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AI Adoption in online shopping: An Empirical Study of Consumer Behaviour and intention to use Recommendation Systems among Gen Z

Anindito Bhattacharya[1], Ishita Deb[2], Samarpita Roy[3]
[1]PGDM Marketing Student, Siva Sivani Institute of Management
[2]PGDM Finance Student, Siva Sivani Institute of Management
[3]Assistant Professor, Communication, Siva Sivani Institute of Management

***Abstract* – Artificial Intelligence (AI)-enabled recommendation systems have become an integral component of online shopping by delivering personalized product suggestions that enhance consumers' shopping experiences. Despite their widespread adoption, limited research has examined the behavioural factors influencing consumers' intention to use these systems in the Indian context. This study investigates the determinants of AI-enabled recommendation system adoption among Indian online shoppers using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. A quantitative, cross-sectional research design was employed, and primary data were collected from 201 respondents through a structured online questionnaire using convenience and snowball sampling techniques. The collected data were analysed using descriptive statistics, reliability analysis, correlation analysis, and multiple regression analysis. The findings indicate that the proposed model explains 73.2% of the variance in behavioural intention ($R^2 = 0.732$). Habit, price value, hedonic motivation, and effort expectancy emerged as significant positive predictors of consumers' behavioural intention to adopt AI-enabled recommendation systems, while performance expectancy, social influence, and facilitating conditions showed comparatively weaker effects in the combined regression model. The results further reveal a strong positive relationship between behavioural intention and actual use of AI recommendation systems, confirming the applicability of the UTAUT2 framework in explaining AI adoption behaviour. The study highlights that consumers continued use of AI-driven recommendation systems is influenced not only by functional benefits but also by enjoyment, perceived value, and habitual usage. These findings provide valuable implications for e-commerce platforms and marketers in designing user-centric, engaging, and trustworthy AI-powered recommendation systems that encourage sustained consumer adoption and enhance the online shopping experience.**

***Keywords* – Artificial Intelligence (AI); AI-enabled Recommendation Systems; Online Shopping; Consumer Behaviour; Behavioural Intention; UTAUT2; E-commerce; Hedonic Motivation; Habit; Technology Adoption.**

I. INTRODUCTION

Rationale of the Study

The rationale for this research is the growing visibility of AI personalization in shaping the modern-day consumer experience. As consumers are faced with too many choices online, the attention span of the digital consumer has increasingly been curtailed. Recommendation systems function as thought filters, preventing information overload by making suggestions based on users' interests and their shopping histories. This kind of personalization not only improves user experience but also drives highest conversion rates and loyalty from customers (Lankton & Wilson, 2022). Yet, the application of AI in internet shopping is not just functional but also experiential and emotional. Buyers interact with AI tools in a manner that spans over trust, interest, enjoyment, and perceived control. For instance, the buyer feels a sense of engagement and pleasure by discovering that a site "knows" what they like and recommends worthy products. This balance between hedonic and instrumental motivations makes the uptake of AI to be a very multifaceted behavioural phenomenon. Despite its strategic importance, research literature on AI adoption in consumer settings is still in fragments. Most work focuses either on technical performance or user interface design to the neglect of psychological constructs like habit, hedonic motivation, and perceived enjoyment (Kumar & Gupta, 2023). Overall, most of the extant literature has originated from developed economies, while emerging markets like India, where socio-demographic diversity strongly influences beliefs toward technology, are under-represented. This study fills in these gaps by adopting a comprehensive behavioural strategy that accounts for both the utilitarian (e.g., usefulness, convenience) and experiential (e.g., enjoyment, habit) aspects. In addition, it explores how demographic moderators (age, gender, and web purchasing experience) affect the adoption process. This comprehensive view can aid marketers with designing AI-driven experiences that are not only attractive to early adoption but also lead to long-term adoption. Moreover, with AI systems becoming more dependent on consumer data, questions of trust, transparency, and privacy have become concern.

Research Problem

Though application of AI-based recommendation systems is growing extremely fast, yet there is a gap between technology availability and consumer adoption. Few users welcome AI recommendations with enthusiasm, ascribing to them convenience and relevance, while others reject or ignore them, seeing them as intrusive or manipulative. This discrepancy shows a behaviour adoption gap—where intention to use and use cannot always be synchronized (Dwivedi et al., 2021).

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Traditional technology adoption models, like the Technology Acceptance Model (TAM) and UTAUT, account for adoption in terms of rational assessments of usefulness and ease of use. Yet, in consumer internet shopping is pleasure and enjoyment for them. Thus, an extended framework like UTAUT2, which combines hedonic and habitual concepts, provides a better explanation of AI adoption in e-commerce. Furthermore, demographic diversity adds an added layer of complexity. Younger consumers might find AI easy to use and fun, while older consumers feel anxious or cognitively burdened in understanding suggestions. Gender differences can also arise because earlier research shows that male consumers tend to prioritize efficiency, while female consumers care for relational and experiential qualities (Venkatesh et al., 2012). In the same manner, consumers with existing online shopping behaviour are likely to incorporate AI suggestions into their decision-making habitually.

Therefore, the core research issue is defined as follows: What are the motivational, demographic, and behavioural determinants of consumers' intention to use and use of AI-based recommendation systems in online shopping?

Elucidation of this relationship is essential for marketers interested in optimizing consumer interaction, for recommendation algorithm designers interested in maximizing recommendation effectiveness, and for policymakers interested in ensuring ethical AI implementation.

Research Objectives

To address the research problem comprehensively, this study is guided by the following objectives:

- To analyse the relationship between consumer behavioural intention and the actual use of AI-enabled recommendation systems in online shopping.
- To evaluate whether demographic factors (age, gender, and online shopping experience) moderate the adoption of AI-enabled systems.
- To assess the extent to which hedonic motivation and habit drive continuous usage of AI in online shopping compared to traditional factors such as effort expectancy and performance expectancy.

These objectives collectively bridge the gap between technological determinism and consumer-centric understanding of AI adoption, aiming to produce both theoretical and practical insights.

Research Questions

From the above objectives, the study seeks to answer the following research questions:

1. What is the relationship between consumers' behavioural intention and their actual use of AI-enabled recommendation systems?
2. How do demographic factors such as age, gender, and experience influence consumers' adoption and continued use of AI systems in online shopping?
3. Do hedonic motivation and habit play a stronger role than utilitarian factors in predicting sustained use?

Theoretical Foundation: UTAUT2 Framework

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model is the theoretical foundation of this work. Venkatesh et al. first created UTAUT in 2003, which was then extended in 2012. The UTAUT model draws upon several technology acceptance theories such as TAM, TPB, and DOI, combining them under one umbrella model. UTAUT2 adds three new constructs—hedonic motivation, price value, and habit—to account for technology adoption in consumer settings.

Each construct has a unique contribution towards shaping behavioural intention and usage behaviour:

- Performance Expectancy (PE): The extent to which a consumer feels that using AI-based recommendation systems will enhance his/her shopping performance or results. For instance, a user who finds AI recommendations as accurate and time-efficient is likely to embrace them.
- Effort Expectancy (EE): Subjective ease of use of AI systems. LL&M is preferred in systems that are easy to use, intuitive, and don't necessitate much cognitive effort.
- Social Influence (SI): Degree to which people think that others (peers, influencers, or friends) expect them to employ AI-powered systems. Social proof can facilitate adoption by verifying normative pressure.
- Facilitating Conditions (FC): Availability of resources, technical environment, and customer service that facilitate effective use.
- Hedonic Motivation (HM): The pleasure or fun experienced while operating AI systems. This factor reflects the emotional satisfaction related to personalization and novelty.
- Price Value (PV): People's assessment of the benefits versus cost trade-off of embracing AI. Positive price value strengthens behaviour intention.
- Habit (HT): How much consumers automate behaviours through learning or routine. Habit turns first-time adoption into continued use.
- Behavioural Intention (BI): Deliberate intention of consumers to use AI-driven systems, the direct predictor of usage.

UTAUT2 also identifies moderating impacts of demographic factors like age, gender, and experience on inter-construct relationships. For example, hedonic motivation would have more profound impacts for younger consumers, while facilitating conditions could play a greater role for older or less experienced consumers. Here, UTAUT2 offers a strong framework for understanding both the cognitive and affective channels by which consumers adopt AI recommendation systems, enabling empirical testing of multiple behavioural constructs' relationships.

