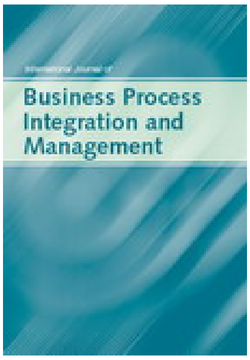

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A study on the factors that impact consumer decision making process in the context of using social media for choosing a hotel in India among students

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Abstract: This study aims to uncover the factors influencing students' hotel selection process in India via social media platforms and to assess the relationships, dependencies, and variances among these factors. The findings provide valuable insights for hotel managers to enhance their business strategies. The study examines how variables such as family income, education level, accompanying persons, online reviews, gender, app usage, and social media platform preferences influence hotel selection and visit frequency. It also investigates the influence of education level and gender on restaurant selection mode preferences. Conducted through probability sampling and a structured questionnaire, the study collected 215 responses online from students in Tamil Nadu, India. Statistical analyses using SPSS software, including discriminant analysis, correlation analysis, regression, chi-square test, and ANOVA, were employed to analyse the data. The findings reveal that social media significantly impacts restaurant selection, with factors such as family income and educational background playing crucial roles. Furthermore, the study suggests that the influence of social media on restaurant decisions is expected to grow in tandem with technological advancements. This research contributes valuable insights for restaurant managers and marketers to enhance their strategies and adapt to the changing landscape of consumer preferences in the digital era.

Keywords: social media; digital marketing; consumer decision-making process; hotels and managers; online behaviour and marketing; India.

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1 Introduction

Modern restaurants implemented Internet and social media marketing aimed at showcasing the restaurants' offerings and culture, interacting with customers, and maintaining their attention and loyalty through visual and narrative content (Dossena et al., 2020). Additionally, only modern restaurant owners discussed the development of an online booking system as a marketing innovation (Sabermajidi et al., 2020). To succeed by exploiting social media in the restaurant business, owners/managers need some capabilities and relevant competencies. Restaurants should increase their technological, relational, marketing, management, business and strategic, innovation, and dynamic capabilities related to social media management (Dossena et al., 2020). These results add to the rapidly expanding field of social media marketing.

There are several known challenges with social media analyses. For example, whilst social media marketing can increase competitiveness, the question remains whether customer 'mood' expressed through online channels is representative of that in a wider market (Park et al., 2016). Furthermore, opinions, emotions, and sentiments are not the same, which means that social media analysis can be more complex than anticipated. The posted messages interest tourism stakeholders greatly (Park et al., 2016), especially when sentiment mining could lead to automatic discovery, analysis, and generalisation of views and opinions. This research captured experiences and perceptions through sentiment analysis, building on related research in the tourism and hospitality context (Park et al., 2016).

In addition, as measuring sentiments is the key to understanding customer feedback which ultimately results in improving service quality and competitive advantages in the hotel industry, many studies employed sentiment analysis. Straightforward approaches use dictionary-based or lexical databases to capture the sentiment from customer reviews while advanced approaches use machine learning techniques (Park et al., 2016) to effectively predict sentiment based on a large number of examples. These approaches showed promising results, but they still have some drawbacks.

Previous studies indicated the urgent need for applying social media data especially big data analytics in the hotel industry since it can provide new insights into factors that have been extensively studied in existing hospitality literature (Fox and Longart, 2016).

Online reviews are one of the main ways to share experiences and to learn first-hand about the experiences of others. Analysing customer sentiments with user-generated content allows researchers to predict customer attitudes toward a product, service, or brand (Park et al., 2016). Knowing the perceptions of consumers can also be a way for businesses to gain a competitive advantage.

Online consumer reviews, in the extant literature, have been studied for purposes such as determining the issues that are important in restaurant reviews (Huang et al., 2015), identification of the main topics used to describe the meal, satisfaction, authenticity dimensions that are of value to customers in dining experiences, exploring perceptions of Asian restaurants (Park et al., 2016), and exploring cultural differences in online reviews. These studies focused mainly on reviews written in English (Huang et al., 2015; Park et al., 2016) but some focused on the limited studies in different languages like Chinese and Japanese. However, there is a huge gap in the extant literature of studies that examine how customers from different cultures or countries perceive ethnic restaurants. It also impacts how a startup operates and communicates in the community. It acts as an electronic word-of-mouth system (Park et al., 2016).

Past research has shown the importance of social media analytics to understand the perception and to identify the events/factors influencing a brand or product performance (Park et al., 2016). However, most research is focused on the customer's perception of the brand or product.

Even though various studies have used Twitter analytics to examine tweets in various contexts, analysing tweets to understand the Indian startup ecosystem has not been done previously. Also, the character limit of Twitter is more than that of general survey questions (Park et al., 2016). This approach could be more helpful in analysing the views on the startup ecosystem.

With the aid of information and mobile technologies, marketers can reveal marketing information to multiple customers simultaneously and, in addition, effectively build social relationships with social media users (Popy and Bappy, 2020). Hospitality and tourism marketers can use social media platforms to create individualised content to increase consumer awareness of products, services, experiences, and brands, thereby gaining the attention and engagement of consumers (Park et al., 2016). It has also been shown that social media may increase interest in and motivate people to attend specific events while increasing their desire to share information about these events.

