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SYMMETRICAL ADOPTION PATTERN OF THE DIGITAL SHARING ECONOMY

Karan MEHTA
Symbiosis International (Deemed University), India
ORCID: 0000-0001-7178-3338

Chetan PANSE [1]
Symbiosis International (Deemed University), India
ORCID: 0000-0003-1633-3400

ABSTRACT

Listing spare homes as tourist accommodations on applications like Airbnb has boosted consumers' adoption of the digital sharing economy (DSE). This research paper aims to develop a variable selection methodology for factors influencing consumers' adoption intention of DSE applications like Airbnb and UBER. The symmetrical adoption pattern (SAP) will assist industry practitioners in designing an accurate investment pattern for the available resources. The research examines feedback from travellers regarding utilized services to develop SAP. The authors adopt NCapture as a data extraction tool and NVivo 12 as a data analysis tool to develop SAP as a variable selection methodology. Sentiment, thematic, and cluster analysis methods of qualitative analysis were employed to extract 19 distinct variables of SAP out of available data and adapt it into the six constructs of the unified theory of acceptance and use of technology (UTAUT2). By identifying the ideal variable for each construct with SAP, the performed study also aims to broaden the understanding of theories linked to the UTAUT2 model.

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INTRODUCTION

Airbnb has become a leading player in the digital sharing economy (DSE), running a vast electronic marketplace worldwide that allows individuals to rent out their homes to tourists looking for accommodation in various locations (Zervas et al., 2017). In northeast India, Airbnb's growth has been

[1] Address correspondence to Dr Chetan Panse (Assoc. Prof.), Symbiosis Institute of Business Management-Pune, Symbiosis International (Deemed University), India. E-mail: chetanpanse@sibmpune.edu.in

substantial, with the number of listings increasing to 1873 by August 2022 (Airbnb, 2022), generating several direct economic opportunities. Organizations like Airbnb have played a pivotal role in building trust between offeror and offeree in the sharing economy (Haridasan & Fernando, 2018). Also, safeguarding hosts from the impact of unforeseen circumstances has boosted their confidence in the platform and their intention to continue using Airbnb has also increased (Thi et al., 2023). In addition, accessibility to online reviews is facilitating a more nuanced understanding of the marketplace and provides unique perspectives on business operations and strategies (Cheng et al., 2022).

Ideally, consumers consider homeowners (offerors) with excellent reviews more reliable than those with lousy reviews. According to Ohlan (2018), about 93% of customers choose their stay depending on online reviews and ratings, though this can vary from destination to destination. By employing research methods like content analysis of online reviews, researchers can uncover emerging patterns and their effects on businesses in tourist destinations (Li et al., 2015). It indicates customer decision-making activity and the degree of experience with the goods and facilities on offer (Sainaghi, 2020). Thus, understanding emerging patterns in online reviews for tourism services innovation is a topic that piques the interest of both academics and practitioners (Sharma et al., 2022).

The rapid expansion of Airbnb has resulted in the emergence of numerous micro, small, and medium-sized enterprises (MSMEs) within the tourism industry, thereby contributing to its overall growth and development (Guttentag & Smith, 2017). MSMEs in the tourism sector often require substantial investments, particularly in areas such as technology adoption and customer retention and relationship management (Piramanayagam & Kumar, 2020). In such cases, accurate resource allocation becomes crucial for achieving business growth objectives (Zervas et al., 2017). According to Bommer et al. (2022), in any business model each variable plays a distinct role in explaining the variance in the criteria that is specifically associated with business objectives. Therefore, it is vital to identify the ideal variables for individual factors in the model prior to resource allocation, as this enables decision-makers to prioritize investments and allocate resources effectively. Ideal variable selection facilitates efficient resource allocation, particularly when resources are limited, and enables decision-makers to focus their efforts on areas that are likely to have the greatest impact on the desired outcome (Qaddoori & Breesam, 2023).

Very few studies have explored the models' variable selection argument, to assist industry practitioners in enhancing the consumers' technology adoption. Zhang et al.'s (2017) study focuses on the variable selection aspect by investigating the key factors that influence Airbnb listing prices. The analysis utilized two models, namely the general linear model (GLM) and the geographically weighted regression (GWR) model, to examine a dataset consisting of 794 samples of Airbnb listings in business units located in Metro Nashville, Tennessee. The findings reveal that the GWR model outperforms the GLM in terms of accuracy and variable selection and the significance of the factors varies across different regions (Zhang et al., 2017). Fu et al.'s (2017) study focuses on the variable selection aspect within unsupervised recommender systems, aiming to optimize the utility of recommendations by considering accommodation benefits, community risks, and personalization constraints. Polson and Sokolov's (2017) study focuses on the variable selection aspect within deep learning, which is a type of machine learning used for nonlinear high dimensional pattern matching and prediction. By adopting a Bayesian probabilistic perspective, their research aims to offer insights into more efficient algorithms for optimization and hyper-parameter tuning (Polson & Sokolov, 2017). According to Noncheva et al. (2009), variable selection plays a crucial role in data analysis. The choice of variables significantly impacts the measurement of efficiency for two reasons. First, the number of efficient Decision Making Units (DMUs) is directly related to the number of variables considered. Second, the selection of variables has a substantial effect on the efficiency measure, especially when the number of DMUs is small or when there is a large number of explanatory variables required for computing efficiency (Noncheva et al., 2009).

Past researches in the field of variable selection has made significant contributions in various contexts, including Airbnb listing prices, unsupervised recommender systems, and deep learning. However, there exists a research gap regarding the need for a comprehensive variable selection methodology that integrates qualitative approaches such as sentiment analysis, thematic analysis, and cluster analysis. The current literature primarily focuses on quantitative approaches and statistical models for variable selection, neglecting the valuable insights that can be derived from qualitative methods. By incorporating sentiment analysis, thematic analysis, and cluster analysis within Nvivo software, the proposed methodology aims to bridge this research gap to provide a more holistic understanding of consumer preferences, motivations, and perceptions.

The utilization of qualitative methods in variable selection offers a unique perspective by allowing researchers to delve into the qualitative aspects of data, uncovering deeper insights beyond numerical relationships (Berkwits & Inui, 1998). Through sentiment analysis, the methodology enables the exploration of emotional aspects and sentiment associated with different variables. Integration of sentiment analysis enables the identification and evaluation of subjective factors that influence consumers' technology adoption. It provides insights into the emotional and attitudinal aspects that may not be captured solely through quantitative measures (Septia Irawan et al., 2022). Thematic analysis facilitates the identification and categorization of underlying themes and patterns, providing a significant understanding of the variables under consideration (Sari & Nazli, 2021). Additionally, cluster analysis allows for the factorization of variables based on similarity, which can uncover meaningful relationships and aid in variable selection. The inclusion of cluster analysis aids in identifying distinct consumer segments with unique characteristics and preferences. This allows for a more targeted and personalized approach in variable selection, recognizing that different segments may have varying drivers and barriers in their adoption of technology (Karobliene & Pilinkiene, 2021).

