, G., 2022). These are the source of information that try to persuade the customers. Studies have suggested that buying decisions are not always rational. People are more emotional when they buy (Liao, C., 2016). Emotion, intuition, and the unconscious mind plays a crucial role in buying decision-making of people (Schwarz, E., 2022). Customers make choices based on their beliefs and some other psychological characteristics.

To make things more profitable marketers used neuroscience to understand the buying patterns of the customers (Kenning, P. H., & Plassmann, H., 2008). Studies have found that people are sensitive to certain colours, smells, and other aspects. This became a well-known tool of marketers as neuromarketing. Though marketers have made a gigantic leap in understanding the complex science of decision-making, one thing that is common in all the decision-making processes is having information in the soul of it (Connolly, T., & Zeelenberg, M., 2002).

The source of the information and type of the information is very vital while understanding the need for buying behaviour. Presently internet is our information source (Ratchford, B. et al., 2007). If we have to find a solution to our problem, we prefer to search for it online. The internet has helped marketers enough in the previous few years that a separate digital marketing domain has appeared.

[1]*Assistant Professor, Ajay Kumar Garg Institute of Management, Ghaziabad*

[2]*Assistant Professor, Ajay Kumar Garg Institute of Management, Ghaziabad*

[3]*Assistant Professor - III Amity School of Insurance, Banking & Actuarial Sciences, Amity University, Noida*

[4]*Assistant Professor, School of Business and Management, Christ (Deemed to be University, Delhi-NCR), Ghaziabad, Uttar Pradesh.*

[5]*Professor, Ajay Kumar Garg Institute of Management, Ghaziabad*

[6]*Assistant Professor, Ajay Kumar Garg Institute of Management, Ghaziabad*

[7]*Assistant Professor, Ajay Kumar Garg Institute of Management, Ghaziabad*

Day by day the internet is pumped with several GB of data in the form of contents. Data verification and credibility is very difficult for such a huge number. Each online search does not necessarily provide reliable information (Lee, C., Kim, J., & Chan-Olmsted, S. M., 2011). Marketers also used their skills to keep their products' information digitally available on these platforms. Over the years huge data have complied that have been used to predict consumer behaviour nowadays. Now marketers knew what stimulates the customers. And with the help of technology, they could manipulate the available information in a manner that customers are made to buy their product.

Such an algorithm has been developed with the help of artificial intelligence so that a customer will see the marketers' product in all the valid information sources (Davenport, T., et al., 2020). In the discussion, till now researchers have tried to draw the efforts by marketers in understanding customer behaviour. Digital marketing, neuromarketing, and artificial intelligence is the new era of marketing tools that understand consumer behaviour. Artificial intelligence is affecting marketers' understanding of consumer behaviour in many ways. It is helping them to persuade customers for buying their products. Researchers have tried to understand the role of AI-based content recommendations for consumers.

According to Duan, Edwards, & Dwivedi (2019), the AI-driven recommendation system makes use of its substantial machine learning skills to offer specialised ideas that are in line with each unique customer's preferences at all points of contact. The AI's training, which is dependent on particular datasets, has an impact on these recommendations. Understanding the makeup of the training datasets is essential since skewed recommendations can be produced by biassed or manipulative datasets (Lam, S. K. T., Frankowski, & Riedl, 2006).

Marketers' try to convenes the buyers for their brands with the help of AI recommendations. It is not always evil. In modern technology enabled business world there exists no product without competitors. To be different, some time the only way remains is advertising and promotion. What we perceive as a bias in the context of buyers, could be the objectivity for the specific band in the context of marketer. The more determination for the product will surely increase the likelihood of purchase. Comprehending the type of bias also helps the marketers for pushing their product and considerable for other for positive persuasion.

The researchers tried to develop an understanding that what types of information bias could be created by AI-based content recommendation and whether will they be impacting the consumers' buying. Researchers have defined the problem statement as, 'The effect of AI biases on consumer buying behaviour.'

2. Literature Review

2.0 Researchers' note for literature review

Researchers around the globe has appreciated the role of literature review process in the research. But popular issues related with any subject often create boundaries in the research if over emphasis is given to existing key terms. Researchers also prefer to quote established processes to avoid validation and to gain acceptance from publisher. It hampers the newness in any research. Further, if a researcher considers established postulates in the study, chances are high that statistical parameters meet the model fit. Again, a better model fit increases the chances of getting the research published in comparison with an average model fit.

Considering these facts researchers have developed a unique method. Researchers have studied literature related with the key topics. Emphasis is laid upon the meta-analysis type of studies. A hypothesized model is established avoiding popular predictors and variables related with research problem.

