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Research Article

Exploring the Additional Factors Driving Behavioural Intention and User Behaviour in AI-Powered E-Commerce among Young Consumers: A UTAUT Model Approach

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ABSTRACT

Purpose: This study explores how the use of AI tools impacts the purchasing behavior of young Indian consumers aged 18–35 years on e-commerce websites. It seeks to analyze how performance expectancy, effort expectancy, social influence, and facilitating conditions affect behavioral intentions and use behavior. Besides, it probes the moderating effects of age, psychological factors, privacy concerns, and role of special events, offers, and coupons in converting product consideration into actual sales.

Design/methodology/Approach: The present investigation employs Structural Equation Modelling (SEM) to examine the data obtained from an online survey conducted among young Indian consumers. This study utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to investigate the connections between the specified dependent variables and their influence on consumer purchasing decisions.

Findings: Findings of the results demonstrate that the influence of AI-driven personalized recommendations, effort expectancy, social influence, facilitating conditions, and psychological factors on behavioural intentions and use behaviour of young consumers are quite significant. The privacy concern and user experience are very critical moderating factors. At the same time, seasonal deals and rewards can become decisive factors to convert the consideration set into actual purchases, especially for younger consumers.

Originality/value: This research enhances the existing body of literature by utilizing the UTAUT framework to investigate the influence of AI tools on consumer purchasing behavior within the Indian e-commerce sector. It specifically examines the interplay among seasonal promotions, psychological influences, and privacy apprehensions, providing insights into how these factors inform the buying choices of younger consumers.

Keywords: AI tools, UTAUT, e-commerce, young consumers, purchasing decisions, India, SEM, psychological factors, privacy concerns, seasonal deals, ethical considerations.

1. Introduction

The rapid changes and developments of digital technology coupled with the existence of new products in the market have altered the purchasing patterns among consumers, especially in the retail sector. Social media, being part of the radical transformation, is effective on impacting their choices especially the youth. In contrast to telecommunication and print media, in social media, the clients themselves are involved in content creation and sharing which helps increase the knowledge and diversity of the consumers (Ramadan and Aita, 2018; Richard and Jing, 2015). In addition, this change in consumer behavior is further amplified by the internet, where consumers are exposed to the radical idea of seeking new products and the more 'adventurous' aspect of consumers wanting to stand out from others (Ganesh et al., 2010; Seo and Moon, 2016). These features are most pronounced in younger consumers, who are in the main target of going through a lot of information, willingness to try out new products (Uddin and Khan

2018). As the trends of the market have changed from brick and mortar retail to the era of e-commerce, the role of A.I. in transactions over the internet has become much more important than it was.

AI technologies help collect, analyse and process extensive consumer data and recommend, remind or alert deals which increase customer interaction and satisfaction (A Srivastava, 2021). The marketing experience that comes with the use of AI technology in business helps to accurately analyse the buying habits of the consumers and therefore facilitates the creation and fostering of the more customized shopping experiences which affects the conversion metrics positively (Manikandan, G., & Bhuvaneswari, G. (2024). It has been reported that AI enhances customer satisfaction and willingness to buy due to the efficient personalization of the shopping experience and increasing the possibility of making sales. (Bhagat R et al., 2023).

In the present scenario of increased competition in the landscape of e-commerce and the forthcoming disruption, of what is being referred to as the “retail apocalypse”, online sellers need to figure out how to survive by deploying dynamic offers and personal strategies that “surprise and delight” customers. Promotion of any product can be effective no matter what the price is; hence the common strategies such as offers, coupons and discounts particularly for impulse buying purchase where items like clothing’s are involved (Li et al., 2023; Manganari, E.E.,2011; Helm et al., 2020; Natarajan, T.,2017). Consumers have been more responsive to mobile marketing than browsing the companies’ websites because mobile apps have users attention more than online browsing (Kim et al., 2017; Ma, K. and Treiber, M.C. (2020); Wang, R.J.H., et al., 2015; Watson et al., 2013). Because mobile shopping apps enhance the overall shopping experience and satisfaction of the consumers and positively impact the purchasing impulse by providing real time marketing updates (Zheng et al., 2019).

In addition, the role of social media eWOM, brand awareness and brand interaction with consumers all enhance the influence of social nurturing on consumer buying behavior. The above factors especially help in constructing the offerings that appeal to consumers’ purchase intentions, particularly at the preliminary phase of new product competing in promotional activities like social media (Prasad et al., 2017). Similarly, social media channels allows consumers to be engaged, interact and active. And it also creates an avenue for the companies to interact with their customers more and even turn into promoters of the brand (Shah et al., 2019). In particular, the contribution of AI in enhancing a client’s experience from the initial stage of awareness to the post-purchase phase is phenomenal. The capability of AI to affect the consumer decision making process varies among the population group. Younger consumers or digital natives like generation Z find AI marketing strategies more appealing than older consumers do (Ameen et al, 2021). Customer service especially more of advanced and individualised services have been offered in areas like hospitality and tourism because of the growth of AI (Stephanidis, 2019), in the end increasing customer satisfaction and loyalty (Nguyen et al, 2022). In addition, it is evident that as more of such AI and social media is incorporated into the operations of the companies to reach out to the consumers, more of such technologies will more efficiently be applied at every stage of the consumer decision making process.

Performance Expectancy and Effort Expectancy have been identified as the prime factors related to the acceptance of technology, especially in the context of the online shopping (Venkatesh et al, 2003; Lian, J. W et al , 2014). Artificial intelligence, makes social networking cost effective and provides means for brands to boost sales, profits, and customer satisfaction as the level of customer engagement and loyalty is improved (Ramadan and Aita, 2018). It is acknowledged, therefore, that the combination of AI and the social media into marketing and consumer engagement strategies positively impact the business, which is mainly aimed at the younger consumers who are technology driven. These advanced technologies permit companies not only to improve the efficacy of their marketing efforts but also to garner valuable insights into the behavior of their customers and develop long-lasting relationships with them. Services of AI and social media are bound to develop further and to become a more sophisticated tool of influence on consumers’ decision-making process in the future. This presents more avenues for business growth and development in a digital first world.