By integrating qualitative approaches within a comprehensive methodology, researchers can gain a more nuanced understanding of the variables' significance, enabling them to make more informed decisions during the variable selection process (Gunter et al., 2011). The current research fills a critical research gap and contributes to the advancement of variable selection methodologies by incorporating qualitative methods and expanding the scope of UTAUT2 model analysis beyond traditional quantitative approaches.

It provides a more comprehensive and holistic understanding of the factors influencing consumers' technology adoption, enabling industry practitioners to make informed decisions in enhancing adoption rates. Overall, the variable selection methodology utilizing sentiment analysis, thematic analysis, and cluster analysis within Nvivo software extends the understanding of past studies by incorporating qualitative approaches and providing a more nuanced exploration of consumer preferences. It enhances the applicability and effectiveness of variable selection techniques, leading to improved decision-making processes for industry practitioners.

Past studies have concluded that the UTAUT2 factors affect tourists through various adoption theories and models (Venkatesh et al., 2012). However, variable selection for each construct for the adoption of sharing economy applications is a novel contribution to the literature. Although past studies have expanded our knowledge and understanding of Airbnb penetration and adoption beyond western and European countries, there is still a substantial knowledge gap regarding developing countries in Asia, Africa and Latin America (Quattrone et al., 2022). Most of the studies on Airbnb, which began in 2015 and have just recently been published, were undertaken by scientists in the US, Canada, and Europe (Andreu et al., 2020; Freire de Mello & de Paula, 2020). According to Guttentag et al. (2018), most research (40.2%) obtained evidence in the US and Canada, followed by 29.5% in Europe and just 1.8% in the Caribbean and Latin America. This creates a gap in the observational data upon which industry implications are based. Conducted research aims to develop a data extraction and qualitative analysis method that can be generalised for further studies in the expansion of DSE.

In light of the global rise of DSE and the transformations in the accommodation business, this research seeks to determine the ideal variables of factors affecting consumers' adoption of DSE applications like Airbnb in India. To accomplish this goal, the authors gather online consumer reviews from Airbnb's website related to tourists' stays in northeast India. They then utilize a blend of sentiment analysis, thematic analysis, and cluster analysis techniques to construct the symmetrical adoption pattern (SAP). The data extraction pattern was completed using NCapture web scraping instrument from January, 2022 to March, 2022. Authors extracted data from all the listed properties in Sikkim, Arunachal Pradesh, Mizoram, Manipur, Tripura, and Nagaland. The pattern and proportions found in this investigation can assist in fine-tuning the evaluation and innovation criteria for particular homestay properties.

Understanding the factors affecting user experience with DSE offerings aims at the following objectives; (1) Understanding the travellers' adoption pattern of DSE offerings at popular tourist destinations, (2) Relevance of UTAUT2 factors towards symmetrical adoption pattern, (3) Identifying ideal variables for each UTAUT2 constructs measuring consumers' adoption intention.

Thus, this research addresses the following problem: What is the variable selection methodology of users' adoption intention theories towards homestay accommodation services in northeast India?

SYMMETRICAL ADOPTION PATTERN DEVELOPMENT

This study will utilise the UTAUT2 framework, an expanded version of the unified theory of acceptance and use of technology (UTAUT). Theory of reasoned action (TRA), theory of planned behaviour (TPB), innovation diffusion theory (IDT), social cognitive theory (SCT), model of personal computer utilisation (MPCU), motivation model (MM), and technology acceptance model (TAM) are the concepts that form the UTAUT2 model (Venkatesh et al., 2012). It strongly predicts consumers' adoption patterns in various scenarios. Venkatesh et al. (2003) designed the UTAUT framework to test the adoption of novel technologies in the consumer market. The four primary factors that impact an adoption intention are 'performance expectancy,' 'effort expectancy,' 'social influence,' and 'facilitating conditions.' Adding two fundamental factors, 'price value' and 'habit,' to the UTAUT2 considerably improved the model's ability to describe customer adoption patterns (Venkatesh et al., 2012). Conducted research develops variable selection methodology for each UTAUT2 framework construct in analysing consumers' adoption intention. The finding that the UTAUT2 constructs in symmetrical adoption patterns reflect travellers' adoption of DSE offerings like homestays also aligns with previous research.

Performance Expectancy

Performance expectancy (PE) describes the degree to which a new system would benefit individuals when performing a specific type of work (Venkatesh et al., 2012), which is equivalent to the perceived usefulness of the TAM. Before the UTAUT, Koufaris (2002) applied the TAM to study online shopping behaviour and discovered that 'perceived usefulness' is the most significant factor in predicting consumer behaviour (Koufaris, 2002). Another research on online travel shopping in the UK by Satama (2014) also proved a positive correlation between 'perceived usefulness' and consumer adoption intention (Satama, 2014). In the background of Airbnb, performance expectancy represents the degree to which consumers believe they would benefit from the app when searching for accommodation. In addition to intentions, the UTAUT framework identified technical attributes like PE as a critical determinant of consumer sentiments in adopting the technological platform. Scholars in the tourism and hospitality industries have noted a considerable effect of PE on individuals' views about adopting DSE offerings (Tamilmani et al., 2022).

Table 1. *Performance expectancy*

Construct	Variable	Literature Support
Performance Expectancy	City	"The use of smartphone applications helps redefine and enhance the satisfaction of a tourist during his/her stay at their preferred tourism city" (Kamboj & Joshi, 2021).
	View	"Among five factors of fun and pleasure derived from using the apps, the highest item is room view." (Ismail et al., 2020).
	Location	"Accommodation location influences consumers' willingness to pay for contactless hospitality services." (Hao et al., 2022).
	Place	"Online textual reviews significantly influence consumers' intention to choose among varied Airbnb place options: entire place, private room and shared room." (Li & Fang, 2022).
	Experience	"Emotions in online reviews are the most predominant determinants of travellers' experience." (Ribeiro et al., 2022).
	Host	"Information provided by the trust mechanisms can deliver the charming points of hosts' services in Airbnb and change the perceived risk of Airbnb into the attractive point." (Yi et al., 2020).
	Time	"Generally, benefits are positive outcomes that result from an action and thus serve as motivators for human behaviour (e.g., quality, revenue), whereas costs are resources that are a must for an action (e.g., money, effort, time, knowledge) and therefore act as deterrents for human behaviour." (Adam et al., 2022).

