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ACCEPTING SOCIAL MEDIA AND NETWORKS FOR SELECTING DESTINATIONS IN THE TOURISM INDUSTRY – A COMBINED STUDY OF IAM AND UTAUT2

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Abstract:

Purpose: *This study is useful in assessing how the use of information technology by consumers is a matter of concern to researchers and practitioners, and in discussing how social media and networking can become a resource of significance by providing a quick solution to the acquisition of a thorough information in the selection of destinations.*
Methods: *Largely grounded in surveys, the study entailed gathering data online of 400 participants who were found across the Indian states of Punjab, Haryana, and Himachal. Virtual snowball sampling and convenience sampling were used to get relevant data in this research. EFA involving SPSS was used to measure data structure and to test whether there was common method bias (Harman single-factor test). Also, Structural Equation Modelling (SEM) using AMOS was used to measure the relationships proposed in the Information Adoption Model (IAM). The reliability was assessed based on the Cronbach alpha, whereas the model fit was evaluated based on such indicators as GFI, AGFI, CFI, RMR, and RMSEA.*
Finding: *The results show that this information greatly aids in the destination selection process. The use of social networking platforms by consumers to retrieve information about hotels through friends, family and people they know can save consumers time, money and help reduce stress.*
Implications: *Additionally, the research identifies the elements of social networking platforms information that consumers take into consideration so that marketers can create more powerful social networking platforms marketing campaigns by meeting the expectation of the consumer.*
Originality: *Our research is further advanced by the use of the in-depth interviews to comprehensively interpret our research. The results demonstrate that all of the variables have a bigger influence on purchase intentions than the information found on social networking sites.*

Keywords:

Social media, Destinations, Travel and Tourism, IAM, UTAUT2.

1. Introduction

When it comes to the tourism industry, every destination has a personality, and this is what determines the decisions made by the travelers depending heavily on what previous tourists say. Individuals tend to be guided by the suggestions, reviews and ratings that have been noted in the media and in advertising to make their travel choices (Kaneknik, 2004). This feedback helps build the mental pictures that the travelers have of such places, which explains why the role of online social networks in the expansion of the industry of tourism is immense. Social networking platforms are used by different industries such as tourism to reach their target markets (Kavoura and Bitsani, 2013). Considering the information-overloaded and even biased character of tourism, educating clients and visitors is crucial and websites, as well as social networking platforms, provide the essential tools. Today, one of the most important information sources is social networking platforms, and most hospitality and tourism organizations use such platforms as Facebook, YouTube, Twitter, and specific apps like Fab and GoIbibo to communicate with their audiences (Xiang and Gretzel, 2010). In the wake of the existing trend, companies are embracing new technologies and strategies of marketing and reconsidering the principles of marketing. There are marketing technologies such as websites, Android and iOS applications (Gulbahar and Yildirim, 2015). The concept of social networking platforms is changing, transforming marketing with useful tactics that resemble the way of sharing user-generated content in iOS or Android applications. Customers are able to inform other customers about products through social networking platforms, as they share their experiences (Blackshaw, 2006). Therefore, the tourism industry employs social networking platforms to pass information and create a meaningful engagement with the consumers to develop long-term relationships. This platform brings about good results and spreads influential information, which must not be ignored by tourism organizations (Xiang and Gretzel, 2010). Social networking platforms is used by consumers to make queries on tourism products, accessing information before making a decision about traveling. It gives the travel industry a chance to interact with the customers and answer their inquiries thereby helping in the establishment of long term relationships. Moreover, social networking platforms illuminates most areas of travel, improving the industry knowledge of the needs and preferences of the users. In doing so the tourism industry will be able to assess the merits and the demerits of the products and services it provides (Dellarocus, 2003). Destinations offer visitors the holistic experience, where the buying of tourism products is characterized by increased illogical and emotional elements, a strong focus on word-of-mouth marketing, and a growing desire to stand out. As a result, tourists to these sites are likely to believe what family and friends tell them rather than others and tend to be sceptical of the conventional mass media advertising (Constantinides and Fountain, 2008). People are interacting more with social networking platforms (SM) due to the internet (Agarwal and Mewafarosh, 2021; Shamsi et al., 2022). In recent years, a few analysts have delved into the different meanings of SM (Wolf et al., 2018). Kaplan and Haenlein (2010) refer to SM as a collection of web-based communication platforms which enable community participation, interaction, sharing of content, and collaboration. The importance of social networking in everyday life is increasing. Over the past ten years, social networking services like Facebook, Instagram, and Twitter have grown significantly. Since the emergence of online media, its adoption has surged, with billions of users now engaged. Current data indicates that 59% of the global population uses SM, with Facebook being the leading platform (Chaffey, 2023). Users can express their thoughts and respond to posts easily, share information, and discover new trends to integrate into their daily routines (Chaffey, 2023). With numerous competing destinations available, potential travelers prefer not to spend excessive time gathering information and shopping around. But they are frequently prepared to pay more for superior quality products that are readily accessible. Additionally, social networking platforms have created substantial opportunities for building and maintaining connections with busy customers (Yadav & Arora, 2012). This strategy reflects the shift in brand storytelling, where marketers lead and empower consumers to influence the narrative's direction (Houghton, 2023). The swift increase in technology access has transformed how travelers plan, organize, and plan their travels. Concurrently, the emergence of social networking sites and Web 4.0's sophisticated features have enabled people to significantly influence travel destinations' reputations through user-generated material, such reviews and shared experiences. Despite these advancements, growing competition among destinations has created an urgent necessity for more innovative and immersive strategies to attract and engage potential tourists (Guttentag 2010; Hays et al. 2013; Loureiro et al. 2020; Lee 2022; Bretos et al. 2023; Hou 2024). With global travel on hold, the industry struggled to maintain destination visibility and engagement. As travelers sought virtual alternatives, it emphasized the crucial role of virtual experiences in sustaining tourism during crises and underscored the significance of technology in the industry's resilience and adaptability (Yang et al. 2021; Yang & Smith 2023).

