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The Mediating Role of Behavioral Intention in AI Adoption for Car Purchasing: A UTAUT-Based SEM Approach

Mahima [1], Dr Pooja Gupta [2]*
[1]Research scholar, School of Commerce and Business Management, GeetaUniversity, Panipat, India
Email id: mahima.2206702012@geetauniversity.edu.in
[2]Associate Professor, School of Commerce and Business Management, Geeta University, Panipat, India
Email id: pgpoojaguptamba85@gmail.com

ABSTRACT

This study aims to ascertain the ways in which intent (BI) and use behavior (UB) are influenced by expectations for performance (PE), expectations of effort (EE), social impact (SI), Conditions that facilitate (FC), hedonic motives (HM), pricing value (PV), and habits (H). The quantitative research method used in this study includes a standardized questionnaire with a Likert scale of five points.

This study uses the “Unified Theory of Acceptance and Use of Technology 2” model as a basis to evaluate how artificial intelligence (AI) applications affect automotive purchasers' purchasing intentions and usage behaviour. Data from vehicle buyers in various areas is analyzed using Modeling Structural Equation (SEM) with AMOS 26 and SPSS 21.

Along with investigating that how artificial intelligence (AI) applications affect the purchasing intentions and usage behaviour of automobile buyers, this study also explores demographic profile , factors influencing the consumers to interact with AI technologies and find out the most interactive AI application used by car purchasers

Keywords: Artificial intelligence applications, purchase intention, usage behavior, chatbot, virtual reality, personalized recommendation system.

INTRODUCTION:

By improving the purchasing experience through analogue recommendations, trust building techniques and more openness, artificial intelligence (AI) has application-like Chatbot, Virtual Assistant and AI operated search engine and virtual tasters. The system’s capacity to precisely comprehend external information, absorbs knowledge from that information, and uses that knowledge to achieve specific goals and tasks through flexible change (Hainyalin & Kalpan, 2019). Future marketing strategies and consumer behavior, including business models, sales processes, and customer service alternatives, appears to be influenced by artificial intelligence (AI) (Devanport et al., 2020). AI applications in retail include supply chain optimization, inventory management, customer service management, sales/customer relationship management, customization and recommendation systems, and task creation for stores (Shankar et al., 2021). In an effort to engage and communicate with customers (both present and potential) more effectively and boost their profits, retailers and service providers are investing more in internet, mobile, and social media platforms (Grewal et al., 2020).

The majority of these because they are more convenient and efficient, gadgets have helped to improve our daily lives. Few people realize that these technologies have the ability to surpass our intelligence and take control of us if they continue to advance and improve (Corina & Ene, 2019). AI enhances the consumer journey by predicting their behavior (Pangkey et al., 2020).

AI enables the creation of ads based on information gathered from millions of customers in less than a minute, claims Nair and Gupta (2021). Artificial intelligence (AI) has performed an extraordinary feat in shaping consumer behavior in the hospitality sector in the form of increased personalization, increased service efficiency, and changing client expectations (Lu et al., 2024). Virtual influencers are becoming a major force in the ever-changing field of influencer marketing (Vinoi et al.., 2025).

1.1 Literature gap

There is little research to exacerbate the impact of AI applications on customer decision making in the Indian passenger automobile market. Most of the studies are non-sector specific studies. All the prominent sectors, specially the automobile sector despite beingone of the highest digital spender, has encountered dearth of academic studies across the globe

1.2 Objectives:

1) To investigate the demographic profile of consumers interacting with AI applications.

2) To find out the factors influencing the consumers to interact with AI technologies.

3) To find out the most interactive AI application used by car purchasers.

4) To study the effect of artificial intelligence applications on buying behavior of car emptor.

2. Conceptual framework

Theories of consumer behaviour are essential for comprehending how customers embrace and engage with new technologies. These theories provide a structure for examining the factors that impact the acceptability of technology in various situations. To comprehend and forecast the adoption and application of technology, a number of concepts and frameworks have been invented. These concepts are frequently used in studies to clarify the processes and justifications for why people or organizations adopt and use new technologies.

2.1 Model of technology acceptance

Two theoretical notions that are thought to be key factors in determining system use are perceived utility and ease of application are the focus of the model. The extent to which an individual feels that utilizing a specific system would improve his or her performance at work is known as perceived usefulness. On the other hand, perceived ease of use describes how much someone thinks a certain technology would be effortless to use. The perspective presented here is far more hopeful, despite the fact that there has been an increasing pessimism in the area over the capacity to find measures that are strongly associated with user acceptability (Davis, 1989).

2.2 Reasoned action and planned behavior theory

Planned Behavior and Reasoned Action theory concentrate on theoretical frameworks that address personal motivational elements as predictors of the propensity to engage in particular actions. The foundation of the TRA and TPB is the idea that intention, which is based on attitudes and societal normative views about the action, is the best indicator of that behavior. Perceived control over behavior performance is an extra construct included in the TPB, which is an extension of the TRA. Through opinions, subjective standards, and perceived control, the TRA and TPB postulate a causal chain that connects behavioral beliefs, normative beliefs, and control beliefs to behavioral intentions and behaviors. Excellent frameworks for conceptualizing, measuring, and identifying the variables influencing behaviors are offered by the TRA, TPB. The TRA focuses on how motivation is determined by cognitive elements, such as beliefs and values. The explanation of behaviors, especially those that are subject to volitional control, has greatly benefited from this approach. It's critical to reevaluate behavioral theories and take into account alternative theory-driven constructs that could improve explanatory power when using them (Fishbein & Ajzen, 1975). TPB extends TRA by including perceived behavioral control which deals with enabling or restricting circumstances that influence intention and behavior (Ajzen, 1991).