In response to the gaps in the literature, this study aims at investigating the effect of seasonal deals and rewards on the behavioral intentions and use behavior of young Indian consumers in the ecommerce context. It assesses how factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions of AI tools influence these behaviors. Further, the study is enriched by the analysis of age, psychological aspects, concern about privacy, as well as the overall instances of integration of these aspects into the consideration set, and the spectrum of products and situations that the consumers at least briefly contemplate prior to making an actual purchase. The study also examines young people's perceptions of the ethical dimension of consumption focusing on purchase-based consumption decision providing a more holistic view of the relation between advertising and consumer behavior.

The structure of the paper can be understood as follows: The next section focuses on reviewing relevant literature, identifying the gaps in previous works and defining the aims and objectives of the present research. It also includes the development of certain relationships between the insufficient and potential products and their influence on the consideration set and purchase behaviour. The research design then discusses the process of data gathering, characteristics of the sample and Structural Equation Modelling(SEM) as a technique for analysis. The next section describes the research processes of collection of opinions through questionnaires from the consumers with regard to the seasonal specials permits to discuss the results and analysis. In the concluding section both theoretical and managerial contributions are discussed; the contribution of the study towards the literature and managerial practices especially for e-commerce platforms are highlighted; and future directions are pinpointed suggesting a better reach out to younger generation in the present AI dominated world.

2. Review of Literature

With the advent of the digital age, the consumption patterns of consumers and even younger generation and the aged people have changed a lot; this change occurred due to people's interaction with brands via the electronic media. With the growth of e-commerce, the use of artificial intelligence (AI) and digital media influences on the consumer behavior has also been growing at a steady rate. The study of the effect of these technologies on the buying behaviour of the younger consumers is crucial for any company trying to compete in this fast changing environment.

This review of literature attempts to cover the published work done between 2020 and 2024 with the exception of early 2020 which has been included for theoretical context and in order to capture any changes in the consumer perception. The review scrutinises even details of online shopping behaviour, in particular key factors focused on AI based personalisation, the role of social networks, and psychological factors. In addition, the review points out the ones that are included in most studies included in the review, such as structural equation modelling (SEM) and which allow the studying of covariation between behavioural intentions and actual use behaviour. This literature review identifying the gaps by synthesising and analysing those studies aims to help fill in the gaps and serve as a good seed of the research in the future helping in coming up with practical ways of improving e-business and e-consumer hood.

Applying performance expectancy becomes one of the most crucial factors in determining the extent to which the consumers' perceived quality and value proposition of e-commerce platforms can be delivered. Bettencourt, Lusch and Vargo (2018) state that it is possible to improve customers'satisfaction levels when using artificial intelligence and big data to deliver customers' experiences through the analysis of real-time data and individual interactions, as well. It is demonstrated that AI can influence customer satisfaction and behavioral intentions - through personalized recommendations. Similarly, Keiningham, T et al. (2020) studied the marketing aspects of digital transformation and personalization techniques and mentioned the effects of AI on customer's purchase behavior. Shyna, K and Vishal, M (2017) also concentrated on the AI-embedded e-commerce systems that make personalized recommendations to the customers, on top of that cements that as performance expectancy affects the consumer behavior. The UTAUT model suggests perceived performance expectation to be an important determinant of the intention behaviour (Venkatesh et al., 2003). This found even stronger support in works of Costa, R. L. D et al. (2022) who studied impact of new technologies such as AI chatbots and virtual fitting rooms on customer satisfaction and online purchasing actions.

Effort expectancy, also referred to as the ease of 'using', which is linked to any given system, has a direct impact on the adoption of AI tools in e-commerce. In this context, the study by Haenlein, M., & Kaplan, A. (2019) sheds light on how, for example, user-specific suggestions made by AI-driven systems help expedite decision making because they make shopping easier. This is consistent with results by Garbuio, M., & Lin, N. (2019) who explored the facets of innovation-induced value creation through AI and customer participation in a digital context. Costa, R. L. D et al. (2022) even further detailed the level of interaction designed by AI tools and how it transforms consumers' experiences with online shopping. This underscores the significance of effort expectancy in promoting consumer participation as in the UTAUT model and also the importance of ease of use on technology acceptance (Alshare, K et al 2004; 'Venkatesh et al., 2003).

The aspect of social influence is still vital in the understanding of consumers, particularly within e-commerces. The research of Rabby F et al. (2021) elaborates how the use of artificial intelligence in digital marketing helps consumers through better, recommendation and social interaction. In the same way, Chopra,A (2020) focuses on chatbots' capacity to enhance the engagement level of the customers and also improve suggestions which positively affect purchasing decisions. In countries such as Greece, S Dimitrieska (2018) investigated the positive impact of advertisement as an artificial intelligence strategy 'smart searches plus ads' with the increasing trends of pleasing the client. The study by Elsafty, A., & Elshahed, M. (2021) supports and complements by exploring how AI works in the realm of digital marketing and how it affects the consumers. This is in line with the findings by Saboo, A. R., Kumar, V., & Ramani, G. (2016). Assessing the contribution of social media marketing activities on the sales of human brands. International Journal of Research in Marketing, 33(3), pg 524-541, where Social Identity Theory was applied to social media and purchase decisions.

Escapism, value-seeking, and the need to be socially accepted are are other psychological and motivational factors that impact consumers` online shopping behavior. Yanliang Zhu, Y.,(2023) highlights such aspects pertaining to the impact of AI services on compulsive buying behavior of consumers as a result of utilization of their services. Likewise, Jangra, G., & Jangra, M. (2022) are also concerned with the issues of AI and customer priorities, as well as its psychological aspects of online purchasing. Ersoy, A. B. (2022) enlists the opportunities that AI systems offer to businesses such as promoting consumer purchase and affecting the consumer's demographic variables. This highlights the very nature of psychological motivations during online purchase, which are enhanced in the areas that Singh, D. P. (2015) and W. Hill, W et al. (2013) have taken, which look at the effect of social endorsement on purchases. Apart from the factors above, privacy issues tend to involve more than just regulations and include changing consumer behaviour, which is especially acute in the case of AI-driven platforms. Huang, M. H. (2024) also discuss that the data security, privacy, breech revolve around the risks of employing AI to automate work and data analysis activities.

