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Factors Influencing the Adoption of Online Pharmacies: A Post-Pandemic Study in Uttarakhand, India

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ABSTRACT

This study explores the key factors driving the acceptance of online pharmacies in Uttarakhand, India, leveraging the Technology Acceptance Model (TAM) and integrating constructs from the extended Unified Theory of Acceptance and Use of Technology (UTAUT 2) and Protection Motivation Theory (PMT).

Using a structured survey methodology, data were collected from 571 respondents across four districts of Uttarakhand: Dehradun, Haridwar, Nainital, and Almora. The research employed a partial least squares structural equation modeling (PLS-SEM) approach for data analysis, ensuring robust insights. The study identifies Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Price Value (PV), Social Influence (SI), Facilitating Conditions (FC), and Perceived Vulnerability (PUV) as critical determinants of behavioral intention toward e-pharmacy adoption. Consumer education emerged as a significant moderating factor, revealing its pivotal role in enhancing the likelihood of telemedicine and e-pharmacy adoption.

This research fills a critical gap in understanding the factors influencing e-pharmacy adoption in India, particularly in the post-pandemic era. The integration of TAM, UTAUT 2, and PMT provides a comprehensive theoretical foundation for future studies on Health Information Technology (HIT) adoption. By examining the intersection of technology, healthcare, and consumer behavior, this study contributes to the evolving discourse on digital transformation in the pharmaceutical industry, paving the way for more inclusive and efficient healthcare delivery systems.

Keywords: *Telemedicine, e-pharmacy, PLS-SEM, online pharmacy, Technology Acceptance Model (TAM), Pharmaceutical industry*

1. INTRODUCTION

Defining an online pharmacy, or e-pharmacy, is complex due to variations in regulations, healthcare infrastructure, operating platforms, drug classifications, and consumer behavior across different countries. However, in a broad sense, an e-pharmacy is a digital platform, such as a website or mobile application that facilitates the purchase and delivery of medicines directly to consumers (Karahoca et al., 2018). According to the Indian Pharmaceutical Association (IPA), e-pharmacies can operate under different business models, including the inventory-based model (where no third parties are involved), the marketplace-based model (where stockists and retailers connect with consumers through a shared online platform), the organized e-pharmacy model, and the generic e-commerce model (Shailendra Sinhasane, 2018).

In India, e-pharmacies cater to two major categories of drugs: prescription medications and over-the-counter (OTC) drugs. During the financial year 2021, the prescription drug segment dominated the market, accounting for 66.41% of the total share (Kumar & Patil, 2024). Many online pharmacy business models integrate teleconsultation services, enabling patients to seek expert medical advice and obtain e-prescriptions from licensed healthcare professionals. This feature allows individuals to access professional healthcare services remotely, eliminating the need for physical visits to a clinic. The significance of telemedicine became particularly evident during the COVID-19 pandemic. For instance, in the United States, prior to the pandemic, only 15% of physicians utilized telemedicine, and just 43% of healthcare centers offered such services. However, after the outbreak, the adoption of telehealth services surged, with 95% of healthcare centers incorporating telemedicine into their practice (Greiwe, 2022). Similarly, Indian online pharmacy ventures have expanded their services to include e-consultations, real-time diagnosis through information and communication technology (ICT), patient education, and home delivery of prescribed medicines (Unni et al., 2021).

Despite the growing presence of e-pharmacies in India, their legal status remains a subject of debate (Deepika et al., 2020). The existing regulatory framework, primarily governed by the Pharmacy Act of 1948 and the Drugs and Cosmetics Act of 1940, lacks explicit provisions regarding the online sale of medicines, as these laws were enacted before the advent of digital commerce. Recognizing the need to address this regulatory gap, the Drugs Controller General of India (DCGI) introduced the draft e-Pharmacy Rules in 2018, which set guidelines for the online sale of pharmaceuticals in India (Dcruz et al., 2022; Deepika et al., 2020; Srivastava & Raina, 2021). Additionally, all Indian e-pharmacies are required to register with the Central Drugs Standard Control Organization (CDSCO), the primary licensing and regulatory authority for pharmaceutical sales in the country. However, these regulations have faced significant opposition from retail pharmacy associations, such as the All-India Organization of Chemists and Druggists (AIOCD), due to concerns over potential business losses (Satheesh et al., 2019).

The expansion of e-pharmacies in India is being driven by increasing digital literacy, improved mobile internet access, and advancements in supply chain management (Srivastava & Raina, 2021). At present, over 50 e-pharmacy startups operate in the country, offering cost-effective medication solutions to consumers (Dcruz et al., 2022). Despite their growing popularity, e-pharmacies pose several risks, including self-medication, inadequate prescription verification, and the potential for long-term dependence on medication due to improper usage. Additionally, unauthorized online pharmacies raise concerns related to data privacy breaches, cyber fraud, and the misuse of personal and financial information (Thalkari et al., 2018). A recent study by Fittler et al. (2022) across European nations, including the Czech Republic, Hungary, Poland, and Slovakia, revealed that while 92.8% of the population was aware of the option to purchase medicines online, the majority still preferred traditional community pharmacies due to safety concerns.