2.4 The Decomposed Theory of Planned behaviors (DTPB)

According to Taylor and Todd (1995), the breakdown of attitudinal beliefs is necessary to gain a deeper comprehension of the connections between structures of belief and root causes of intention. According to the diffusion of innovation theory, the three key attributes of an innovation that affect acceptance are compatibility, complexity, and relative advantage. Compared to the pure TPB and TRA models, the decomposed TPB model has a higher explanatory power.

2.5 The Unified Theory of Acceptance and Use of Technology (UTAUT)

According to the idea, usage intention and behavior are directly influenced by four major constructs: performance expectancy, effort expectancy, social influence, and facilitating factors. The influence of the four main constructs on usage intention and behavior is thought to be mediated by age, gender, previous experience, and deliberate use. The degree to which a person thinks that utilizing technology would enable him or her to achieve improvements in job performance is known as performance expectancy. Effort expectation is the level of convenience that comes with using digital technology. The extent to which a person believes that significant others such as peers, superiors, subordinates, etc. think that he or she ought to use technology is known as social influence. Facilitating circumstances or conditions offers assistance to users with regard to both the software as well as hardware required to operate on e-commerce, as well as e-commerce interoperability with various platforms and applications (Venkatesh et al., 2003).

2.6 The Unified Theory of Technology Acceptance and Use 2

Hedonic drive, monetary value, and habit are the three constructs that UTAUT2 integrates into UTAUT. The impacts of these dimensions on behavioral intention and technology use are thought to be moderated by individual variations, including identity, gender, and level of experience and age. The enjoyment or pleasure that comes from using a technology is known as hedonic motivation, and it has been demonstrated to be a significant factor in deciding the adoption and usage of technology. The price value of technology is the monetary cost that the user must pay. Experience and habit are the final two related but separate elements added to UTAUT (Venkatesh et al., 2012).

To help comprehend the elements influencing the adoption of technologies, several theoretical models have been put forth. UTAUT is one of the most well-known and reliable models for describing how people accept technology.

2.7 Conceptual framework and hypothesis development

2.7.1 Expectations for performance (PE)

According to Venkatesh et al. (2003), the PE is Performance expectancy is the extent to which an individual believes that using technology would help him or her perform better at work. The degree to which a person feels that utilizing technology will improve his or her performance at work is known as performance expectancy (McLean & Osei-Frimpong, 2019). Thus, the following theory is proposed in light of this:

H1: Performance expectancy influence Users' intention to adopt AI applications.

2.7.2 Expectations of effort (EE)

According to Venkatesh et al. (2003), the degree of comfort that comes with utilizing digital technology is known as effort expectation. In a research setting effort expectancy is one of the basic predictor of technology uptake or adoption (Wirtz et al., 2019). According to earlier studies, the degree of comfort that comes with using technology appears to have an impact on its use (Fridin & Belokopytov, 2014). Thus, it is theorized based on this that:

H2: Effort expectancy influence Users' intention to adopt AI applications.

2.7.3 Social Impact (SI)

Social influence is the degree to which an individual feels that important others, including peers, superiors, subordinates, etc., think that he or she should adopt technology (Venkatesh et al., 2003). Our suggested idea in this regard is as follows:
H3: Users' intention to adopt AI applications is influenced by Social Influence.

2.7.4 Conditions that facilitate (FC)

Facilitating circumstances or situations provides support to users in terms of both the software and hardware required to use a newly introduced technology. This viewpoint is based on the concept of adoption; an information system is dependent on an initial assessment of the user's degree of competence with the newly introduced technology (Venkatesh et al., 2003).

H4: Users' intention to employ AI applications is influenced by Facilitating conditions.

2.7.5 Hedonic Motives (HM)

Hedonic motive is a delightful feature, joy, or enjoyment those results from utilizing technological advancements without any unique additional benefits (Venkatesh et al., 2012). Hedonic motivation has a significant role in influencing the behavior of consumer (Holbrook & Hirschman, 1982), and when assessing acceptance and technology use beforehand, the element associated with the enjoyment and pleasure gained from use might be viewed as essential (Brown & Venkatesh, 2005;Childers et al., 2001).
H5: Intention of users to employ AI applications is influenced by Hedonic Motivation.

2.7.6 Price Value (PV)

Users' cognitive compromise regarding the apparent benefits of application and its cost is known as price value (Venkatesh et al., 2012). As a result, PV is a metric that quantifies the overall advantage of a technology. In actuality, the goal is always enhance the profit. It suggests that people will bear the expense of technology if its adoption and use result in benefits. According to earlier research, price and value influence favorably consumers' adoption of technology, which is a process that is improving in and of itself (Palau-Saumell et al., 2019; Moorthy et al., 2019).
H6: Intention of users to employ AI applications is influenced by Price value.