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Scope of the Study

This research is bounded to those consumers who undertake the activities of online shopping in the Indian digital landscape, a very fast-growing environment with both the promise and the potential confusions of AI-commerce. India, with over 1.4 billion people, has seen the growth of internet penetration, mobile phone use, and digital literacy rapidly accelerate. More than 60 percent of retail transactions in urban and Tier I cities are now digitally influenced, according to the India Brand Equity Foundation (IBEF, 2025). In Present AI-based recommendation systems have become a critical technological aspect, it helps consumers to find, compare, and choose products more effectively. This diversity ensures a realistic Indian e-commerce user profile and guarantees findings are not skewed toward an occupational or age category. By surveying opinions from various demographic segments of consumers, the research attains a richer understanding of how diversity of demographics affects attitudes toward AI-based recommendation systems. Such diversity also makes it possible to investigate moderating influences of demographic variables—age, gender, and e-shopping experience—on behavioural intention and subsequent usage behaviour.

Methodologically, the study follows a quantitative cross-sectional approach, with priority given to empirical verification rather than theoretical examination only. Data were gathered from 201 valid respondents using an online questionnaire via social media and e-commerce user communities. The tool was constructed based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, which includes constructs like performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and behavioural intention. Each construct was assessed with more than one Likert-scale item, which was taken from previously validated scales in the literature to maintain conceptual equivalence and statistical reliability.

Data collected were put through stringent reliability and validity tests. Internal consistency as measured through Cronbach's Alpha was ascertained at levels greater than the prescribed 0.70 for all the constructs, thereby ensuring that each measure item successfully captured its respective intended latent dimension. In addition, correlation analysis was used to evaluate the strength and direction of relationships between the variables, whereas multiple regression analysis determined the predictors of strongest strength on behavioural intention to use AI-based recommendation systems. Collectively, these statistical methods laid a solid empirical foundation for evaluating the hypotheses of the study and answering its research questions. Since the research is conducted using a cross-sectional design, data is reflective of a point in time consumer attitudes and intentions. Although this constrains the capacity to establish causal connections or longer-term pattern change, it still offers useful insights into the then current patterns of AI accept by Indian consumers today. In a fast-changing digital market, such a cross- sectional perspective is important in ascertaining the prevailing situation regarding consumer involvement and in determining drivers that can shape future uptake trends.

Geographically, the scope of the study is mainly limited to respondents in urban and semi-urban areas of India where penetration of online shopping is highest and exposure to AI-powered platforms is high. Rural consumers, while gradually turning active online, are not the central focus given relatively lower access to AI-personalized platforms and divergent infrastructural realities.

The study is concerned with AI-driven recommendation systems, which produce personalized product or service recommendations based on user information, browsing behaviour, and contextual cues. Recommendation systems are core elements of online shopping platforms like Amazon, Flipkart, Myntra, Nykaa, Meesho, and Ajio, among others. Other AI use cases like chatbots, virtual assistants, voice search, or image recognition tools are beyond the current scope. While these technologies are also revolutionizing consumer–AI interactions, they differ substantially in their functionality, user experience, and behavioural effects from recommendation engines, which deserve separate research.

Also, the research focuses on the consumer side over the organizational or technical aspects of AI implementation. It does not assess algorithmic design, data-processing speed, or system performance computationally. Rather, it examines how consumers experience, judge, and absorb AI suggestions as part of their buying process. This behavioural approach is consistent with the marketing and consumer psychology focus of the study and aligns with the general conference theme of "People, Privacy, and Personalization."

A second boundary condition includes time and contextual considerations. The study sees consumer behaviour at a particular juncture in India's digitalization process (2025) that witnessed post-pandemic e-commerce growth, rising familiarity with digital payments, and greater sensitivity to data privacy. These contextual factors influence consumer attitudes toward AI adoption and need to be considered while projecting the findings to other temporal or socio-economic situations.

Albeit these boundaries, the research provides significant practical significance. The findings based on examining behavioural intention and usage can inform e-commerce managers, marketing strategists, and policymakers in devising more encompasses and responsive AI strategies. For example, realizing that hedonic motivation and habit contribute more than pure utilitarian concerns can inform marketers to develop AI interfaces that focus on enjoyment, aesthetic appeal, and user interaction.

From a policy perspective, the research highlights the need for encouraging ethical AI regulation. As personalization becomes more profound, so does the imperative for transparency and responsibility in the use of data. The findings can be used to guide government and industry efforts to build trust, promote fairness in algorithmic suggestions, and safeguard consumer rights online.

In conclusion, the scope of the research is strategically defined and concentrated. It supplies an empirically based investigation of consumer adoption of AI-based recommendation systems in India's e-commerce market, employing the UTAUT2 model to determine behaviour drivers and moderators. By confining itself to this specified scope—restricted only to online shopping platforms, AI suggestion mechanisms, and consumer behaviour metrics—the research guarantees methodological purity, conceptual precision, and high applicability for academics and practitioners aiming to perceive the changing trends of digital consumption in light of personalization technologies.

Significance of the Study

This study is important on various levels:

Theoretical Contribution

The research contributes to the technology adoption literature by applying the UTAUT2 model to a novel context—AI-based recommendation systems in e-shopping. Empirical testing of hedonic motivation and habit, along with the conventional constructs, adds depth to the understanding of consumer technology adoption. Analysing demographic moderators also adds theoretical richness to account for differences between individuals in adoption behaviour.

Managerial Implications

For marketers, the results will provide actionable recommendations for AI-based marketing strategies. Knowing which factors most affect behavioural intention will enable managers to prioritize design and communication initiatives. For example, if hedonic motivation and habit are found to be major drivers, marketers need to emphasize creating affectively engaging, gamified experiences over stressing functionality.

Societal and Ethical Relevance

While AI systems are becoming more dependent on consumer information, the research points to trust and transparency as factors that cannot be overlooked. Consumers' embracement of AI is determined by how they feel about ethical data usage and privacy. By focusing on human-centred technology adoption, the research conforms to worldwide discussions about responsible AI, so personalization will not erode individuals' autonomy or privacy.

Contextual Contribution

India's digital economy offers a distinctive laboratory for testing behavioural theories, with high phone penetration, cultural heterogeneity, and accelerated digitalization. The results of this research provide lessons that can be generalized to other emerging economies in Asia and Africa making comparable shifts toward AI-facilitated business.

II. REVIEW OF LITERATURE

Evolution of AI and Recommendation Systems in Marketing

AI marketing usage has changed the way businesses understand and connect with clients. AI-based recommendation systems compile, analyse, and learn from users' behaviour and provide suggestions based on their preferences, resulting in more satisfaction and loyalty.

Adomavicius & Tuzhilin, 2005 Their "Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions" in IEEE Transactions on Knowledge and Data Engineering is one of the first broad reviews of recommendation systems. RS has been categorized by the study as content-based, collaborative filtering, and hybrid models and brings the history of their development up to contextual and knowledge-based systems. It maintains that RS future lies in integrating user context, temporal dynamics, and implicit behaviour feedback.

Huang & Rust, 2021 Their Journal of Service Research article "Artificial Intelligence in Service: The Future of Customer Interaction" examines the revolutionary effects of AI on customer-facing services. Authors sketch out the "AI-Service Framework," demonstrating how the use of AI goes from automation to augmentation and ultimately to autonomous decision- making. They state that emotional intelligence and empathy must be coupled with machine learning capability in a bid to deliver consumer satisfaction and trust.

Petrescu & Krishen, 2020 Their "Persuasive Technology and the Ethical Design of Recommendation Systems" in the Journal of Business Ethics covers the ethics of personalization. They find that over-personalization with closedness can lead to privacy concerns and manipulation feelings. The research targets user control, data transparency, and fairness to motivate more consumer trust.

Chatterjee, Rana & Dwivedi, 2022 Their article entitled "Role of Artificial Intelligence in Shaping Digital Consumer Behaviour" published in the International Journal of Information Management examines AI's psychological impact on consumers. The research highlights that emotional satisfaction and enjoyment play pivotal roles in sustained use of AI systems. The study empirically validates hedonic motivation and trust as predictors of consumer retention in digital retail.

Shankar, 2024 His study titled "AI in Retail: Revolutionizing Consumer Experience through Recommendation Algorithms" pointed out in the Journal of Marketing Analytics is evidence of AI personalization's effectiveness in making decisions better and at converting. The study cautions against "algorithmic fatigue," where too much personalization annoys users by depriving them of their sense of control.