As seen in Table 1, past literature justifies that selected performance expectancy variables influence consumers' adoption of new technology-based offerings. However, existing studies do not explain the methodology of choosing particular variable as a performance expectancy variable in adoption intention. Hence, the authors propose the following question for conducted research;

RQ1: *What is the variable selection methodology for identifying variables that contribute to the performance expectancy construct in UTAUT2 technology adoption model?*

Effort Expectancy

Perceived ease of use in Davis et al.'s (1989) TAM framework is considered a vital factor in a person's perception of utilising a technology-based platform (Davis et al., 1989). Parallel to this, the UTAUT discovered that attitude partly mediates the impact of effort expectancy on adoption intention (Venkatesh et al., 2003). The UTAUT2 refers to effort expectancy as an effort individual thinks it should take to use a new system (Venkatesh et al., 2012). Empirical research shows that the easier a system is for one to use, the more people will adopt it. In this study, 'effort expectancy' represents the degree of ease to avail of the service through an application, including simplicity and convenience. Amaro and Duarte (2013) indicated that the perception of the convenience of using a system could positively affect consumer adoption intention. Scholars in the tourism and hospitality industries reported conflicting findings about the connection between sentiment change and effort expectancy. For example, studies on hotel information desk technologies and vacation website groups discovered that ease of use is a critical factor in a person's opinion (Dwivedi et al., 2019).

On the contrary, simplicity of utilisation is a non-significant predictor of user sentiment in Wang and Jeong's (2018) study on the Airbnb website and Chang and Caneday's (2011) work on travellers' usage of digital platforms. Past literature findings are conflicting but still state that effort expectancy significantly influences consumers' adoption of new technology-based offerings.

Table 2. *Effort expectancy*

Construct	Variable	Literature Support
Effort Expectancy	Road	"There appears to be a positive relationship between destination location and transportation on the rural homestay choice. Therefore, the government, destination marketers, homestay operators and owners need to work together to ensure accessibility of the destination, proper signage to provide directions to homestays, good road connectivity and availability of alternative modes of transportation." (Dey et al., 2020)
	Walking	"Availability of authentic tourism experiences within walking distance from the homestay influences guests' adoption intention" (Sánchez-franco & Alonso-dos-santos, 2021)

As summarized in Table 2, past literature justifies that effort expectancy variables influence consumers' adoption of new technology-based offerings. However, there is a need to explain the variable selection methodology of each effort expectancy variables in the adoption intention. Hence, the authors propose the following question for the current study;

RQ2: *What is the variable selection methodology for identifying variables that contribute to the effort expectancy construct in UTAUT2 technology adoption model?*

Facilitating Condition

In their deconstructed TPB, Taylor and Todd (1995) highlighted the similarities between enabling circumstances and interpreted behavioural control. According to Venkatesh et al. (2003), enabling circumstances complement the impact of PE and EE as determinants of behavioural intention in the UTAUT framework. According to Venkatesh et al. (2003), to use a given technology, customers must feel they have access to the necessary organisational resources and technical architecture, known as the 'facilitating conditions (FC)' (Venkatesh et al., 2003). Past research on customer technology uptake confirms the strong impact of facilitating circumstances on behavioural intention (Rana et al., 2016). However, the hotel and tourist industries revealed mixed results for this association. Kam et al. (2018) discovered that perceived behavioural control (a root construct for facilitating conditions) is a substantial indicator of buyer intentions among users of Airbnb in the US. In contrast, Mao and Lyu (2017) discovered that the impact was non-significant for users aiming to make a repeat purchasing decision (Kam et al., 2018; Mao & Lu, 2017). Past literature findings are conflicting but still state that FC significantly influences consumers' adoption of new technology-based offerings. Conducted research seeks to conclude the uncertainties related to facilitating conditions with SAP adoption.

Table 3. *Facilitating conditions*

Construct	Variable	Literature Support
Facilitating Conditions	Water	"If hot water is unavailable, hosts can ensure that guests are aware of this issue before accepting the booking." (Lee et al., 2023)
	Kitchen	"Kitchen is identified as an attribute consumers emphasise in describing their Airbnb experience." (Xi et al., 2022)
	Room	"The study revealed that Airbnb users valued the local interactions and experiences in neighbourhoods while hotel guests appreciated room amenities and food and beverage more." (Cheng & Jin, 2019)

Based on the relevant literature, Table 3 shows that facilitating condition variables influence consumers' adoption of new technology-based offerings. However, earlier studies do not suggest the accurate methodology for selection of ideal facilitating condition variables in adoption intention. Hence, the following question is proposed;

RQ3: *What is the variable selection methodology for identifying variables that contribute to the facilitating condition construct in UTAUT2 technology adoption model?*

Social Influence

Social influence (SI) means the degree to which an individual feels influenced by surrounding groups (Venkatesh et al., 2012). Many empirical data have validated SI as a core variable in TAM. One example from the literature is Teng et al.'s (2015) study on travellers' plans to stay in sustainable accommodations in Taiwan and their future purchases on the

DSE website Airbnb. However, for different groups of consumers, 'voluntary' and 'non-voluntary' social influence can sometimes bring contradictory results. Venkatesh et al. (2003) discovered that for voluntary consumers, social influence does not have a significant effect on their adoption intention; however, for the non-voluntary group, social influence becomes a significant predictor. The UTAUT model confirmed the importance of the link between social influence and intention; also, adding this connection increased the conceptual model's capacity for explanation (Mao & Lyu, 2017). Under the background of Airbnb, which is still relatively new to Indian consumers, the number of customers is not significant, but the kind of SI. Past literature on tourism and hospitality research states that social influence significantly influences consumers' adoption intention.

Table 4. *Social influence*

Construct	Variable	Literature Support
Social Influence	Local	"The findings suggest that participants were prevented from choosing Airbnb accommodations over hotels, when they presented a lack of local experience, in consumers' review about their past experiences at the destination." (Del Chiappa et al., 2021)
	Taxi	"Consumers hesitate to choose Airbnb accommodations over hotels when they identify a lack of public transport (taxi stand) near the homestay in consumers' review about their past experiences at the destination." (Teh et al., 2020)

As seen in Table 4, past literature justifies that social influence variables influence consumers' adoption of new technology-based offerings but does not clearly explain the variable selection methodology for each social influence variables in adoption intention. Hence, the authors propose the following question;

RQ4: *What is the variable selection methodology for identifying variables that contribute to the social influence construct in UTAUT2 technology adoption model?*

Price Value

The UTAUT2 framework notably includes a pricing component since the exchange between a technology's expense and usefulness is a crucial indicator of consumers' behavioural intentions (Venkatesh et al., 2012). So et al. (2018) showed that value for money was notably significant when examining price characteristics influencing expedition tourists' experience and buying intentions. Additionally, past research on online learning has also discovered cost as a significant factor influencing consumers' behavioural intention to adopt new technologies (Tarhini et al., 2017).

Under the background of Airbnb, price value is a vital stimulus factor because homestay prices are often lower than those of hotel rooms of the same grade, which can be a significant competitive advantage for homestay accommodation platforms (Hasan & Stannard, 2023). According to numerous past studies, deciding whether to use Airbnb significantly depends on factors like price (Guttentag, 2016; Mao & Lu, 2017; Satama, 2014; Tussyadiah & Pesonen, 2018; Yang & Ahn, 2016).