2.7.7 Habit (H)

The Habit (H) is the degree by which learning leads to automatic behavior (Venkatesh et al., 2012). Individuals who internalize habits may not consider, recognize, or assess the motivations behind their behavior due to repeated repetition (Ouellette and Wood, 1998).

Thus, the following theory is proposed in light of this:
H7: The intention of users to employ AI applications in car buying is influenced by Habit.

Facilitating condition and Habit are the only two constructs which directly influence use behavior (UB). Facilitating Conditions are referred as the accessibility of resources, infrastructure, and support that make it simpler for users to adopt and maintain technology. If customers have access to AI-powered tools, technical assistance, and seamless integration with their purchase path, they are more likely to participate in sustained use. Habit measures the extent to which users adopt an automatic behavioral habit while using AI apps. When customers routinely utilize AI-powered chatbots, virtual assistants, and search engines to make automobile purchasing decisions, their reliance on these technologies becomes habitual, resulting to direct use conduct (Venkatesh et al., 2012). Thus, the following theories are proposed in light of this:

H8: Facilitating circumstances have a substantial impact on customers' use of AI apps while buying a car.

H9: Habit significantly influences consumers' Usage Behavior of AI applications in car buying.

2.7.8 Behavioral Intent (BI)

The extant by which a person intends to carry out a certain activity is known as behavioral intent. The power of a user's behavioral intention determines their actual behavioral performance. As a result, users' actual behavior can be predicted using behavioral intent (Venkatesh et al., 2012). It is a variable that precedes actual usage behavior in the UTAUT paradigm.
As a result, the following theories are put forth:

H10 (a): The relationship between AI application usage behavior and performance expectancy can be mediated by buying intention.

H10 (b): The connection between effort expectancy and AI application usage behavior can be mediated through buying intention.

H10 (c): The connection between social influence and usage behavior of AI applications is mediated by buying intention.

H10 (d): The correlation within facilitating circumstances and use behavior of AI applications can be mediated by buying intention.

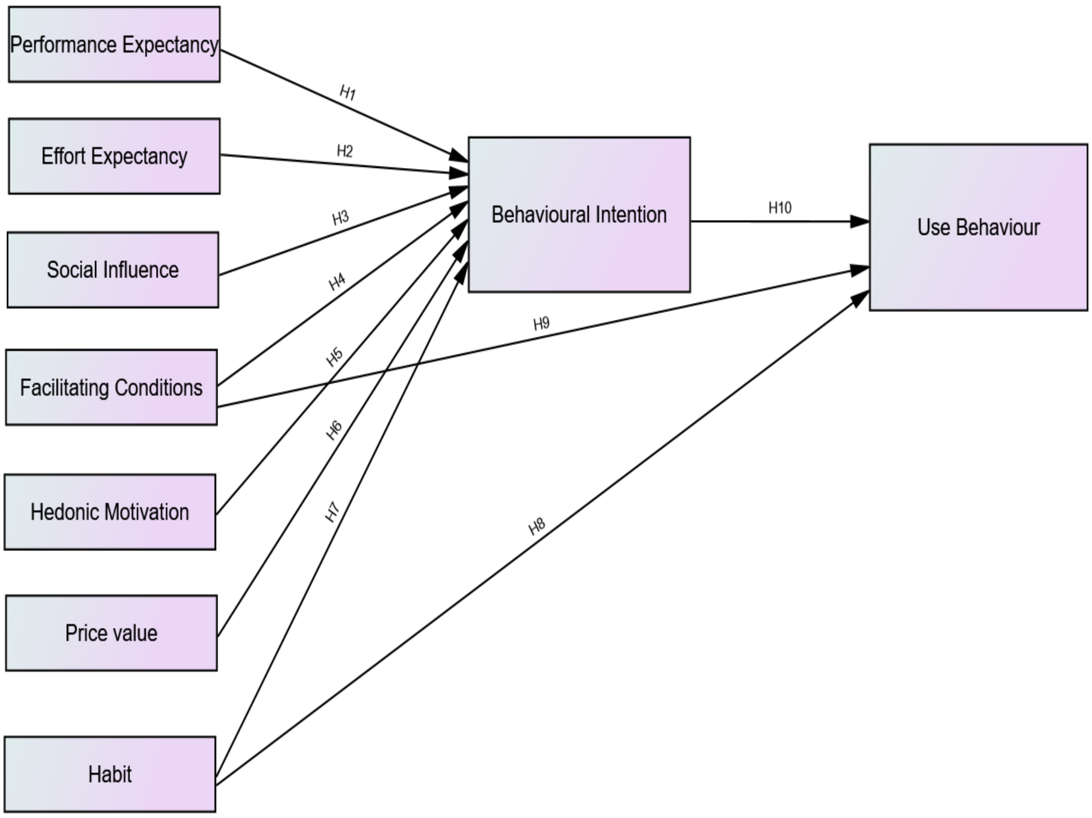
H10 (e): The connection between hedonic motives and use behavior of AI applications can be mediated through buying intention.

H10 (f): The connection between price value and usage behavior of AI applications can be mediated through buying intention.

H10 (g): The connection between habit and usage behavior of AI applications is mediated by buying intention.

Thus, in light of the above-mentioned hypotheses, the UTAUT model serves as the theoretical foundation for assessing the adoption behavior of AI technology in Indian car market, is displayed in Figure 1.