This study aims to investigate the factors influencing the adoption of e-pharmacies in the post-pandemic era. While numerous studies have explored the acceptance of e-commerce platforms across different sectors using various theoretical models (Fedorko et al., 2018; Vărzaru et al., 2021; Yu et al., 2005), limited research has been conducted on the factors driving consumer adoption of e-pharmacies. As e-pharmacy falls under the domain of Health Information Technology (HIT), it differs significantly from conventional e-commerce platforms (Ahlan & Ahmad, 2014). This study seeks to bridge this research gap by examining the key determinants that influence consumer engagement with online pharmacies in the post-pandemic landscape.

Background of Models and Theories Used in the Study

To achieve the study's objective, an integrated model has been developed by combining the antecedents of the Technology Acceptance Model (TAM), the Extended Unified Theory of Acceptance and Use of Technology (UTAUT 2), and the Protection Motivation Theory (PMT).

Technology acceptance model (TAM):

The Theory of Reasoned Action (TRA) provides a fundamental framework for studying various complex human behaviors, including the acceptance of new technologies. Several models and theories based on TRA have been developed and validated over the years. In 1986, Fred Davis introduced the Technology Acceptance Model (TAM). Prior to this, Fishbein and Ajzen proposed the Theory of Planned Behavior (TPB) in 1970 (Ajzen, 1980).

In TAM, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are the key constructs influencing an individual's intention to adopt a new technology. PEOU refers to an individual's perception that using a new technology will be effortless (Holden & Karsh, 2010). Studies indicate that if a system is easy to use, it significantly impacts behavioral intention (BI) (Venkatesh & Davis, 2000). In this study, if customers perceive an e-pharmacy platform as user-friendly, they are more likely to adopt it. Various dimensions of PEOU include ease of use (Hu et al., 1999; Tung et al., 2008a; Yi et al., 2006), low mental effort (DJ et al., 2003), and ease in achieving desired outcomes (Liu & Ma, 2006; Tung et al., 2008b).

Perceived Usefulness (PU) is defined as an individual's perception that adopting a new technology will enhance performance. Researchers have consistently found PU to be a strong predictor of technology acceptance (Hu et al., 1999; Rouidi et al., 2022). The modified TAM has been widely applied in telemedicine acceptance studies globally (Dünnebeil et al., 2012; Maarop et al., 2011; Rho et al., 2014). This study incorporates PU and PEOU as key factors.

H1: Perceived Usefulness (PU) positively influences Behavioral Intention (BI) toward e-pharmacy adoption.

H2: Perceived Ease of Use (PEOU) positively influences Behavioral Intention (BI) toward e-pharmacy adoption.

Extended Unified Theory of Acceptance and Use of Technology (UTAUT 2):

The original UTAUT model was introduced by Venkatesh et al. (2003) to explain technology adoption within organizational settings. However, with the rapid evolution of consumer-oriented technologies, it became essential to explore the factors influencing individual adoption. To bridge this gap, Venkatesh et al. (2012) developed UTAUT 2, which retained the four core constructs of UTAUT (facilitating conditions, performance expectancy, social influence, and effort expectancy) while incorporating additional factors, including price value, habit, and hedonic motivation.

UTAUT 2 has been extensively utilized in Health Information Technology (HIT) studies, such as telemedicine (Adenuga et al., 2017; Kohnke et al., 2014; Shiferaw et al., 2021), teleconsultation (Vidal-Alaball et al., 2020), and mobile health (Mbelwa et al., 2019; Sezgin et al., 2018). This study examines three UTAUT 2 constructs—Price Value (PV), Social Influence (SI), and Facilitating Conditions (FC)—as determinants of behavioral intention regarding e-pharmacy adoption.

Price Value (PV) refers to the cognitive assessment of a technology's perceived benefits relative to its financial cost (Brown & Venkatesh, 2005). Research suggests that when perceived value exceeds monetary cost, technology adoption rates increase (Owusu Kwateng et al., 2019). Social Influence (SI) pertains to the impact of peers and close relations on an individual's decision to adopt new technology (Venkatesh et al., 2003). Facilitating Conditions (FC) represent the availability of support systems and resources that enable technology adoption. Greater availability of facilitating conditions enhances the likelihood of adoption (Alba & Hutchinson, 1987).

H3: Price Value (PV) positively influences Behavioral Intention (BI) toward e-pharmacy adoption.

H4: Social Influence (SI) positively influences Behavioral Intention (BI) toward e-pharmacy adoption.

H5: Facilitating Conditions (FC) positively influence Behavioral Intention (BI) toward e-pharmacy adoption.

Protection Motivation Theory (PMT):

2. The adoption of Health Information Technology (HIT) differs significantly from that of other technological products (Ahlan & Ahmad, 2014; Sun et al., 2013). Studies indicate that PMT exhibits stronger predictive power in health and risk-related behavior contexts compared to other technology acceptance models (Balla & Hagger, 2024; Gao et al., 2015). Research confirms that health threat evaluation—measured through perceived severity and perceived vulnerability—has a significant positive correlation with consumer intentions to adopt HIT.

H6: Perceived Vulnerability (PUV) positively influences Behavioral Intention (BI) toward e-pharmacy adoption.

H7: Behavioral Intention (BI) positively influences E-Pharmacy Adoption (EPA).