1.1 Objective of the study

1.1.1 To investigate how Argument Quality and Source Credibility affect the Information Usefulness when choosing travel destinations.
1.1.2 To investigate how Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Trust, Performance Expectancy, and Effort Expectancy affect social networking platforms users' Behavioural Intention (BI) while choosing travel destinations.
1.1.3 To examine how Information Usefulness affects social networking platforms users' BIs while selecting travel destinations.
1.1.4 To investigate how users' BIs affect their Information Use when choosing travel destinations.

2. Literature Review

The way information is interpreted can vary based on the recipient's background and their attitude towards the source (Ismagilova et al., 2020). Consequently, the degree of influence on each recipient can differ. This variability has sparked interest in how consumers understand and process information (Elwalda et al., 2021). There appears to be a difference in online behavior between younger and older individuals (Confente & Vigolo, 2018). Research indicates that social networking platforms usage tends to decrease with age (Henderson, 2020; Hruska & Maresova, 2020). Younger people typically exhibit more suitable social networking platforms behaviors and adapt to social applications more readily than their older counterparts (Leist, 2013; Puriwat & Tripopsakul, 2021). Conversely, older consumers are usually not keen on adopting new internet-based applications (Obal and Kunz, 2013; Thanasrivanitchai et al., 2017) and lack social interaction as much as younger consumers do (Yuksel et al., 2016). According to earlier research, social networking platforms are less commonly utilized by older people compared to the younger population (Meiler-Rodríguez et al., 2012; Quinn, 2018; Waycott et al., 2016). Nonetheless, some research has indicated that mobile social networking platforms can facilitate connections for elderly individuals with their family and friends (Khoo & Yang, 2020) and help meet their social needs (Nam, 2021). According to Zhu (2021), even though the elderly are underrepresented on social networking platforms, they are also impacted by it just like younger individuals. Such difference in the attitudes towards the use of social networking platforms among age groups highlights the importance of additional research. The Information Adoption Model (IAM) developed by Sussman and Siegal (2003) is a combination of Technology Acceptance Model (TAM) (Davis, 1989) and Elaboration Likelihood Model (ELM) (Petty et al., 1981). IAM suggests that information obtained through both central and peripheral routes can impact consumers (Sussman & Siegal, 2003). The central route refers to the quality of the information itself, whereas the peripheral route is the part that is not connected with the main message (Cheung et al., 2008; Elwalda et al., 2021). Here, the peripheral route is the credibility of the source, and the central route is the quality of the argument (Cheung et al., 2008; Elwalda et al., 2021; Sussman and Siegal, 2003). Previous studies highlighted argument quality as a key aspect of information quality (Alhemimah, 2019; Elwalda et al., 2021). The studies of social networking platforms acceptance suggest that UTAUT2 model (Unified Theory of Acceptance and Use of

Technology 2) is more suitable to explain the behavior of users (Gharaibeh et al., 2020; Mishra et al., 2022; Shoheib and Abu-Shanab, 2022). This observation aligns with the study conducted by Tuten (2020), which shows that UTAUT2 is the most effective in clarifying differences in intentions to use social networking applications. Although rather new, the UTAUT model has proved its suitability, validity, and reliability in technology adoption studies in different settings (Yongbiao and Xinyu, 2025).

Recent studies that use the UTAUT2 model present valuable information on the features that inspire the use of social networking platforms in different industries. Du and Liang (2024) state that the influence of performance expectancy, effort expectancy, social influence, and hedonic motivation on continued use of social networking platforms is also substantial, which is why it is important to promote the environment and motivating benefits of continued usage. Alarcon-Urbistondo et al. (2024) focused on the supposed amusement as a key element of promoting the intention to adopt social networking platforms in medical training since it is an immersive experience as a key motivation to adopt it. Just like this, Puiu and Udristioiu (2024) focused on the area of education, whereby task-technology fit and usage pleasure played a substantial role in determining social networking platforms usage, and system quality played a crucial role in ensuring a successful implementation. To ensure maximization of engagement and adoption, these findings indicate the need to have a properly designed social networking platforms infrastructure in the tourism industry. Venkatesh et al. (2012) claim that the model is an improvement over previous theories to give more insight on technological acceptance as perceived by the consumer. They assert that UTAUT2 accounts for greater diversity in behavioral intentions compared to TAM. Venkatesh et al. (2012) proposed the UTAUT2 model with three more determinants of behavioral intention, i.e., hedonic motivation, price value, and habit, alongside trust, in addition to the existing four determinants in UTAUT, i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions. They have suggested that the actual usage behavior of technology is determined by its intended application. Additionally, performance expectancy, effort expectancy, social influence, and behavioral intention to use the technology facilitating conditions, hedonic motives, price value, and habit, all of which have an impact on the use behavior. However, these two constructs habit and enabling factors—have direct effects on use behavior in addition to their indirect effects through behavioral intention.