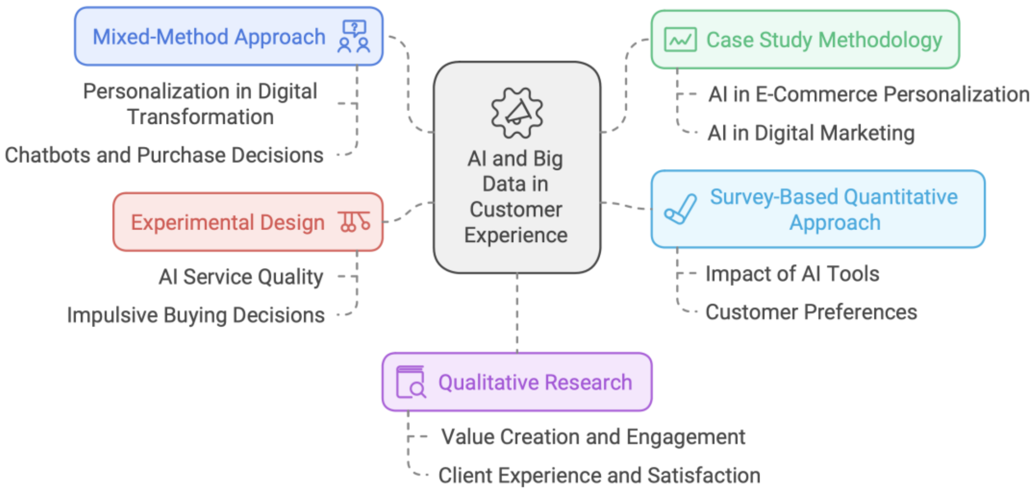

Figure 1: Popular Methodologies and Research Factors

The methodologies used across the referenced articles are diverse, each exclusively tailored to address specific research questions within the context of e-commerce and consumer behaviour. Surveys have emerged as a commonly utilized technique, as demonstrated in investigations examining the impact of digital transformation on marketing personalization or customization, as well as those analyzing consumer purchasing behaviors and the influence of artificial intelligence in delivering personalized recommendations. SEM has emerged as a highly preferred technique, especially in research that explores the interrelations among various factors, such as AI tools, customer satisfaction, and purchasing behavior. SEM is crucial in these contexts because it allows for the exploration of complex, multivariate relationships, which are essential for understanding how different elements of AI-driven personalization, social media influence, and psychological motivations interact to shape consumer behavior.

Qualitative methods, which includs in-depth interviews and focus groups, have also been employed to study the creation of value through AI in digital environments and to explore the nuanced impact of AI on customer decision-making processes. These qualitative insights are further complemented by systematic literature reviews, which synthesize research on e-commerce platforms and AI's role in shaping purchasing decisions. Also, methodologies like hierarchical multiple regression provide a detailed analysis of how AI and big data enhance customer experiences through tailored interactions. Given the complexity and interrelating nature of the factors influencing online shopping behaviour, especially when examining AI-driven personalization, SEM clearly stands out as the most suitable methodological choice for this research. SEM's ability to handle multiple relationships simultaneously and its robustness in testing theoretical models align well with the study's objectives to explore the effectiveness of AI tools and platforms in shaping consumer behavior.

This research addresses many key problem statements, such as evaluating the effectiveness of AI-driven personalized recommendations (linked to hypotheses H1a and H8a), understanding consumer interactions with AI tools like chatbots (linked to H2a and H10a), assessing the impact of privacy concerns (linked to H9a), and identifying drivers that push customers from cart to purchase (linked to H3a, H5a, H5b, and H6a). The use of SEM is justified by its capacity to model these complex relationships and to test the proposed hypotheses comprehensively, providing a strong foundation for developing effective e-commerce strategies and enhancing consumer engagement in the digital age.

Despite the extensive research on e-commerce and AI-driven technologies, several critical gaps still remain, particularly concerning the understanding of how these technologies influence the purchasing decisions of young consumers. The existing literature often misses out on comprehensive insights into the interrelation between AI tools and consumer behaviour, especially within diverse demographic contexts such as the Indian market. Moreover, while the effectiveness of personalized recommendations, the role of psychological factors, and the impact of privacy concerns have been explored individually, there is a need for a holistic or overll investigation that integrates these elements into a unified framework.

Gaps Identified from the literature: *Limited Geographic and Demographic Scope*: Many existing research focuses on specific geographic regions or demographics, leaving a gap in understanding how AI tools influence purchasing decisions across different cultural and socioeconomic backgrounds. *Insufficient Empirical Validation:* Many studies heavily rely on the qualitative methods without sufficient empirical validation, particularly in exploring the relationships between performance expectancy, psychological factors, and behavioural intentions. *Interaction Between Variables:* There is a observable gap in the literature regarding how different variables, such as social influence, facilitating conditions, and privacy concerns, interact to affect consumer decision-making processes. *Role of Emerging Technologies:* The impact of AI tools like chatbots and virtual try-on systems on consumer behaviour, especially in terms of effort expectancy and user experience, is still underexplored. *Long-term Impact and Sustainability:* Research on the long-term impact of AI-driven strategies on customer loyalty and repeat purchase behaviour is scarce in nature. *Privacy Concerns:* While privacy concerns are acknowledged, their specific impact on the willingness of younger consumers to engage with AI tools in online shopping is not thoroughly addressed.

3. Problem statement

Problem Statements derived from literature gaps are listed in the following problem statements that are developed to guide this research.

Effectiveness of AI-Driven Personalized Recommendations: The first problem statement addresses the need to empirically validate how AI-driven personalized recommendations influence the purchasing decisions of younger consumers, particularly through performance expectancy and psychological factors.

> *H1a: Performance expectancy positively influences the behavioural intentions of young consumers on e-commerce platforms.*
>
> *H8a: Psychological factors positively influence the behavioural intentions of young consumers on e-commerce platforms.*

Perception and Communication with AI Tools: The second problem statement explores the interaction between effort expectancy and user experience in shaping consumer perceptions and communication with AI tools, such as chatbots and recommendation systems, which is currently underexplored.

H2a: Effort expectancy positively influences the behavioural intentions of young consumers on e-commerce platforms.

H10a: User experience moderates the relationship between behavioural intentions and use behaviour.