3.

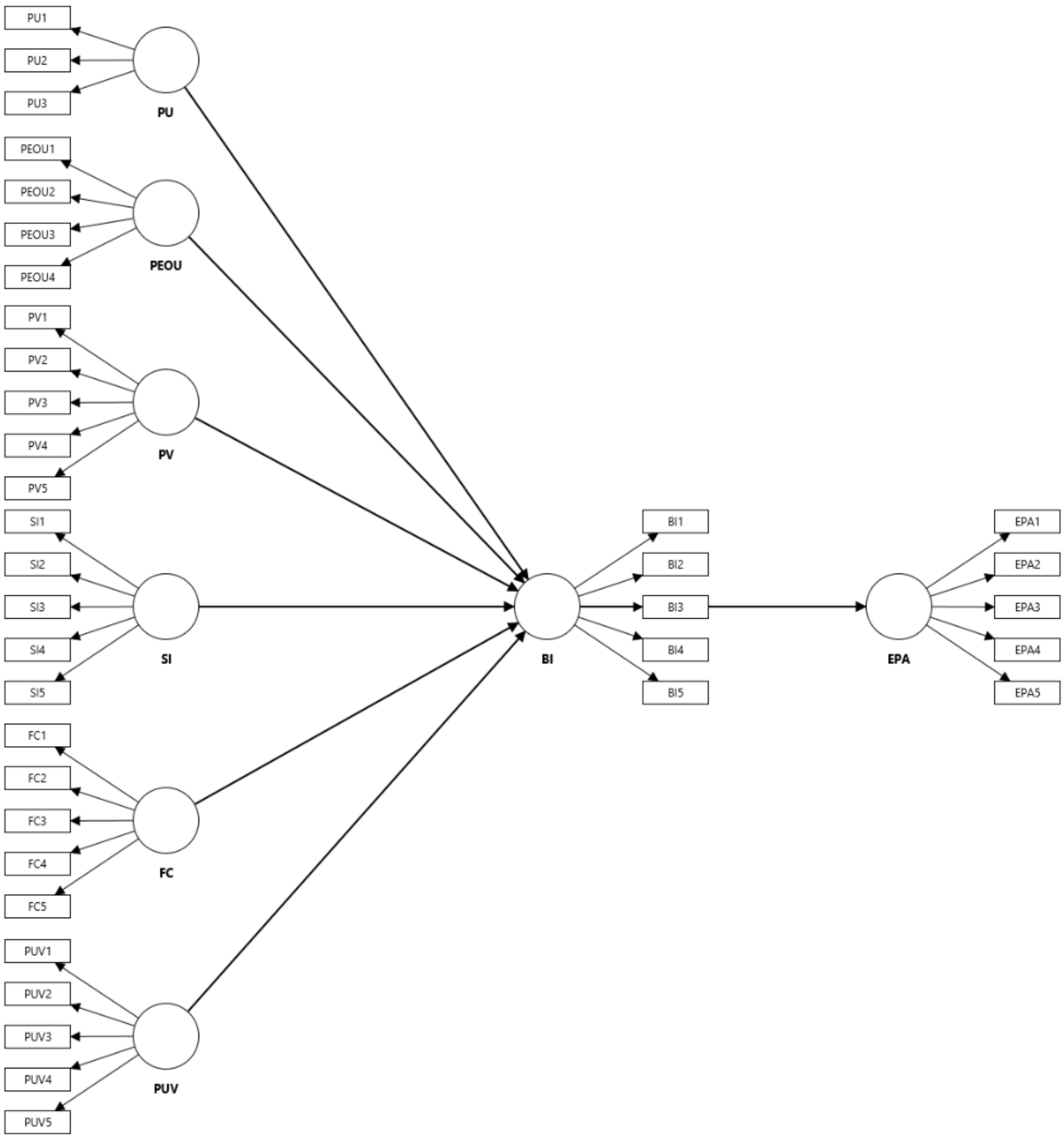

Figure 1: Proposed Model (Source: Author's own work)

(Note: PU= Perceived Usefulness, PEOU= Perceived ease of use, PV= Price Value, SI= Social Influence, FC= Facilitating Condition, PUV= Perceived Vulnerability, BI= behavioural intention, EPA=e-pharmacy adoption)

Research Methodology

This study employed an online structured survey research method to examine the proposed research model and hypotheses. The questionnaire was structured into two sections: the first gathered demographic details of the respondents, while the second consisted of a seven-point Likert scale to assess key variables relevant to the study's objectives.

Data collection took place between September 2024 and January 2025 using purposive sampling techniques. Responses were gathered from four districts of Uttarakhand—Dehradun, Haridwar, Nainital, and Almora—through online platforms such as WhatsApp and Facebook. The measurement items used in the study were adapted from existing literature and modified to align with the online pharmacy context (Table 1). Respondents were assured of data confidentiality, and informed consent was obtained before participation (Podsakoff et al., 2003).

To determine the appropriate sample size, G*Power software was utilized, with the statistical power set at 0.80 as recommended by Faul et al. (2009). The minimum required sample size was 103. A total of 600 responses were collected, of which 29 were incomplete, leaving 571 valid responses for the final analysis.