Although online brand communities are developed through the collaboration of marketers and customers, marketers also publish information to generate increased interaction with customers on social media. Park et al. (2016) investigated tweets referring to cruise vacations and classified three types of Twitter user groups (commercial, news/blogs, and private groups), revealing that news/blogs and commercial groups posted content more frequently than private groups (i.e., comprising individual customers). In social media, developing relationships with users (known as 'following' or 'friending') is more important than merely creating content.

In the food and beverage industry, some research has been done on the social media impact on select restaurants and locations. For example, Park et al. (2016) used Twitter analysis to explore diner perceptions of Asian restaurants while Lepkowska-White et al. (2019) analysed small restaurant's social media strategies to identify challenges and successes of using social media as a monitoring tool. However, a research gap exists regarding the use and evaluation of social media tools for promoting food and beverage products.

As a primary and effective technique to analyse social media and consumer-generated content, text mining is widely used to analyse a substantial volume of complex unstructured textual data and extract meaningful information from a large amount of available social media data. Text mining focuses on automatically exploring and identifying the hidden but useful patterns, trends, or rules from the textual data such as emails, customer reviews, and messages, and then creating interpretations or models to explain questions and discover new knowledge (Park et al., 2016). With the wide adoption of social media platforms, text mining has become one of the most significant techniques for businesses and organisations to analyse their social media data to understand their customers, competitors, and business environment, as well as provide better support for making strategic and operational decisions.

In addition, Park et al. (2016) examine dining perceptions of Chinese, Japanese, Korean, and Thai restaurants on Twitter through text mining and sentiment analysis. Overall, their study suggests that feeling about food quality is more positive while feeling about service quality and food culture skews to negativity in the four selected Asian restaurants in the USA.

Information diffusion through social media platforms has resulted in raising awareness of brands, helping customers form attitudes, and affecting their decision-making (Park et al., 2016). Online consumer reviews have become an important opportunity for marketing communications since many consumers search for online reviews as the first step in shopping (Park et al., 2016).

Therefore, stakeholders can interact instantly to avoid a bad reputation that can be disastrous for the destination (risk management). The knowledge extraction about the feelings of visitors for specific locations can be derived from their shared posts in location-based social networks with sentiment analysis (Park et al., 2016). Therefore, the integration of this information with spatio-temporal data can uncover patterns and provide more insights into the geographical dimension of the destinations examined.

The third most popular type of analysis was those related to comparison. Among these studies, analysis of variance (Park et al., 2016) was used more frequently than chi-square and t-test. Travellers have different reactions to the information from social networks regarding travel planning. Social media allows for obtaining consumer perception, popular words, and emotional state in comments (Park et al., 2016). Consumer preferences can be identified by analysing social media data, which can help service providers to plan more personalised services.

Social media marketing has become increasingly influential within the hotel industry in India, playing a pivotal role in shaping consumer behaviour and brand perception. Hotel brands across the country are leveraging various social media platforms to engage with their target audience, drive brand awareness, and ultimately boost bookings (Marchand et al., 2021).

One notable aspect of the current state of social media marketing in the Indian hotel industry is the widespread adoption of platforms such as Facebook, Instagram, Twitter, and increasingly, TikTok. Hotels are actively using these platforms to showcase their properties, highlight amenities, and share engaging content such as stunning visuals, virtual tours, and user-generated content. Instagram, in particular, has emerged as a popular platform for visually appealing content, with hotels utilising features like stories, IGTV, and reels to connect with their audience in creative ways (Bushara et al., 2023).

Social media has become an essential tool for reputation management within the Indian hotel industry. Hotels are closely monitoring and responding to customer feedback and reviews on platforms like TripAdvisor, Google Reviews, and Facebook. Positive reviews are being amplified through social media channels to reinforce brand credibility and trust, while negative feedback is addressed promptly to mitigate any potential damage to the hotel's reputation (Ye et al., 2023).

Influencer marketing has also gained momentum within the Indian hotel industry, with hotels collaborating with travel influencers and content creators to reach new audiences and drive engagement. Influencers are being invited for sponsored stays, experiences, and collaborations, with their content shared across social media platforms to showcase the hotel's offerings to a wider audience (Alipour et al., 2024).

The rise of user-generated content has transformed social media into a powerful tool for word-of-mouth marketing within the Indian hotel industry. Guests are sharing their experiences, photos, and recommendations on social media platforms, influencing their peers' decisions and creating authentic connections with hotel brands. Hotels are actively encouraging and incentivising guests to create and share content, thereby expanding their reach and amplifying their brand presence across social media channels (Melnychuk et al., 2024).

2 Literature review

To understand the factors that impact the consumer decision-making process in the context of using social media for choosing a hotel in India and to evaluate the extent to which these factors affect the consumer decision-making process all the journals of the Scopus database were considered from 2010 to 2022. The Software R Studio is used to statistically analyse these journals which have the keywords 'consumers decision making' + 'social media'. In the Scopus database from 2010 to 2022, 110 research papers were found to have the keywords 'consumers decision making' + 'social media'.

2.1 Information about the selected research papers

The 110 research papers considered were from 93 different sources, which include journals, books, etc. The yearly growth rate % is 18.92, and the average citation per paper is 17.83, as given in Table 1. In these 110 research papers, there were 366 keywords, and there were about 271 authors who had written papers on these topics. There are 17 authors of single-authored research papers. Authors have co-authored about 18 papers with 2.65 co-authors per paper. Among the various types of documents, there are 68 articles, one book, 14 book chapters, 25 conference papers, and two review papers.