Table 5. *Price value*

Construct	Variable	Literature Support
Price Value	Area	"Geographical areas have a moderating effect on the relationship between various hotel-related influencing factors and Airbnb." (Yi et al., 2021)
	Comfortable	"Marketers and Airbnb hosts should focus on creating comfortable, clean and attractive lodging attributes, along with providing personalised services and access to unique local cultures." (Li et al., 2019)
	Stay	"It has been commonly recognised that the growing popularity of peer-to-peer accommodation can be partly attributed to its providing guests with unique stay experiences." (Zhang & Fu, 2020)

Past literature justifies that price value variables influence consumers' adoption of new technology-based offerings (Table 5). However, a variable selection methodology for each price value variables in adoption intention should be developed. Hence, the authors propose the following question;

RQ5: *What is the variable selection methodology for identifying variables that contribute to the price value construct in UTAUT2 technology adoption model?*

Habit

The development of habits and prospective usage of technologies depend on having a sufficient understanding of their features (Limayem et al., 2007). The level of contact, comfort and exposure developed with advanced technology over time might establish certain habits (Venkatesh et al., 2012). As a user does certain behaviours repeatedly, these habits are frequently unintentional and unplanned. Past studies conclude that consumers' routine behaviour influences how likely they are to utilise digital platforms. Hence, the applications that travellers are familiar with should have a favourable impact on their intent to use/ promote DSE products/services (Nikou & Bouwman, 2014). Habit has been the primary factor influencing users' behavioural intentions to adopt DSE-based platforms across the globe (El-Masri & Tarhini, 2017; Herrero et al., 2017). According to

Megadewandanu et al. (2017), habit is a primary motivator for Indonesians to utilise digital payment apps. Another investigation using 1096 respondents' data indicated that consumer habits have a significant role in determining travellers' behavioural intention to use of homestay accommodation services online (Rabiei-Dastjerdi et al., 2022). Another study concluded that cheaper costs via accommodation platforms are a significant motivator behind the consumer shift from hotels to homestays (Li et al., 2016). Identical findings indicate that habit influences both the offeror's and the offeree's behavioural intentions to engage in a technology-based transaction (Jakkaew & Hemrungrote, 2017). Past studies conclude the significance of consumers' habit shifts in adoption intention.

Table 6. *Habit*

Construct	Variable	Literature Support
Habit	Food	"Availability of consumers' preferred food cuisine attracts them to adopt specific accommodation." (Han et al., 2021)
	Home	"A key operant or value co-creation resource is Airbnb home, described as a "home away from home" that includes features of a home such as a bedroom and a kitchen. Such home benefits reflect the main physical product that guests obtain through Airbnb." (So et al., 2018)

Past literature explains that habit variables influence consumers' adoption of new technology-based offerings (Table 6). However, there is a need to develop a variable selection methodology for each habit variables in adoption intention. Hence, the authors propose the following question for this research;

RQ6: *What is the variable selection methodology for identifying variables that contribute to the habit construct in UTAUT2 technology adoption model?*

RESEARCH METHODOLOGY

Research Design

This research adopts sentiment, cluster and thematic analysis approaches to qualitatively analyse the collected data (Refer to Figure 1). In the initial phase, the study focused on available resources like scholarly publications, textbooks, and web pages, as well as an empirical investigation into the notions of Airbnb and UTAUT2. In addition, consumer reviews data on, locations or accommodations, and regional variations of available rentals on the Airbnb site was used. The data was gathered in August 2022 and covered the reviews posted from August 2018 to August 2022.

The study began with a qualitative analysis phase, which included sentiment analysis, thematic analysis, and cluster analysis to identify relevant variables related to the experience of staying in an Airbnb accommodation. After the variables were identified, the variables were adopted into the UTAUT2 constructs.

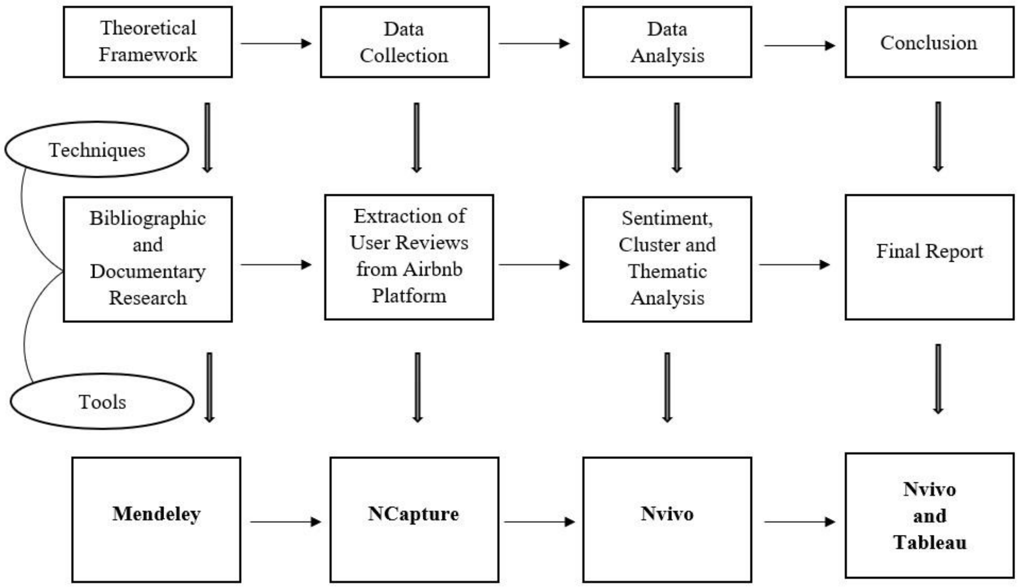

Figure 1. *Research Design*

As seen in Figure 1, first, the study adopts Mendeley to conduct bibliographic and documentary research to identify a standard gap in the accuracy of past studies in providing industrial assistance. Second, to collect data on tackling the identified gap, the study extracts consumer reviews on the Airbnb website using NCapture as an instrument of web scraping. Third, the study utilises Nvivo to extract consumer sentiment about availed service, themes of behaviours that influenced their decision to adopt a homestay accommodation and clusters that can represent a set of behavioural patterns. At last, the authors extract dashboards representing performed analysis using Tableau as a visualization tool.

Data Collection

To extract the data from the Airbnb web page, the study utilised Web Scraping technology, which automatically collects various unorganised content from web pages and organises it into logical frameworks like worksheets (Saurkar et al., 2018). NCapture was employed in this study to retrieve the data regarding consumers' experience with a particular homestay from each listing. Further, the reviews were gathered into one

XLSX file, handled by removing duplicate listings, and then manually integrated into 106 different DOC files representing reviews associated with individual homestay accommodation.