2.1 Argument Quality: Erkan and Evans (2016) defined quality of the argument as the strength and reliability of the source, which aids customers in acquiring knowledge and information. In a later study, they (2018) characterized argument quality as relating to both the timeliness of the information provided and its accuracy.

2.2 Source Credibility: According to Erkan and Evans (2016), source credibility refers to the trustworthiness of the information provider. A reliable source plays a serious role in distributing accurate info and knowledge to users. Shu and Scot (2014) highlighted that source credibility is a key factor in information adoption, distinguishing between weak and strong sources to understand the influence of social and online media on destinations.

2.3 Information Usefulness: Information usefulness pertains to how much a user believes that a specific technology or medium can positively impact and improve their job performance, as noted by Jacob et al. (2017). Hua et al. (2017) describe the usefulness of social networking platforms as its ability to capture the information users want, along with the confidence they have in its features, leading to the generation of valuable content for sharing and enhancing their decision-making processes.

2.4 Performance Expectancy: Lutfie and Marcelino (2020) said that The degree to which a person thinks that utilizing a particular technology would improve their job or task performance is known as performance expectation.

Effort Expectancy: Venkatesh et al (2012) said The degree to which a person thinks utilizing a specific technology would be effortless is known as effort expectation.

2.5 Social Influence: Venkatesh et al (2012) said that social influence as the effect of outside factors on a person's choice to use technology. It incorporates things like peer pressure, the views of influential people, and social standards.
Facilitating Conditions: Venkatesh et al (2003) said that the degree to which a person feels that there is a technological and organizational framework in place to enable the system's use is known as the enabling condition.. Zhou et al (2010) said that using social networking platforms requires a particular kind of skill, the availability of technical infrastructure, and access to resources.

2.6 Hedonic Motivation: Venkatesh et al (2012) define Hedonic Motivation as the pleasure or enjoyment individuals derive from using technology. It goes beyond functional utility to include the emotional satisfaction and pleasure derived from utilizing a technology.

2.7 Price Value: Venkatesh et al (2012) defined as a cost assessment in the organizational setting. Using technology in the customer's context could involve a higher financial cost to the customers. We will define it as the association between price value and service value, and cognitively compare the utilities (benefits) of using new systems with the financial cost that will be paid for using such systems.

2.8 Trust: According to Koksal (2016), establishing personal trust is essential since it tends to lessen consumers' anxieties and doubts, which lowers the complexity of decisions and increases adoption intentions.

2.9 Habit: Habit involves the automatic and routine use of technology in daily life. It reflects how individuals have integrated technology usage into their everyday routines (Venkatesh et al, 2012).
BI: Im et al (2011) said that an individual's and user's BI is impacted more by others' opinions and social norms followed by users or adopted by them.
Information Use: Cheung et al (2008) defined it as a process in which consumers intentionally use a piece of information. It is behaviour; customers consider this behaviour one of the main activities that they display on effective online platforms. Chen et al (2014) also indicate that information adoption has a positive impact on the intention to choose tourist destinations.

3. Hypotheses Development And Statistical Tools

3.1 Argument Quality (AQ) and Information Usefulness (IU)

Users can leave anonymous reviews on social networking platforms platforms, which complicates the evaluation of the Argument Quality of those reviews, as noted by Jain et al. (2021). The quality of information is gauged by its persuasiveness (Kumar et al., 2021). Sussman and Siegal (2003 found that quality of argument is a key predictor of Information Usefulness.
H-01: Argument Quality has a substantial impact on Information Usefulness.

3.2 Source Credibility (SC) and Information Usefulness (IU)

Sussman and Siegal (2003) assert that the trustworthiness of the source is an important determinant of information value. Erkan and Evans (2016) emphasize that a credible source heavily influences consumers' perceptions of information helpfulness. Ismagilova et al. (2020) state that information from a highly credible source is considered valuable and beneficial.
H-02: Source Credibility has a substantial impact on usefulness of information

3.3 Information Usefulness (IU) and BI (BI)

Vol. 12 Issue 1s (April, 2026)
ISSN: 2208-2190 Pages- 22-40

Research by Leong et al. (2022) and Khwaja et al. (2020) indicates that social networking platforms users are more likely to act on reviews they find useful. Several prior studies have also found a positive relationship between Information Usefulness and BI (Dachyar & Banjarnahor, 2017; Erkan & Evans, 2016; Nadlifatin et al., 2022; Tyagi et al., 2022).
H-03: Information Usefulness has a noteworthy impact on BI.

3.4 Performance Expectancy (PE) and BI (BI)

Performance expectations directly influence the intention to use social networking platforms (Wu, 2015). Current literature suggests that performance expectancy could be a crucial factor in the adoption of social networking platforms (Lim et al., 2019; Wong et al., 2015). Some studies indicate that younger individuals may be more impacted by performance expectancy regarding their behavioral intentions than older adults, with this influence diminishing with age (Cimperman et al., 2016; Venkatesh et al., 2012; Isa & Wong, 2015).
H-04: Performance Expectancy has a substantial impact on BI.

3.5 Social Influence (SI) and BI (BI)

Research indicates that Social Influence significantly affects Behavioral Intention regarding social networking platforms and technology adoption (Ramadani et al., 2014; Wu, 2015). Pentina et al. (2012) suggest that Social Influence drives the intention to engage with social networking applications. In addition, it has been demonstrated that Social Influence affects the intention to use social networking platforms significantly (Abdat, 2020; Salloum et al., 2018a; Ramadani et al., 2014) with younger users being predominant as the users of such platforms (Beneke et al., 2016; Rezaei, 2018).
H-05: Social Influence has a substantial impact on BI.