2.2 Annual production of selected research papers

The annual production of these 110 journals is shown in Table 2, in the year 2019 a maximum number of 19 articles was published on the topic, and the least number of articles on this topic was published in the years 2010, 2011, and 2012. In the year 2021, there were 17 articles published on this topic, in the year 2018, there were 15 articles, in the year 2020 there were 12 articles, in the year 2016 there were 11 articles, and ten articles in the year 2017. In July 2022 there are eight articles published on the topic. While six articles were published in the year 2014 on the topic, five articles were published in the year 2015, four articles in the year 2013, and one article in the year 2010, 2011, and 2012.

The graph in Figure 1 illustrates the distribution of annual publications on the topic from 2010 to 2022.

Table 1 Main information about the research papers

Description	*Results*
MAIN INFORMATION ABOUT DATA	
Timespan	2010: 2022
Sources (Journals, Books, etc)	93
Documents	110
Annual Growth Rate %	18.92
Document Average Age	3.87
Average Citations per doc	17.83
References	1
DOCUMENT CONTENTS	
Keywords Plus (ID)	366
Author's Keywords (DE)	365
AUTHORS	
Authors	271
Authors of single-authored docs	17
AUTHORS COLLOBORATION	
Single-authored docs	18
Co-Authors per Doc	2.65
International co-authorships %	0
Document TYPES	
Article	68
Book	1
Book chapter	14
Conference paper	25
Review	2

Table 2 Annual production

Year	*Articles*
2019	19
2021	17
2018	15
2020	12
2016	11
2017	10
2022	8
2014	6
2015	5
2013	4
2010	1
2011	1
2012	1

Table 3 Author contribution over time

Author	*Year*	*Freq*	*TC*	*TCpY*
Ghalamkari A	2018	2	3	0.600
Hosseini M	2018	2	3	0.600
Li B	2019	2	35	8.750
Li M	2013	2	1	0.100
Mason AN	2021	2	28	14.000
Mason K	2021	2	28	14.000
Narcum J	2021	2	28	14.000
Zhang J	2013	2	1	0.100
Abdallah EB	2021	1	0	0.000
Abouelgheit E	2013	1	10	2.500
Aditya S	2021	1	12	2.400
Agarwal G	2019	1	1	0.333
Ahuja V	2018	1	0	0.000
Akter S	2020	1	12	2.400
Al Adwan A	2019	1	1	0.500
Alhakimi W	2018	1	1	0.500
Benlian A	2021	1	8	1.000
Benlian A	2021	1	62	8.857
Charoensuksai N	2015	1	76	8.844
Charoensuksai N	2016	1	4	0.571
Lin X	2019	1	77	19.250
Lin X	2022	1	0	0.000
Pick M	2020	1	0	0.000
Pick M	2021	1	14	7.000
Thies F	2014	1	6	0.667

2.3 *Author contribution over time*

The authors who contributed to this topic are shown in Table 3, Kalamkari, G.A. and Hosseini, M. each published two papers in the year 2018, these articles are cited three times each, and the times cited per year is 0.6. Li, B. is cited a maximum of 35 times during the year 2019 and the times cited per year is 8.75. Other authors like Mason, A., Mason, K. and Narcum, J. are each cited 28 times in the year 2021 with 14 times cited per year. These authors have given two papers each in the year 2021. Zang, J. has published two papers in the year 2013 on this topic. Benlian, A.'s paper in the year 2016 is cited 62 times with times cited per year being 8.857. Charoensuksai's paper in the year 2014 is cited 76 times with 8.444 times cited per year. Lin, X.'s paper in the year 2019 has the most citations of 77 times with 19.250 times cited per year. Pick, M. published a paper in the year 2021 which is cited 14 times with 7.00 times cited per year. Abouelgheit, E. published a paper in the year 2019 with a citation of ten times and 2.500 times cited per year. Aditya, S. and Akter, S. each published one paper in the year 2018, both are cited 12 times with 2.400 times cited per year. Benlian, A. published one more paper in the year 2015, which is cited eight times with 1.000 times cited per year. This F has published a paper in the year 2014, it is cited six times with 0.667 times cited per year. Charoensuksai published one more paper on the topic in the year 2016, it was cited 4 times with 0.571 times cited per year. Li, M. and Zhang, J. have both published two papers each in year 2013 on the topic with 0.100 times cited per year. Al Adwan, A. and Al Hakimi, W. have each published one paper on the topic in the year 2021 with 0.500 times cited per year. Agarwal, G. has published one paper in the year 2020 with 0.333 times cited per year. Ahuja, V. published one paper in the year 2019, Abdallah, E.B. published one paper on the topic in the year 2021, Pick, M. has published one more paper on the topic in the year 2020 and Lin, X. has also published one more paper on the topic in the year 2022.

2.4 Most relevant authors

Table 4 lists the most relevant authors who have contributed to the topic during the period 2010 to 2022. Thies, F., Wessel, M. and Zang, J. have each contributed three articles on the topic. Benlian, A., Charoensuksai, Ghalamkari, A., Hosseini, M., Li, B., Li, M. and Lin, X. have each contributed two papers on the topic in the period considered. This can be pictorially shown in Figure 2.