2.1 AI in business and perception bias

The tendency to see ourselves and our surroundings via a subjective lens despite our trust in objective judgement is referred to as perception bias. Our viewpoints are subconsciously influenced by our expectations and presumptions, which we are unaware of. The potential for AI-driven suggestions to reinforce and amplify racial and gender biases has drawn criticism in academic and media circles. The extent to which people are prepared to question AI-based recommendations when they detect bias, however, is poorly understood. To fill in this information gap, researchers M. Gupta, C. M. Parra, and D. Dennehy (2021) looked at how people's commitment to national cultural norms affects their readiness to challenge AI-generated suggestions in the case of perceived racial or gender bias. The study gathered information from 387 survey participants in the US and discovered that those who support cultural ideals like collectivism, masculinity, and uncertainty avoidance are more likely to be successful in challenging AI-based recommendations.

AI services that draw insights from a large corpus of data and incorporate those insights in human-in-the-loop decision environments are being used to build new decision-support systems. They promise to transform industries like health care by making better, more affordable, and timely decisions. However, expecting people to trust AI systems out of the box is unreasonable if they have been shown to discriminate across a variety of data usages: unstructured text, structured data, or images.

As a result, AI systems carry risks such as failing to recognise people or objects, introducing errors in their output, and causing unintended harm. In response, Srivastava, B., and Rossi, F. (2019) propose ratings as a means of communicating bias risk, as well as methods for rating AI services for bias in a black-box fashion without access to service training data. Our method is intended to work not only on single services, but also on service composition, which is how complex AI applications are built. Thus, rather than rating the entire system, the proposed method can be used to rate the severity of bias in a composite application, such as a chatbot, by rating its constituent services and then composing the rating.

2.2 Bias and consumer behaviour

In order to evaluate the potential bias in the context of consumer behaviour, Schmidt and Bijmolt (2020) carried out a meta-analysis with a specific focus on measuring customers' willingness to pay for various consumer items. Their research showed that this prejudice has a significant impact on how eager consumers are to spend and how they behave while making purchases.

Yang, Tang, Men, and Zheng (2021) investigated the impact of customers' perceived values, including hedonistic and utilitarian values, on impulsive purchasing behaviour (IBB) in the context of mobile commerce (m-commerce). They also looked at the moderating role that interpersonal influence has in the relationship between consumers' perceived values and their IBB. They gathered survey information from 199 people in China.

The research's conclusions are as follows:

Consumers' perceived values, which include both perceived utilitarian and hedonic worth, are substantially influenced by the environment.

Hedonic value assessment by consumers has a significant and direct influence on their impulsive purchasing behaviour.

IBB is significantly influenced by the relationship between perceived hedonic value and interpersonal influence.

These findings highlight the significance of comprehending how environmental stimuli, perceived values, and interpersonal influences shape consumers' purchasing decisions in the context of mobile commerce, and they provide useful insights for m-commerce retailers looking to improve and encourage consumer impulse buying behaviour.

2.3 AI and consumer behaviour

Given the growing and developing market, particularly in the digital space, tracking the client journey has become more difficult due to the changing marketing landscape. Customers now have a variety of new purchasing options, and they may communicate their preferences, attitudes, and ideas via a number of different platforms and channels. Artificial intelligence (AI) has become widely used as a solution to improve the digital experience and deliver personalised content in response to the demand for excellent customer care across digital platforms.

The amount of customer-curated data that is currently accessible in our digital age is expanding. To properly collect and use this data, many marketers have turned to AI. Real-time client insights can be gathered and used by firms to create customised digital marketing campaigns. While there is still work to be done to ensure that AI-based applications are widely used, businesses are beginning to understand the critical role that AI plays in digital marketing strategies, particularly in terms of enhancing the customer experience throughout the purchasing path.

Using the framework of the customer decision journey, Rabby, Chimhundu, and Hassan (2021) conducted a literature review of AI-based digital marketing solutions intended to improve the online consumer experience. Their study carefully explores how AI-integrated digital marketing affects customer purchasing patterns.

Artificial intelligence (AI) is now widely used in marketing, with marketers using it to predict consumer purchase trends. The potential for creating a framework of consumer behaviour using artificial neural networks was explored by Srivastava and Singh (2021) in their assessment of a research paper on consumer behaviour and ANNs. This framework, which is built on artificial neural networks, has the potential to analyse and anticipate consumer behaviour more precisely. The study also considers the idea of creating a machine learning model with artificial intelligence to track and predict consumer spending trends given the dynamic nature of consumer behaviour.

In conclusion, AI is becoming more and more crucial in the field of digital marketing, providing solutions to the problems brought on by the complex customer journey and the changing nature of the market. The customer experience is being improved by these AI developments, which are also giving marketers insightful information about consumer behaviour and buying habits.