3.6 Hedonic Motivation (HM) and BI (BI)

There are varying views on the effects of Hedonic Motivation on Behavioral Intention; some studies reveal a positive influence (Çera et al., 2020; García Botero et al., 2018; Salloum et al., 2019), while others report a negative effect (Mehta et al., 2019; Venkatesh et al., 2003). Hedonic Motivation, related to fun and entertainment, can induce people to use social networking platforms (Sitar-Taut, 2021).
H-06: Hedonic Motivation has a substantial impact on BI.

3.7 Effort Expectancy (EE) and BI (BI)

Studies indicate that older adults are less impacted by Effort Expectancy in regards to their Behavioral Intention than younger adults (Chang et al., 2019). Technology is generally easy to navigate among the younger generation, and may not be easy among older people. Effort Expectancy is proved to have a positive impact on social networking platforms use (Wu, 2015) and on intentions to use social networking platforms commerce services (Gharaibeh et al., 2018).
H-07: Effort Expectancy has a substantial impact on BI.

3.8 Price Value (PV) and BI (BI)

Price value is an important determinant of the intention to adopt new technology (Palau-Saumell et al., 2019). However, Gharaibeh et al. (2020) argue that price value has a limited influence on the intention to use mobile commerce applications, and this also applies to social networking platforms. Age significantly moderates the relationship between price value and behavioral intention (Venkatesh et al., 2012).
H-08: Price Value has a substantial impact on BI.

3.9 Trust and BI

Trust is crucial for BI concerning social networking platforms adoption, as noted by Ramadani et al. (2014) and Wu (2015). Pentina et al. (2012) indicated that Trust drives the

intention to engage with social network applications. Research corroborates that Trust significantly influences intentions related to social networking platforms use (Abdat, 2020; Salloum et al., 2018a; Ramadani et al., 2014).
H-9: Trust has a substantial impact on BI.

3.10 Facilitating Conditions (FC) and Behaviour Intention (BI)

Facilitating Conditions are vital in information technology systems (Suksa-ngiam & Chaiyasoonthorn, 2015). Previous studies indicate they importantly influence user behavior when adopting new technologies (Venkatesh et al., 2012; Venkatesh et al., 2003). Puriwat and Tripopsakul (2021) also found that Facilitating Conditions affect Behavioral Intention regarding social networking platforms applications like Facebook.
H-10: Facilitating Conditions have a substantial impact on BI.

3.11 Habit and BI (BI)

Research suggests that Habit affects social networking platforms usage (Khang et al., 2014). Limayem et al. (2007) observed that regular use of information technology leads to the formation of automatic behaviors as a Habit. Habit is a substantial factor influencing technology use (Escobar-Rodríguez & Carvajal-Trujillo, 2014), and previous studies have shown that it positively affects social networking platforms applications (Hsiao et al., 2015; Hossain, 2019).
H-11: Habit has a substantial impact on BI.

3.12 BI (BI) and Information Use (IU)

Han et al. (2021) state that BI significantly mediates the connection between Information Use and Behavioral Intention. Consistent with findings from Venkatesh et al. (2003; 2012), BI to engage with social networking platforms strongly influences actual Information Use (Huang, 2018). This perspective was further supported by Salloum et al. (2018), who noted that the intention to use social networking applications greatly affects Information Use.
H-12: BI has a substantial impact on Information Use.

3.13 Data Analysis and Statistical Tools

To investigate the effects of different factors on BI and Information Use, the statistical software AMOS was used in conjunction with tools like, Table 1 displays frequency statistics, ANOVA, Independent Sample T-tests, Chi-Square tests, Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM).

Table 1. *Used Statistical Tools*

S. No.	Research Objective	Statistical Tool / Technique Used	Purpose / Explanation
1	Descriptive statistics	Frequency tables and graphical presentation	Frequency tables and graphical representations are used to simplify and visualize the most important features of the data obtained that allow understanding the distribution and central tendencies, which contributes to a better understanding of the demographic profile and financial behaviors of the participants.
2	Study to determine the reliability of the questionnaire	Cronbach's Alpha	The Cronbach's Alpha method assesses the interior consistency of the questionnaire, with a high value indicating that the items effectively measure the same underlying concept.
3	To examine the effect of	Structural Equation Modelling (SEM)	The use of SEM to test the influence constructs was based on the fact that it enables complex

Vol. 12 Issue 1s (April, 2026)
ISSN: 2208-2190 Pages- 22-40

	the Independent Variable on the Dependent Variable		relationships among several variables to be tested simultaneously.
4	To assess the linkage between Constructs	Structural Equation Modelling (SEM)	SEM was also utilized to evaluate the strength and direction of the connection between constructs, helping to clarify how changes in one variable relate to changes in another.
5	To measure the impact of the Independent Variable on the Dependent Variable.	Structural Equation Modelling (SEM)	SEM measures the impact of dependent variables on BI and Information use, adeptly handling several predictors for a thorough understanding of the relationships.
6	To examine the impact of BI on Information Use.	Structural Equation Modelling (SEM)	Furthermore, SEM was used to investigate the impact further, enabling the exploration of both direct and indirect effects, which illuminates the overall influence.
7	To investigate the moderating role of the mode of delivery and gender	Independent Sample t-test and Chi-square Test	Techniques such as the Independent Sample T-test and Chi-square test were applied to explore moderating effects, allowing for group comparisons and identifying variations in the association between independent and dependent variables across different groups (e.g., varying delivery methods or genders).