Northeast India is a group of 8 states: Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura, and Assam. In the study, the authors have considered seven states except for Assam for collecting data regarding consumers' experience with the Airbnb application. Airbnb lacks accuracy in presenting the correct response to consumers' desired location queries. The local areas of each state in northeast India more or less overlap in response to searched locations for booking. Assam, the centre of the northeast region, presents significant overlapping with neighbouring states' sites in response to consumer queries. Location accuracy is an essential predictor of symmetrical adoption patterns, and Assam's extreme overlapping of location affects the validity of extracted dataset. Hence, the authors eliminate Assam in the data collection process.

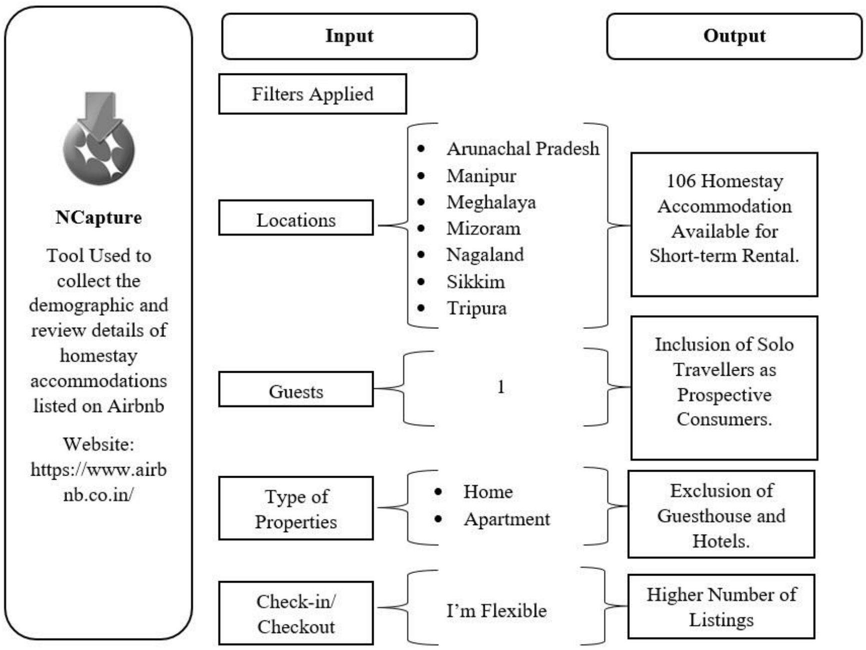

Figure 2. *Data collection Process*

Further, Figure 2 displays the filters utilised in the 'data collection project'. The selection of filtering criteria and parameters is employed to derive the exact number of homestay listings in the region. The share of all four types of accommodation: Hotel, Guesthouse, Apartment and Homestay vary in every state. Regarding the 1873 listings on Airbnb in northeast India, hotels continue to be the most popular kind of lodging, totalling 614 (32.78%) of the places, whereas 187 (9.98%) are guest houses, 273 (14.57%) are apartments, and 568 (30.32%) are homestays.

The authors applied the 'I am flexible' date and pricing filter criteria to work on the higher number of listings. Among the available type of accommodations, home and residence are the ones that accurately represents sharing economy (Mody et al., 2017). Hence 'Home' and 'Apartment' filters are applied to the kind of stay category to avoid the hotels and guesthouse listings on Airbnb. The data collection project lasted from August 1st to 15th, 2022. After employing the data collection process shown in Figure 2, the authors collected 2,181 consumer reviews linked to 165 postings.

Further, the authors removed listings with zero comments and ratings and overlapping listings in multiple regions from the data. There were 2,001 reviews of 106 homestay accommodations left when the procedure was complete. In the collected data of 106 homestay accommodations, Arunachal Pradesh (8.70%), Manipur (7.90%), Meghalaya (25.73%), Mizoram (1.82%), Nagaland (15.64%), Sikkim (38.34%), and Tripura (1.87%) was the geographical location of the Airbnb properties. Hence, they are considered targeted tourism areas for conducted research.

QUALITATIVE ANALYSIS AND FINDINGS

Sentiment Analysis

Sentiment analysis defines attitudes and emotions in texts using natural language processing to quantify personal information effectively. It identifies users' opinions and extracts four types of mind sets: positive, negative, neutral, and not sure from the inserted data sets (Farhadloo & Rolland, 2016). Sentiment analysis is a profound electronic method to retrieve emotion from the textual content, Twitter posts, and web 2.0 applications, enabling users to share their opinions about services they have been using. We can evaluate a significant quantity of information and generate views that potentially assist consumers and businesses in accomplishing their objectives. Due to such characteristics, sentiment analysis implies fields such as business, sociology, and information technology (Septia Irawan et al., 2022).

In sentiment analysis' initial stages, categorical segmentation only classified thoughts or reviews as either favourable or unfavourable. However, NVivo 12 now supports the extraction of up to 4 feelings, as seen in Figure 3 (Ali, 2020; Kharde & Sonawane, 2016). The authors conducted a sentiment analysis using NVivo 12 Plus to determine consumers' attitude patterns toward homestay accommodation (Refer to Figure 3). NVivo sentiment analysis works on expressions of sentiments in the content inserted with data sets.

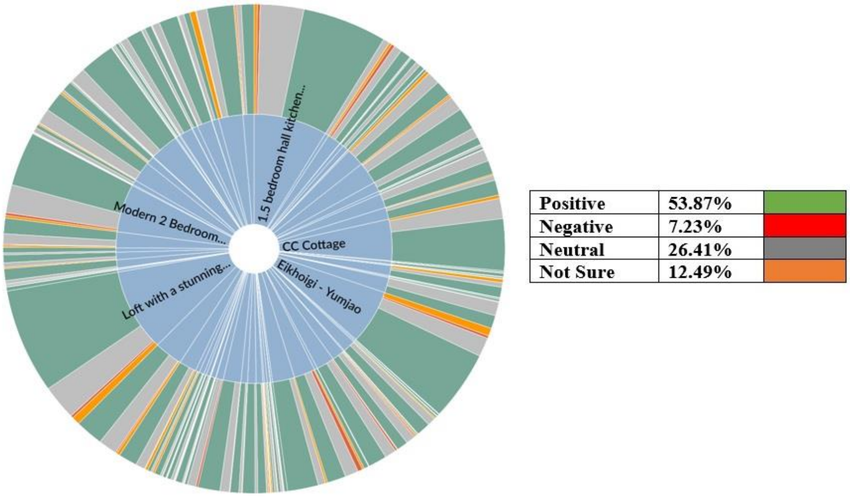

Figure 3. *Sentiment Analysis*

In this study, authors have taken out individual sentiments and collectively presented them in four types of attitude nodes: Positive, Negative, Neutral, and Not sure. As per Figure 3, 53.87% of consumers show a positive attitude, and 7.23% show a negative attitude towards sharing economy offerings. In comparison, 26.41% are neutral, and 12.49% are unsure how they feel about DSE offerings through applications like Airbnb. Here, the higher proportion of positive attitudes calls for identifying whether there lies any adoption pattern towards DSE offerings through online platforms (Applications).