3. Hypothesis & Research Model

3.0 Researchers' note for Hypothesis & Research Model

Based upon the studies and anticipated effect areas researchers have developed a 05-point scale to measure the opinion of respondents about the effect of the content on the buying decision of buyers. A set of 30 (items) questions have been tested for validity and reliability of the research tools. No predefined item related with any factor was used. These 30 (items) questions were reduced to 25 as the face validity if tested. Further, a pilot survey has been conducted (*4.1 Sampling and data collection)* among 250 respondents. The researchers have used dimension reduction (factor analysis) on the collected data. KMO value 0.739 and sig value 0.000 in Bartlett's Test (Annexure-02, Table-3.1) suggested that data is suitable for factor analysis. Scree plot shows that these 25 questions extracted 5 factors (Annexure- 01, Fig.-3.1). The total variance explained table shows that 05 items have eigen value above 01 and in total these 05 explains 78.352% variance (Annexure-02, Table-3.2). Loading below 0.400 were supresses and acceptable measurement model has been developed (Annexure- 01, Fig.-3.2). Reliability Statistics table suggested that Cronbach's Alpha for the tool is 0.835 and Cronbach's Alpha if item deleted column suggested that there is no significant change if we remove any of these items from questionnaire. The higher Cronbach's Alpha value suggested that items in the questionnaire are focused and the tool is reliable. With the nature of these items the factors have been names as:

Conformity bias, Anchoring bias, Availability heuristic bias, Fear of missing out (FOMO), and buying behaviour.

3.1 Conformity bias due to AI-based content recommendation persuade buying behaviour

According to the psychological concept of conformity bias, people have a tendency to match their decisions or behaviours with those of a group they believe to be making wise choices. The effect it has on how ideas, fashions, and behaviours spread among human communities is what is being looked at. To demonstrate this, we offer a model of qualitative behavioural transmission that includes three different sorts of people: "potential trend followers," "trend imitators," and "trend pioneers." In this model, nonlinear biassing affects how trends are adopted.

This model has sigmoidal conformity bias, which is notable because it can cause abrupt and major swings in trend adoption, sometimes known as "tipping-point" transitions. Niche styles and behavioural habits suddenly become very popular during these changes. A traditional, linear incidence model based on epidemiology, on the other hand, is unable to foresee these tipping points. This shows that the quick and significant shifts in the popularity of trends may be significantly influenced by conformity bias.

3.2 Anchoring bias due to AI-based content recommendation persuade buying behaviour

An example of a cognitive bias known as anchoring bias is the tendency for people to place an excessive amount of weight on the first piece of information they come across while making a decision. People's judgements and decisions are influenced by this early information because it acts as a reference point or anchor for assessing and processing future information.

Heuristics are a class of systematic biases and mental shortcuts that have been identified by behavioural economics research as having an impact on decision-making. Contrary to the traditional assumption of neoclassical economics, which holds that people are consistently rational and seek to maximise their utility while adhering to their "true" preferences, these biases and heuristics frequently show that people's decision-making is highly context-dependent.

An analysis by Reisch and Zhao (2017) charts the progression of research from neoclassical economics to behavioural economics. They talked about how consumer policy research and the study of consumer behaviour have been significantly impacted by behavioural economics. These behavioural principles give useful guidance for creating consumer policies in addition to making a significant contribution to our understanding of consumer behaviour. These insights can be used in a variety of contexts, such as choosing products, promoting healthy eating, and promoting sustainable consumption. In short, behavioural economics has contributed to a more complex and realistic understanding of how people make decisions, which has consequences for developing public policies that take into account actual consumer behaviour..

3.3 Availability heuristic bias due to AI-based content recommendation persuade buying behavior

The availability heuristic, also known as the availability bias, is a cognitive short-cut that involves using examples that are easily accessible or can be quickly recalled when evaluating a certain subject, idea, approach, or choice. In spite of the mathematical risk of dying in a car accident being far higher than that of dying as an airline passenger, people may develop a phobia of flying as a result of hearing about plane crashes.

Due to its accessibility and ease, people frequently choose to shop online because they think it can help them save money. In contrast to offline environments, Niza Braga and Jacinto (2022) argue that the context of online purchasing can engage low-effort processing, resulting in heuristic decision-making. By examining how online shopping environments can spur expectations of resourcesaving and affect the use of heuristic cues in consumer decision-making, this research makes an important addition. The study also takes into account these results' constraints and ramifications..