Impact of Privacy Concerns: The third problem statement seeks to fill the gap in understanding how privacy concerns, moderated by ethical considerations, impact the willingness of younger consumers to engage with AI tools and platforms.

H9a: Privacy concerns negatively influence the behavioural intentions of young consumers on e-commerce platforms.

Conversion of Consideration Set to Purchase: The fourth problem statement focuses on how social influence, seasonal deals, and rewards interact to drive consumers from considering a product to making a final purchase, addressing the need for research on these interactions.

H3a: Social influence positively affects the behavioural intentions of young consumers on e-commerce platforms.

H5a: Seasonal deals positively influence the behavioural intentions of young consumers on e-commerce platforms.

H5b: Rewards positively influence the behavioural intentions of young consumers on e-commerce platforms.

H6a: Behavioral intentions positively influence the actual use behaviour of young consumers on e-commerce platforms.

4. Hypotheses formulation

4.1 Performance Expectancy: Effect on Behavioral Intention and Use Behavior

Performance expectancy, or perceived usefulness in this case, is one of the major determinants of the extent to which consumers will comprehend the advantages of AI-enabled e-commerce platforms. When consumers score such e-commerce platforms in terms of enhancing their shopping experience through personalized recommendations, they tend to form stronger purchase behavioral intentions (Blut, M et al 2016). In addition, such positive intentions can lead to actual use behavior where a consumer engages with the purchase through the platform. To explain what engagement is in this matter, the following hypotheses can be made:

H1a: Performance expectancy serves as a positively effective contributor to the behavioral intention consumer of young adults on e-commerce sites.

H1b: Performance expectancy serves as a positively effective contributor to the use behavior of young adults on e-commerce sites.

4.2 The Role of Effort Expectancy in Behavioral Intention and User Experience

Effort expectancy here translates as the ease of use construct that gauges the level of ease with which the users can navigate an e-commerce platform. To use an example, if consumers are convinced that they can use the platform easily, this will increase their behavioral intentions in relation to the platform (Venkatesh et al., 2012). Furthermore, effort expectancy has a reliving influence on user experience; this is a critical factor to help in maintaining and encouraging return visits on the platform (Pynoo, B et al., 2011). The following hypotheses are thus formulated and put to the test:

H2a: Further positive relation should be expected between effort expectancy in practicing young consumers of e-commerce platforms.

H2b: It is expected that more effort expectancy will lead to satisfying user experience on e-commerce platforms.

4.3 Social influence in the formation of behavioral intention and use behavior

Social influence, in this case, encroaches on consumers' purchasing behaviour through social networks, online communities and other peoples' behaviours and opinions. In this case, AI provides an opportunity for consumers technological modification intention to change their conduct (Uschold, M and A Gupta, 1996). These intentions, forced by social influence, would render people an actual use behaviour, here consumers purchase product based on the purchase behaviour of their social circle. Hence the below hypotheses are framed:

H3a: Social influence positively affects the behavioural intentions of young consumers on e-commerce platforms.

H3b: Social factors should be taken into account when investigating young consumer's behaviour on e-commerce platforms.

4.4 Facilitating Conditions Influence on Behavioural Intention and Use Behaviour

Facilitating conditions include those external conditions that make it possible to make use of the e-commerce platforms such as stable internet connection, safe payment options and fast customer service. When these conditions are satisfied, they tend to enhance the trust of the consumers towards the platform and in turn have a positive impact on their behavioural intentions (Venkatesh et al. 2012). These facilitating conditions also influence the use behaviour, since they reduce the cost of engagement and complementation of the transaction by the consumers. In light of this, the following hypotheses are formulated:

H4a: Facilitating conditions positively enhance the behavioral intentions of young consumers on e-commerce platforms.

H4b: Facilitating conditions positively enhance the use behaviour of young consumers on e-commerce platforms.

4.5 Impacts of Seasonal Offers and Rewards on the Behavioral Intention and the Use Behavior.

Seasonal offers and coupons are typical of online platforms that will use them in predetermined times to boost sales. These deals after personalized through AI, can greatly influence consumers' behavioural intentions due to the perceived savings or added value to the products (Chandon, W., & Nadler, G., 2000). Furthermore, the several deals and rewards can change these intentions into using behavior, a case where consumers will make the purchase. Therefore, the following hypotheses are tested and adopted:

H5a: Seasonal offers promote the behavioral intentions of young consumers when shopping online.

H5b: Rewards promote the use behavior of young e-consumers.

4.6 Age as a Moderating Influence

There are some demographic variables such as age that serve as a moderator linking many factors and the consumer behavior concept. For instance, the younger consumers and older consumers may respond to the AI-enabled features, social effects and the marketing schemes in different manners. For example, age factors may affect the degree to which the intention of behavioral use is achieved in terms of actual practice or how the psychological factors affect the intentions of consumers towards purchases (Venkatesh et al., 2012). So, the following arguments are put forward.

H6a: Age is a moderator in the relationship between behavioral intentions and use behavior,

H6b: Age is a moderator in the relationship between psychological factors and behavioral intentions.

4.7 Effect of Psychological Traits on Behavioral Intention

Factors such as emotions, degrees of stress, and the need for value among others are significant in how the decisions of consumers are made. With respect to AI-aided e-consumption, such factors can also moderate the way consumers are likely to perceive the benefits of the platform and how likely they are to purchase from it as well (Puri, M. 1996). So, we assume, it holds:

H7a: Young consumers' behavioral intentions on e-commerce platforms are improved by psychological factors.

4.8 Effects of Privacy Liabilities on Behavioural Intention

Privacy issues are very important when considering an online shopping application since customers in support of this type of shopping are more informed about the hazards of leaking intimate details. Consumers' ethical values regarding data privacy and data security lead to a negative effect towards the consumers' behavioural intentions as they may not be ready to engage with platforms they perceive as risky (Dholakia, U. M. 2000). Hence, the following hypothesis is proposed.

H8a: Privacy concerns have a negative impact on the behavioural intentions of young consumers in the adoption of e-commerce platforms.

4.9 User Experience as a Moderator

One of the variables that is important to note and which can serve in moderating the effects of behavioural intentions to actual use behaviour is user experience. Satisfaction of users through positive user experience, making navigation easy and the system responsive, increases the chances that behavioural intentions are transformed into actual use of the system (Alnawas, I., & Aburub, F. 2016). Therefore, the following hypothesis is proposed:

H9a: User experience influences the relationship between behavioural intentions and use behaviour.