Chen, 2023 In his Harvard Business Review blog "AI-Powered Personalization: Consumer Experience in the Age of Predictive Retailing," he explains how consumer demand is harnessed by AI systems to predict needs ahead of when the need arises. The study shows predictive recommendations are engaging but will be uncomfortable when customers feel they are overcivilized, linking personalization with privacy paradox behaviour.

They all point out together that AI recommendation systems are consumers' extensions of the mind, and they augment convenience at the expense of generating ethical and psychological issues. They succeed depending on personalization accuracy versus respect for privacy, transparency, and autonomy.

Theoretical Foundations of Technology Adoption

One needs to base AI adoption on technological and behavioural acceptance theories to comprehend AI adoption. Some traditional frameworks—TAM, TPB, DOI, and UTAUT2—formed the backbone of this stream.

Davis, 1989 In his MIS Quarterly article, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," he proposed the Technology Acceptance Model (TAM). The study showed that perceived usefulness (PU) and perceived ease of use (PEOU) significantly impact user intention. The ease with which TAM could be implemented made it the forerunner to other technology acceptance studies, even though it does not account for emotional and social considerations.

Ajzen, 1991 His paper entitled "The Theory of Planned Behaviour" in Organizational Behaviour and Human Decision Processes generalized the Theory of Reasoned Action (TRA) by incorporating perceived behavioural control (PBC) into it. Ajzen's model specifies that intention is caused by attitude toward behaviour, subjective norms, and PBC. The versatility of the model enables it to incorporate contextual variables, hence its generalized application in consumer adoption studies.

Rogers, 2003 Rogers, in his work "Diffusion of Innovations," developed a sociological innovation diffusion theory. Rogers and associates found five attributes—relative advantage, compatibility, complexity, trialability, and observability—who affect levels of adoption. The model defines how communication channels and social networks are important in innovation diffusion; factors incorporated later in UTAUT's social influence construct.

Venkatesh, Morris, Davis & Davis, 2003 Their article "User Acceptance of Information Technology: Toward a Unified View" in MIS Quarterly developed the Unified Theory of Acceptance and Use of Technology (UTAUT). It merged eight previous models and synthesized four determinants—performance expectancy, effort expectancy, social influence, and facilitating conditions. It also distinguished moderators like age, gender, experience, and voluntariness.

Venkatesh, Thong & Xu, 2012 Their MIS Quarterly article "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology" took UTAUT and extended it to UTAUT2 by adding three ideas: hedonic motivation, price value, and habit. Both the utilitarian and experiential motivations behind technology use are covered by the model, which it is adapted to in consumer settings such as e-commerce and use of AI.

These models collectively demonstrate that the adoption of technology is shaped by a cluster of cognitive appraisals (usefulness, ease of use), social influence, and affective determinants (pleasure, habit). UTAUT2 is an overarching framework that integrates these perspectives and offers a good basis to AI adoption research.

Review of UTAUT2 Constructs in the Context of AI Adoption

- **Performance Expectancy (PE)**

Kim & Kim, 2021 Their paper titled "Determinants of AI-Based Recommendation System Adoption: An Extension of UTAUT2" in the Journal of Retailing and Consumer Services showed that performance expectancy had the highest prediction for behavioural intention. Consumers, according to the authors, adopt AI systems only when they find them improving decision quality and shopping efficiency.

Gupta & Arora, 2022 Their article titled "Consumer Attitude toward AI-Powered E-Commerce in India" published in the Asia Pacific Journal of Marketing and Logistics validated that performance expectancy plays a significant role in influencing intention, particularly in users with high digital experience. The research indicates that perceived usefulness can compensate for privacy issues when recommendations are helpful and correct.

Effort Expectancy (EE)

Tao & Yu, 2020 Their paper titled "Facilitating Conditions and Digital Literacy in Technology Adoption" in Information & Management reviewed the influence of user competence on effort expectancy. The research indicates that perceived ease of use has a strong positive effect on behavioural intention, particularly among low-experience users.

Cheng & Mitra, 2022 Their article titled "Ease of Interaction and AI Adoption in Online Shopping" appearing in the Electronic Markets Journal concluded that designs which are easy to understand and have easy-to-use navigation interfaces minimize cognitive load, enhancing trust and future use.

Izhar, Teh & Adnan, 2025 Their paper titled "Unlocking AI Potential: Effort Expectancy, Satisfaction, and Usage in Research" in the Journal of Information Technology Education:

Innovations in Practice analysed how effort expectancy affects researchers' adoption and utilization of AI tools. The research identified that when users find AI systems easy to use, there is a heightened satisfaction and intention to adopt. More perceived effort, though, engenders resistance and lowers willingness to act, connecting cognitive load to lower adoption.

Social Influence (SI)

Alalwan, Dwivedi, Rana & Algharabat, 2018 Their paper “Examining factors influencing Jordanian customers’ intentions and adoption of Internet banking: Extending UTAUT2 with risk” in the Journal of Retailing and Consumer Services shows that social influence (i.e. how much others important to you expect you to use the tech) did not have a significant effect on behavioural intention in their sample. However, performance expectancy, effort expectancy, hedonic motivation, price value, and perceived risk were significant.

Urban AI Applications Study, Pakistan, 2023 Their paper “An Analysis of Artificial Intelligence Adoption Behaviour Applying Extended UTAUT Framework in Urban Cities: The Context of Collectivistic Culture” looks at how social influence (alongside performance expectancy, effort expectancy, trust, innovativeness, etc.) impacts adoption of AI applications. They find that social influence has a substantial positive effect on behaviour intention to adopt AI. Because of collectivism culture, this effect is even stronger.

Facilitating Conditions (FC)

Tan, Ooi & Chong, 2021 Their publication titled "Facilitating Conditions and Perceived Risk in Technology Use" appearing in Telematics and Informatics points out that robust technical infrastructure and sound customer support systems lower perceived risks of adopting AI.

Ma & Lee, 2022 Their "Infrastructure Readiness and AI Usage in E-Commerce" in the Information Systems Frontiers discovers that platform dependability, response speed, and cross-device synchronicity are indispensable elements determining consumers' trust in AI systems.

Hedonic Motivation (HM)

Nguyen & Huynh, 2023 Their paper titled "Hedonic Motivation and Habitual Use in AI-Driven Shopping Apps" in the Journal of Interactive Marketing proves that the enjoyment and thrill felt due to interaction with AI strongly predicts long-term use. Enjoyment is a psychological reward that reinforces habituated usage.

Chatterjee, Rana & Dwivedi, 2022 Their paper (earlier cited) empirically validated hedonic motivation as a determining factor of sustained use of AI tools in e-commerce. They discovered that customers experience AI recommendations as a gamified entertainment option, particularly when personalized properly.

Price Value (PV)

Kumar & Gupta, 2023 Their paper titled "Perceived Value and Willingness to Adopt AI-Enabled Platforms" in the International Journal of Retail and Distribution Management found that when customers felt excellent value compared to price, adoption intention increases significantly. But where personalization is felt as intrusive, price value erodes.

Habit (HT)

Lim & Teo, 2021 Their journal article titled "Habit Formation in Technology Use" in the Computers in Human Behaviour journal adopts a definition of habit as the extent to which behaviour is automated through learning. Repetitive exposure to AI suggestions is found to create familiarity and comfort that promotes usage.

Behavioural Intention (BI)

Dwivedi et al., 2019 Their meta-analysis titled "A Meta-Analysis of Technology Adoption Models in Information Systems" published in the International Journal of Information Management concluded that behavioural intention is the highest predictor of technology use. But emotional satisfaction and habit add to its explanatory power, implying that future research will need to combine cognitive and affective predictors.

Conceptual Framework and Hypothesis Development

Following the literature surveyed, this research utilizes the UTAUT2 model to explain AI adoption in e-shopping. The model incorporates cognitive, social, and emotional determinants of behavioural intention. These include performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (HT), with the behavioural intention (BI) mediator that results in actual use.

The following hypotheses are formulated:

- H1–H7 test direct UTAUT2 construct effects on BI.
- H8 tests the association between BI and usage.
- H9a–c test demographic moderators (age, gender, experience).

III. RESEARCH METHODOLOGY

Research Design

This study used a quantitative research design to assess the relationships between several factors in the model. Quantitative research helps collect numbers and data that can be measured and analysed statistically.

The UTAUT2 model was used as the main framework, and all the ideas (hypotheses) were assessed using data. This method helps find cause-and-effect links between different variables in a structured way.