The study employed the variance-based Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which is particularly suited for predictive research. Data analysis was conducted using SmartPLS 4.0 software (Ringle et al., 2024). A two-stage analytical process was followed, as suggested by Hair et al. (2014, 2019). In the first stage, the reliability and validity of the measurement model were assessed. In the second stage, the structural relationships between variables were evaluated using a bootstrapping technique with 10,000 resamples (Hair et al., 2019).

Table 1: The measurement items

Sl.	Name of the construct	Source	Number of items
1	Perceived Usefulness (PU)	(Gupta et al., 2021; Xiao & Goulias, 2022)	3
2	Perceived ease of use (PEOU)	(Karahoca et al., 2018)	4
3	Price Value (PV)	(Ahalawat et al., 2024; Han & Han, 2023; Nayak et al., 2023)	5
4	Social Influence (SI)	(Gao et al., 2015; Venkatesh et al., 2012)	5
5	Facilitating Condition (FC)	(López et al., 2016; onaolapo & Oyewole, 2018)	5
6	Perceived Vulnerability (PUV)	(Itani & Hollebeek, 2021; Karahoca et al., 2018)	5
7	behavioural intention (BI)	(Gao et al., 2015; Venkatesh et al., 2012)	5
8	e-pharmacy adoption (EPA)	(Chung, 2016; Featherman & Pavlou, 2003)	5

Common method bias checks:

To assess whether common method bias (CMB) was present in the dataset, Harman's single-factor test was conducted (Harman, 1976). The analysis revealed that a single factor accounted for 36.84% of the total variance, which is well below the accepted threshold of 50% (Podsakoff et al., 2003). Therefore, CMB was not a concern in this study.

4. RESULTS AND DISCUSSIONS

Descriptive analysis

The demographic profile of the respondents is summarized in Table 2. In terms of age distribution, the largest proportion of respondents fell within the 31–40 age group (25.6%), followed by those aged 51 years and above (19.4%), 18–25 years (18.9%), 25–30 years (18.6%), and 41–50 years (17.5%).

Regarding gender, the sample consisted of 51.5% male and 48.5% female respondents. Educational qualifications varied, with a majority having at least a Class 10 education (22.4%), followed by Class 12 (20.5%), postgraduate degrees (19.8%), and PhDs (18.9%).

The study included respondents from four districts in Uttarakhand. Among them, the highest proportion was from Dehradun (28.5%), followed by Nainital (24.3%), Almora (23.8%), and Haridwar (23.3%).

Table 2: Respondents' demographic profile (N= 571)

Demographic item	Categories	Frequency	%
Age	18 – 25 years	108	18.9
	25–30 years	106	18.6
	31–40 years	146	25.6
	41–50 years	100	17.5
	More than 51 years	111	19.4
	Total	571	100.0

Gender	Male	294	51.5
	Female	277	48.5
	Total	571	100.0
Education Qualification	Class 10	128	22.4
	Class 12	117	20.5
	Graduate	105	18.4
	Postgraduate	113	19.8
	PhD	108	18.9
	Total	571	100.0
District	Dehradun	163	28.5
	Haridwar	133	23.3
	Nainital	139	24.3
	Almora	136	23.8
	Total	571	100.0

Source: Authors own work

Assessment of the measurement model

The measurement model was evaluated following the recommendations of Hair, Risher, et al. (2019). Internal consistency was assessed using Cronbach's Alpha, rho_A (Dijkstra-Henseler's rho), and composite reliability (CR), while convergent validity was examined through factor loadings, Average Variance Extracted (AVE), and CR (Table 3 and Figure 1).

The CR values ranged from 0.890 to 0.950, falling within the recommended threshold of 0.70 to 0.95. Additionally, all constructs had a Cronbach's Alpha value exceeding 0.70, confirming strong internal consistency and reliability (Hair et al., 2017). The factor loadings for all items were between 0.857 and 0.939, surpassing the minimum threshold of 0.708 (Hair, Risher, et al., 2019). The AVE values for all constructs exceeded 0.50, indicating satisfactory convergent validity (Henseler et al., 2015).

Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT) (Table 4). Since the square root of each construct's AVE was greater than its correlations with other constructs (highlighted in bold and italics), discriminant validity was confirmed (Hair, Risher, et al., 2019). Additionally, the HTMT values for all constructs remained below the 0.85 threshold, further supporting discriminant validity (Ab Hamid et al., 2017).

Table 3: Measurement model: item loading, construct reliability and convergent validity

Construct	**Items**	**Factor Loadings**	**Cronbach's alpha**	**rhoA**	**CR**	**AVE**
Behavioural Intention (BI)	BI1	0.857	0.934	0.934	0.950	0.791
	BI2	0.919				
	BI3	0.907				
	BI4	0.897				
	BI5	0.864				
E-Pharmacy	EPA1	0.818	0.906	0.919	0.930	0.728