Figure 1 Distribution of annual production (see online version for colours)

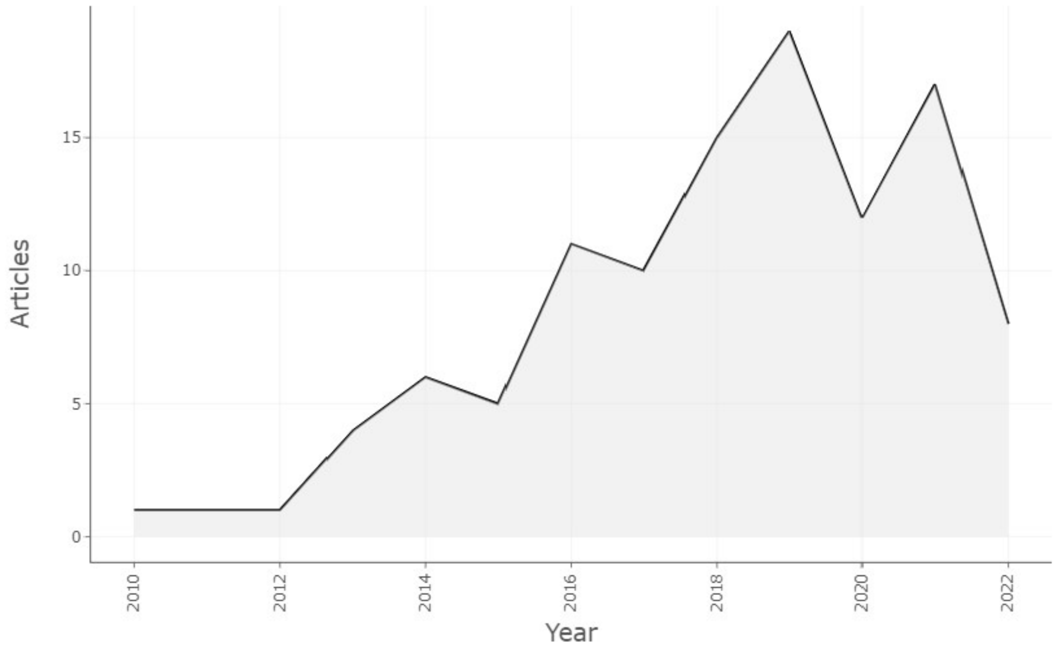


Figure 2 Authors's contribution on the topic (see online version for colours)

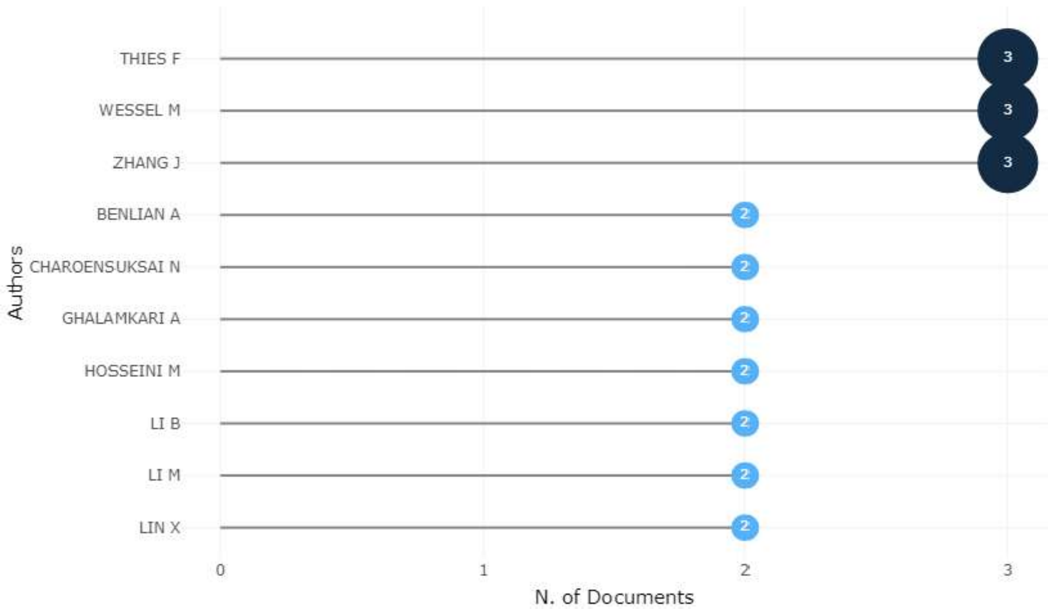


Figure 3 Relevance degree vs. development degree of the keywords (see online version for colours)