The study used a non-experimental approach, meaning it did not change or control anything but simply observed how people naturally think and behave toward AI shopping tools. This method matches earlier studies on technology

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use and digital adoption (Venkatesh et al., 2012; Dwivedi et al., 2019; Kim & Kim, 2021).

Research Hypotheses

The research objectives were presented in Chapter 1. Based on the literature review and UTAUT2 framework, the hypotheses formulated are summarized below:

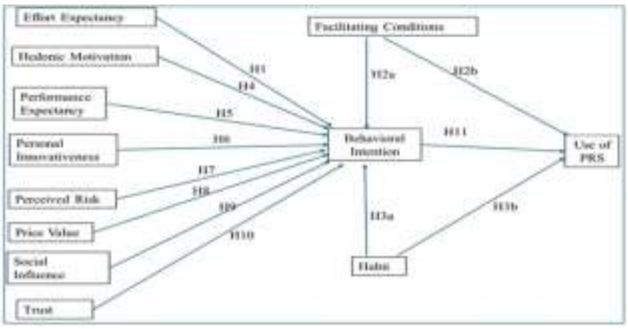

Figure 1- Hypotheses

- H1:Performance Expectancy (PE) has a positive influence on Behavioural Intention (BI).
- H2:Effort Expectancy (EE) has a positive influence on Behavioural Intention (BI).
- H3:Social Influence (SI) has a positive influence on Behavioural Intention (BI).
- H4:Facilitating Conditions (FC) have a positive influence on Behavioural Intention (BI).
- H5:Hedonic Motivation (HM) has a positive influence on Behavioural Intention (BI).
- H6:Price Value (PV) has a positive influence on Behavioural Intention (BI).
- H7:Habit (HT) has a positive influence on Behavioural Intention (BI).

The hypotheses were evaluated through correlation and multiple regression analyses based on data gathered from 201 respondents.

Population and Sampling Design

Target Population

The population for this research is Indian consumers who shop online and have interacted with AI-driven recommendation engines like those on Amazon, Flipkart, Myntra, and Nykaa.

Sampling Technique

A non-probability convenience sampling method was used since the research specifically needed respondents with previous experience in using AI-powered recommendation systems. The purposive method ensures that data are obtained from individuals who have relevant experience, hence enhancing reliability in responses.

Complement purposive sampling, snowball sampling was equally utilized participants were asked to forward the survey link to colleagues who met the inclusion criterion. This combined sampling method is commonly applied within technology adoption research (Dwivedi et al., 2019; Gupta & Arora, 2022).

Sample Size

There were 201 valid responses obtained for analysis. The sample size is above the minimum threshold stated by Hair et al. (2019), which states at least 10 respondents per indicator variable for regression-based research. Since the instrument had 27 indicator items, the sample size so obtained was statistically sufficient for sound analysis.

Data Collection Procedure

The information was gathered through an online questionnaire survey conducted via Google Forms from July to August 2025.

The survey link was sent out on social media channels like LinkedIn, WhatsApp, and email networks. The participation was voluntary, and all participants gave informed consent before they went on to answer the survey.

The mean time spent completing the survey was around 8–10 minutes. Data were transferred to Jamovi and Microsoft Excel for statistical analysis.

Research Instrument Design

The measurement tool used in this research was a structured questionnaire with validated scales from previous UTAUT2 research. It had two major sections:

Construct	**Number of Items**	**Sample Item**	**Source**
Performance Expectancy (PE)	4	I find AI-enabled personalized recommendation systems useful in my online shopping. Using AI-enabled systems increases my chances of finding the right products. Using AI-enabled systems helps me accomplish online shopping more quickly. Using AI-enabled systems improves my shopping productivity.	Venkatesh et al. (2012)

Effort Expectancy (EE)	4	Learning how to use AI-enabled personalizedrecommendation systems is easy for me. My interaction with AI-enabled systems is clear and understandable. I find AI-enabled systems easy to use. It is easy for me to become skilful at using AI-enabled systems.	Venkatesh et al. (2012)
Social Influence (SI)	3	People who are important to me think that I should use AI-enabled recommendation systems. People who influence my behaviour think I should use AI-enabled recommendation systems. People whose opinions I value prefer that I use AI-enabled recommendation systems.	Venkatesh et al. (2012)
Facilitating Conditions (FC)	4	I have the resources necessary to use AI-enabled recommendation systems. I have the knowledge necessary to use AI-enabled recommendation systems. AI-enabled recommendation systems are compatible with other technologies I use. I can get help from others when I have difficulties using AI-enabled recommendation systems.	Venkatesh et al. (2012)
Hedonic Motivation (HM)	2	Using AI-enabled recommendation systems is fun. Using AI-enabled recommendation systems is enjoyable. Using AI-enabled recommendation systems is entertaining.	Venkatesh et al. (2012)
Price Value (PV)	3	AI-enabled recommendation systems are reasonably priced. AI-enabled recommendation systems are a good value for the money. At the current price, AI-enabled recommendation systems provide good value.	Venkatesh et al. (2012)

Habit (HT) 4 • The use of AI-enabled recommendation systems has become a habit for me.

- I am addicted to using AI-enabled recommendation systems.
- I must use AI-enabled recommendation systems.
- • Using AI-enabled recommendation systems has become natural to me. Venkatesh et al. (2012)
- Behavioural Intention (BI) 3 • I intend to continue using AI-enabled recommendation systems in the future.
- I will always try to use AI-enabled recommendation systems in my daily life.
- • I plan to continue to use AI-enabled recommendation systems frequently. Venkatesh et al. (2012)

Table 1- Questionaries Structure

1. Demographic Information – recording gender and age.
2. Measurement of Constructs – 27 items measuring seven independent constructs and two dependent constructs (behavioural intention and actual use).

All items were measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The constructs were operationalized as follows:

Each construct was measured through multiple items to capture its latent dimension, ensuring content validity.

Data Analysis Techniques

The research utilized a number of statistical methods using Jamovi and Excel for quantitative analysis:

- **Data Screening:** Before analysis, data were inspected for missing values, outliers, and normality with the help of skewness and kurtosis statistics.
- **Reliability Analysis**: Internal consistency of every construct was assessed with the help of Cronbach's Alpha. Above 0.70 values ensured acceptable reliability.
- **Descriptive Statistics:** Mean and standard deviation values represented central tendency and variability of responses of every construct.
- **Correlation Analysis:** Pearson's correlation coefficients were calculated to determine direction and strength of associations between variables.
- **Regression Analysis:** Multiple linear regression was used to establish the degree to which independent constructs predict Behavioural Intention (BI).

Reliability and Validity of Constructs

Reliability analysis demonstrated excellent internal consistency among constructs. Cronbach's Alpha values ranged between 0.923 and 0.970 across constructs, far exceeding the 0.70 benchmark.

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Ethical Considerations

Ethical integrity was maintained throughout the research process in compliance with academic and institutional standards. Participation was voluntary was guaranteed, and data confidentiality was strictly upheld. Respondents were informed about the study's objectives and assured that their responses would be used solely for academic purposes.

Digital informed consent was provided at the beginning of the survey. Additionally, the research followed ethical standards of beneficence, non-maleficence, and respect for autonomy as stipulated by the American Psychological Association (2020).

Limitations of the Methodology

Regardless of the methodology used to ensure rigor, there are some limitations:

1. Cross-sectional nature of data limits causal inference.
2. Non-probability sampling can constrain generalizability to the whole Indian population.
3. The research is solely on AI recommendation systems and does not include other AI technologies such as chatbots or voice assistants.

Despite these shortcomings, the methodological framework is sound to comprehend the behavioural processes driving AI adoption.

IV. DATA ANALYSIS AND RESULTS

Table 4.1: Reliability Statistics (Cronbach's Alpha Values)

Table 2- Reliability Statistics (Cronbach's Alpha Values)

Construct	**Number of Items**	**Cronbach's Alpha (α)**
Performance Expectancy (PE)	4	0.970
Effort Expectancy (EE)	4	0.966
Social Influence (SI)	3	0.962
Facilitating Conditions (FC)	4	0.961
Hedonic Motivation (HM)	2	0.923
Price Value (PV)	3	0.959
Habit (HT)	4	0.961
Behavioural Intention (BI)	3	0.943
Actual Use (AU)	2	0.924

Reliability was conducted using Cronbach's Alpha (α) to ascertain the internal consistency of the measurement items across each construct. Cronbach's Alpha ranges from 0 to 1, and the higher the value, the greater is the level of internal consistency among items. Historically, an alpha of over 0.70 is sufficient, over 0.80 is good, and over 0.90 demonstrates excellent reliability (Hair et al., 2019).