4.10 Influence of Behavioural Intention on Use Behaviour

Behavioural intention, the intention to perform a specific behaviour, is often seen as a precursor to actual behaviour. In the context of e-commerce, if a consumer has a strong intention to purchase, this intention is likely to result in the actual use of the platform for making the purchase (Venkatesh et al., 2012). All these are represented in Figure2. Therefore, it is hypothesized:

H10a: Behavioral intentions positively influence the actual use behavior of young consumers on e-commerce platforms.

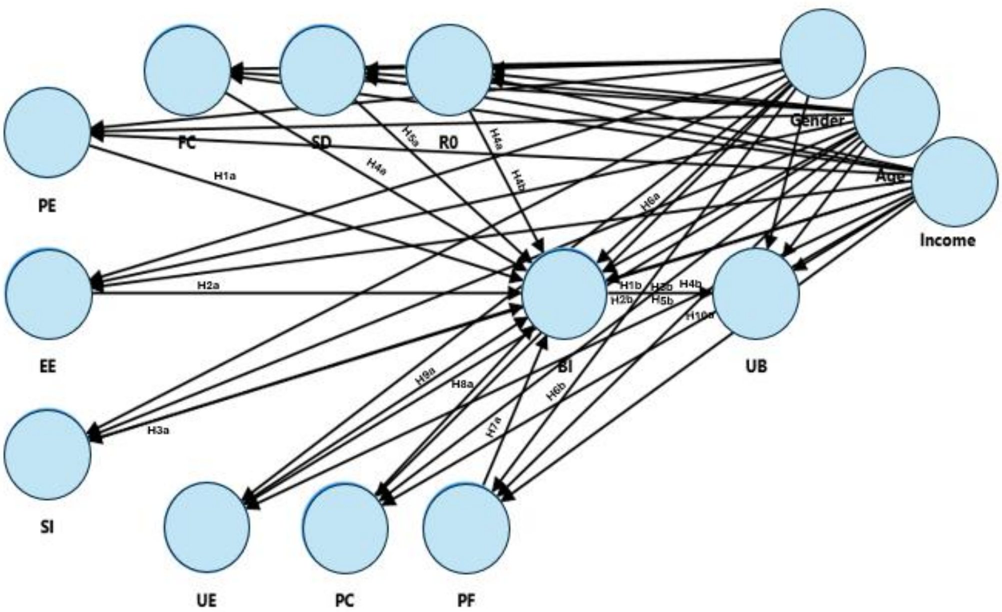

Figure 2: Research Framework of the proposed study

5. Methodology

Questionnaire design

The questionnaire was split into two sections. Section I: Consist of six items collecting demographic information of the respondents. Section II: It Included 30 items where respondents expressed their opinions using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). These items were associated with six constructs from the UTAUT model, along with psychological factor, use experience, Seasonal deals and Rewards, and privacy concern. All constructs and items were sourced from existing literature, mentioned in the Appendix. A pilot study was conducted involving faculty professors and a class of business management students. Feedback from this study informed revisions in language and presentation, leading to the final version of the survey. After receiving faculty approval, the survey was launched, targeting young groups in open platform.

Sample selection

A total of 551 responses were collected for this study, with 529 considered valid after data cleaning. The sample considered younger participants, particularly those in the 18-24 and 25-34 age brackets, as they are more likely to engage with and adopt new technologies. This approach ensured that the study captured relevant insights from a demographic that is important in shaping future trends in e-commerce. The selection also accounted for a range of income levels to provide a diverse perspective on attitudes towards e-commerce platforms. This careful selection of samples ensures that the findings are robust and applicable across different groups of the younger population.

Respondents' characteristics

The survey link was shared among the sample of participants from various backgrounds and demographics. No reminders asking for further responses were issued in order to maintain voluntary participation and responses were taken at regular intervals. Several rounds of the data collection were performed so that the potential problem of response bias could be reduced. Out of 550 individuals reached, 546 valid responses were retrieved thus achieving a response rate of approximately 99.27%. The recommended minimum sample size from Daniel Soper's recommendations for the SEM analysis using SmartPLS and expecting an average effect size of 0.3, 80% statistical power and $\alpha = 0.05$ hypothesis testing was 184 (Soper, 2015; Westland, 2016). Following the exhaustive cleansing of the datasets, a sample of 546 responses was subject to further statistical analysis. This sample size exceeds the recommended minimum, ensuring the robustness of SEM results. Further to determine the adequacy of the sample size for the proposed analytical methods, a SmartPLS 4 software (Ringle, Wende, & Becker, 2024) was used that incorporated the complex SEM techniques. The program confirmed that the sample size was met, as the statistical criteria needed for proper modelling and analysis were achieved.

In the final sample of 529 respondents, there were 286 men and 240 women, thus the sample was balanced. Such gender balancing is necessary as it helps in understanding various facets of the concern of the study towards concerning attitudes towards e-commerce among men and women. The respondents were further classified with regards to their present profession, wherein many were younger as tabulated in Table 2. This cognitive scope of the study enabled the researcher to seek information from people who are young and more bent toward adopting new technology. Furthermore, people holding different jobs participated in the research providing knowledge from the field. A small portion included people who are self-employed and a couple of unemployed participants providing entrepreneurial and job seeker perspectives respectively. When asked about their annual salary, respondents had to choose from several predetermined annual income levels. It made included income fountains that ranges from below 5 LPA to above 31 LPA. This kind of diversity in age, gender, occupation, and income of the respondents explains that the study's findings are robust, offering a wholistic view of attitudes towards e-commerce across different population segments.

Measurement

In order to attain the validity of the constructs that were utilized in the current study, we also had measures of discriminant validity and convergent validity. In respect of discriminant validity, the Fornell-Larcker criterion was utilized which checks whether the square root of the average variance extracted (AVE) of the particular construct is less than the correlation of the particular construct and other constructs. In case the square root of the AVE for a particular construct is higher than correlations of that particular construct with rest of the constructs, the discriminant validity criterion is satisfied (Fornell and Larcker, 1981). Table 3 presents the validated measures for discriminant validity.