Adoption (EPA)	EPA2	0.783				
	EPA3	0.888				
	EPA4	0.883				
	EPA5	0.890				
Facilitating Condition (FC)	FC1	0.887	0.926	0.929	0.944	0.772
	FC2	0.889				
	FC3	0.894				
	FC4	0.885				
	FC5	0.837				
Perceived ease of use (PEOU)	PEOU1	0.806	0.838	0.867	0.890	0.669
	PEOU2	0.860				
	PEOU3	0.757				
	PEOU4	0.845				
Perceived Usefulness (PU)	PU1	0.911	0.918	0.927	0.948	0.859
	PU2	0.929				
	PU3	0.939				
Perceived Vulnerability (PUV)	PUV1	0.863	0.925	0.928	0.943	0.769
	PUV2	0.885				
	PUV3	0.894				
	PUV4	0.877				
	PUV5	0.867				
Price Value (PV)	PV1	0.803	0.886	0.914	0.915	0.683
	PV2	0.833				
	PV3	0.827				
	PV4	0.818				
	PV5	0.850				
Social Influence (SI)	SI1	0.890	0.930	0.933	0.947	0.780
	SI2	0.884				
	SI3	0.883				
	SI4	0.867				
	SI5	0.894				

Source: Authors own work

(Note: PU= Perceived Usefulness, PEOU= Perceived ease of use, PV= Price Value, SI= Social Influence, FC= Facilitating Condition, PUV= Perceived Vulnerability, BI= behavioural intention, EPA=e-pharmacy adoption)

Table 4: Discriminant Validity

Fornell-Larcker criterion

	BI	EPA	FC	PEOU	PU	PUV	PV	SI
BI	***0.889***							
EPA	0.413	***0.853***						
FC	0.442	0.419	***0.879***					
PEOU	0.379	0.444	0.510	***0.818***				
PU	0.432	0.401	0.466	0.436	***0.927***			
PUV	0.425	0.592	0.468	0.408	0.374	***0.877***		
PV	0.367	0.426	0.356	0.374	0.332	0.421	***0.826***	
SI	0.451	0.518	0.454	0.486	0.415	0.602	0.382	0.883

(Note: PU= Perceived Usefulness, PEOU= Perceived ease of use, PV= Price Value, SI= Social Influence, FC= Facilitating Condition, PUV= Perceived Vulnerability, BI= behavioural intention, EPA=e-pharmacy adoption)

HTMT Ratio

	BI	EPA	FC	PEOU	PU	PUV	PV	SI
BI								
EPA	0.441							
FC	0.473	0.452						
PEOU	0.413	0.494	0.566					
PU	0.462	0.431	0.499	0.487				
PUV	0.454	0.644	0.506	0.455	0.403			
PV	0.388	0.467	0.376	0.416	0.345	0.447		
SI	0.480	0.556	0.487	0.538	0.447	0.649	0.402	

(Note: PU= Perceived Usefulness, PEOU= Perceived ease of use, PV= Price Value, SI= Social Influence, FC= Facilitating Condition, PUV= Perceived Vulnerability, BI= behavioural intention, EPA=e-pharmacy adoption)