Thematic Analysis

After conducting sentiment analysis, the authors conducted a thematic analysis to identify the themes of similar traits that formed consumers' positive attitudes towards a DSE offering. Laurence (2016) states that thematic analysis is a collection of methods used to derive a set of guidelines and explanatory goals from the information or by evaluating conversations and subsequently enables a thorough comprehension. Any piece of data can be categorised using thematic analysis by converting its features into essential themes that allow it to compare with several relevant criteria. Thanks to thematic analysis, investigators can now go above just counting clear-cut phrases or sentences (Ritchie & Jiang, 2019).

Table 7. *Coded Themes*

Theme	Associated Files	Associated References	Review Example
City	22	30	'Mr X is a good host. Location is around 7-8 kms from the main Gangtok city, the best part being close to the various sightseeing points. Thank you for your kind hospitality.'
View	31	42	'Its a pleasant and clean home stay with a beautiful view. Ideal for laidback holiday, away from city congestion and pollution. The host is very warm and food tastes good'
Location	37	49	'A very good and peaceful location with the best value for money!'
Place	64	138	'The place is really clean, spacious, and homely, and in a quiet neighbourhood. The hosts are really kind. I'd definitely recommend without hesitation.'
Experience	40	66	'It was an amazing experience staying at your place. The rooms were comfortable and cosy. Thank you for all your help and assistance. Hope to come back soon!!!'
Host	51	86	'Beautiful decorated and spacious house. A whole list of amenities. Top end interior and finishing. Quaintly located. Great hosts. And amazing people. All in all, Baraang House assures you of a brilliant stay in Gangtok.'
Time	29	38	'Lovely place and great, thoughtful hosts! They were in touch from the time of booking and we're very forthcoming with any relevant details. Would love to book once again!'
Road	19	28	'awesome stay, host is very nice.it is just in 15 min walk from MG road. pubs are also nearby. recommended to those who are looking for nice home stay'
Walking	25	38	'Great place to stay. local taxi stand is just few steps away which can take you to MG market in 2 minutes or if you prefer walking then it's 15 mins walk. Hosts are cool and they provide can services also if you need it.'
Room	38	57	'Had a pleasant stay. The room was spacious, very clean, with all amenities. Would like to visit once again.'
Water	24	30	'Good place but we had to face water supply issues'
Kitchen	20	28	'Very nice and clean place. Not far away from MG road. Very good hospitality. Very good kitchenette with microwave, hot plate, electric kettle, refrigerator. Definitely value for money.'
Area	26	36	'The place is really good. It is in development area about 10mins walking from MG Marg. The host is very courteous and responsive. Had an amazing stay at his place.'
Comfortable	25	32	'Really luxurious, peaceful and comfortable stay with great amenities. must go for it.'
Stay	62	112	'Amazing stay experience. Much Recommended!!'
Local	35	55	'Awesome hospitality and continuous support for local activities. Definitely a place to stay.'
Taxi	28	41	'Very comfortable stay. Close to taxi-stand.'
Food	39	62	'good place ... value for money and tasty food'
Home	24	34	'It was home away from home. Located at a prime spot. Only issue was parking. But above all the host were amazing. Local food from the owner's kitchen was excellent. Overall a big recommendation.'

In thematic analysis, the analytical components are coupled with information findings to produce a theme, and the created theme explains most of the information. Here, general industry knowledge is required to show the connections among the many data sets collected from various categories of individuals (Alhojailan & Ibrahim, 2012). The thematic analysis provides display subjects and graphical frameworks similar to the virtual environment and connections (Walters, 2016). The creation of themes in thematic analysis depends less on constantly originating from quantitative methods and more on whether it generates something pertinent to the broader story (Vaismoradi et al., 2013).

A theme collects several data points that make up the study's findings. The first step in the thematic analysis is creating a unique data set for each sample. Secondly, comments are coded using NVivo 12 Plus by creating nodes (Variable) for each reference (Review Comment) in the collected information. Every node/ theme symbolises a subject, thought, notion, viewpoint, or emotion. Thirdly, the resulting encoded nodes are presented in a table format (Refer to Table 7).

In Table 7, associated files and associated references represent the number of homestays and the number of reviews that form an individual theme. The themes' names are assigned using the 'Auto Code' function of NVivo 12 Plus. While conducting thematic analysis, diverse themes might call for adopting codes that might be inappropriate to represent the themes accurately. The thematic analysis ends with a summary of the thematic network. The thematic network is critical to developing constructs from generating initial codes, searching for an initial theme, and reviewing the initial theme to form a revised theme. These constructs unveil the adoption patterns underlying visitors' preferred attributes while choosing a sharing economy-based offering (Braun & Clarke, 2006). Hence, in the fourth stage of the thematic analysis, the authors evaluate the number of associated references and files to understand the impact frequency associated with each theme. The initial themes are either identified as constructs of the adopted theories and models or considered as discrete variables.

Cluster Analysis

The phrase 'cluster analyses relate to an experimental and explanatory analytical method that divides variables extracted in thematic analysis into data clusters with a higher degree of similarity than occurrences beyond the cluster (Uprichard, 2009). Cluster analysis is a technique that can give scholars cross-validation to find a trustworthy information pattern

(Uprichard, 2009). By combining nodes (themes) with identical phrases, comparable property data, or identical scripting, the software tool NVivo 12 can perform cluster analysis to identify trends (Bazeley, 2002). According to Bazeley (2002), evaluating findings is a crucial benefit of performing a cluster analysis based on nodes' correlation. The resulting network diagram in NVivo is the average correlation among nodes. It is determined using the Pearson correlation coefficient (-1 = least similar, 1 = most similar) upon commonalities in the recurrence distribution (Bazeley, 2002). Cluster analysis was used in the current research to arrange themes into comparable clusters. Individual clusters represent the frequency and characteristics of an event in a particular node.

Cluster analysis focuses on information compression to perform data mining in the conducted research. After identifying themes as supporting variables to the UTAUT2 framework, the authors perform cluster analysis to categorise variables into unique clusters (Constructs). First, the authors eliminate the nodes that produce redundant data for the investigation to strengthen the accuracy of data. For example, the authors eliminated the 'Great Place' node due to its small number of references and associated files and repetitive inclusion as a child node in the 'Place' theme. Further, the study utilises cluster analyses to tribe themes into uniform groupings (Refer to Figure 4).