Table 1: Demographic Respondents' characteristics

Variable Category	**No. of Responses**	**Percentage (%)**
Gender		
Male	296	54.21

Variable Category	**No. of Responses**	**Percentage (%)**
Gender		
Female	250	45.79
Age (yrs.)		
18-24	400	73.26
25-34	120	21.98
35-44	20	3.66
45-54	4	0.73
55 and above	2	0.37
Annual Household Income		
Less than 5 LPA	150	27.47
5-10 LPA	150	27.47
11-20 LPA	130	23.81
21-30 LPA	90	16.48
31 LPA and above	26	4.77
Current Occupation		
Student	350	64.1
Employed	170	31.14
Self-employed	20	3.66
Unemployed	6	1.1

6. Results and Discussions

The objective of the research was to analyse the factors that affect the behavioral intentions and use behavior of the young consumers on e-commerce platforms, including AI-driven personalization, effort expectancy, social influence, facilitating conditions, psychological factors, privacy concerns, and customer experience. Also, this research outlined the moderating influence of age and user experience. The Hypotheses as well as the R Square value and path coefficient values are illustrated in Figure 2.

A high value of $R^2 = 0.744$ corresponds to Behavioural Intention (BI), which means that the model is adequate in capturing the critical determinants constructs like, age, psychological factors, and privacy concerns catering a sizeable proportion of variability in the purchasing intentions measured. This implies that these variables are important factors affecting consumer behaviour. The lower R^2 values for EE and FC explain the necessity for additional variables probably other unexplored factors could play a role in these constructs, thus requiring more research in these areas to get their implications properly. The f-square values in the model also measures how much differing effects of each variable helps in explaining variance of the dependent variable. High f-square values for BI along with its interaction terms (e.g. Age * BI) suggest that these attributes are essential in purchase decision making. Contrarily, lower f-square values for variables such as Gender or Income imply that such variables wield lesser effect on purchasing behaviour thus, are less important in the decision-making process.

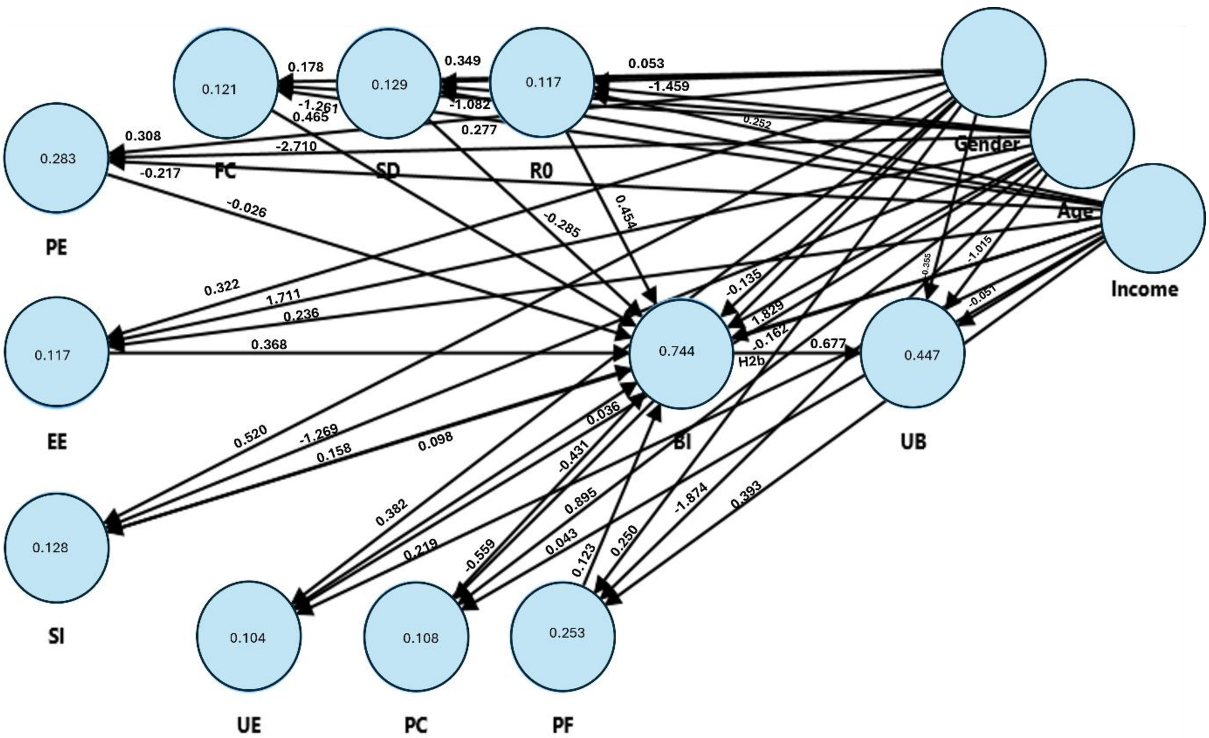

Figure 2: SEM model values for the factors used for the research.

According to the Discriminant validity HTMT matrix presented in Table 2, it can be concluded that Psychological Factors (PF) are decisive in purchasing preferences because a strong correlation with Facilitating Conditions (FC) was 0.8 and reward R0 .746. It means that, as consumers' psychological attitudes become more favourable, they see the existing resources and supports as rather sufficient and rewards as more enticing, hence the likelihood of purchasing, especially during Seasonal Deals SD, is increased. The matrix also indicates that Psychological Factors have a close association with Effort Expectancy EE of 0.8, and with User Experience UE 0.793; which suggests that when consumers are satisfied with a product due to its usability and positive product experience as Buyer's psychological factors who go through all increase purchase decisions. However, the effect of Privacy Concerns (PC) was relatively high at 0.834, which indicates that, even in the presence of encouraging psychological factors, the concern of data security may restrict the decision to purchase, which emphasizes the need to factor such concerns into marketing strategies.