4. Research Methodology

Respondents from the Indian states of Punjab, Haryana, and Himachal Pradesh provided online data for this study, which is mostly survey-based. Four months were dedicated to collecting data. In this case, the pertinent data for the current investigation were gathered using the virtual snowball sampling and convenience sampling techniques. The usefulness of virtual snowball sampling in social networking platforms research led to the selection of this method. It is consistent with the research done by Brunet and Baltar (2012). Some of the respondents' data was collected manually. WhatsApp, Email, and Instagram were used to post the link to the online questionnaire that was created for the current study based on a Google survey. Additionally, the author's connections received an offer to complete the questionnaire via WhatsApp and Facebook Messenger. These are the two most often used platforms in India for sharing online surveys with contacts using mobile social networking platforms apps. As they distributed the survey tool, each respondent was asked to forward the link through the online survey to their contacts in their groups via WhatsApp and Facebook Messenger to establish a network of contacts. Data was gathered from 400 participants using an online questionnaire that required all fields to be completed before submission, resulting in no missing values. Each survey item was assessed using Cronbach's alpha, with results exceeding .70, in line with Nunnally's (1978) guidelines. Given that the data relied on self-reports, there is a possibility of Common Method Bias (CMB) (Podsakoff et al., 2003). Given that the mediator and dependent variables' data were gathered all at once, CMB could still influence the results. To evaluate this statistically, we performed Harman's single-factor

Vol. 12 Issue 1s (April, 2026)
ISSN: 2208-2190 Pages- 22-40

analysis (Shkoler & Tziner, 2017; Manohar et al., 2019). Utilizing SPSS 20.0 software, Exploratory Factor Analysis (EFA) discovered that the variance of the single factor was 26.348%, which is lower than the overall variance of 50%. This indicates that CMB was not a concern in the data, as per Table 2.

Table 2. *Short Summary of Factor Analysis.*

Aspect	Finding	Interpretation
Common Method Bias	1st factor explains 26.3% of % variance	Less than 50%, so common-method bias is not a main concern.
No. of Extracted Factors	12 factors (Eigenvalue > 1)	It means data is multidimensional.
Cumulative Variance	69.4%	In social science studies, the whole variance explained is acceptable.
Conclusion	Data validity is acceptable	The variables are unique and free from extreme bias.

If one factor accounts for more than half of the total variance, the study is likely to have common method bias. Since the total variance recovered by one component is 26.348%, which is below the suggested threshold of 50%, as indicated in Table 2, there is no issue with common method bias in these data. The information was gathered using a Google Form, and each response was designated as necessary. There was no longer any chance of missing data values.

4.1. Demographic profile of respondents

The defendants' characteristics are accessible in Table 3. Specifically, 49.8% of the 400 users were male, while the remaining 50.3% were female. Moreover, Table 3 shows the respondents' ages, educational backgrounds, and daily social networking platforms use time.
Summary of Key Details
The sample comprises 400 participants.
The majority are young adults, especially those in their 20s and 30s.
Gender representation is well-balanced.
The majority engage with social networking platforms at a moderate to heavy level.
Over 80% of participants hold at least a bachelor's degree, suggesting a high level of education.

Table 3. *Demographic Details of the Respondents.*

		Frequency	Percent
Age (In Years)	13-20 years	66	16.50%
	20 – 24 years	140	35.00%
	25-30 years	96	24.00%
	31-35 years	60	15.00%
	Above 35 years	38	9.50%
	Total	400	100.00%
Gender	Male	199	49.80%
	Female	201	50.30%
	Total	400	100.00%
Daily Usage of Social networking	Less than one hour	135	33.80%
	1 to 4 hours	181	45.30%

Vol. 12 Issue 1s (April, 2026)
ISSN: 2208-2190 Pages- 22-40

platforms			
	More than 4 hours	84	21.00%
	Total	400	100.00%
Educational Background	Secondary	71	17.80%
	Graduate/Undergraduate	204	51.00%
	Post Graduate and above	125	31.30%
	Total	400	100.00%

This age bracket can be used in research pertaining to technology, media usage, and online lifestyles, where the population is young, well-educated, and tech-savvy.

5. Results

Table 4 describes the descriptive statistics of 12 factors that were measured on the 400 respondents. These are Information Use, Behavioral Intention, Source Credibility and Effort Expectancy among others. The mean, standard deviation, skewness, kurtosis, and minimum and maximum ranges of each variable will be described.

Table 4. *Descriptive Analysis.*

	Mean	**Std. Deviation**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
Information Use	3.483	0.778	-1.099	0.987	1.000	5.000
BI	3.439	0.865	-0.566	-0.295	1.200	5.000
Information Usefulness	3.516	0.842	-0.917	0.591	1.000	5.000
Argument Quality	3.531	0.822	-0.836	0.138	1.000	5.000
Source Credibility	3.505	0.828	-0.704	0.193	1.143	5.000
Performance Expectancy	3.440	0.792	-0.747	0.580	1.000	5.000
Social Influence	3.433	0.867	-0.740	-0.159	1.000	5.000
Hedonic Motivation	3.328	0.844	-0.503	-0.280	1.000	5.000
Effort Expectancy	3.475	0.831	-0.521	0.015	1.000	5.000
Price Value	3.412	0.830	-0.630	-0.243	1.000	5.000
Trust	3.366	0.828	-0.739	0.076	1.000	5.000
Facilitating Condition	3.386	0.824	-0.673	0.136	1.000	5.000
Habit	3.498	0.857	-0.949	0.375	1.000	5.000

Descriptive statistics indicate that the respondents tended to give positive perceptions in all dimensions with their mean scores ranging in the range of about 3.33 to 3.53 in a 5-point scale. The best rated variables were Argument Quality (M = 3.531) and Information Usefulness (M = 3.516) which confirms that the participants found the quality and usefulness of the information especially high. On the other hand, the Hedonic Motivation had the

Vol. 12 Issue 1s (April, 2026)
ISSN: 2208-2190 Pages- 22-40

smallest mean score (M = 3.328), which displayed that the respondents were less impacted by the factors that were related to enjoyment. There was moderate variability in the responses, as the standard deviations were between approximately 0.79 and 0.87.