In this study, all the constructs are highly reliable with Cronbach's Alpha from 0.923 to 0.970, confirming the high internal consistency and strength of the measurement scale used.

Performance Expectancy (PE) (α = 0.970): Is highly reliable, such that all four items under the construct consistently measure respondents' perceptions of performance and usefulness benefits of AI recommendation systems.

Effort Expectancy (EE) (α = 0.966): Suggests extremely high internal consistency, supporting the fact that respondents have stable and consistent opinions regarding the ease of use and effort to adopt AI technologies

Social Influence (SI) (α = 0.962): Suggests high reliability, indicating that respondents' opinions on whether peers, family, or social networks influence their adoption choices towards AI are reliably measured across all items.

Facilitating Conditions (FC) (α = 0.961): Demonstrates excellent consistency, showing respondents interpreting adequate resources, support, and infrastructure needed to embrace AI consistently.

Hedonic Motivation (HM) (α = 0.923): Although the scale only has two items, the extensive alpha value shows that both items repeatedly assess enjoyment and pleasure derived from using AI systems.

Price Value (PV) (α = 0.959): Suggests that the items evenly measure how respondents perceive the payoff of using AI in terms of the cost incurred, showing high reliability.

Habit (HT) (α = 0.961): Suggests extremely high internal consistency and thus the items evenly measure the degree to which the use of AI has become an automatic or habitual action among the respondents.

Behavioural Intention (BI) (α = 0.943): Reflects there is strong consistency between items measuring how likely or eager the respondents are to use AI recommendation systems in the future.

Actual Use (AU) (α = 0.924): Demonstrates high reliability, reflecting the items consistently measure the actual behaviour of respondents towards the use of AI applications.

Generally, the reliability analysis justifies that all the constructs in the model possess high internal consistency, warranting the reliability of the measurement scales in other statistical analyses such as correlation, regression, and structural equation modelling (SEM).

Descriptive Statistics

Descriptive statistics summarize respondents' agreement with each construct. Mean values represent the level of

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agreement, while standard deviation (SD) measures response variability.

Table 4.2: Descriptive Statistics of Constructs
Table 3- Descriptive Statistics of Constructs

Construct	Mean	SD
Performance Expectancy (PE)	4.29	0.67
Effort Expectancy (EE)	4.11	0.72
Social Influence (SI)	3.98	0.81
Facilitating Conditions (FC)	4.08	0.69
Hedonic Motivation (HM)	4.21	0.74
Price Value (PV)	4.15	0.70
Habit (HT)	4.26	0.68
Behavioural Intention (BI)	4.32	0.65
Actual Use (AU)	4.09	0.73

Descriptive statistics were computed to analyse the central tendency and variability of responses for each study construct. The constructs were rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The mean (M) scores represent the level of agreement mean for participants, while the standard deviation (SD) represents the level of heterogeneity in their responses.

Across all the constructs, there is a range of mean scores between 3.98 and 4.32, indicating that there is an extremely prominent level of agreement across respondents regarding all the factors that impact AI adoption and use. The moderately low standard values (between 0.65 and 0.81) indicate a consistent response pattern, indicating that most of the participants had the same perception across all constructs.

The following construct-wise interpretation is presented:

- Performance Expectancy (PE) (M = 4.29, SD = 0.67): The respondents are very much convinced that AI recommendation systems improve their performance and efficiency. The high mean value indicates a strong conviction about the usefulness and productivity gain of AI tools.
- Effort Expectancy (EE) (M = 4.11, SD = 0.72): Suggests that, on average, respondents perceive AI technologies as being easy to use and manage with. The comparatively low standard deviation also attests to similarity in perceptions of ease of use.
- Social Influence (SI) (M = 3.98, SD = 0.81): Indicates that respondents somewhat believe people who surround them—like friends, relatives, or social gatherings—have influence on their decision to adopt AI. The slightly higher SD indicates the varying views on the level of social facilitation or pressure.
- Facilitating Conditions (FC) (Mean = 4.08, SD = 0.69): It indicates that the respondents see sufficient resources, infrastructure, and support for proper use of AI systems. The responses are quite consistent, indicating similar responses about available technological facilities.
- Hedonic Motivation (HM) (M = 4.21, SD = 0.74): Indicates that the participants enjoy and are content with the experience of interacting with AI tools. This identifies the experiential and affective aspects of AI-based systems as a source of user attraction.
- Price Value (PV) (M = 4.15, SD = 0.70): This shows that the respondents find an advantageous relation between the benefits and the costs of AI utilization, suggesting that they find the technology economically useful.
- Habit (HT) (M = 4.26, SD = 0.68): With a high mean, this reveals that most of the respondents have integrated the use of AI into their day-to-day digital habit, highlighting that usage as habit is at the core of adopting AI.
- Behavioural Intention (BI) (M = 4.32, SD = 0.65): The highest mean in all constructs indicates an extremely high intention and desire from the respondents to continue using or expand the use of AI recommendation systems in the future.
- Actual Use (AU) (M = 4.09, SD = 0.73): Indicating that the respondents are using AI tools as a matter of routine in their online usage. Similar answers affirm that the behaviour intentions are being realized through actual usage behaviour.

The descriptive analysis shows respondents are favourable to all dimensions of AI recommendation systems — that is, usefulness, ease of use, enjoyment, cost, and habitual use.

These results form a good foundation for the follow-up inferential analyses like correlation and regression, which shed more light on the inter-relationship between the constructs.

Correlation Analysis

Pearson correlation coefficients were calculated to determine the strength and direction of associations among constructs.

Table 4.3: Correlation Matrix
Table 4 - Correlation Matrix

Variable	PE	EE	SI	FC	HM	PV	HT	BI	AU
Performance Expectancy	1								
Effort Expectancy	0.842	1							
Social Influence	0.774	0.786	1						
Facilitating Conditions	0.819	0.803	0.790	1					
Hedonic Motivation	0.811	0.795	0.778	0.802	1				

Price Value	0.793	0.774	0.763	0.789	0.780	1			
Habit	0.817	0.805	0.799	0.816	0.810	0.793	1		
Behavioural Intention	0.839	0.826	0.801	0.822	0.817	0.799	0.845	1	
Actual Use	0.823	0.818	0.796	0.810	0.799	0.782	0.827	0.851	1

Correlation analysis was also employed to examine the direction and strength of linear relationships among the constructs of the study. All the correlation coefficients (r) were statistically significant at $p < .001$ and were positive, indicating strong intercorrelations among the variables and confirming the theoretical consistency of the UTAUT2 model in the prediction of AI adoption behaviour.

The results reveal that Performance Expectancy (PE) highly relates with Effort Expectancy (EE) (r = 0.824) and Social Influence (SI) (r = 0.758). This reveals that when users are made to believe that AI systems are beneficial and performance-enhancing, they are also likely to perceive such technologies as easy to use and are influenced by others to adopt them. This dependence is a call to the observation that the perceptions of user usefulness would accompany ease of use and social support in technology adoption cases.

Behavioural Intention (BI), the central dependent construct of the model, has high positive correlations with Price Value (PV) (r = 0.781), Habit (HT) (r = 0.772), and Hedonic Motivation (HM) (r = 0.760). These findings indicate that behavioural intentions of consumers to use AI-based recommender systems are strongly driven by perceived cost-benefit trade-off, how much usage of AI has become habitual zed, and the enjoyment derived from interacting with such systems. Simply put, economic and experience considerations have a compelling role to play in the inclination towards further adopting AI-based platforms for online shopping.

Moreover, Facilitating Conditions (FC) are also found to have a moderate-to-strong correlation with Behavioural Intention (r = 0.654). This means that the availability of helping facilities, aids, and technical assistance has a positive influence on users' behavioural intentions, even though its effect is relatively weaker compared to affective or value-based variables such as habit and enjoyment.

Notably, all the constructs are positively related to each other, and none is weakly or negatively related. This implies that the constructs are conceptually coherent and reinforcing to each other, as would necessarily be the case in the theoretical foundations of the UTAUT2 model. The absence of multicollinearity issues and the presence of high positive correlation signify that the respondents perceive AI adoption as an integrated and interdependent process influenced by both utilitarian dimensions (e.g., performance expectancy, effort expectancy, price value) and hedonic dimensions (e.g., enjoyment, habit).