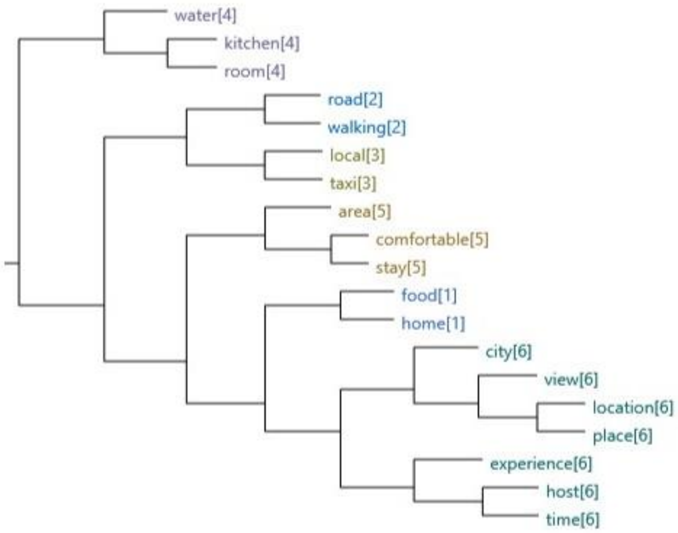

Figure 4. *Cluster Analysis – Theme Grouping*

As seen in Figure 4, to derive the number of factors that can adopt the available themes, the authors did a cluster analysis of the remaining 19 themes and used the 'Number of Clusters' feature of NVivo to divide 19 available themes into 6 clusters. Further, with the assistance of past literature, authors adopted each cluster into the ideal factor of the UTAUT2. The study categorised 19 themes into six constructs, 'Performance Expectancy', 'Effort Expectancy', 'Facilitating Condition', 'Social Influence', 'Price Value' and 'Habit'.

DISCUSSION

Conducted research aims to provide industry insights regarding variable selection for each customer's needs and desires towards DSE offerings like homestay accommodation. The website reviews that customers gave after utilising the services are the starting point for this study. By measuring consumer experience, the study attempts to design a symmetrical adoption pattern. Working backwards from the highest classification (the widest) to the first class of variables, the authors develop SAP by answering six research questions. Initially, sentiment analysis of NVivo 12 Plus was employed to verify the collective positive polarisation of gathered reviews among four attitude nodes: positive, negative, neutral, and unsure. Then, the thematic analysis generated 19 themes that the study adopted as distinct variables of the UTAUT2 framework. Lastly, the study utilised the cluster analysis method of NVivo 12 Plus to arrange themes in a logical structure (Refer to Figure 5).

As appeared in Table 7, the analysis revealed that the theme "place" emerged as the most frequently mentioned and influential variable influencing consumer adoption intention. Terms like "market," "spacious," "organized," "food," and "nearby" were associated with this variable. Positive sentiments such as "amazing," "decent," "ideal," "brilliant," and "recommend" were prevalent, while terms like "beautiful" and "perfect" referred to perceptual qualities and perceptions associated with the variable. The themes "home," "stay," "location," "room," "local," and "place" were connected to adjectives like "unique," "comfortable," and "pleasant." Additionally, terms like "host" and "hostess" were frequently mentioned, indicating the importance of homeowners in the discussions.

The findings of this study align with previous research, which highlighted the significance of factors like cleanliness, location, home environment, hosts, neighbourhood, and recommendations in digital consumer evaluations (Cheng & Jin, 2019; Ding et al., 2020; Guttentag & Smith, 2017; Ju et al., 2019; Li et al., 2019; Luo & Tang, 2019; Sainaghi, 2020; Tussyadiah & Pesonen, 2016; von Hoffen et al., 2018). Additionally, the findings of this study also align with the UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) framework, as the identified themes can be utilized as variables for the UTAUT2 factors. The UTAUT2 model includes constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value, which collectively influence users' adoption intention.

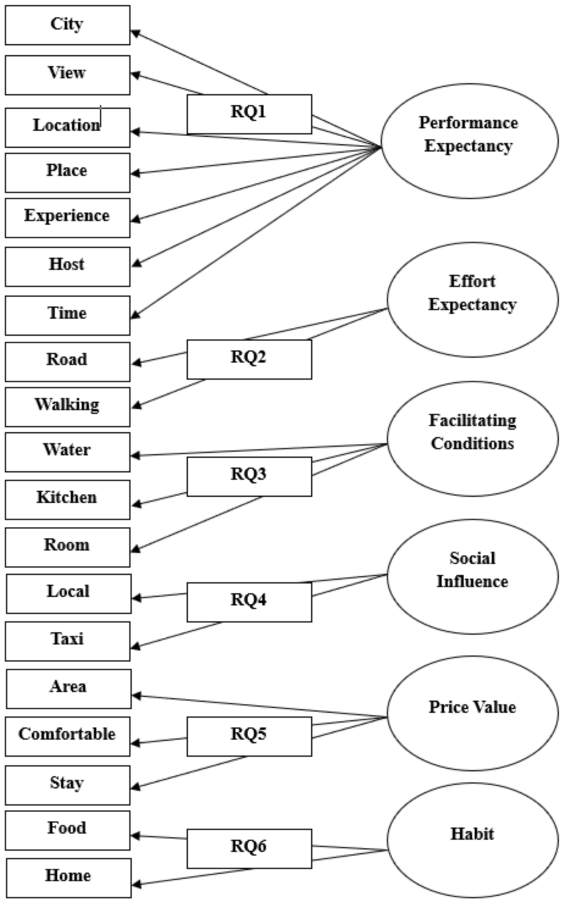

Figure 5. *Research Model*

The identified themes, such as "place," "home," "stay," "location," "room," "local," and "host," correspond to these UTAUT2 factors. For example, the theme "place" relates to performance expectancy, indicating that consumers' adoption intention is influenced by the perceived performance or quality of the accommodation. Similarly, the themes "home" and "stay" align with hedonic motivation, as they reflect the desire for a unique and pleasant experience during the stay. Furthermore, the themes related to the host, such as "host" and "hostess," align with the social influence factor, indicating that consumers' adoption intention can be influenced by the interactions and recommendations from the host. Additionally, the themes related to location, cleanliness, and neighbourhood align with facilitating conditions, as they represent factors that make the adoption of homestay accommodations easier and more convenient.

Overall, the identified themes can be seen as variables that capture the essence of the UTAUT2 factors and contribute to understanding consumers' adoption intention in the context of homestay accommodations. By incorporating these themes as variables in the UTAUT2 model, researchers and industry practitioners can gain a comprehensive understanding of the factors that influence users' adoption intention and make informed decisions based on these findings.

Moreover, the symmetrical adoption pattern enhances the resource allocation process for MSMEs in Asia by providing a systematic approach to variable selection. It assists industry practitioners in making well-informed decisions by considering the specific objectives of their businesses. By incorporating this methodology, MSMEs can allocate their resources more effectively, ensuring that investments are focused on variables that are most relevant to their desired outcomes and target market.

THEORETICAL AND PRACTICAL IMPLICATIONS

From a theoretical perspective, we list themes adopted into the UTAUT2 construct that can be assessed, matched, and further evolved in potential experiments. This research adds to the industrial and academic discussions on the novel types of tourist consumption by investigating a validation for the subjective variables of homestay accommodation through SAP. The study looks into one necessary step of the procedure associated with the visitors' encounters. It will broaden the understanding of which variables are appropriate in consumer feedback and which elements homeowners can ask consumers to rate throughout and after the visit. The findings can be a valuable source of information for subsequent investigations of UTAUT2-associated theories.