Figure 1 Conceptual framework



3. Methodology for research

3.1 The research design

In an attempt to extensively analyze how AI applications influence consumer's decision to buy passengers automobile, this research use a quantitive research method. This research employs constructs of the Unified Theory of Technology Acceptance and Use in analyzing the hypothesized hypothesis. Through a survey Based approach that provides room for in depth study, 384 participants from different major locations, including Delhi, Sonipat, Bahadurgarh, Noida and Ghaziabad were requested to give their views in an attempt to get relevant primary data.

3.2 Sampling and Data Collection

Online platform was used in the process of developing and disseminating a well-crafted questionnaire for research purposes. The specific target of this questionnaire was those individuals who have recently purchased a passenger car or are considering the possibility of buying one. The proposed sampling method is area wise proportionate cluster sampling. The target population is separated into mutually exclusive categories known as clusters in proportionate cluster sampling. To reach such a target population, convenience sampling approach was employed to make the collected data represent and be accessible. In addition to testing the different UTAUT2 components, including price value, habit, hedonic inspiration, social influence, expectation of performance and effort, purchase intention, and usage behavior, and the questionnaire also consisted of a section that was especially used for collecting demographic information. To acquire a thorough profile of the respondents, the demographic component of the questionnaire inquired about their gender, age, financial status, level of education, and location of residence.

3.3 Primary data collection

Automobile users in the Delhi NCR area will be the study's universe since the researcher finds value in examining how digital marketing affects the behavior of automobile buyers in this area (see table 1). A Cross-sectional descriptive investigation was conducted with primary data. The study employed a standard survey with a Likert scale with five points. With a value of z of 95%, a margin of error of 3.5%, and p value of 0.5, which implies maximum variability, the sample size was established using the population proportion approach (see table 2).

Table 1 Population for the study

Area With RTOCode	Total no of registeredvehicle	Targeted population
Delhi (DL)	9000000	2700000
Sonipat (HR10)	280000	84000
Gurugram (HR26)	1060000	318000
Bahadurgarh (HR13)	160000	48000
Noida (UP16)	810000	243000
Ghaziabad (UP14)	910000	273000
Total	**12220000**	**3666000**

(Source: According to RTO Registration and author analysis)

Table 2 Sampling details of research study

S.NO.	Area	Target population	% of totalpopulation	Proportion insample
1	Delhi	2700000	73.65	283
2	Sonipat	84000	2.29	9
3	Gurugram	318000	8.67	33
4	Bahadurgarh	48000	1.31	5
5	Noida	243000	6.63	25
6	Ghaziabad	273000	7.45	29
	Total	**3666000**	**100**	**384**

3.4 Measurement and Instrumentation

All UTAUT2 qualities were evaluated using Likert scale of five points, with 1 indicating strong disagreement and 5 indicating strong agreement. A pilot sample was done to confirm the validity and reliability of the questionnaire prior to the gather full-scale data.

3.5 Data analysis

The demographic data was analyzed using SPSS 21 to provide frequency distributions, mean values, and standard deviations that shed light on the respondents' characteristics. For every build, Cronbach Alpha was calculated to confirm internal consistency. Gaskin produced model fit indices, which were used to assess the fit of model. Construct validity was verified using the average of variance extracted (AVE) method and Composite Reliability (CR). Criteria of Fornell & Larcker were used to evaluate discriminant and convergent validity. The relationships between UTAUT2 components and their impact on AI-driven automobile buying behavior were examined using Modeling with structural equations, or SEM. The significance & strength of the relations were evaluated using normalized regression weights and path analysis.

4. Result and Discussion:

4.1 Descriptive analysis:

The demographic composition of the participants provides significant information about how different segments of the population consume and perceive AI technologies with regard to consumer behavior. Chatbots and virtual assistants are the most widely used AI application followed by augmented reality and personalized recommendation system (see figure 2). Respondents (particularly those between 35-44 years of age) were more accepting and engaged in using AI-based technologies (see table 3). 62.5% of male and 37.5% of female use AI application while making a decision to buy a car (see table

4). The respondents having masters and bachelors degree are found more familiar with AI applications (see table 5). Income of 38.8%of respondents using AI applications falls in the bracket of 25000-50000 and income of 27.3% of respondents' falls in the bracket of 50000-100000 (see table 6). 54.2% of respondents who are using AI applications are private sector employees (see table 7).