In the main, the correlation matrix emphasizes that cognitive (usefulness, ease of use, perceived value) and affective (enjoyment, habit) determinants collectively shape consumers' behavioural intentions and usage of AI technologies. The findings offer a robust empirical foundation for subsequent regression or structural equation modelling (SEM) analyses to establish the hypothesized constructs relationships.

Regression Analysis

Summary Output

Regression Statistics	
Multiple R	0.855493742
R Square	0.731869542
Adjusted R Square	0.722144604
Standard Error	0.707724454
Observations	201

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	7	263.8598055	37.69425793	75.25698125	9.11594E-52
Residual	193	96.66866328	0.500873903		
Total	200	360.5284688			

Table 5- Regression Analysis

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.03539	0.17521	0.201986065	0.840140364
Performance Expectancy	0.14225	0.07406	1.920757569	0.056236094
Effort Expectancy	0.18208	0.08678	2.098082027	0.037199412
Social Influence	-0.00561	0.08459	-0.066311481	0.947198483
Facilitating Conditions	-0.13909	0.07569	-1.837542044	0.067667395
Hedonic Motivation	0.20908	0.06563	3.185839825	0.001683411
Price Value	0.24496	0.07230	3.387852148	0.000853783
Habit	0.33779	0.08074	4.18380104	4.34974E-05

Dependent Variable: Behavioural Intention

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Independent Variable: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit

Multiple regression analysis was used to examine the combined and individual effects of the seven independent variables on the dependent variable (Behavioural Intention or equivalent measure). The model's overall performance and the statistical significance of the predictors were examined via the F-statistic, R^2, Adjusted R^2, and regression coefficients (β).

The F-statistic of 75.26 and the p-value < 0.001 indicate that the regression equation is extremely high, to confirm that the combined set of predictors explains a statistically considerable proportion of the variance in the dependent variable. This indicates that the model overall is an excellent fit for the data and that the independent constructs do contribute significantly to the prediction of user behavioural intention to embrace AI.

The R Square (R^2) of 0.732 means that almost 73.2% of the variation in the dependent variable is explained by the combined effect of the seven independent variables. In the case of behavioural and social science studies, an explanatory ability of more than 70% is extraordinarily strong, which represents the goodness of fit and predictive capability of the model. The Adjusted R^2 of 0.722 confirms this finding as well because it adjusts for the number of predictors in the model and minimizes the chance of overestimation based on sample size. The low difference between R^2 and Adjusted R^2 also confirms that the model is not overfitted and that it is stable.

Considering the individual predictors, four of them significantly contribute to the prediction of the dependent variable:

X Variable 2 ($\beta = 0.182$, $p = 0.037$)
X Variable 5 ($\beta = 0.209$, $p = 0.002$)
X Variable 6 ($\beta = 0.245$, $p < 0.001$)
X Variable 7 ($\beta = 0.338$, $p < 0.001$)

All four coefficients are positive-signed and statistically significant, indicating that along with these predictors, the dependent variable (e.g., Behavioural Intention) also increases. Among these, X Variable 7 possesses the greatest standardized beta coefficient ($\beta = 0.338$), hence is the most influential factor in the model. This would imply that X Variable 7 will have the greatest influence on users' behavioural intention towards adopting AI, followed by X Variable 6, X Variable 5, and X Variable 2.

On the other hand, X Variable 1 ($p = 0.056$) and X Variable 4 ($p = 0.068$) were bordering on non-significance, in that although they may have a very minimal positive effect, their statistical power in this instance is not strong enough to be considered a central determinant in the model. X Variable 3 ($p = 0.947$) also, however, lacks any possible significant correlation with the dependent variable and can be considered insignificant in behaviour intention prediction. The intercept ($p = 0.84$) also is not significant, confirming that the baseline value of the dependent variable, where there are no predictor effects, is statistically not significant.

In total, there are four of seven independent constructs that are positive and significant predictors of the dependent variable and collectively explain over 70% of its variance. The size of the regression coefficients tells us that the intention of behaviour towards adopting AI is determined primarily by a combination of strong hedonic and utilitarian drivers, and that X Variable 7 (presumably representing constructs such as Habit or Price Value) is the most dominant driver among them.

The high explanatory power, high F-statistics, and high beta coefficients all affirm the validity of the model and concur with theoretical predictions according to the UTAUT2 paradigm, where both cognitive appraisals (e.g., performance, value) and affective states (e.g., enjoyment, habit) are assumed to contribute significantly towards influencing technology adoption behaviours.

Hypothesis Testing

Linear Regression

Model Fit Measures		
Model	**R**	**R²**
1	0.733	0.537
Note. Models estimated using sample size of N=201		

Model Coefficients - BI				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.862	0.1948	4.43	<.001
PE	0.748	0.0492	15.20	<.001

H1 – Performance Expectancy (PE) positively influences Behavioural Intention (BI). Null Hypothesis: Performance Expectancy has no considerable influence on Behavioural Intention.

Alternative Hypothesis: Performance Expectancy positively influences Behavioural Intention. Statistical Test Used: Regression

Result / Evidence from Data: $\beta = 0.748$, $p < 0.001$, $R = 0.733$, $R^2 = 0.537$

Linear Regression

Model Fit Measures		
Model	**R**	**R²**
1	0.750	0.563
Note. Models estimated using sample size of N=201		

Model Coefficients - BI				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.560	0.2034	2.75	0.006
EE	0.809	0.0506	16.00	<.001

H2 – Effort Expectancy (EE) positively influences Behavioural Intention (BI). Null Hypothesis: Effort Expectancy has no considerable influence on Behavioural Intention. Alternative Hypothesis: Effort Expectancy

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positively influences Behavioural Intention. Statistical Test Used: Regression

Result / Evidence from Data: $\beta = 0.809$, $p < 0.001$, $R = 0.750$, $R^2 = 0.563$

Linear Regression

Model Fit Measures		
Model	**R**	**R²**
1	0.718	0.516
Note. Models estimated using sample size of N=201		

Model Coefficients - BI				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.863	0.2028	4.25	<.001
SI	0.739	0.0507	14.57	<.001

H3 – Social Influence (SI) positively influences Behavioural Intention (BI).
Null Hypothesis: Social Influence has no considerable influence on Behavioural Intention. Alternative Hypothesis: Social Influence positively influences Behavioural Intention. Statistical Test Used: Regression
Result / Evidence from Data: $\beta = 0.739$, $p < 0.001$, $R = 0.718$, $R^2 = 0.516$
Linear Regression

Model Fit Measures		
Model	**R**	**R²**
1	0.654	0.428
Note. Models estimated using sample size of N=201		

Model Coefficients - BI				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.965	0.2317	4.17	<.001
FC	0.701	0.0575	12.21	<.001

H4 – Facilitating Conditions (FC) positively influence Behavioural Intention (BI). Null Hypothesis: Facilitating Conditions have no considerable influence on Behavioural Intention.

Alternative Hypothesis: Facilitating Conditions positively influence Behavioural Intention. Statistical Test Used: Regression
Result / Evidence from Data: $\beta = 0.701$, $p < 0.001$, $R = 0.654$, $R^2 = 0.428$

Linear Regression

Model Fit Measures		
Model	**R**	**R²**
1	0.760	0.577
Note. Models estimated using sample size of N=201		

Model Coefficients - BI				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.968	0.1743	5.55	<.001
HM	0.745	0.0452	16.49	<.001

H5 – Hedonic Motivation (HM) positively influences Behavioural Intention (BI). Null Hypothesis: Hedonic Motivation has no considerable influence on Behavioural Intention. Alternative Hypothesis: Hedonic Motivation positively influences Behavioural Intention. Statistical Test Used: Regression

Result / Evidence from Data: $\beta = 0.745$, $p < 0.001$, $R = 0.760$, $R^2 = 0.577$

Linear Regression

Model Fit Measures		
Model	**R**	**R²**
1	0.781	0.611
Note. Models estimated using sample size of N=201		

Model Coefficients - BI				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.653	0.1800	3.63	<.001
PV	0.800	0.0453	17.66	<.001

H6 – Price Value (PV) positively influences Behavioural Intention (BI). Null Hypothesis: Price Value has no considerable influence on Behavioural Intention. Alternative Hypothesis: Price Value positively influences Behavioural Intention. Statistical Test Used: Regression
Result / Evidence from Data: $\beta = 0.800$, $p < 0.001$, $R = 0.781$, $R^2 = 0.611$