Table 5. *Correlation of the Variables*.

	CR	AVE	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
F1	0.865	0.62	0.787												
F2	0.921	0.625	0.34	0.791											
F3	0.787	0.553	0.158	0.205	0.743										
F4	0.908	0.623	0.354	0.558	0.192	0.789									
F5	0.872	0.534	0.284	0.343	0.129	0.331	0.731								
F6	0.875	0.587	0.136	0.283	0.191	0.237	0.222	0.766							
F7	0.806	0.589	0.216	0.234	0.258	0.305	0.217	0.12	0.767						
F8	0.901	0.648	0.11	0.194	0.34	0.107	0.091	0.081	0.198	0.805					
F9	0.851	0.592	0.262	0.353	0.268	0.32	0.314	0.163	0.34	0.315	0.77				
F10	0.839	0.638	0.293	0.322	0.242	0.311	0.31	0.173	0.386	0.289	0.595	0.799			
F11	0.9	0.6	0.618	0.652	0.308	0.695	0.445	0.302	0.334	0.251	0.418	0.408	0.775		
F12	0.894	0.632	0.41	0.408	0.554	0.412	0.297	0.271	0.426	0.505	0.591	0.622	0.605	0.795	
F13	0.782	0.546	0.193	0.285	0.358	0.281	0.182	0.213	0.273	0.216	0.431	0.405	0.394	0.656	0.739

Table 5 shows the correlation matrix that indicates moderate and predominantly positive relationships among the variables, i.e., F1 (Argument Quality), F2 (Source Credibility), F3 (Performance Expectancy), F4 (Habit), F5 (Facilitating Conditions), F6 (Trust), F7 (Hedonic Motivation), F8 (Price Value), F9 (Effort Expectancy), F10 (Social Influence), F11 (Information Usefulness), F12 (Behavioral Intention), and F13 (Information Use) implying substantial connections within the model. There are significantly good correlations between Intention Usefulness (IU) and Argument Quality (AQ) with the value of 0.618 and Source Credibility (SC) with the value of 0.652. Moreover, Behavioral Intention (BI) is correlated with Performance Expectancy (PE) with a 0.554 and with Price Value (PV) with a 0.505 indicating that the aforementioned factors have a substantial influence on behavioral intention. On the contrary, constructs like Trust, Hedonic Motivation (HM) and Social Influence (SI) show weaker correlations with other variables, which means that they do not affect the model as much. In general, the trends of the correlations demonstrate a coherent dataset with theoretically anticipated correlations in relation to technology adoption.

5.1. Main Results' Finding

5.1.1 Demographic Analysis:

The table below is an organized summary and a description of the results of gender-wise comparison presented in the table.

Table 6. *Independent Samples t-test.*

Gender		N	Mean	Std. Deviation	t-value	p-value
Information Use	Male	199	3.379	0.824	2.701	.007**
	Female	201	3.587	0.716		
BI	Male	199	3.229	0.906	4.970	.0001**
	Female	201	3.647	0.770		
Information Usefulness	Male	199	3.332	0.925	4.435	.0001**
	Female	201	3.697	0.707		
Argument Quality	Male	199	3.402	0.898	3.149	.002**
	Female	201	3.658	0.719		
Source Credibility	Male	199	3.458	0.854	1.139	.256
	Female	201	3.552	0.800		
Performance Expectancy	Male	199	3.312	0.832	3.267	.001**
	Female	201	3.567	0.730		
Social Influence	Male	199	3.295	0.925	3.208	.001**
	Female	201	3.570	0.783		
Hedonic Motivation	Male	199	3.296	0.808	.750	.453
	Female	201	3.360	0.880		
Effort Expectancy	Male	199	3.477	0.826	.057	.955
	Female	201	3.473	0.838		
Price Value	Male	199	3.342	0.855	1.700	.090
	Female	201	3.483	0.801		
Trust	Male	199	3.315	0.847	1.236	.217
	Female	201	3.417	0.809		
Facilitating Condition	Male	199	3.222	0.814	4.033	.0001**
	Female	201	3.549	0.804		
Habit	Male	199	3.384	0.903	2.685	.008**
	Female	201	3.612	0.795		

A comparative analysis of male (N = 199) and female (N = 201) respondents in relation to different constructs is performed in Table 6 using standard deviations, mean scores, t-values, and p-values. The results show if gender differences are statistically significant.