3.4 FOMO due to AI-based content recommendation persuade buying behavior

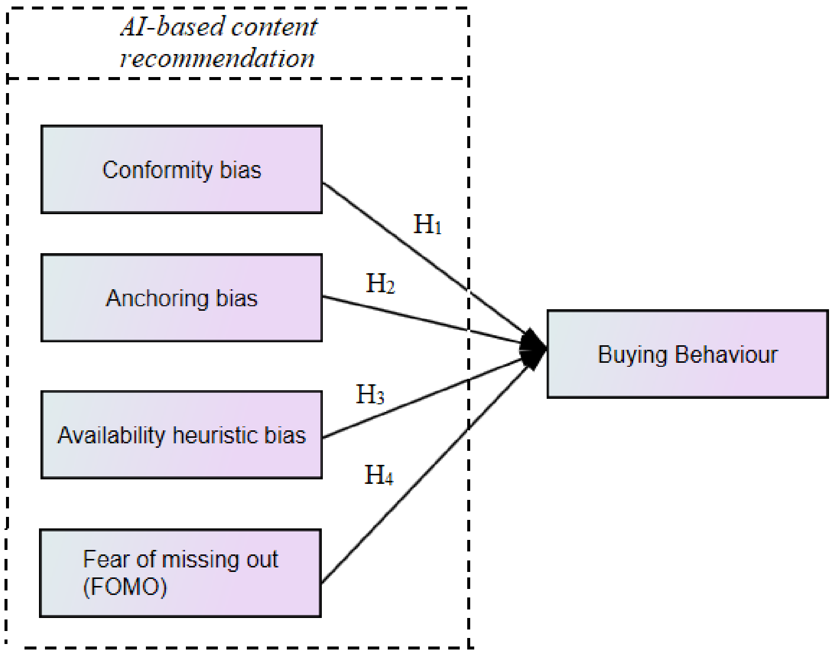
According to Przybylski, Murayama, DeHaan, and Gladwell (2013), the dread that people have of missing out on social gatherings, novel experiences, successful investments, or enjoyable pursuits is known as FOMO. The dread of missing out on different social or fun activities is known as FOMO, and it is frequently viewed by researchers as a personality trait or as a generic form of anxiety.

Because it can affect how people react to messages that make use of FOMO-related appeals, FOMO is of special relevance to researchers who study consumer behaviour as well as marketing professionals. These pitches seek to elicit from customers context-specific FOMO reactions. Researchers also investigate how specific feelings may lessen or strengthen the effect of such appeals on consumers' inclinations to buy hedonic goods or experiences.

The findings of an experiment using vignettes, which are presented in this context, show that FOMO-heavy appeals might in fact affect customers' purchase intentions. These appeals have the capacity to either raise consumers' intentions to make a purchase by raising their expectations of happiness and self-improvement or weaken consumers' intentions to make a purchase by raising their expectations of regret over the costs connected with the suggested hedonic service or experience. This study clarifies how FOMO may be cleverly used in marketing to affect consumer behaviour..

Based upon the assumption a hypothesized research model is proposed as in Fig-01

Fig 01- Hypothesized model



Source: Researchers own elaboration

4. Methodology

4.0 Researchers' note for Methodology

Researchers have used self-developed scale for the measurement of the key variables. Respondents for the research are individual buyers using online buying platforms of different products in India (Swiggy, Blinkit, Filpkart, Amazon,1mg). The researchers have sought help of delivery persons for identifying such respondents in the geographical area of Delhi NCR. With the concert of respondents, the researchers have visited each respondent at least 02 times with a gap of not less than 30 days. The collected data has been tabulated in SPSS 22 and analysis with the of same software along with AMOS 20. The data is collected in 02 part. Pilot survey consists 250 responses. Final data that has been used for final analysis is based upon 534 responses. Researchers have ensured that none of the respondents in pilot survey become a part of final data. The researchers have tested the hypothesis with the help of regression analysis. Due weight of each type of biases have been examined to suggest suitable the type of content recommendation that could generate more buying decisions. The results of the Harman single factor method were reported in this section. The study investigates the common method bias in responses using exploratory factor analysis with the assumption of one factor. This is known as the Harman single factor method. According to the findings, a single factor accounts for 22.708 percent (Annexure-02, table 3.1 a) of the variance in responses to all customer retention statements. As a result of the study, it is possible to conclude that the responses received in the study are free of the common method bias problem. All of the study's conclusions are free of bias as a result of hypothesis testing and statistical analysis.

4.1 Sampling and data collection

Every buyer can be considered as the population for the present researcher as mostly people use internet for product search. Whether they purchase online or offline they are exposed to algorithm and artificial intelligence-based advertisements and information. To ensure the effect of AI based content recommendation researchers have limited the sample to the online buyers only. The data has been collected with the help of convenience sampling. Your study's sample size of 534 participants is greater than the advised 129-person minimum sample size. According to the 2009 work by Erdfelder, Faul, Buchner, and Lang, this minimal sample size was calculated using the G*Power software with specified settings, such as an effect size of 0.3, an alpha level of 0.05, and a power level of 0.95.