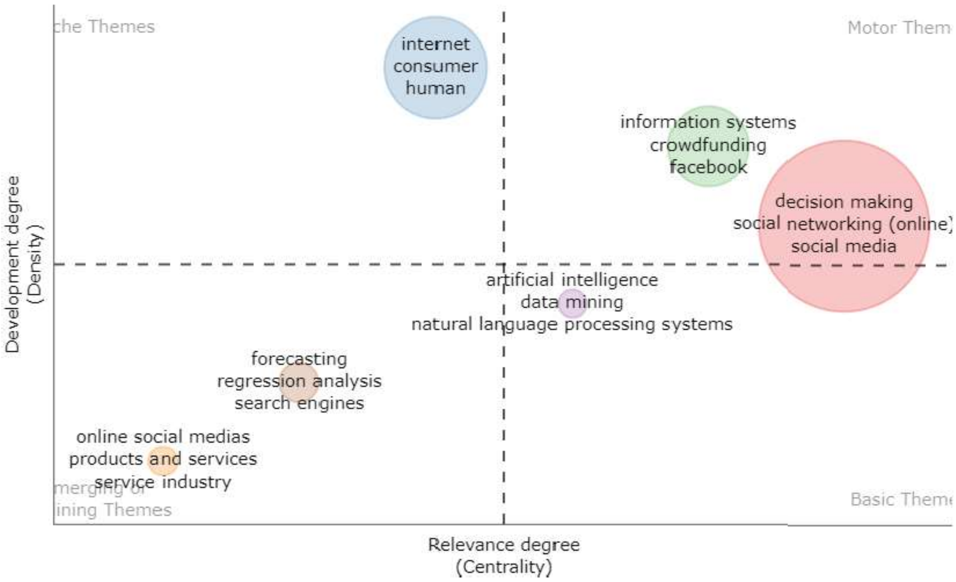
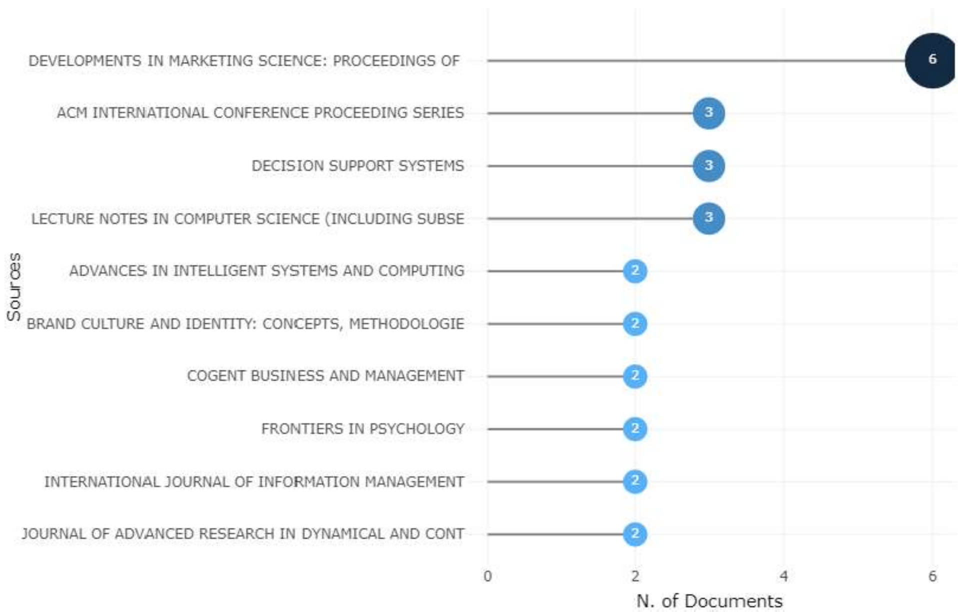


Figure 4 The journals which have published the topic the most (see online version for colours)



2.5 *Occurrences of keywords*

Table 5 shows the frequent occurrences of the keywords; ‘decision making’ occurs the most by 43 times in the 110 papers considered. ‘Social networking (online)’ occurred 27 times. ‘Social media’ occurred 24 times and ‘consumer decision making’ occurred 21 times. The keywords ‘commerce’ occurred 12 times, ‘sales’ occurred 11 times, and ‘consumer behaviour’ occurred ten times. The keyword ‘electronic commerce’ has occurred nine times, the keyword ‘economic and social effects’ and the keyword ‘internet’ have each occurred six times. The other keywords shown in the graph do not have significant occurrences. The relevance of the keywords with the density of the keywords can be seen in Figure 3.

Table 4 Most relevant authors

Authors	*Articles*	*Articles fractionalised*
Thies F	3	1.17
Wessel M	3	1.17
Zhang J	3	1.75
Benlian A	2	0.67
Charoensuksai N	2	1.00
Ghalamkari A	2	1.00
Hosseini M	2	1.00
Li B	2	0.53
Li M	2	0.75
Lin X	2	0.83

Table 5 Occurrences of keywords

Words	*Occurrences*
Decision Making	43
Social Networking (online)	27
Social Media	24
Consumer Decision Making	21
Commerce	12
Sales	11
Consumer Behavior	10
Electronic Commerce	9
Economic and Social Effects	6
Internet	6