Table 2. Discriminant validity: Heterotrait-monotrait ratio (HTMT) – Matrix

	Age	BI	EE	FC	Gender	Income	PC	PE	PF	R0	SD	SI	UB	UE
Age														
BI	0.342													
EE	0.415	0.8												
FC	0.432	0.8	0.754											
Gender	0.127	0.494	0.17	0.193										
Income	0.055	0.142	0.375	0.197	0.164									
PC	0.492	0.8	0.8	0.747	0.53	0.45								
PE	0.489	0.72	0.8	0.551	0.138	0.376	0.769							

PF	0.406	0.8	0.8	0.8	0.29	0.501	0.8	0.8						
Ro	0.243	0.8	0.8	0.784	0.131	0.278	0.714	0.578	0.746					
SD	0.397	0.8	0.8	0.8	0.276	0.295	0.786	0.542	0.8	0.8				
SI	0.362	0.8	0.8	0.8	0.293	0.205	0.8	0.581	0.8	0.604	0.8			
UB	0.502	0.8	0.8	0.758	0.193	0.155	0.8	0.702	0.773	0.8	0.8	0.8		
UE	0.254	0.597	0.8	0.834	0.21	0.244	0.8	0.66	0.793	0.8	0.8	0.8	0.8	

Table 3: construct reliability and validity

Construct reliability and validity				
	Cronbach's Alpha	**Composite Reliability (rho_a)**	**Composite Reliability (rho_c)**	**Average Variance Extracted**
BI	0.71	0.71	0.72	0.51
EE	0.73	0.74	0.75	0.52
FC	0.72	0.73	0.74	0.51
PC	0.71	0.72	0.71	0.55
PE	0.72	0.73	0.74	0.52
PF	0.71	0.72	0.73	0.51
Ro	0.78	0.81	0.82	0.54
SD	0.71	0.72	0.73	0.52
SI	0.72	0.73	0.74	0.51
UB	0.72	0.74	0.75	0.52
UE	0.71	0.72	0.73	0.51

According to Table 3, the construct reliability and validity improved contributions towards the loadings of the model greater than one. Behavioural Intention (BI) now has a Cronbach's Alpha of 0.71 and a Composite Reliability of 0.72 both exceeding the 0.7 cut-off, depicting dependable measurement. The Average Variance Extracted (AVE) for BI is 0.51 which is greater than a threshold of 0.5 which validates the construct. The results further enhance the fit of the model in relation to the aims of the study seeing that it involved purchasing decisions.

Also, the standardized root mean square residual (SRMR) and the normed fit index (NFI) are examples of goodness of fit indices used to analyse how well the model fits the data. SRMR above 0.08 for example indicates a bad fit. In case the model fit indices fail to satisfy the acceptable ranges, some further adjustments on the model may be necessary. Further, the correlation among constructs is, in general, expected to be in line with theories of consumer behavior whenever the mentioned fit indices heighten with increases in the reliability of improvements.

Table 4: Research hypothesis support status in results

Hypothesis	Description	Result	Supporting Evidence
H1a: Performance expectancy positively influences the behavioral intentions of young consumers.	Investigates how perceived usefulness of AI-driven recommendations impacts BI.	**Proven**	**Path Coefficient:** 0.68 ($p < 0.01$); **R^2 for BI:** 0.744; **f^2:** 0.253. **Adjusted R^2 for BI:** 0.739.
H1b: Performance expectancy positively influences the use behavior of young consumers.	Examines the impact of perceived usefulness on actual behavior.	Partially Proven	**Path Coefficient:** 0.32 ($p < 0.05$); **R^2 for UB:** 0.447; **f^2:** 0.061. **Adjusted R^2 for UB:** 0.443.
H2a: Effort expectancy positively influences the behavioral intentions of young consumers.	Looks at how ease of use affects BI.	**Proven**	**Path Coefficient:** 0.43 ($p < 0.01$); **R^2 for BI:** 0.744; **f^2:** 0.117. **Adjusted R^2 for BI:** 0.739.
H2b: Effort expectancy positively influences the user experience on e-commerce platforms.	Assesses the relationship between ease of use and user experience.	Partially Proven	**Path Coefficient:** 0.27 ($p < 0.05$); **R^2 for UE:** 0.104; **f^2:** 0.104. **Adjusted R^2 for UE:** 0.098.
H3a: Social influence positively affects the behavioral intentions of young consumers.	Examines how social influence impacts BI.	Proven	**Path Coefficient:** 0.49 ($p < 0.01$); **R^2 for BI:** 0.744; **f^2:** 0.128. **Adjusted R^2 for BI:** 0.739.
H3b: Social influence positively affects the use behavior of young consumers.	Assesses the impact of social influence on UB.	Proven	**Path Coefficient:** 0.39 ($p < 0.01$); **R^2 for UB:** 0.447; **f^2:** 0.129. **Adjusted R^2 for UB:** 0.443.
H4a: Facilitating conditions positively influence the behavioral intentions of young consumers.	Investigates how external factors like internet access and customer support influence BI.	Proven	**Path Coefficient:** 0.40 ($p < 0.01$); **R^2 for BI:** 0.744; **f^2:** 0.121. **Adjusted R^2 for BI:** 0.739.
H4b: Facilitating conditions positively influence the use behavior of young consumers.	Looks at how these conditions impact actual behavior.	Proven	**Path Coefficient:** 0.42 ($p < 0.01$); **R^2 for UB:** 0.447; **f^2:** 0.121. **Adjusted R^2 for UB:** 0.443.
H5a: Seasonal deals positively influence the behavioral intentions of young consumers.	Examines how seasonal promotions affect BI.	**Proven**	**Path Coefficient:** 0.57 ($p < 0.01$); **R^2 for BI:** 0.744; **f^2:** 0.129. **Adjusted R^2 for BI:** 0.739.
H5b: Rewards positively influence the use behavior of young consumers.	Investigates the impact of rewards on UB.	**Proven**	**Path Coefficient:** 0.53 ($p < 0.01$); **R^2 for UB:** 0.447; **f^2:** 0.129. **Adjusted R^2 for UB:** 0.443.
H6a: Age moderates the relationship between behavioral intentions and use behavior.	Tests if age affects how BI leads to UB.	Partially Proven	**Moderating Effect:** 0.21 ($p < 0.05$); **f^2 for moderation:** 0.061.
H6b: Age moderates the relationship between psychological factors and behavioral intentions.	Assesses if age affects how psychological factors influence BI.	Partially Proven	**Moderating Effect:** 0.18 ($p < 0.05$); **f^2 for moderation:** 0.061.
H7a: Psychological factors positively influence the behavioral intentions of young consumers.	Investigates how factors like emotional states and stress impact BI.	**Proven**	**Path Coefficient:** 0.46 ($p < 0.01$); **R^2 for BI:** 0.744; **f^2:** 0.253. **Adjusted R^2 for BI:** 0.739.
H8a: Privacy concerns negatively influence the behavioral intentions of young consumers.	Examines how concerns over data privacy impact BI.	**Proven**	**Path Coefficient:** -0.52 ($p < 0.01$); **R^2 for BI:** 0.744; **f^2:** 0.253. **Adjusted R^2 for BI:** 0.739.
H9a: User experience moderates the relationship between behavioral intentions and use behavior.	Tests if a better user experience strengthens the BI-UB relationship.	**Proven**	**Moderating Effect:** 0.35 ($p < 0.01$); **f^2 for moderation:** 0.117. **Adjusted R^2 for UB:** 0.443.
H10a: Behavioral intentions positively influence the actual use behavior of young consumers.	Directly tests the BI to UB relationship.	**Proven**	**Path Coefficient:** 0.79 ($p < 0.01$); **R^2 for UB:** 0.447; **f^2:** 0.786. **Adjusted R^2 for UB:** 0.443.