In fact, the sample size in your study, which was 534, exceeds the "50 times rule of thumb" for analysis using artificial neural networks (ANNs). The minimum sample size should, according to this guideline, be at least 50 times as large as the number of adjustable parameters in the neural network. The lowest advised sample size in your situation, where there are 5 parameters in the neural network, would be 250 (50 multiplied by 5). As a result, your sample size of 534 is not only significantly larger than the advised minimum but also big enough to do ANN analysis, giving your research and analysis a solid foundation.

5. Results

1- Multiple regression

Multiple regression analysis employs the variable selection method of stepwise regression. It seeks to determine which independent variables are most pertinent to include in a regression model (Table I). Stepwise regression entails methodically including or excluding model variables in accordance with statistical criteria.

Variables Entered/Removed			
Model	Variables Entered	Variables Removed	Method
1	Anchoring bias	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	Conformity bias	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Heuristic bias	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	FOMO	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
a. Dependent Variable: Buying behaviour			

Table I: Variables Entered/Removed (Step wise Multiple corelation)

Source: Researchers' data analysis

2- An assessment of a regression model's performance, including how well the independent variables account for variance in the dependent variable, is often provided in the "Model Summary" section (Table II). You referenced "model 4" in your explanation and said that the listed independent variables can account for about 95% of the variation in the dependent variable.

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.928[a]	.861	.861	1.69531
2	.964[b]	.930	.930	1.20499

3	.973[c]	.948	.947	1.04111
4	.977[d]	.954	.954	.97492
a. Predictors: (Constant), Anchoring bias				
b. Predictors: (Constant), Anchoring bias, Conformity bias				
c. Predictors: (Constant), Anchoring bias, Conformity bias, Heuristic bias				
d. Predictors: (Constant), Anchoring bias, Conformity bias, Heuristic bias, FOMO				

Table II: Model Summary (Step wise Multiple corelation)

Source: Researchers' data analysis

3- ANOVA Table

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9452.363	1	9452.363	3288.848	.000[b]
	Residual	1529.003	532	2.874		
	Total	10981.365	533			
2	Regression	10210.357	2	5105.178	3515.979	.000[c]
	Residual	771.008	531	1.452		
	Total	10981.365	533			
3	Regression	10406.890	3	3468.963	3200.398	.000[d]
	Residual	574.476	530	1.084		
	Total	10981.365	533			
4	Regression	10478.567	4	2619.642	2756.155	.000[e]
	Residual	502.798	529	.950		
	Total	10981.365	533			
a. Dependent Variable: Buying behaviour						
b. Predictors: (Constant), Anchoring bias						
c. Predictors: (Constant), Anchoring bias, Conformity bias						
d. Predictors: (Constant), Anchoring bias, Conformity bias, Heuristic bias						
e. Predictors: (Constant), Anchoring bias, Conformity bias, Heuristic bias, FOMO						

Table III: ANNOVA Table (Step wise Multiple corelation)

Source: Researchers' data analysis

For Model 04,

P-value (Sig value): During hypothesis testing, the p-value evaluates the strength of the evidence in opposition to the null hypothesis. A significance threshold (alpha) of 0.05 (or 5%) is frequently selected in many statistical analyses (Table III). This indicates that the result is regarded statistically significant if the p-value is less than 0.05, indicating that there is strong evidence against the null hypothesis. You appropriately state in your explanation that the result is significant with a p-value of.000 (less than 0.05), as you did. F-ratio: The F-ratio, also referred to as the F-statistic, is used in regression analysis and analysis of variance (ANOVA). The variance between groups (also known as the model variance) and the variance within groups (also known as the error variance) are the two variances that are measured. A higher F-ratio indicates that the model is capable of explaining a sizable portion of the data variation. You claimed that an efficient model has an F-ratio greater than

1, but it's vital to remember that how you interpret the F-ratio depends on the context of your study and the degrees of freedom involved. The model is statistically significant if the F-ratio exceeds the critical value for a specified alpha level (often 0.05).

4- Coefficients Table

Coefficients box show the linear regression equation coefficients for the various model variables. The "B" values are the coefficients for each variable (Table IV). In model 04 we could predict buying behaviour as

BB (y) = 0.589 + .403 Anchoring bias + .284 Conformity Bias + .259 Heuristic Bias+ .233 FOMO.

The Significance (Sig.) figures should be 0.05 or below to be significant at 95 percent. A value of .000 means the figure is too small for three decimal place representation.