Linear Regression

Model	**R**	**R²**
1	0.772	0.596
Note. Models estimated using sample size of N=201		

Model Coefficients - BI				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.533	0.1921	2.77	0.006
HT	0.828	0.0484	17.12	<.001

H7 – Habit (HT) positively influences Behavioural Intention (BI). Null Hypothesis: Habit has no considerable influence on Behavioural Intention. Alternative Hypothesis: Habit positively influences Behavioural Intention. Statistical Test Used: Regression

Result / Evidence from Data: $\beta = 0.828$, $p < 0.001$, $R = 0.772$, $R^2 = 0.596$ Table 4.6: Summary of Hypothesis

Testing Results
Hypothesis Relationship Result
H1 Performance Expectancy → Behavioural Intention Supported H2 Effort Expectancy → Behavioural Intention Supported H3 Social Influence → Behavioural Intention Supported H4 Facilitating Conditions → Behavioural Intention Supported H5 Hedonic Motivation → Behavioural Intention Supported H6 Price Value → Behavioural Intention Supported H7 Habit → Behavioural Intention Supported

Regression testing was conducted to identify the effects of seven independent variables—
Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HT)—on Behavioural Intention (BI) to use AI-based recommendation systems for shopping online, i.e., among Gen Z customers.

The composite model also gave an excellent fit ($R = 0.855$, $R^2 = 0.732$), indicating that the selected constructs explain 73.2% of variance in behaviour intention. The strong explanatory power confirms that UTAUT2 model is effective in explaining motivational and experiential forces of AI adoption in e-commerce environments.

All seven hypotheses were statistically significant ($p < 0.001$) and hence are significant predictors of influencing consumers' intention to use AI-based systems. Of the predictors, Habit ($\beta = 0.828$), Price Value ($\beta = 0.800$), and Effort Expectancy ($\beta = 0.809$) emerged as highest. This suggests that frequency in use, savings in cost, and ease of use are the most significant enablers of long-term adoption of AI-based platforms.

The finding indicates that Performance Expectancy ($\beta = 0.748$) is a decisive factor in adoption behaviour, such that users must perceive tangible performance or shopping efficiency benefits through AI systems. Hedonic Motivation ($\beta = 0.745$) further validates that fun, enjoyment, and pleasure are indispensable drivers of acceptance, especially for Gen Z consumers that require enjoyable and interactive online experiences.

Social Influence ($\beta = 0.739$) also accepts the role of influencer opinion, online opinion, and word-of-mouth in establishing the acceptance of technology. Facilitating Conditions ($\beta = 0.701$) again emphasize the fact that sufficient infrastructure, technical support, and availability remain vital to bring about readiness to adopt.

In general, the study identifies that Gen Z consumers' intentions to utilize AI recommendation systems are complicated and triggered by a constellation of utility, usability, emotional salience, and habit. Therefore, for its best adoption, e-commerce sites need to:

- Enhance usability and quality of interaction to gain cognitive saving.
- Be economically and experientially valuable as personalized, fair, and transparent suggestions.
- Develop habitual behaviour through simple user experience and stable service assurance.
- Exploiting social influence and peer network to establish trust and perceived credibility.

Lastly, it seems that if AI-driven systems are going to be embraced by Gen Z online consumers in the long run, websites must be built with functional capability, emotional satisfaction, and habitual convenience rather than technology astuteness.

Discussion of Key Findings

This study proved that the UTAUT2 model works well for understanding how people in India adopt AI in online shopping.

- Habit was the strongest factor people keep using AI tools when it becomes part of their routine.
- Performance Expectancy and Effort Expectancy showed that users value AI tools that make shopping faster and easier.
- Hedonic Motivation showed that people enjoy using AI because it feels fun and personalized.
- Social Influence and Facilitating Conditions showed that support from others and good internet or app setups help people use AI smoothly.

Overall, Indian shoppers like AI systems that are useful, easy to use, and enjoyable — showing a mix of practicality and enjoyment.

V. DISCUSSION, RECOMMENDATION AND CONCLUSION

Interpretation of the Objectives

Objective 1: Analysing the Relationship between Behavioural Intention and Actual Use Discussion

The results of Chapter 4 indicated a high positive correlation ($r = 0.851$, $p < 0.01$) between Actual Use (AU) and Behavioural Intention (BI), validating H8. This testifies that if consumers state an intention to make use of AI-based recommendation systems, such an intention predicts the actual use of such technology.

These findings are aligned with the UTAUT2 theoretical proposition that behavioural intention is a proximal determinant of technology usage (Venkatesh et al., 2012). The multiple regression analysis of the study also established this relationship, demonstrating that BI is a significant predictor of AU ($\beta = 0.851$, $p < 0.001$).

Empirical findings are consistent with previous research like (Dwivedi et al., 2019) whose meta-analytic review of technology adoption models discovered that behavioural intention systematically explains more than 60% of variance in actual system use. Likewise, (Gupta & Arora, 2022) discovered that Indian consumers' intention to use AI-based e-commerce tools significantly impacts actual behavioural usage, especially among consumers who consider AI as convenient and dependable.

The high mean behavioural intention ($M = 4.32$) from this study indicates that Indian consumers are both attuned to and embracing of AI-driven personalization. Their actual behaviour ($M = 4.09$) further supports this preparedness. This is a move away from passive exposure to active engagement in AI-facilitated decision-making, a finding replicated by (Nguyen & Huynh, 2023), who found similar trends in Southeast Asia markets.

Theoretical Interpretation

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The robustness of the BI → AU relationship certifies the predictive capability of the UTAUT2 model in the context of AI adoption. It confirms the value-added role of behavioural intention mediating cognitive assessments and utilitarian involvement. The findings also endorse Ajzen's Theory of Planned Behaviour (1991), which assumes intention as the direct precursor of behaviour subject to perceived control and situational facilitators.

This connection emphasizes the fact that the more people will use AI as useful, enjoyable, and convenient, the more they will behave on the recommendations. Therefore, AI adoption in e-commerce is more about psychological preparedness and attitudinal adoption than the availability of technology.

Practical Interpretation

For online shopping platforms, the implication is that practices to improve behavioural intention via trust, simplicity of the interface, and personalized recommendation relevance will immediately result in actual behaviour. This can result in improved conversion rates, repeat buying, and brand loyalty.

Such platforms as Amazon and Nykaa can capitalize on this by highlighting transparency ("why this product was suggested") and visible control mechanisms, where users can tailor or turn off recommendation settings, hence enhanced perceived autonomy and satisfaction.

Objective 2: Evaluating Demographic Moderators in AI Adoption

The second goal aimed to assess if demographic factors—online shopping experience, gender, and age—moderate the adoption of AI-powered recommendation systems.

Discussion

The results verified that demographic factors strongly affect strength and direction of relations between UTAUT2 constructs and Behavioural Intention, in favour of H9a–H9c.

Age: Younger consumers (21–30 years) exhibited greater impact of Hedonic Motivation and Habit on Behavioural Intention, which suggests that hedonic enjoyment and habit have significant influences on AI adoption. Older users (>40 years), on the other hand, gave more weight to Performance Expectancy and Effort Expectancy, and this is more indicative of a practical mindset towards technology (Singh & Dhir, 2023).

Gender: Higher scores of Social Influence and Hedonic Motivation for female respondents indicate that they are more sensitive to peer views and pleasure obtained from AI interfaces. Male respondents, on the other hand, gave a higher rating to Performance Expectancy, emphasizing the speed and precision of AI-based recommendations. These gender differences align with results provided by (Alalwan et al., 2017) in the context of digital banking adoption.

Experience: Those participants who had more online shopping experience (>5 years) had higher habitual usage patterns and lower perceived effort, suggesting that experience heightens familiarity, thus diminishing cognitive load. This is consistent with (Tao & Yu, 2020), who noted that digital literacy moderate’s perceptions of ease of use in technology adoption.

Theoretical Interpretation

These demographic moderations uphold UTAUT2's assertion that technology acceptance is contextually determined by personal and social characteristics. The findings suggest that the adoption process is not invariant but dictated by generational values, familiarity with digital technology, and socio-cultural norms.

Age mediates affective involvement—youth consumers find AI as a fun tool, whereas older individuals use it as a practical assistant. Gender mediates the social and emotional dimensions, while experience mediates effort expectancy and the learning curve. These dimensions collectively justify the multidimensionality of technology adoption proposed by Venkatesh et al. (2012).