The Female respondents (Mean = 3.587) showed a much better Information Use than males (Mean = 3.379) with a statistically substantial difference (t = 2.701, p =.007). This implies that females are more active in terms of information. The difference between BI is also considerably high as the females (Mean = 3.647) have much greater intentions compared to males (Mean = 3.229). The fact that the t-value was very large (t = 4.970, p =.0001) implies higher chances of adoption or continued use by females. Generally, the findings show that the female respondents have reported high mean scores in most of the constructs. The difference between the genders was found to be statistically substantial in Information Use, BI, Information Usefulness, Quality of the argument, Social Influence, Performance Expectancy,

Vol. 12 Issue 1s (April, 2026)
ISSN: 2208-2190 Pages- 22-40

Facilitating Conditions, and Habit. There were however no substantial gender differences in Source Credibility, Hedonic Motivation, and Effort Expectancy, Price Value, and Trust.

5.1.2 SEM Analysis and Discussion

This encompasses a covariance SEM analysis done in AMOS 4.0. The model fit description shows that, the CMIN/DF ratio (Chi-Square/DF) is 2.152, which is within acceptable limits and indicates that the model fits well. The AGFI (Adjusted Goodness of Fit Index) is 0.731 and the GFI (Goodness of Fit Index) is 0.75 which is a moderate fit but a little less than the optimal value of 0.9. TPI (Tucker-Lewis Index), GPI and IFI (Incremental Fit Index) are above 0.9 which indicates that the proposed model is well aligned with the actual data. The RMSEA (Root Mean Square Error of Approximation) = 0.04, which means that the fit is excellent as a value below 0.05 is considered excellent. The indices of parsimony such as PNFI (Parsimony Normed Fit Index) and PCFI (Parsimony Comparative Fit Index) are both greater than 0.8, which indicates that the model has a reasonable level of complexity to the data. At level 0.01, the Hoelter index value is 201, which means that there is a good fit with a sample size of 201 and above. In general, the model fit summary justifies suitability of the hypothesized relationships.

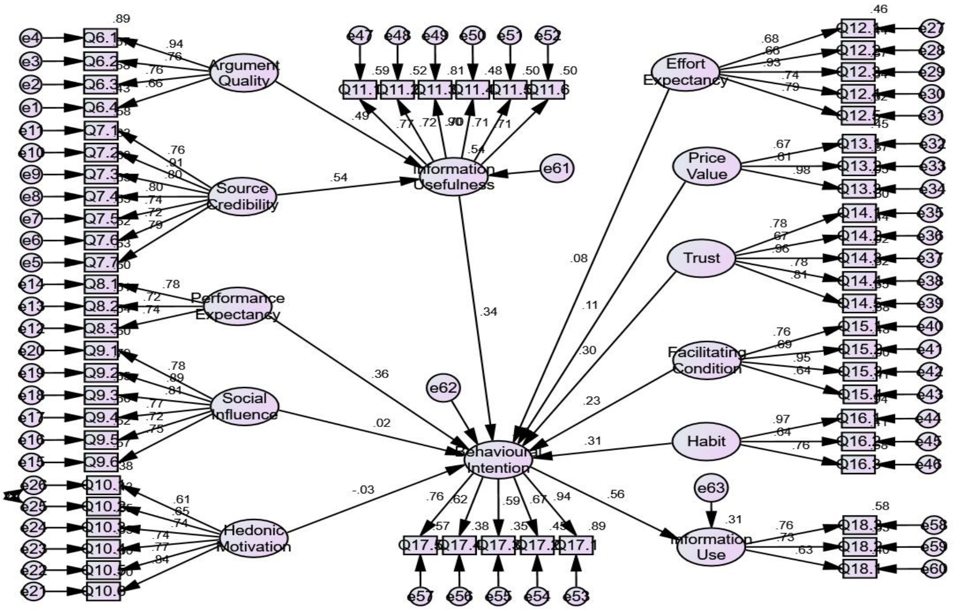

Figure 1. Path Analysis of Structural Model

Table 7. *Results of Hypotheses Testing*

			Unstd Estimate	**Std. Estimate**	**S.E.**	**C.R.**	**p-value**	**Accepted/ Rejected**
Information Usefulness	<---	Argument Quality	0.658	0.492	0.072	9.168	***	Accepted
Information Usefulness	<---	Source Credibility	0.56	0.541	0.052	10.744	***	Accepted
BI	<---	Performance Expectancy	0.422	0.358	0.058	7.306	***	Accepted

BI	<---	Social Influence	0.021	0.02	0.043	0.48	0.631	Rejected
BI	<---	Hedonic Motivation	-0.026	-0.029	0.038	-0.676	0.499	Rejected
BI	<---	Habit	0.262	0.312	0.036	7.215	***	Accepted
BI	<---	Facilitating Condition	0.247	0.231	0.046	5.395	***	Accepted
BI	<---	Trust	0.306	0.304	0.043	7.086	***	Accepted
BI	<---	Price Value	0.13	0.11	0.049	2.671	0.008	Accepted
BI	<---	Effort Expectancy	0.101	0.08	0.052	1.922	0.055	Rejected
BI	<---	Information Usefulness	0.34	0.335	0.045	7.609	***	Accepted
Information Use	<---	BI	0.493	0.56	0.052	9.414	***	Accepted

All the latent variables, including Argument Quality, Source Credibility, and Social Influence, are represented by different observable items (such as Q1, Q2, Q3, etc.). The strength of how well each item characterizes its corresponding latent variable is indicated by factor loadings, shown by the numbers next to the arrows (e.g., .70, .80, .90), with loadings over 0.70 deemed strong. Majority of these constructs have high loadings indicating correct measurement and reliability. Information Usefulness directly depends on the Quality of the Argument, with a path value of 0.49, which shows that the higher the Argument Quality, the higher the Information Usefulness. Also, the path coefficient between Source Credibility and Information Usefulness is positive (0.31) indicating that the higher the Source Credibility the higher the Information Usefulness. The Performance Expectancy, Habit, Facilitating Conditions, Trust, Price Value, and Information Usefulness have a substantial influence on behavioral intention with the path values of 0.40, 0.31, 0.23, 0.30 and 0.34 respectively. Table 7 presents the results of the structural equation model, with the unstandardized and standardized estimates, standard errors (S.E.), critical ratios (C.R.), p-values, and the conclusion on the hypotheses.