2.6 *Most relevant sources*

Table 6 shows the most relevant sources which published articles on the topic during the period 2010 to 2022. The journal titled 'Developments in Marketing Science: Proceedings of the Academy of Marketing Science' has published the most, that is six articles on the topic. Three journals, 'ACM International Conference Proceeding Series', '*Decision Support Systems'* and 'Lecture Notes in Computer Science', have each published three articles on the topic. Many other journals have published at least two articles each on the topic. '*Advances in Intelligent Systems and Computing*', '*Brand Culture and Identity: Concepts, Methodologies, Tools and Applications*', '*Cogent Business and Management*', '*Frontiers in Psychology*', '*International Journal of Information Management*' and *Journal of Advanced Research in Dynamical and Control Systems* have each published two articles on the topic. A few journals namely – '*The Academy of Strategic Management Journal*', '*Advances in the Human Side of Service Engineering*', '*African Journal of Hospitality, Tourism and Leisure*', '*Annals of Tourism Research*', '*Applied Ergonomics*', '*BMJ OPEN*', '*British Food Journal*', '*Business Horizons*', '*Computers in Human Behaviour'* and '*Contemporary Issues in Social Media Marketing*', have each published one article on the topic. Apart from these journals, there are a few conference proceedings like 'IEEE International Conference on Systems, Man and Cybernetics', '2015 International Conference on Affective Computing and Intelligent Interaction, ACII 2015', '2022 International Conference on Decision Aid Sciences and Applications, DASA 2022', '23rd European Conference on Information Systems, ECIS 2015' and '24th Workshop on Information Technology and Systems' have each published one article on the topic. The graphical representation of the most relevant sources can be seen in Figure 4.

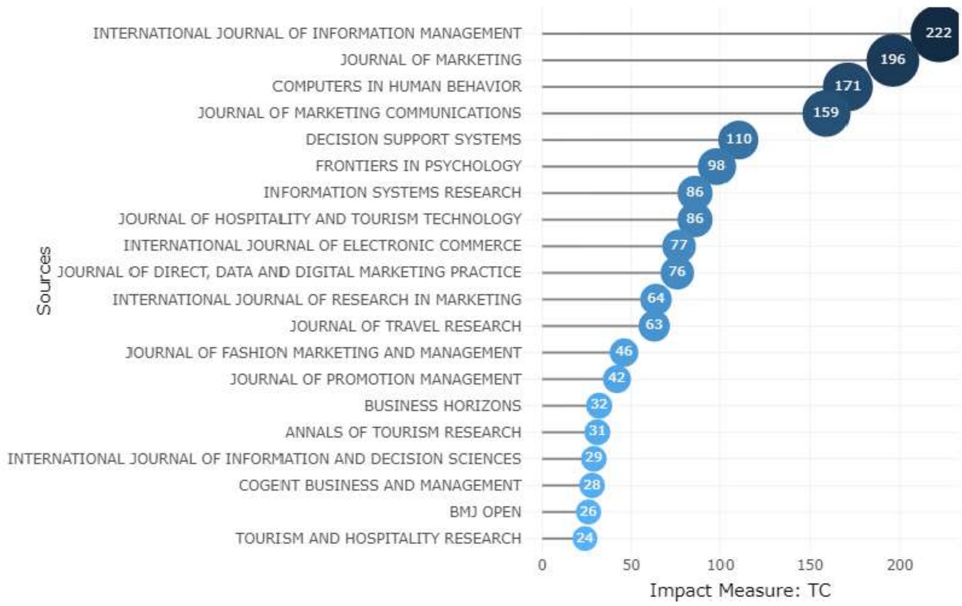
Table 6 Most relevant sources

Sources	*Articles*
Developments in Marketing Science Proceedings of the Academy of Marketing Science	6
ACM International Conference Proceeding Series	3
Decision Support Systems	3
Lecture notes in Computer Science (including subseries lecture notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	3
Advances in Intelligent Systems and Computing	2
Brand Culture and Identity: Concepts, Methodologies, Tools, and Applications	2
Cogent Business and Management	2
Frontiers in Psychology	2
International Journal of Information Management	2
Journal of Advanced Research in Dynamical and Control Systems	2
2015 International Conference on Affective Computing and Intelligent Interaction, ACII 2015	1
2022 International Conference on Decision and Sciences and Applications, DASA 2022	1
23rd European Conference on Information Systems, ECIS 2015	1
24th Workshop on Information Technology and Systems	1
Academy of Strategic Management Journal	1
Advances in the Human Side of Service Engineering	1
African Journal of Hospitality, Tourism and Leisure	1
Annals of Tourism Research	1
Applied Ergonomics	1
BMJ Open	1
British Food Journal	1
Business Horizons	1
Computers in Human Behaviour	1
Conference Proceedings – IEEE International Conference on Systems, Man and Cybernetics	1
Contemporary Issues in Social Media Marketing	1

Table 7 Source impact

Element	*H_index*	*G_index*	*M_index*	*TC*	*NP*	*PY_start*
International Journal of Information Management	2	2	0.333	222	2	2017
Journal of Marketing	1	1	0.143	196	1	2016
Computers in Human Behaviour	1	1	0.200	171	1	2018
Journal of Marketing Communications	1	1	0.111	159	1	2014
Decision Support Systems	2	3	0.250	110	3	2015
Frontiers in Psychology	1	1	0.333	98	1	2020
Information Systems Research	1	1	0.100	86	1	2013
Journal of Hospitality and Tourism Technology	1	1	0.167	86	1	2017
International Journal of Electronic Commerce	1	1	0.250	77	1	2019
Journal of Direct, Data and Digital Marketing Practice	1	1	0.111	76	1	2014
International Journal of Research in Marketing	1	1	0.167	64	1	2017
Journal of Travel Research	1	1	0.143	63	1	2016
Journal of Fashion Marketing and Management	1	1	0.250	46	1	2019
Journal of Promotion Management	1	1	0.250	42	1	2019
Business Horizons	1	1	0.167	32	1	2017
Annals of Tourism Research	1	1	0.333	31	1	2020
International Journal of Information and Decision Sciences	1	1	0.250	29	1	2019
Cogent Business and Management	1	2	0.500	28	2	2021
BMJ Open	1	1	0.111	26	1	2014
Tourism and Hospitality Research	1	1	0.200	24	1	2018
Management Science	1	1	0.250	20	1	2019
Worldwide Hospitality and Tourism Themes	1	1	0.250	20	1	2019
Applied Ergonomics	1	1	0.200	18	1	2018
Economics, Management, and Financial Markets	1	1	0.200	16	1	2018
Industrial Management and Data Systems	1	1	0.250	15	1	2019