Figure2 Most Interactive AI application used

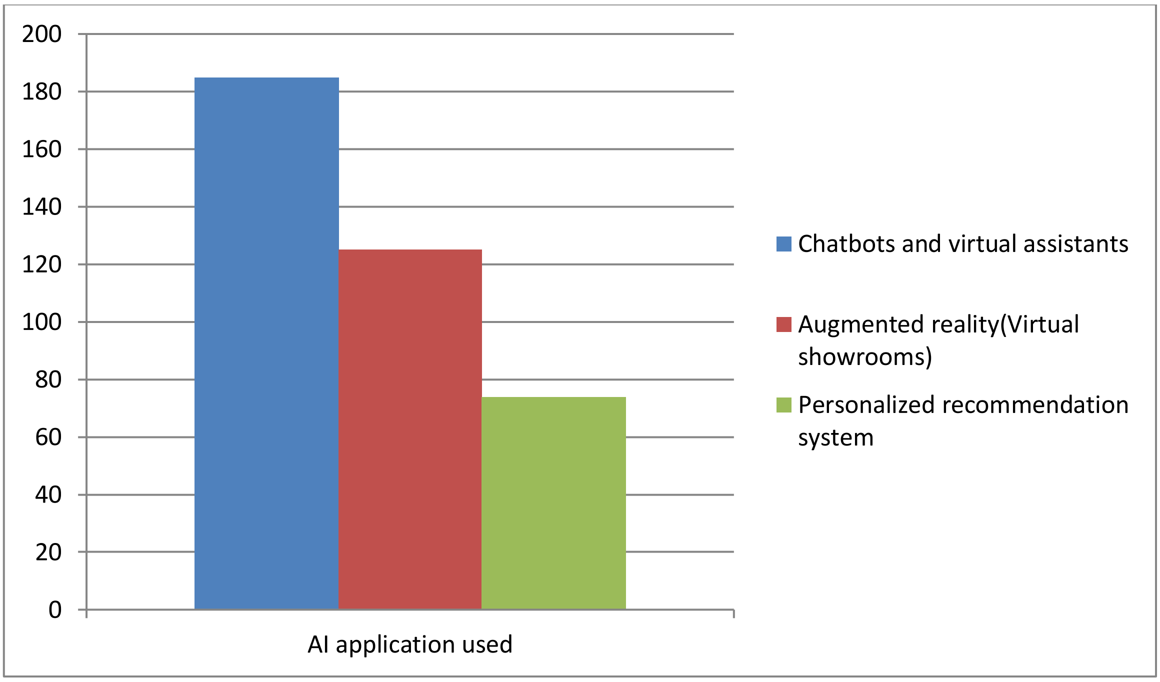


Table 3

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 25	36	9.4	9.4	9.4
	25-34	201	52.3	52.3	61.7
	35-44	120	31.3	31.3	93.0
	45-54	24	6.3	6.3	99.2
	55 and above	3	.8	.8	100.0
	Total	384	100.0	100.0	

Table 4

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	240	62.5	62.5	62.5
	Female	144	37.5	37.5	100.0
	Total	384	100.0	100.0	

Table 5

Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below high school	11	2.9	2.9	2.9
	High school	19	4.9	4.9	7.8
	Diploma	18	4.7	4.7	12.5
	Bachelor's degree	147	38.3	38.3	50.8
	Master's degree	157	40.9	40.9	91.7
	Doctorate	32	8.3	8.3	100.0
	Total	384	100.0	100.0	

Table 6

Income

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below25000	57	14.8	14.8	14.8
	25000-50000	149	38.8	38.8	53.6
	50000-100000	105	27.3	27.3	81.0
	100000-200000	59	15.4	15.4	96.4
	Above 200000	14	3.6	3.6	100.0
	Total	384	100.0	100.0	

Table 7

Occupation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Self employed	41	10.7	10.7	10.7
	working professional	44	11.5	11.5	22.1
	Private sector employee	208	54.2	54.2	76.3
	Government employee	44	11.5	11.5	87.8
	Freelancer	24	6.3	6.3	94.0
	Retired	13	3.4	3.4	97.4
	Unemployed	10	2.6	2.6	100.0

	Total	384	100.0	100.0	

4.2 Confirmatory factor analysis

To confirm the discriminant appropriateness and convergence of measurement variables, an analysis to confirm the factors was carried out. X2 = 723.420, P =.000, DF = 288.000, CMIN/DF =2.512, CFI=0.944, SRMR=0.039 and RMSEA=0.063 verify the quality of the measurement model employed in this investigation (see table 9).

4.2.1 Cutoff points for measurements of model fit

The fit of the model for confirmation factor analysis, or CFA, is divided into three categories by Gaskin and Lim (2016): good, great, and dreadful. The RMSEA (Poor >.08, tolerable > 0.06, outstanding < 0.06), SRMR (Poor >.10, tolerable > 0.08, outstanding < 0.08), CFI (Poor <.90, tolerable < 0.95, outstanding > 0.95), and Chi-Square (χ^2/df) (Poor >5, tolerable > 3, outstanding >1) are the absolute fit indices. These standards help researchers determine model fit and are used to assess the CFA model (see table 8).

Table 8

Cutoff Criteria

Measure	Terrible	Acceptable	Excellent
CMIN/DF	> 5	> 3	> 1
CFI	<0.90	<0.95	>0.95
SRMR	>0.10	>0.08	<0.08
RMSEA	>0.08	>0.06	<0.06
P Close	<0.01	<0.05	>0.05

Table 9

Model Fit Measures

Measure	Estimate	Threshold	Interpretation
CMIN	723.420	--	--
DF	288.000	--	--
CMIN/DF	2.512	Between 1 and 3	Excellent
CFI	0.944	>0.95	Acceptable
SRMR	0.039	<0.08	Excellent
RMSEA	0.063	<0.06	Acceptable
P Close	0.000	>0.05	Not Estimated

4.2.2 Reliability & validity of measuring scale

To make sure the method of measurement was reliable; validity and reliability were assessed in this study. Cronbach Alpha as well as Composite Reliability (CR) was employed to evaluate reliability, and convergent & discriminant validation were used to examine validity.