The study draws practical ramifications for homeowners to fully comprehend and enhance their rankings. The study concludes that it is helpful for homeowners to acknowledge and strengthen their pages and broaden their awareness by concentrating on the most pertinent theme for the consumers. Such implications can assist entrepreneurs and marketers in gaining a competitive advantage over their rivals. The predicted enhancement in the standard of the offering, which emerges from benchmarking amongst competitors, is a practical application of the research's findings. This study also concludes that Airbnb's homeowners may utilise the highest-valued themes as a rating criterion; it provides a chance for homestay to be rated by explicit user opinions.

Additionally, this research simplifies the individual part of hosts, mobile applications, communities, and consumers in this equilibrium. It is due to the interaction between owners and guests throughout a vacation trip, which enhances travellers' leisure activity. The study concludes that industry practitioners must regularly analyse consumer reviews through SAP to improve the service in DSE. Along with industry practices, the outcomes can assist in designing and guiding regional government initiatives related to tourist development and urban city planning. This discovery points to a hole in the ease of availing particular experiences and accommodations northeast India offers. The study concludes that a large portion (7.23% Negative, 26.41% Neutral, 12.49% Unsure) of tourists that travelled to northeast India were not at ease with the service they opted for, which can subsequently impact sharing their experiences with the rest of the world. It significantly affects the techniques that let users engage with the regional way of life and have authentic experiences. The authors conclude that enjoying native life is vital to Airbnb customers in northeast India. It is essential to mention that view from the room, nearby tourism experiences, and transportation availability at a homestay significantly impact consumer adoption.

In addition, the objectives of this research paper were successfully achieved through a comprehensive study of the adoption patterns of sharing economy applications, specifically focusing on Airbnb services in northeast India. Firstly, Objective 1 was accomplished by gaining an understanding of the travellers' adoption patterns of digital sharing economy offerings at popular tourist destinations in the region. Objective 2 was fulfilled by assessing the relevance of the UTAUT2 factors in influencing the symmetrical adoption pattern observed. Lastly, Objective 3 was met by identifying ideal variables for each UTAUT2 construct, which measured consumers' adoption intentions. The study concluded that the adoption of a symmetrical pattern of UTAUT2 constructs can provide valuable insights for the tourism industry, aiding in the development of targeted interventions to improve the adoption of sharing economy mobile apps. The research paper's contribution lies in expanding the understanding of DSE application adoption, presenting a symmetrical pattern in the UTAUT2 model, and providing variable selection methods for each construct. The integration of qualitative approaches, such as sentiment analysis, thematic analysis, and cluster analysis within Nvivo software, offered a more comprehensive and nuanced understanding of consumer preferences, motivations, and perceptions. These findings empower industry practitioners to make informed decisions and enhance technology adoption rates in the tourism industry.

Further, to look at tourist management from an established hotel unit's perspective, an important aspect is to help top administrators get used to the fact that short-term home rentals are a conventional type of lodging service. The hosts must be regarded as 'tourist entrepreneurs' to establish the homestay segment as significant competition. This approach can assist in creating novel regulations like enhancing the service in terms of something material (type of residence perks) or immaterial (type of cultural connection).

LIMITATIONS AND SCOPE FOR FUTURE RESEARCH

This study acknowledges certain limitations and suggests potential areas for future research. The study did not focus on Assam as the research area due to overlapping properties with other north-eastern Indian states. Additionally, the number of listings obtained may be a topic of interest for scholars to investigate the significance of chosen search parameters. Another limitation is the inability to gather visitor demographic data, which restricts the generalizability of the chosen sample beyond the sampled group in the Asian continent.

To further advance the field, future researchers are encouraged to explore SAP by conducting a comparative study between Airbnb and hotels, analysing commonalities and variations in rankings across different types of accommodations. They can also investigate the variations in the Airbnb service globally and in other parts of Asia, considering different societies and geographical areas. Furthermore, a qualitative analysis examining how homeowners rely on customer evaluations to identify future changes in their offerings could be conducted using interviews or focus groups. Additionally, a field study collecting relevant data on homestay listings in Assam could enable a comparative analysis of regional SAP. These avenues for future research would contribute to a deeper understanding of the subject matter and provide valuable insights for the industry.

CONCLUSION

This research paper has contributed to the understanding of the adoption of digital sharing economy (DSE) applications, specifically focusing on the unique occurrences in the national and regional tourist activities of India's northeast region. By examining the characteristics of consumers' expectations of Airbnb services in northeast India, the authors have presented a symmetrical pattern of UTAUT2 constructs in adoption intention, expanding the current knowledge in this field.

The findings of this study have significant implications for the resource allocation decisions made by homestay accommodation organizations in their efforts to increase market share. The variable selection methodology developed for each construct within the UTAUT2 model provides valuable insights for enhancing adoption rates. While the relative contribution of each construct may vary depending on the context, identifying the ideal variable for each construct can offer valuable insights for specific settings or scenarios.

Knowing the precise variables that influence technology adoption can help identify the relative importance of these factors in driving adoption intention. This information can be utilized to develop targeted interventions aimed at improving specific variables and constructs, thereby increasing adoption rates. Furthermore, obtaining precise variables allows for comparisons with other studies conducted in different contexts or populations, enabling a better understanding of the generalizability of the findings.

In the tourism industry, the variable selection methodology for individual constructs within the UTAUT2 model can aid in identifying potential areas for improvement in the design and development of travel planning apps. This information can guide tourism organizations and app developers in enhancing features that improve user experience and incorporating social recommendations to drive adoption rates.

Moreover, the integration of qualitative approaches such as sentiment analysis, thematic analysis, and cluster analysis within the variable selection methodology represents a significant advancement in the field. By combining qualitative and quantitative methods, the proposed methodology offers a more comprehensive and nuanced understanding of consumer preferences, motivations, and perceptions related to technology adoption. This holistic approach overcomes the limitations of relying solely on quantitative techniques, enabling industry practitioners to make more informed decisions and improve technology adoption rates.

The symmetrical adoption pattern (SAP) is not limited to the UTAUT2 model but can also be applied to extract insights on various aspects of consumer behaviour, such as preferences and sentiment towards specific amenities or locations. This information can be utilized by MSMEs, such as Airbnb hosts, to optimize their listings and increase sales. At the organizational level, platforms like Airbnb can develop machine learning algorithms based on SAP to create host assistance portals.

In conclusion, SAP provides a comprehensive approach to studying the tourism industry, particularly within the context of the sharing economy and platforms like Airbnb. The insights derived from SAP empower organizations to make informed decisions, improve their offerings, and better cater to the needs and preferences of their customers. Future research can further refine and explore this methodology to enhance its effectiveness and applicability across various domains.

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