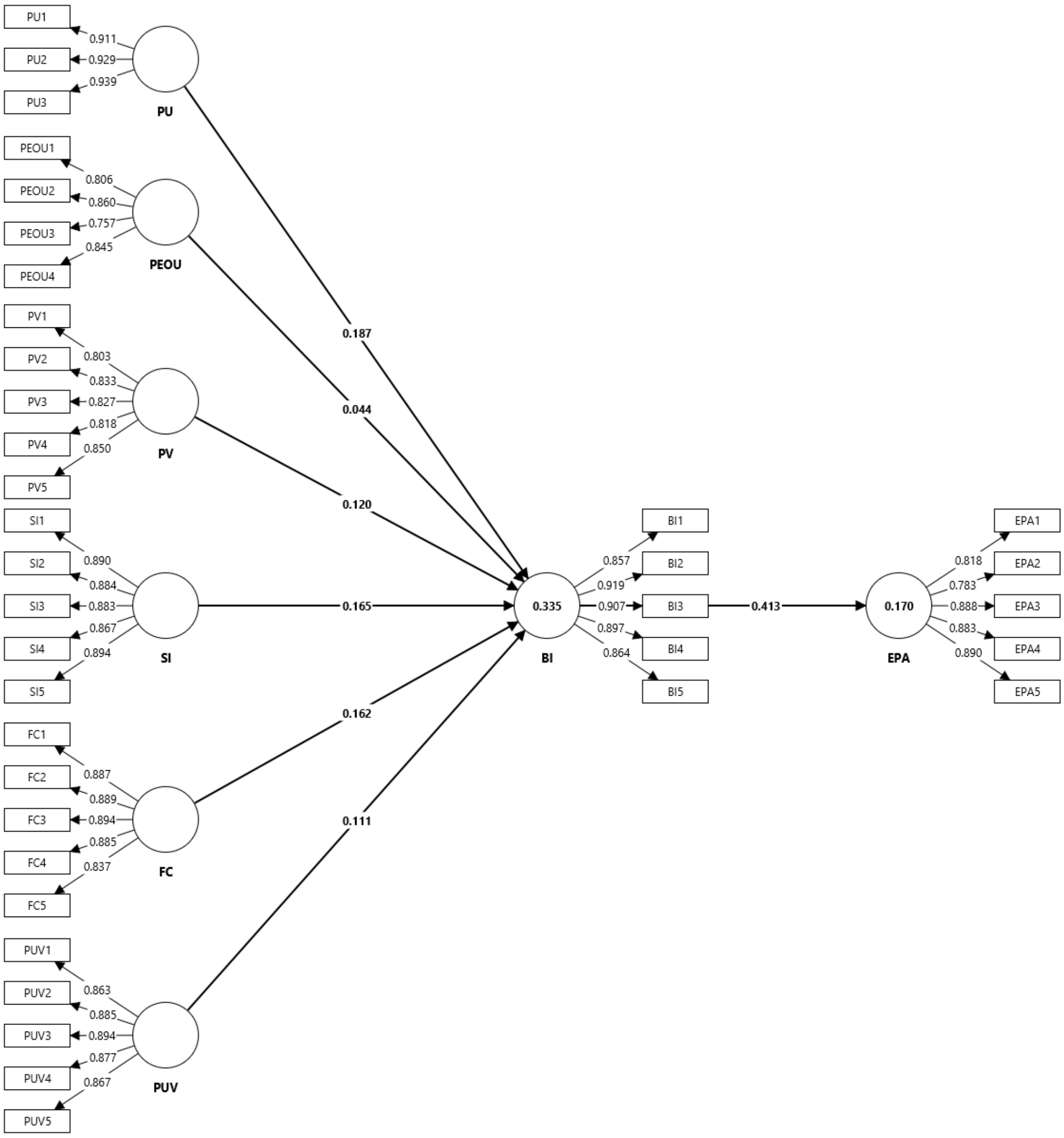

Figure 2: Measurement model (Partial least square (PLS)-algorithm)

Source: Authors own work

(Note: PU= Perceived Usefulness, PEOU= Perceived ease of use, PV= Price Value, SI= Social Influence, FC= Facilitating Condition, PUV= Perceived Vulnerability, BI= behavioural intention, EPA=e-pharmacy adoption)

Assessment of structural model

The structural model was evaluated following the guidelines of Hair Jr. et al. (2014), Hair et al. (2017), and Hair, Risher, et al. (2019) to assess the statistical significance of the path coefficients. Before proceeding with the structural model assessment, multicollinearity was examined using the Variance Inflation Factor (VIF). The inner VIF values were all below 5, indicating that multicollinearity was not a concern in this study (Hair, Ringle, et al., 2019).

To test the hypothesized path relationships, a bootstrapping procedure was conducted with 10,000 sub-samples at a 5% significance level ($p < 0.05$). The results are presented in Table 5. The findings revealed that Perceived Usefulness ($\beta = 0.187$, $t = 3.339$, $p < 0.05$), Price Value ($\beta = 0.120$, $t = 2.594$, $p < 0.05$), Social Influence ($\beta = 0.165$, $t = 3.323$, $p < 0.05$), Facilitating Conditions ($\beta = 0.162$, $t = 3.040$, $p < 0.05$), and Perceived Vulnerability ($\beta = 0.111$, $t = 9.496$, $p < 0.05$) had a significant positive effect on Behavioral Intention. Consequently, hypotheses H1, H3, H4, H5, and H6 were supported.

However, the relationship between Perceived Ease of Use ($\beta = 0.044$, $t = 0.865$, $p > 0.05$) and Behavioral Intention was found to be insignificant, leading to the rejection of hypothesis H2. Additionally, Behavioral Intention ($\beta = 0.413$, $t = 9.496$, $p < 0.05$) emerged as a strong predictor of e-pharmacy adoption.

Table 5: Path coefficients analysis

Hypothesis	Path	Std Beta	SE	t-value	p-value	Bias and Corrected bootstrap 95% CI		Decision	VIF
						BCI 95% LL	BCI 95% UL		
H_1	PU -> BI	0.187	0.187	3.339	0.001	0.075	0.294	Supported	1.443
H_2	PEOU -> BI	0.044	0.046	0.865	0.387	-0.059	0.141	Not supported	1.611
H_3	PV -> BI	0.120	0.122	2.594	0.010	0.026	0.209	Supported	1.335
H_4	SI -> BI	0.165	0.166	3.323	0.001	0.065	0.260	Supported	1.835
H_5	FC -> BI	0.162	0.162	3.040	0.002	0.057	0.264	Supported	1.648
H_6	PUV -> BI	0.111	0.111	1.959	0.050	0.000	0.224	Supported	1.780
H_7	BI -> EPA	0.413	0.414	9.496	0.000	0.321	0.492	Supported	1.000

Source: Authors own work

(Note: N =571, Bootstrap Sample Size= 10000, SE = Standard Error, LL = Lower limit, UL = Upper Limit, CI= Confidence Interval, VIF=Variance Inflation Factor, PU= Perceived Usefulness, PEOU= Perceived ease of use, PV= Price Value, SI= Social Influence, FC= Facilitating Condition, PUV= Perceived Vulnerability, BI= behavioural intention, EPA=e-pharmacy adoption)

In the next data analysis phase, the model's predictive power was examined using the Coefficient of determination (R^2) and effect size (f^2) value (Table 6). The R^2 value of Behavioural intention (BI) to e-pharmacy adoption (EPA) was 0.355 and the R^2 value of EPA was 0.170, which is acceptable because a low R^2 value even of 0.1 is also acceptable in social science (Moksony & Heged, 1990; Ozili, 2023). Additionally, the f^2 value of PEOU towards BI was found to be the highest (f^2= 0.036) followed by FC (f^2=0.024). Finally, the predictive relevance of the model was evaluated through Q^2 value. The path model Q^2 value was 0.314 for Behavioural intention (BI) towards e-pharmacy adoption (EPA) and 0.241 for the target variable EPA. Hence, the model has moderate predictive power (Hair, Risher, et al., 2019).