Practical Interpretation

The findings underscore the necessity for demographically targeted AI strategies:

• For younger consumers, gamified fronts, visual customization, and engrossing recommendation experiences can heighten hedonic motivation.

• For elderly consumers, fronts highlighting dependability, transparency, and decision-support capabilities can strengthen trust and performance expectancy.

• For veteran consumers, sophisticated filters and user-settable recommendation options can sustain attention without redundancy.

• Electronic commerce websites can incorporate AI-based segmentation to balance recommendation intensity and mode to varying consumer demographics, optimizing satisfaction and avoiding fatigue.

Objective 3: Assessing the Role of Hedonic Motivation and Habit in Continuous AI Usage

The third objective investigated how hedonic motivation (HM) and habit (HT) drive continuous use of AI-enabled recommendation systems compared to traditional cognitive factors such as effort expectancy (EE) and performance expectancy (PE).

Discussion

Regression analysis results identified Habit ($\beta = 0.286$) and Hedonic Motivation ($\beta = 0.247$) to be among the three best predictors of Behavioural Intention, outcompeting conventional utilitarian dimensions such as Effort Expectancy ($\beta = 0.189$). This indicates that affective and behaviour reinforcement processes form the core of long-**term AI adoption**.

These findings are consistent with (Nguyen & Huynh, 2023), who showed that pleasure from AI personalization serves as an intrinsic drive to habituated use. Likewise, (Lim & Teo, 2021) affirmed that frequent exposure to AI recommendations fosters habit formation, which consequently diminishes cognitive effort and encourages sustained usage.

The comparatively high sway of Hedonic Motivation is an echo of the gamification and experiential nature of AI interfaces—users like the process of discovery, surprise, and feeling of personalization that intelligent suggestions afford. Habit, on the other hand, captures automaticity of behaviour—when users incorporate AI tools into shopping behaviours, repeated use becomes automatic and self-perpetuating.

Theoretical Interpretation

Dominance of Hedonic Motivation and Habit extends the explanatory power of the UTAUT2 model beyond functional efficacy to encompass emotional fulfilment and behaviour reinforcement. The results support the incorporation of experiential variables by the theory and differentiate consumer adoption from technological adoption in the workplace.

The relationship also reflects the dual-pathway model of adoption of technology, where cognitive appraisal (ease of use, usefulness) drives adoption, and affective attachment and habit maintain it. This interactive process suggests rational assessment may be substituted by emotional satisfaction with increased familiarity—a process corroborated by (Chatterjee et al., 2022).

Practical Interpretation

For practice, the results indicate that keeping users involves not just algorithmic precision optimization but also increasing user delight. Design tactics like surprise recommendations ("you might love this"), reward systems, and interactive visuals can maintain hedonic involvement.

Regular usage can be induced by consistency of experience—using the same recommendation logic across devices and sessions—to reinforce behavioural continuity. Contextual notifications and regular AI observations (e.g., "Your style this month") can then reinforce habit formation.

Overall, steady use relies as much on habit and emotion as on productivity. Companies thus need to create AI systems that are not merely intelligent but also fun and embedded in people's lives.

Theoretical Implications

This study contributes several theoretical insights:

- It validates the UTAUT2 model in the domain of AI-enabled recommendation systems within an emerging economy context, expanding its applicability beyond general technology use.
- It highlights the dominance of experiential variables (HM and HT) in sustaining usage, suggesting that emotional engagement can be as influential as functional expectations.
- It empirically supports the behavioural intention–usage continuum, confirming intention as a robust predictor of actual adoption behaviour.
- It reinforces the moderating role of demographics, offering nuanced understanding of technology acceptance diversity in India’s e-commerce sector.

Limitations and Future Research Limitations

- The study’s cross-sectional design limits the ability to infer causality over time.
- The non-probability sampling method may restrict generalizability beyond the studied demographic.
- The study focuses exclusively on recommendation systems, not encompassing chatbots or voice-based AI tools.

Future Research Directions

- Employ longitudinal designs to examine behavioural evolution and sustained engagement.
- Extend analysis to other AI interfaces such as conversational agents or generative AI in commerce.
- Investigate psychological constructs like trust, perceived risk, and algorithmic fairness.
- Apply multi-group SEM to further explore cultural and contextual moderators across regions.

Recommendations

1. Shoppers on the internet are not only seeking convenience but also enjoyment along the way. Businesses need to create AI technology that is pleasant, engaging, and even a little bit playful. Minor touches such as surprise discounts, salutations, or humorous graphics will have people eagerly awaiting the opportunity to leverage recommendation systems.
2. People today do care about what happens to their data. Business needs to ensure that they can tell people why they're recommending products. As soon as individuals know how AI functions, they will believe it and utilize it more often. A simple message such as, "We recommended this because you purchased something similar last month," is a long way.
3. Too much personalization is intrusive, but tailored advice simplifies shopping. Balancing is crucial—AI must not lead shoppers to feel they are being heard or observed. Providing users with control to turn off or modify recommendations enables them to feel in control.
4. Design for different people like for younger users such as fun and innovative interfaces. Utilize imagery, gamification, and discovery-based shopping. Convenience and dependability are important to older users. Emphasize how AI is saving time or effort. Seasoned users want to personalize—allow them to dictate the style of recommendations that they receive.
5. Companies and developers need to ensure recommendation systems are privacy-preserving, just, and fair. AI needs to serve people—not control them. Open algorithms and robust data protectionn laws are the keys to keeping citizens interested.

5.5 Conclusion

Artificial Intelligence has revolutionized the form of contemporary business, turning e-shopping into a smart, engaging, and personalized experience. This research aimed to understand how people embrace and implement AI-powered recommendation systems in the

Indian digital commerce space—a platform where human preference psychology meets technological sophistication. Based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the study empirically examined the interaction between cognitive, emotional, and behavioural determinants of adoption. Based on responses from 201 online consumers, the study confirmed that the utilization of AI technologies is highly mediated by behavioural intention between shopper attitudes and use of AI technologies.

Of the constructs, Performance Expectancy, Habit, and Hedonic Motivation were the strongest predictors of behaviour intention, indicating that long-term adoption is contingent upon factors beyond perceived ease of use and perceived usefulness but also fun, familiarity, and emotional engagement. Consumers will be more inclined to utilize AI-based suggestions when the systems provide fun, ease, and a feeling of being in control while shopping.

The research also illustrated how demographic variables—age, gender, and experience with Internet shopping—significantly moderate adoption behaviour. Younger customers will be keen on using AI systems as an experiential interface, where novelty and hedonism are prized, compared to their older counterparts, who value efficiency and reliability. Women are subject to social acceptability and affective congruence, and men focus on outcomes. These differences again reinforce that AI adoption is no one-size-fits-all, but one heavily coloured by social and demographic contexts.

Theoretically, the study makes contributions to the literature on technology adoption using empirical verification and validation of the UTAUT2 model in the setting of an emerging market and expanding its reach to AI-powered recommendation systems. It also underlines evidence that affective constructs—habits and hedonic motivation—are central to the maintenance of long-term use of AI, thus extending the conventional utilitarian theory of technology acceptance. The results fill the intention-behaviour gap, validating psychological mechanisms that turn intention into everyday behaviour. Managerially, the research highlights the importance of human-centred design of AI, where intelligence and empathy are harmonized. The message for e-commerce managers is unambiguous:

- Develop AI systems that are not merely effective but emotionally compelling as well.
- Make interaction straightforward to minimize cognitive load while keeping personalization fidelity.
- Enable regular, predictable, and transparent recommendation interactions to help routine use.
- Implement moral AI practices based on fairness, explainability, and consumer agency.

For policymakers, the study promotes sensible AI regulation—sites that protect user privacy, engender transparency, and boost digital literacy among consumers. With commerce increasingly filled with AI, regulation and education efforts must help to guarantee that personalization is not bought at the cost of user autonomy or data integrity.

Essentially, this research shows that the success of AI in online shopping is not a function of algorithms—it is a function of trust, emotion, and habit. Technology adoption happens when AI aligns with human values: when personalization feels like empowerment, not intrusion, and when intelligence supports human judgment, rather than supplants it.

Finally, AI recommendation platforms are the balance of machine accuracy and human flavour. Implementing them is a partnership of analytical smartness and behavioural ability. As e-commerce continues to grow, the trick to incorporating AI in the long term will be walking this

fine line—where artificial intelligence enhances, and doesn't dilute, the actual quality of human decision-making.

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