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.598	.350		1.710	.088
	Anchoring bias	1.000	.017	.928	57.348	.000
2	(Constant)	-1.636	.267		-6.121	.000
	Anchoring bias	.611	.021	.567	29.075	.000
	Conformity bias	.486	.021	.446	22.848	.000
3	(Constant)	-2.808	.247		-11.379	.000
	Anchoring bias	.471	.021	.437	22.456	.000
	Conformity bias	.318	.022	.292	14.327	.000
	Heuristic bias	.373	.028	.302	13.465	.000
4	(Constant)	-3.177	.235		-13.523	.000
	Anchoring bias	.403	.021	.374	19.092	.000
	Conformity bias	.284	.021	.260	13.412	.000
	Heuristic bias	.259	.029	.210	8.924	.000
	FOMO	.233	.027	.195	8.684	.000

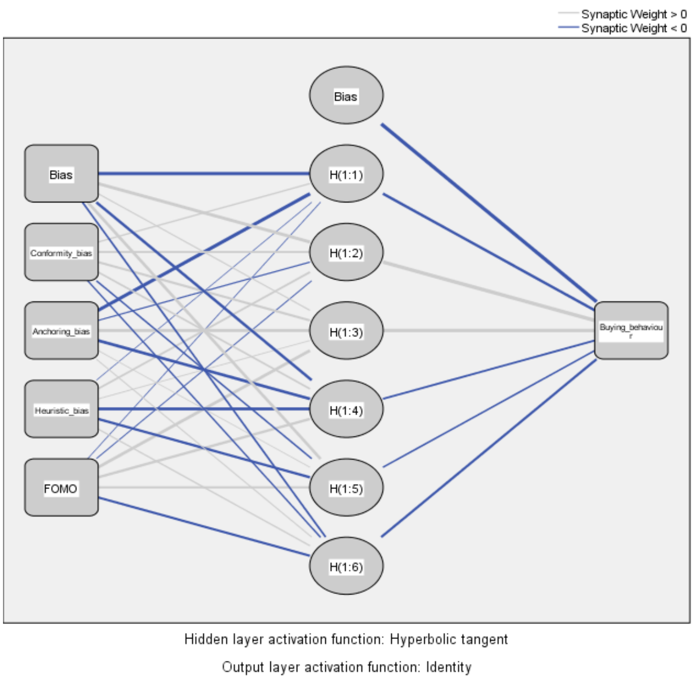
a. Dependent Variable: Buying behaviour (BB)

Table IV: Coefficients Table (Step wise Multiple corelation)

Source: Researchers' data analysis

5- Multi Layer Network

Fig 02- Multi Layer Network



Source: Researchers' data analysis

6- Hypothesis Testing

a- Conformity bias due to AI-based content recommendation persuade buying behaviour. The values of t test and sig value in the model 04 from table 4.4 suggested that there is significant impact of conformity bias on buying behaviour. Test values in table 4.3 and 4.2 supports the fact.

b-Anchoring bias due to AI-based content recommendation persuade buying behaviour. The values of t test and sig value in the model 04 from table 4.4 suggested that there is significant impact of conformity bias on buying behaviour. Test values in table 4.3 and 4.2 supports the fact.

c-Availability heuristic bias due to AI-based content recommendation persuade buying behaviour. The values of t test and sig value in the model 04 from table 4.4 suggested that there is significant impact of conformity bias on buying behaviour. Test values in table 4.3 and 4.2 supports the fact.

d- FOMO due to AI-based content recommendation persuade buying behaviour. The values of t test and sig value in the model 04 from table 4.4 suggested that there is significant impact of conformity bias on buying behaviour. Test values in table 4.3 and 4.2 supports the fact.

6. Discussion

This section is the independent interpretation of the findings and solely the authors' expressions about the study. AI gives you such insight into the buyer's mind that a standard marketer will not be able to do. But there are also some ethical concerns. Is the AI impact negative? What if such technology-born bias is used for a political campaign or propaganda or controversial issues? One of the biggest critiques of AI-based marketing is that it takes advantage of the customers. Manipulation is the act of playing upon others' hopes and fears to get them to act in a certain manner. In such circumstances, all the marketing can be considered as manipulation. Just because AI could do it in a better way than others, we cannot persecute the technology. Surely for some people technology is a devil but in a world of information and a pool of brands to fill customer needs it may be a guide for most. The idea of AI making marketing manipulative is not absurd. Surely it could affect the mind of buyer's mind than anything else. But everything we interact with influences us in some way or another. Even now the research paper has affected your opinion of AI on buying behaviour.