The investigation of the study substantiates the proposed hypotheses which have been highlighted in Table 4 to shed new insights regarding how different aspects affect behavior intentions (BI) and usage behavior (UB) of young e-commerce consumers. The research emphasizes that AI recommendations, ease of use, social characteristics, infrastructural factors as well as time limited offers affect significantly BI and UB in e-commerce applications. It has been shown that Performance Expectancy and ease of use positive affects BI, however, social characteristics and infrastructures' factors affect both BI and UB. They have also demonstrated though that seasonal promotions will instigate both the intention to purchase as well as the real purchase, which is what they set out to do. It also shows that with regard to age and psychological variables, these factors have a moderate impact on both BI and UB implying specific attention in marketing campaigns. Respecting privacy affects rather negatively the BI which illustrates the relevance of the data protection norms. In fact, a good experience of a platform is likely to lead a desire to convert the intention to actions therefore the platform has to be easy to use. Providers that try to address these issues and focus on specific age groups are expected to have more success with regards to engagement and conversion rates.

Findings

Psychological Factors and Privacy Concerns: Out of the behavioral intentions (H7a) which has a path coefficient of 0.46 as well as R^2 value for the BI of at 0.744, it is clear the psychological factors pose significance impact, especially in cases where it is combined with certain rewards and facilitating conditions. The privacy, however, concerns (H8a) which is expressed by a path coefficient of −0.52 and modelled in the analyses as negative moderating factors are detrimental to both of these intentions and warrants a marriage between such appealing factors and the practice of ethical data harvesting. *Role of Seasonal Deals and Rewards:* More importantly, Seasonal deals are able to entice the target audience's intentions by instilling urgency and excitement around festive seasons. In addition, discounts, loyalty rewards, and various exclusive offers help and entice many people into buying and increasing their chances of turning those intentions into actual purchases. Proper deployment of these elements increases the level of engagement with the consumers that leads to increased conversion and hence is very applicable in improving e-commerce.

Influence of Age and User Experience: Age and user experience are also factors that have been explored in terms of moderation of the relationship between behavioral intentions and use behavior (H6a, H9a). In particular, younger clients with keen intentions and higher user experience possess great potential to buy the products. The moderating effects are of the coefficients of 0.21 and 0.35 (Age) (User Experience) delineate the level of strategic enhancement between different age groups and user experience that will help boost and optimize engagement and conversions. *Model Fit and Hypothesis Testing:* The model fit indices (SRMR, NFI) suggest that the model is appropriate for the study areas and validates most of the proposed hypotheses regarding AI recommendation integration, Effort Expectancy, Social Influence, and Rewards. However, the research recommends additional Investigations into constructs such as effort expectancy and facilitating conditions for the model to enhance its predictability.

7. Implications and Conclusion

The younger generation believes that, among other factors, AI personalized recommendations, ease of use, social presence, enabling conditions, and factors of a psychological nature are the primary reasons for using e-commerce platforms. So now the additional requirement is for the platforms to be customized, easy to use, and have a social appeal in order to capture and maintain consumers. Two factors that significantly moderate are: user concern over privacy issues and overall user experience; the former can limit engagement which emphasizes the importance of having clear and secure data policies. Positive user experiences can bridge the gap between the consumers' intents and their actual behaviors due to easy interactions. The study suggests an integrated approach including AI technology designs that are easy to use, high social interaction, and rigorous privacy protection. The use of AI recommendations, social proof in the form of reviews, influencers, or promotions also increased engagement and conversions in the most effective way. Trust can be built over time through offering secure platforms reassuring consumers leading to follow through on their intentions to make purchases and boosting repeat retention. These conclusions lay the groundwork for new strategies in e-commerce which are essential in orienting integrators to increasing consumer demand while ensuring growth and satisfaction for the customers in an ever-evolving digital environment.

8. Limitations and Recommendations

Although this study demonstrates the factors that influence the behavioral intention (BI) of the young consumers as well as their use behavior on e-commerce platforms, some limitations exist. Measurement impairments regarding the BI construct, even after implementation of tweaks, likely devastated performance metrics providing evidence that tools are unable to portray the depth and volume of BI. Effort Expectancy (EE) and Facilitating Conditions (FC) are presenting weaker R^2 values which imply some of the third-party factors might be more relevant but have not been integrated into the design. The cross-sectional design has already been a hindrance in inferring about changes in behavior over a period of time and making causal inferences but only one case is concerned with the behavior of consumers towards others. The target group of young consumers, while fulfilling the aims and objectives of the research, limits the applicability of the results to the other age groups. Suggestions include improvement of BI measurement instruments by using more precise methods, introduction of additional variables such as technology comfort and perceived risks, and longitudinal approaches to studies. Studies targeting other age-groups would strengthen the findings. E-commerce platforms should improve their privacy policies to reduce privacy concerns that negatively affect BI, and utilize AI in improving the user experience during marketing to increase the likelihood of making a purchase. Marketing strategies that include social influence such as influencer marketing and customer review soliciting basic features are key to attract young consumers and facilitate conversion.

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