Table 6: Model explanatory power

Predictor(s)	Outcome(s)	R^2	f^2	Q^2
PU	BI	0.355	0.036	0.314
PEOU			0.002	
PV			0.016	
SI			0.022	
FC			0.024	
PUV			0.010	
BI	EPA	0.170	0.205	0.241

Source: Authors own work

5. DISCUSSIONS

Research has established that online pharmacies have gained widespread acceptance in India, particularly during the COVID-19 pandemic (Bhatt et al., 2024; Miller et al., 2021; Oriakhi et al., 2024). As a result, the market for online pharmacies in India is projected to reach $801.34 million by 2030 (TechSci Research, 2024). This study critically analyzes key factors influencing consumer behavior in purchasing medicines through online pharmacies.

The findings reveal several determinants of Behavioral Intention (BI) to adopt e-pharmacies, utilizing constructs from the Technology Acceptance Model (TAM), the extended Unified Theory of Acceptance and Use of Technology (UTAUT 2), and Protection Motivation Theory (PMT). The PLS-SEM analysis identified five primary antecedents—Perceived Usefulness (PU), Price Value (PV), Social Influence (SI), Facilitating Conditions (FC), and Perceived Vulnerability (PUV)—all of which positively influenced BI. Furthermore, BI was found to be a crucial mediator in predicting e-pharmacy adoption. This suggests that consumers are more likely to adopt e-pharmacies when they perceive the service as beneficial, cost-effective, socially endorsed, technologically supported, and capable of reducing health risks.

However, Perceived Ease of Use (PEOU) did not show a significant impact on BI, leading to the rejection of H2. This suggests that users prioritize functionality and outcomes over ease of use when considering e-pharmacy adoption. Given the widespread penetration of smartphones and digital platforms, many users may already be accustomed to online transactions, making PEOU a less critical factor. This finding aligns with previous research, further supporting the notion that utility and reliability outweigh ease of navigation in e-pharmacy adoption.

Managerial and Theoretical Implications:

The relationships identified in this study offer valuable insights for e-pharmacy marketers and policymakers seeking to enhance adoption rates. To further investigate which constructs require greater attention, an Importance-Performance Map Analysis (IPMA) was conducted (Ringle & Sarstedt, 2016).

The results, as shown in Table 7 and Figure 2, indicate that Behavioral Intention (BI) is the most influential factor in e-pharmacy adoption, with the highest importance score (0.413) and a performance score of 52.025. A one-unit increase in BI is likely to result in the most significant improvement in adoption performance. Perceived Usefulness (PU) follows as the second most impactful construct, with an importance score of 0.077 and a performance score of 51.701. Strengthening PU by highlighting the practical benefits of e-pharmacy services could lead to substantial improvements in adoption rates.

Social Influence (SI) and Facilitating Conditions (FC) also play critical roles, with importance scores of 0.068 and 0.067, respectively. SI reflects the impact of social networks on adoption, while FC emphasizes the necessity of adequate resources and technological infrastructure to facilitate usage. In contrast, Perceived Ease of Use (PEOU) has the lowest importance score (0.018) and a performance score of 47.470, indicating its minimal influence on adoption performance.

Based on these insights, stakeholders—including e-pharmacy developers, marketers, and policymakers—are encouraged to focus on enhancing Behavioral Intention by strengthening Perceived Usefulness, Price Value, and Perceived Vulnerability. Strategic efforts in these areas are likely to have the most substantial impact on overall adoption performance, ensuring a more widespread acceptance of e-pharmacy services in India.