There is no such buy button in the brain. Buttons are there to just trigger emotions and information biases. People say that data is oil in the modern world. Day by day unified data is piling on the servers of business organizations. This 'Big Data' could easily feed information to the neural networks and with the help of machine learning the business world could find a manipulative AI. An AI that could easily create biases in the mind of the buyers. That could pose the specific brand as superior to others. The content recommendation-related issues have been exhibited in the present research paper. Conformity bias, anchoring bias, availability heuristic bias, and FOMO are merely the tip of the iceberg. Mobile phones and apps have access to our contacts, friends, and the people around us. They keep the track of the places we visit the thing we search for online and our expenditure patterns. AI can predict our moves and we could easily fall prey to technology. Up to the ethical limits, these are helpful but could be used unfairly by marketers. AI use a number of data set to identify patterns and trends to provide recommendations. Recommendations based upon AI usually follow the pattern of the user. Now a days internet devices like mobile phones, laptops use email id to function like search engine and web browser. It means if a if a laptop is used for any product the search pattern will be recorded for that email id. IP address can easily locate the area of user and the available sellers start approaching the user with the help of AI based recommendation. Consider an example when a person search for an electronic device on web browser. Out of several options he clicks a brand whenever he searches. All such information will be recorded. The same data set is used by AI recommendation algorithms. If someone search a product in the same area, mostly likely same brand will appear at the top of the search. In the present study, it has been found that what conformity bias, anchoring bias, availability heuristic bias, and fear of missing out are the most effective in persuasion of buyer. If the recommendation text, video or advertisement is using such information that could impulse and inclination of buyer towards the brand it will be helpful. Buyers' nature can be used by the marketers.

Generally, while watching an advertisement mostly people are aware that advertisements are framed to impact any certain type of emotion. Most of the narratives in the advertisements by actors are persuasive effort. Gradually customers get less influenced by advertisement. But search information on search engines still seems genuine to buyers as search engine optimization, AI based recommendations and machine learning are still not common. When people search any information, top 2-3 contents usually appear as 'ad'. Under the guidelines of government, they have to be shown as paid content. But if the companies can influence the buyers search with the help of AI & machine learning they will be able to create more likelihood and bias of customers towards their product.

7. Conclusion

Artificial Intelligence increasingly helps humans to make decisions. Algorithms help doctors to reach a diagnosis or a judge to reach the verdict. AI can be useful to make good decisions. The marketplaces are no exception in the use of AI. There is also a downside though to the impact of AI on human decision-making because it can also create biases. It is very important to understand the limitations of our system. AI does not understand the context the way humans do and it is not equipped to deal with the problems that are the fundamentally quite complex problem of human nature. We should keep this in mind while placing these systems in various workflows that society, ethics, and sustainability is really important. Also, it should be ensured that AI-based systems have enough transparency and accountability mechanisms to ensure that we know who is in charge of how the AI system performs and can appeal to if there is any mistake made or we are denied wrongfully. That is the missing part of the puzzle that researchers believe we don't have for now. If we don't have control over how AI is working, we must find that our lives are being shaped by the decisions of AI that have been made by other human beings and marketers. So, the AI which through machine learning has been trained to be able to suggest decision alternatives can be used in conjunction with humans to come to a more accurate decision. The code of ethics and legal structure that is governing and regulating ethical advertising will limit the misuse of AI too. Consumers' rights and ethics should be a part of the learning of the neural networks and most of them could be contributing to making an ethical AI. It's the need of the hour that regulations like advertising bodies make the legal framework as 'they must see it coming'.

References:

[1] Bissell, J. J. (2015). Conformity bias and catastrophic social change. *Tipping Points: Modelling Social Problems and Health*, 168-182.

[2] Solomon, M., Russell-Bennett, R., & Previte, J. (2012). *Consumer behaviour*. Pearson Higher Education AU.

[3] Frederiks, E. R., Stenner, K., & Hobman, E. V. (2015). Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *Renewable and Sustainable Energy Reviews*, *41*, 1385-1394.

[4] Connolly, T., & Zeelenberg, M. (2002). Regret in decision making. *Current directions in psychological science*, *11*(6), 212-216.

[5] Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*, 24-42.

[6] Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International journal of information management*, *48*, 63-71.

[7] Erdfelder, E., Faul, F., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, 41(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149.

[8] Gupta, M., Parra, C. M., & Dennehy, D. (2021). Questioning racial and gender bias in AI-based recommendations: Do espoused national cultural values matter? *Information Systems Frontiers*, 1-17.

[9] Ji, C., Mieiro, S., & Huang, G. (2022). How social media advertising features influence consumption and sharing intentions: the mediation of customer engagement. *Journal of Research in Interactive Marketing*, *16*(1), 137-153.

[10] Kenning, P. H., & Plassmann, H. (2008). How neuroscience can inform consumer research. *IEEE transactions on neural systems and rehabilitation engineering*, *16*(6), 532-538.