The results show that Argument Quality (0.492, $p < 0.001$) and Source Credibility (0.541, $p < 0.001$) not only affect Information Usefulness, but do so significantly and strongly. This means that information that is organized, logical and presented by credible sources is seen as more useful to users.

A number of factors have a substantial influence on BI. Performance Expectancy (= 0.358, $p < 0.001$) has a positive impact on BI which means that users are more likely to use the system when they think that it will enhance their performance. Also, Habit (= 0.312, p) is found to have a positive strong influence, which emphasizes the importance of habitual use in determining intention. In addition, Facilitating Conditions (= 0.231, $p < 0.001$) and Trust (= 0.304, $p < 0.001$) have an additional substantial impact on BI, which demonstrates that a positive environment and system trust are important.

Price Value (= 0.110, p = 0.008) is exhibiting a lesser, but statistically substantial and positive influence on BI, which indicates that users consider cost-benefit considerations when making their intentions to use.
In contrast, Social Influence ($\beta = 0.020$, $p = 0.631$) and Hedonic Motivation ($\beta = –0.029$, $p = 0.499$) do not have a substantial effect on BI, suggesting that peer pressure and enjoyment are not critical in this scenario. The influence of Effort Expectancy (= 0.080, p = 0.055) is also rejected, and it indicates that the ease of use is not significantly influencing intention at the traditional levels of significance.
In addition, BI is positively impacted by Information Usefulness (= 0.335, $p < 0.001$), which means that the perceived usefulness of information has a direct positive impact on intentions to use it. Finally, Behaviour Intention has a strong impact on Information Use (0.560, $p < 0.001$), thus supporting the notion that more powerful intentions result in actual use.
Overall, the findings highlight the importance of the usefulness, trust, habit, and facilitating conditions factors in influencing the BI and information use, and the social and hedonic conditions are not as critical in the model under consideration.

6. Conclusion

Using social networking platforms, customers can easily communicate, pool, and exchange useful information on their travel experiences, which goes a long way in helping them make a decision on their choice of destination. Using social networking platforms, people will be able to save time, finances, and unwarranted stress by getting information on where to stay based on the recommendation of trusted friends, family, and colleagues. The main purpose of this paper is to discuss the impact of social networking platforms on the destination choice, using Instagram as an example. According to our research results, factors like Quality of argument and Source Credibility in terms of Information usefulness and otherwise, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Trust, Habit on terms of Behavioral Intention and Information Use have a stronger impact on purchasing intentions than social networking platforms information alone. To discuss these findings in more depth, we used in-depth interviews. The social networking platforms sites most preferred by consumers are very useful to marketers wishing to conduct social networking platforms marketing. Moreover, the research also shows which aspects of social networking platforms information consumers take into account; by matching the expectations of the consumers, the marketers are able to create more effective social networking platforms marketing tools. This is supported by the IAM framework suggested by Sussman and Siegal (2003), and UTAUT, UTAUT2 suggested by Venkatesh et al. (2012) which complements the literature and sheds more light on the influences of factors on consumer propensity to use social networking platforms-supplied destination information.

7. Implications

The results of this research are set to provide meaningful information on consumer behavior to key industry players in the tourism industry such as destination marketers, travel agencies, government agencies, and policymakers. The insights would be useful to tourism organizations and marketers to promote their travels through the social networking sites. They should also understand how social networking sites are important in tourism industry since these sites are critical in interacting with customers. The use of online networking sites in a marketing strategy can give users the necessary and relevant information. As a result, one can consider different types of destination promotion, including creation of destination pages/accounts on the diverse social networking platforms, posting of regular information on key sites, enabling past and present tourists to communicate with each other, and creating online communities where latest experiences can be shared. Trust and risk are also considered as some of the important factors that affect consumer behavior in the study. The marketers and the local governments can take efforts to build trust and decrease the risk perception of the prospective consumers like gathering and distributing testimonials of a varied audience. Furthermore, the governments will be able to speak out publicly about their opposition to criminal activities on the social networking sites and assist tourists within their territories. Finally, governments and policy makers can think about embracing branding exercises of the destinations in the social networking platforms and inviting good businesses to their destinations.

8. Directions For Future Study And Limitations

It is important to recognise the limitations of the current investigation. The results of this study may apply to populations with comparable sociocultural backgrounds because it was conducted on people who lived in the Indian states of Punjab, Haryana, and Himachal Pradesh. Additionally, due to time constraints, the study's data was collected using an online Google poll that employed the virtual snowball technique, which may have issues with sample representativeness and sampling bias. Future research on the uptake of mobile social networking platforms is thought to be able to address these limitations. Although this study was carried out in the Indian states of Punjab, Haryana, and Himachal Pradesh, other populations from different geographical areas could be the subject of future research utilizing the concepts used in this investigation. It ignored the other social networking platforms in favor of concentrating on Instagram. Future research may shed light on other social networking platforms platforms that haven't been discussed here. This would allow academics to significantly add to the corpus of knowledge about the adoption and use of social networking platform applications.

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