Figure 5 Source impact measure: TC (see online version for colours)



2.7 Source impact

Table 7 shows the source impact using h index, g index, and m index, it also shows the number of times cited, number of publications, and publication year. The journal titled '*International Journal of Information Management'* has an h index of 2, a g index of 2, and m index of 0.333. This journal has been cited 222 times, this journal has published two publications on the topic in 2017. The journal titled '*Decision Support System*' which was published on the topic has an h index of 2 and g index of 3 and an m index of 0.250. It has been cited 110 times and three papers were published by this journal on the topic in the year 2015. '*Journal of Marketing Communications'* has been cited 159 times and has published one article on the topic during the year 2014. '*Journal of Marketing'* is cited 196 times and has published one article on the topic in the year 2016. The Journal titled '*Computers in Human Behaviour*' has published one article on the topic in the year 2018 and is cited 171 times. '*Cogent Business and Management*' has an h index of 1, g index of 2, and m index of 0.500; it has published two articles in the year 2021 and is cited 28 times, this journal has the highest m index. The graphical representation of the source impact, in terms of times cited, is shown in Figure 5.

2.8 Research gap

Based on the literature review the following were identified as the major factors impacting the decision-making process of the customers in the Indian scenario. The level of the impact of these factors needs more in-depth analysis.

- *Reviews and ratings* – these play a major role in deciding to visit the hotel/restaurant, people tend to look up online information and reviews about the restaurant, food, ambiance, and the service on the whole. The reviews and ratings help them choose the place or not. Having best-in-class consumer-generated ratings and reviews is a key success factor.
- *Quality online presence* – a quality online presence for the hotel/restaurant is considered one of the most important factors in the existence of the hotel/restaurant. Social media, a website with all updated information, the integrity of the content available online, etc. describes the management's online quality presence.
- *App preference* – to study which online application the users prefer and the variable associated with it.
- *Frequency of visiting a restaurant* – the variable associated with the frequency of a customer visiting a restaurant in a particular period.

2.9 The significance of the study

Though social media marketing has emerged as a prevalent method for corporations to reach consumers, a detailed analysis of the impacting factors, is lacking in the literature.

2.10 Statement of the problem

To understand the factors that have both positive and negative impacts on the consumer's decision-making process in the context of using social media for choosing a Hotel in India among students and to help the managers of Indian hotels formulate strategies for better business efficiency.

2.11 Scope of the study

The role of social media and the influence, it has on the decision-making process of the consumers, while choosing a hotel in India among students. This research helps in understanding the factors that help consumers decide to choose a hotel to dine in, it also aims to understand the process of consumer decision-making.

2.12 Objectives/purpose of the study

- To identify the major impact factors on the consumers' decision-making process in the context of using social media for choosing a hotel in India among students.
- To analyse the level of impact of these identified factors.
- To suggest a model that can strategically help the hotel managers overcome the negative effects that may affect the business.

2.13 Research questions

- What are the primary factors influencing students' decision-making process when selecting a hotel in India through social media platforms?
- To what extent do demographic variables (such as age, gender, and educational background) influence students' reliance on social media for hotel selection in India?
- What role does user-generated content, such as reviews and ratings, play in shaping students' perceptions and preferences regarding hotels in India on social media platforms?
- How do students' past experiences with hotels in India, shared or encountered through social media, influence their decision-making process for future hotel selections?

3 Research methodology

3.1 Sample size

The sample size for this study is 215. Students from different colleges in Tamil Nadu and neighbouring states were approached for the study. The researchers have collected filled questionnaires from these students through online mode. The researchers have adopted the probability sampling technique and have collected data from students whoever is amenable and ready to give information for the study.

3.2 Research instruments

A well-structured questionnaire was used as a research instrument for this study. Part 1 of the questionnaire consists of the demographic profile of the respondents and Part 2 consists of questions related to the impact of social media in the decision-making process of choosing a hotel in India.

3.3 Data collection

In this study, a quantitative exploratory study is adopted in this study. Students using social media to choose hotels in India were the target respondents for this study. Utilising both interviews with general consumers who use social media and structured questionnaires adopted from Radwan et al. (2020), researchers aimed to comprehensively probe into participants' preferences and perceptions. The questionnaires, designed with well-formulated questions, provided a cost-effective and efficient means to gather responses from a large sample size, allowing for quantitative analyses such as correlation and regression.

3.4 Data analysis procedures

The data collected were entered into SPSS software and various statistical tools were used to analyse the data. Discriminant analysis was used in this study to establish and classify the variables and to assess the relationship between the dependent variable of family monthly income and the independent variable of factors for preferring a restaurant.

Correlation analysis was used to assess the relationship between the dependent variable of the family monthly income of the respondents and the independent variable of the frequency of visiting a restaurant.