[11] Lam, S. K. T., Frankowski, D., & Riedl, J. (2006). Do you trust your recommendations? An exploration of security and privacy issues in recommender systems. In *Emerging Trends in Information and Communication Security: International Conference, ETRICS 2006, Freiburg, Germany, June 6-9, 2006. Proceedings* (pp. 14-29). Springer Berlin Heidelberg.

[12] Lee, C., Kim, J., & Chan-Olmsted, S. M. (2011). Branded product information search on the Web: The role of brand trust and credibility of online information sources. *Journal of Marketing Communications*, *17*(5), 355-374.

[13] Liao, C., To, P. L., Wong, Y. C., Palvia, P., & Kakhki, M. D. (2016). The impact of presentation mode and product type on online impulse buying decisions. *Journal of Electronic Commerce Research*, *17*(2), 153.

[14] Madhavan, M., & Kaliyaperumal, C. (2015). Consumer buying behavior-an overview of theory and models. *St. Theresa Journal of Humanities and Social Sciences*, *1*(1), 74-112.

[15] Osterwalder, A., Pigneur, Y., Bernarda, G., & Smith, A. (2015*). Value proposition design: How to create products and services customers want*. John Wiley & Sons.

[16] Ratchford, B. T., Talukdar, D., & Lee, M. S. (2007). The impact of the Internet on consumers' use of information sources for automobiles: A re-inquiry. *Journal of Consumer Research*, *34*(1), 111-119.

[17] Rabby, F., Chimhundu, R., & Hassan, R. (2021). Artificial intelligence in digital marketing influences consumer behaviour: a review and theoretical foundation for future research. *Academy of Marketing Studies Journal*, *25*(5), 1-7.

[18] Schwarz, E. (2022). Emotion Index: When Do Emotions Trigger Buying Impulses?. In *Neuro-Advertising: Brain-friendly advertising for more success in your market* (pp. 29-66). Wiesbaden: Springer Fachmedien Wiesbaden.

[19] Schmidt, J., & Bijmolt, T. H. (2020). Accurately measuring willingness to pay for consumer goods: a meta-analysis of the hypothetical bias. *Journal of the Academy of Marketing Science*, *48*, 499-518

[20] Srivastava, B., & Rossi, F. (2019). Rating AI systems for bias to promote trustable applications. *IBM Journal of Research and Development*, *63*(4/5), 5-1.

[21] Srivastava, G., & Singh, N. (2021). Artificial intelligence to predict consumer behaviour: A literature survey. *Recent Trends in Communication and Electronics*, 367-371.

[22] Yang, F., Tang, J., Men, J., & Zheng, X. (2021). Consumer perceived value and impulse buying behavior on mobile commerce: The moderating effect of social influence. *Journal of Retailing and Consumer Services*, *63*, 102683.

[23] Reisch, L. A., & Zhao, M. (2017). Behavioural economics, consumer behaviour and consumer policy: state of the art. *Behavioural Public Policy*, *1*(2), 190-206.

[24] Liang, X., Hu, X., Meng, H., Jiang, J., & Wang, G. (2022). How does model type influence consumer and online fashion retailing? *International Journal of Retail & Distribution Management*, *50*(6), 728-743.

[25] Hakan, B. O. Z. (2019). Anchoring Effect: A Myth or Reality?. *Ekonomik ve Sosyal Araştırmalar Dergisi*, *15*(1), 33-47.

[26] Alwosheel, A., van Cranenburgh, S., & Chorus, C. G. (2018). Is your dataset big enough? Sample size requirements when using artificial neural networks for discrete choice analysis. Journal of Choice Modelling, 28(September 2018), 167–182. https://doi.org/ 10.1016/j.jocm.2018.07.002.

[27] Good, M. C., & Hyman, M. R. (2021). Direct and indirect effects of fear-of-missing-out appeals on purchase likelihood. *Journal of Consumer Behaviour*, *20*(3), 564-576.

[28] Hodkinson, C. (2019). 'Fear of Missing Out'(FOMO) marketing appeals: A conceptual model. *Journal of Marketing Communications*, *25*(1), 65-88.

[29] Przybylski, A. K., Murayama, K., DeHaan, & C. R.,Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. Computers in Human Behavior, 29(4), 1841- 1848.

[30] Niza Braga, J., & Jacinto, S. (2022). Effortless online shopping? How online shopping contexts prime heuristic processing. *Journal of Consumer Behaviour*, *21*(4), 743-755.

[31] Kuruppu, G. N., & De Zoysa, A. (2020). COVID-19 and panic buying: an examination of the impact of behavioural biases. *Available at SSRN 3596101*.