Reliability

"Error in measurement," or the extent by which a scale of measurement consistently or reliably assesses the things it is supposed to measure, is the main problem of reliability, according to McDowell and Newell (1996). Cronbach alpha was used to gauge the measuring reliability of scale. The findings show that for every measurement model construct, the Cronbach alpha coefficient was higher than 0.80. Nunnally and Bernstein (1994) claimed that a coefficient value of more than 0.70 indicates that the measurement scale satisfies the necessary psychometric requirements and is therefore appropriate for use in measurement.

The Cronbach alpha for each AI adoption construct in auto purchasing is displayed in the table. Composite Reliability (CR) is used to measure internal coherence in Confirmatory Factor Analysis (CFA) and Modeling of structural equation (SEM). According to Nunnally & Bernstein (1994), exceptional internal consistency is indicated by a CR score greater than 0.80. All constructs in the model have Composite Reliability (CR) values more than the specified cutoff of 0.80, signifying adequate to excellent internal coherence (see table 10).

Table 10

Cronbach alpha and composite reliability

Constructs	No of statements	Cronbach alpha	Composite reliability
Expectancy for performance(PE)	3	.865	0.821
Expectancy for effort(EE)	3	.848	0.857
Social impact(SI)	3	.810	0.874
Facilitating circumstances(FC)	3	.921	0.923
Hedonic motive(HM)	3	.912	0.913

Pricing value(PV)	3	.894	0.942
Habits(H)	3	.868	0.869
Behavioral intention	3	.914	0.915
Use behavior	3	.853	0.908

4.2.3 Standardized Regression Weights

Regression coefficients are naturally occurring metrics of interest for synthesizing the multivariable connections between quantitative variables. The straight pooling of regression coefficients is meaningless as exposure is frequently assessed using various metrics and approaches in different research. Standardized regression coefficients could provide an answer in this situation. These are the approximations that come from a study that was conducted on variables whose variances have been normalized to one (Vittinghoff et al., 2012).Standardized regression weights (β) represents strength & path of relationships among factors in a regression or Structural Equation Modeling (SEM) usually range between -1 and 1. A standardized regression weight greater than zero.70 indicates a strong relationship, values between 0.40 and 0.70 suggests an average relationship, Weights between .10 and .40 indicates week relationship and values under 0 are considered as negligible (Kline, 2015). Regression weights between independent (exogenous) and a dependent (endogenous) latent variable of constructs indicate strong relationship (see table 11 & figure 3).

Table 11

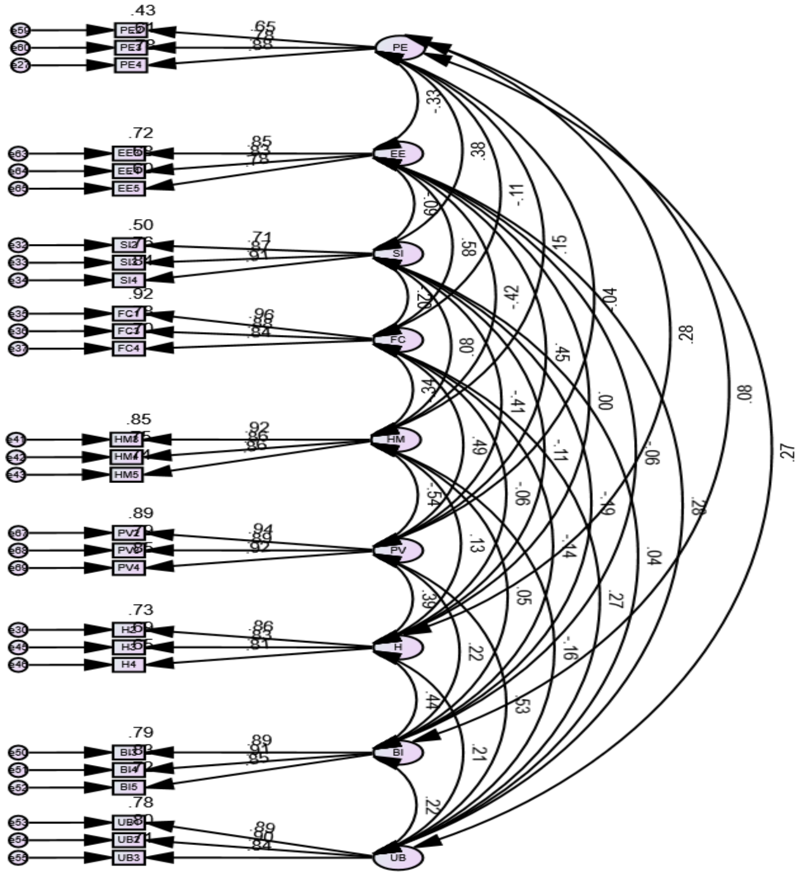
Standardized Regression Weights

			Estimate	
SI2	<---	SI	.706	
SI3	<---	SI	.875	
SI4	<---	SI	.915	
FC1	<---	FC	.959	
FC3	<---	FC	.882	
FC4	<---	FC	.839	
HM3	<---	HM	.922	
HM4	<---	HM	.864	
HM5	<---	HM	.858	
H2	<---	H	.856	
H3	<---	H	.828	
H4	<---	H	.805	
BI3	<---	BI	.891	
BI4	<---	BI	.912	
BI5	<---	BI	.849	
UB1	<---	UB	.886	
UB2	<---	UB	.895	
UB3	<---	UB	.845	
PE2	<---	PE	.653	
PE3	<---	PE	.784	
PE4	<---	PE	.884	
EE3	<---	EE	.847	