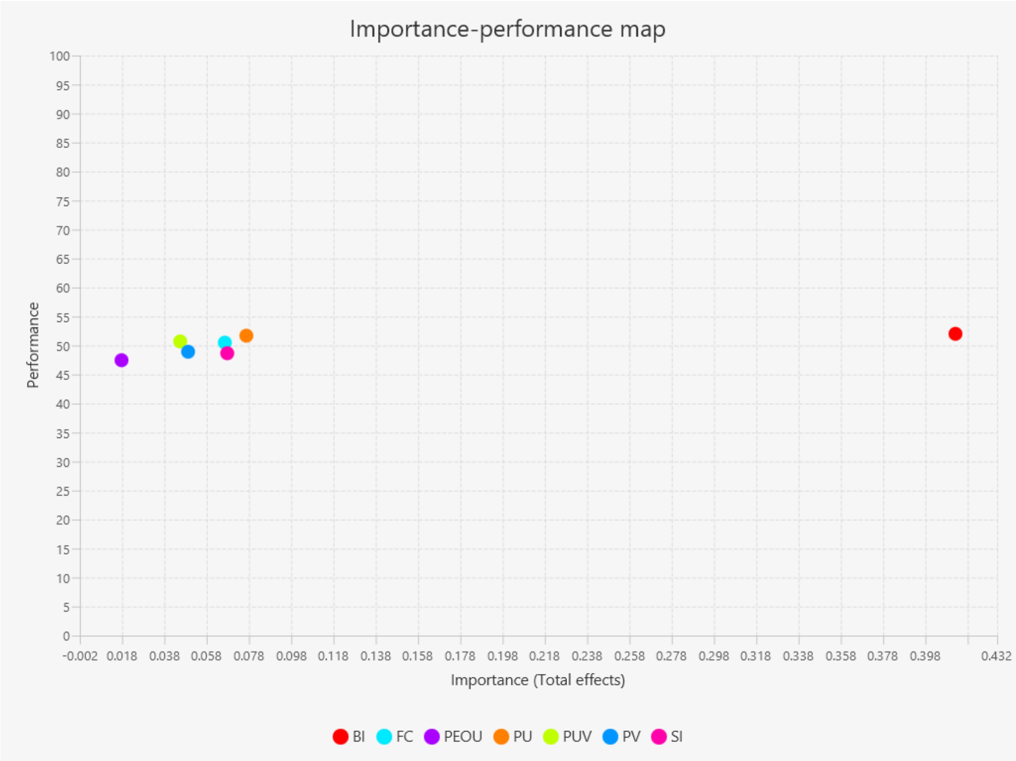

Figure 2: Importance Performance Matrix

Table 7: IPMA

Construct(s)	Importance	Performance
BI	0.413	52.025
FC	0.067	50.508
PEOU	0.018	47.470
PU	0.077	51.701
PUV	0.046	50.717
PV	0.050	48.935
SI	0.068	48.674

Limitations and Future Scope of the Study

This study makes a significant contribution to understanding the factors influencing the acceptance of online pharmacy platforms in Uttarakhand, India, using the Technology Acceptance Model (TAM) and other theoretical frameworks. However, several limitations should be acknowledged to ensure a balanced perspective and provide directions for future research.

First, the study is geographically restricted to four districts of Uttarakhand—Dehradun, Haridwar, Nainital, and Almora. While these districts represent a diverse demographic mix, the findings may not be fully generalizable to other regions of India with different socio-economic, cultural, and infrastructural characteristics. Future research could extend its scope to a broader geographical area, incorporating regional variations in consumer behavior and digital health adoption.

Second, the study employs a purposive sampling technique, which, while useful for targeting specific respondent groups, may introduce selection bias and limit the representativeness of the sample. Future studies could benefit from probabilistic sampling methods to enhance the robustness and generalizability of findings across different population segments.

Third, the research relies on self-reported data collected through an online survey. Self-reported responses are susceptible to biases such as social desirability and recall errors, potentially affecting data reliability. Future research could adopt a mixed-method approach by incorporating qualitative techniques such as in-depth interviews or focus group discussions to gain richer insights into consumer perceptions and behavioral motivations.

Additionally, the study's cross-sectional design limits its ability to capture evolving consumer attitudes and behavioral shifts over time. A longitudinal approach in future research could provide a deeper understanding of how e-pharmacy adoption trends change, particularly in the post-pandemic digital health landscape.

The measurement of constructs and hypotheses in this study is primarily based on established models such as TAM, UTAUT2, and PMT. While these frameworks offer a strong theoretical foundation, the rapid evolution of technology and consumer preferences necessitates continuous refinement. Future studies could explore new determinants, such as artificial intelligence-driven personalization, blockchain-enabled security measures, and advancements in privacy protection, to assess their impact on e-pharmacy adoption.

Furthermore, this study does not comprehensively address the regulatory and legal challenges surrounding e-pharmacy in India. Given the evolving nature of digital healthcare regulations, future research should examine the role of legal frameworks, policy interventions, and compliance mechanisms in shaping consumer trust and industry growth. Understanding these regulatory aspects could help policymakers and industry stakeholders create a more structured and supportive environment for e-pharmacy expansion.

Ethical concerns related to data privacy, cybersecurity threats, and potential misuse of e-pharmacy platforms remain underexplored. Future studies should investigate these issues in greater detail to ensure that digital healthcare solutions are implemented ethically and securely. Addressing these concerns will be crucial for fostering long-term consumer confidence and sustainable growth in the e-pharmacy sector.

Despite these limitations, this study provides a strong foundation for future research on e-pharmacy adoption in India. By addressing the outlined challenges, future studies can offer deeper insights into consumer behavior, regulatory considerations, and technological advancements, ultimately contributing to the development of a more effective and consumer-friendly digital healthcare ecosystem.

6. DECLARATIONS

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Conflict of Interest: The authors confirm that there are no conflicts of interest associated with this publication.

Informed Consent: Informed consent was obtained from all participants involved in the study, ensuring their voluntary participation and understanding of the research's purpose. All participants provided consent for their anonymized data to be included in the publication. The authors have not intentionally engaged in or participate in any form that may be hateful to another person.

Data Availability: Data supporting the analysis & findings of this study are available from the corresponding author and may be provided upon reasonable request.

Competing Interests: The authors declare that there are no competing interests relevant to this work.

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