			Estimate	
EE4	<---	EE	.825	
EE5	<---	EE	.776	
PV2	<---	PV	.945	
PV3	<---	PV	.886	
PV4	<---	PV	.923	

Figure 3

Standardized regression weights



4.3 Model validity

Convergent as well as discriminant validity was used to evaluate the validity of model, making sure the constructs measure what they are supposed to. The Extracted average variance (AVE), employed to evaluate convergent validity, need to be larger than 0.50 to show that the constructs indicates a significant percentage of the variance in their indicators (Fornell & Larcker, 1981).Model's Convergent validity is ensured as the latent construct explains at least half of the variation in the indicators that are linked to it (see table 12). Convergent validity was also ensured in the concerned model through composite reliability, all of which were above .70 (Hair et al., 2014). For assessing discriminant validity Heterotrait-Monotrait (HTMT) ratio as well as Fornell-Larcker criterion was employed. Square root of every constructs' AVE must be more than its association with other constructs. The outcome suggested discriminant validity by ensuring that each construct is distinct from others. HTMT ratio, less than .90 suggested that the construct under study were not strongly connected and they demonstrate different concepts (Henseler et al., 2015). Convergent & discriminant validity is assessed on the basis of standard set by Fornell and Larcker (1981) and

Hu and Bentler (1999), which is measured using James gaskin's (2019) stat tool plugin for master validity. This plugin simplify the procedure of computing composite reliability (CR), AVE & HTMT proportions (Gaskin et al., 2019) (See table 12 and 13).

Table 12

Validity Analysis

	CR	AVE	MSV	MaxR(H)	SI	FC	HM	H	BI	UB	PE	EE	PV
SI	0.874	0.700	0.169	0.904	**0.837**								
FC	0.923	0.800	0.333	0.945	-0.198***	**0.895**							
HM	0.913	0.777	0.296	0.919	0.085	-0.341***	**0.882**						
H	0.869	0.689	0.197	0.871	-0.115*	-0.056	0.130*	**0.830**					
BI	0.915	0.782	0.197	0.919	-0.191***	-0.140*	0.054	0.444***	**0.884**				
UB	0.908	0.767	0.284	0.910	0.040	0.267***	-0.161**	0.212***	0.224***	**0.876**			
PE	0.821	0.607	0.145	0.855	0.380***	-0.105†	0.147*	0.283***	0.083	0.268***	**0.779**		
EE	0.857	0.667	0.333	0.861	-0.090	0.577***	-0.423***	-0.002	-0.062	0.283***	-0.332***	**0.817**	

PV	0.942	0.843	0.296	0.947	-0.411***	0.487***	-0.544***	0.394***	0.224***	0.533***	-0.045	0.449***	**0.918**

Table 13

HTMT Analysis

	SI	**FC**	**HM**	**H**	**BI**	**UB**	**PE**	**EE**	**PV**
SI									
FC	0.154								
HM	0.078	0.358							
H	0.108	0.070	0.137						
BI	0.187	0.160	0.056	0.447					
UB	0.054	0.279	0.170	0.213	0.213				
PE	0.406	0.117	0.149	0.259	0.071	0.239			
EE	0.095	0.569	0.419	0.008	0.066	0.290	0.327		
PV	0.404	0.501	0.549	0.402	0.230	0.533	0.079	0.444	

Significance of Correlations:

† $p < 0.100$

* $p < 0.050$

** $p < 0.010$

*** $p < 0.001$

4.4 Hypothesis testing

Standardized estimates and bootstrapped confidence intervals (95% bias-corrected) were used in AMOS 26's structural equation modeling to assess proposed relationships in UTAUT2. With a lower limit of 0.238 and an upper limit of 0.507, the table indicates that the route from performance expectation (PE) to Behavioral Intention (BI) had a positive standardized estimate of 0.378. The hypothesis is confirmed because P value is lower than .05 and the confidence interval did not include zero, indicating a substantial and meaningful direct effect. A strong direct influence was also suggested by the path from social influence (SI) to behavioral intention (BI), which produced an estimate of 0.206 and a p value=.002 with a lower limit of 0.282 and an upper limit of 0.116.

Likewise, an estimate of 0.167 was obtained for the path from facilitating condition (FC) to behavioral intention (BI), with a P value of.004 and lower and upper bounds of -0.261 and -0.076, respectively, indicating a substantial direct influence. A substantial direct influence was also suggested by the estimate of 0.272 obtained from the path from habit (H) to behavioral intention (BI), which had a lower limit of 0.139 and an upper limit of 0.416 with a P value of.001. A strong direct influence was also suggested by the estimate of 0.236 obtained from the path from habit

(H) to usage behavior (UB), which had a lower limit of 0.135, an upper limit of 0.331, and a P value of.001.

A strong direct influence was also suggested by the estimate of 0.154 obtained from the path from facilitating condition (FC) to usage behavior (UB), which had an upper bound of 0.248 and a lower bound of 0.053. Likewise, an estimate of 0.231 was obtained for the path from behavioral intentions (BI) to usage behavior (UB), with a lower limit of -0.327 and an upper limit of -0.121, indicating a strong direct influence. The effect is not statistically significant, however, because the interval contains zero. The path from Expectancy for effort (EE) to BI, on the other hand, had an estimate of 0.113, but its confidence interval was between -0.034 and 0.266, with a p value of.215.

Similar to this, the estimate for the path from price value (PV) to BI was 0.141, with confidence interval from 0.026 to 0.257. However, P value >.05 suggests that the influence is not directly or statistically significant. Similarly, the route from hedonic motivation (HM) to BI had a P value of.192 and an estimate of 0.086, but its confidence interval was between -0.201 and 0.023, meaning that even though the interval includes zero, the effect is not statistically significant (Table 14).

Table 14 Standardized Regression Weights:

Parameter			Estimate	Lower	Upper	P	Interpretation
BI	<---	PE	.378	.238	.507	.001	H1 =Accepted
BI	<---	EE	.113	-.034	.266	.215	H2=Rejected
BI	<---	SI	-.206	-.282	-.116	.002	H3=Accepted
BI	<---	FC	-.167	-.261	-.076	.004	H4=Accepted
BI	<---	H	.272	.139	.416	.001	H5=Accepted
BI	<---	PV	.141	.026	.257	.052	H6=Rejected
BI	<---	HM	-.086	-.201	.023	.192	H7=Rejected
UB	<---	H	.236	.135	.331	.001	H8=Accepted
UB	<---	FC	.154	.053	.248	.009	H9=Accepted
UB	<---	BI	-.231	-.327	-.121	.002	H9=Accepted

4.5 Mediation Results

The analysis also studies the mediating role of Behavioral Intention (BI) in the UTAUT2 framework, particularly in linking key antecedents to Use Behavior (UB). Table showed several significant indirect effects. Expectancy for performance (PE) had significant but indirect effect on UB (estimate = -.035, CI = -.174 to -0.060), mediated by BI, indicating that perceived usefulness influences actual technology use through the user's intention. In addition, social impact (SI) and Facilitating circumstances (FC) also demonstrated significant indirect effects on UB through BI, with estimates of -.106, P=.001 (CI = -.033 to .104) and -0.69, P=.003 (CI = .13 to 0.058), respectively. Similarly, habit (H) and price value (PV) also demonstrated significant indirect effects on UB through BI, with estimates of .022 (CI = .131 to -.028) and .031 (CI = -.074 to -.008), respectively. In contrast, Effort Expectancy (EE) and hedonic motivation (HM), with estimates of -.031, P=.162 (CI=-.087 to .006) and .062, p=152(CI=.004 to .063) did not show significant indirect effects, as their influence on BI was not statistically significant (see table 15).

Table 15

Mediation effect

Parameter	Estimates	Lower	Upper	P value	Interpretation
UB←BI ←PE	-.035	-.174	-.060	.001	H10(a)=Accepted
UB←BI ←EE	-.031	-.087	.006	.162	H10(b)=Rejected
UB←BI ←SI	-.106	.033	.104	.001	H10(c)=Accepted
UB←BI ←FC	-.069	.13	.058	.003	H10(d)=Accepted
UB←BI ←H	.022	.131	-.028	.001	H10(e)=Accepted

UB←BI ←PV	.031	-.074	-.008	.033	H10(f)=Accepted
UB←BI ←HM	.062	.004	.063	.152	H10(g)=Rejected

5. Conclusion

Through the lens of UTAUT2 model, this investigation examined how artificial intelligence (AI) affects consumer behavior in car-buying decisions, with a focus on mediation role of behavioral intent (BI). The results showed that behavioral intention was positively impacted by price value, habit, and performance expectation. Behavioral intention (BI) was negatively impacted by social impact (SI) and conditions that facilitate (FC). As per these findings, people are more likely to adopt AI technologies if they are convinced that they will be practical, reasonably priced, and consistent with their current behavioral patterns. In contrast, Hedonic motivation and effort expectation had no discernible impact on behavioral intention and, as a result, had no substantial indirect effects on use behavior. Significantly, these categories and actual Use Behavior (UB) were mediated by Behavioral Intention. Through the mediation of behavioral intention, the analysis demonstrated that characteristics such as price value and habit had a large beneficial indirect impact on usage behavior. Through behavioral intent, several constructs, such as expectancy for performance (PE), social impact (SI), and facilitating circumstances (FC), had major detrimental indirect effect on use behavior. Utilization behavior (UB), which is mediated by behavioral intention (BI), was not significantly impacted by constructs such as expectancy for effort (EE) and hedonic motives (HM).

5.1 Study limitations

There are several issues with this research. The results are based on replies from respondents in specific parts of India and do not provide a global perspective. Despite being cross-sectional, only a small number of respondents (N = 384) were able to complete the research in a comparatively short period of time. Customers acquire new information through experience; therefore the respondents' opinions could change over time. Future researchers may conduct a longitudinal study with a bigger sample size in order to generalize the findings. A more differentiated understanding of technology adoption trends may result from future research that looks at how various demographic traits modify the connections found in the UTAUT model. Finally, incorporating additional components such as happiness, trust, and personal creativity could help refine the UTAUT model and provide a more thorough awareness of the variable that influence adoption of new technology and behavior of users..

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