Correlation analysis was also used to assess the relationship between the dependent variable of the educational status of the respondents and the independent variable of app preference for making an order from a restaurant.

Regression analysis was used to assess the predictability of the model. The analysis was done with a dependent variable of online reviews for selecting a restaurant and independent variables of gender, family income, educational status, person accompanying, app preference, and social media platform preference.

ANOVA was used to find the significant variance between the dependent variable of online reviews for selecting a restaurant and independent variables of gender, family income, educational status, person accompanying, app preference, and social media platform preference.

Pearson chi-square test was used to find if there is an association between the independent variable of preference of mode for choosing a restaurant and the dependent variable of gender.

4 Data analysis and interpretation

In this quantitative exploratory study, probability sampling is adopted, tools for data collection used in this study are interviews and questionnaires for collecting primary data which proves to be less expensive and comprehensive when compared to other methods. The questionnaire consists of a set of well-formulated questions to probe and obtain responses from the respondents. The interviews were conducted with general consumers using social media.

This data collection is a process of gathering and measuring information on variables of interest in an established systematic fashion that enables the respondents to answer stated research questions, test hypotheses and evaluate outcomes.

4.1 Statistical analysis methods used

- *Discriminant analysis* is a versatile statistical method often used by market researchers to classify observations into two or more groups or categories. In other words, discriminant analysis is used to assign objects to one group among several known groups.
- *Correlation analysis* is a statistical method used to measure the strength of the linear relationship between two variables and compute their association. Correlation analysis calculates the level of change in one variable due to the change in the other.
- *Regression analysis* is a powerful statistical method that allows you to examine the relationship between two or more variables of interest. Regression Analysis examines the influence of one or more independent variables on a dependent variable.
- *ANOVA* is a way to find out if survey or experiment results are significant. In other words, they help you to figure out if you need to reject the null hypothesis or accept the alternate hypothesis. You're testing groups to see if there's a difference between them.
- *Pearson's Chi-square test* is a statistical test for categorical data. It is used to determine whether the data are significantly different from what is expected.

Table 8 Analysis case processing summary

	Unweighted cases	*N*	*Percent*
Valid		214	99.5
Excluded	Missing or out-of-range group codes	0	0.0
	At least one missing discriminating variable	0	0.0
	Both missing or out-of-range group codes and at least one missing discriminating variable	1	0.5
	Total	1	0.5
Total		215	100.0

4.2 Discriminant analysis

Discriminant analysis was used in this study to establish and classify the variables and to assess the relationship between the dependent variable of family monthly income and the independent variable of factors for preferring a restaurant. Table 8 shows there were 214 valid samples used for the data analysis.

Table 9 Summary of canonical discriminant functions

Wilks' Lambda				
Test of function(s)	*Wilks' Lambda*	*Chi-square*	*df*	*Sig.*
1	0.843	35.913	2	< 0.001

From Table 9, it is inferred that the Wilks' Lambda which tested for statistical significance associated with the discriminant function is 0.843, which transforms to a Chi-square value of 35.913 with 2 degrees of freedom. The model is significant at 0.001 which is well below the hypothetical value.

From Table 10, it is inferred that there is a 65.4% overall predictability in this function. The classification table shows that respondents who have a family monthly income from Rs. 10,000 to Rs. 50,000 are more accurately classified with 90.7%. For respondents who have a family monthly income from Rs. 50,000 to Rs. 100,000 are accurately classified with 67.2%. For respondents who have a family monthly income of more than Rs. 100,000 have classified with an accuracy of 29.7%. This helps the researchers in understanding the respondent's income predictability.

4.3 Correlation analysis

The correlation coefficient was used to assess the relationship between the family monthly income of the respondents and the frequency of visiting a restaurant. From Table 11, it is inferred that the Pearson correlation coefficient is 0.063, showing a positive correlation between the variables family monthly income and frequency of visiting a restaurant.

The correlation coefficient was used to assess the relationship between the educational status of the respondents and app preference for making an order from a restaurant. From Table 12, it is inferred that the Pearson correlation coefficient is 0.476, showing a high positive correlation between the variables of educational status and App preference for making an order from a restaurant.

4.4 Regression

Regression analysis was used to assess the predictability of the model. The analysis was done with a dependent variable of online reviews for selecting a restaurant and independent variables of gender, family monthly income, educational status, person accompanying, app preference, and social media platform preference. The method used under regression was the backward excluding method; in which the variables with the highest insignificant probability are excluded in every iteration.

From Table 13, it is inferred that the variables – person accompanying, preference of social media platform, and educational status are removed in the following order due to the highest insignificant probabilities in four iterations.

Table 10 Classification results

		Family monthly income	*Predicted group membership*			
			Rs.10,000–50,000	*Rs. 50,000–100,000*	*More than Rs. 100,000*	*Total*
Original	Count	Rs.10,000–50,000	78	1	7	86
		Rs. 50,000–100,000	13	43	8	64
		More than Rs. 100,000	29	16	19	64
	%	Rs.10,000–50,000	90.7	1.2	8.1	100.0
		Rs. 50,000–100,000	20.3	67.2	12.5	100.0
		More than Rs.100,000	45.3	25.0	29.7	100.0

Note: a. 65.4% of originally grouped cases were correctly classified.

Table 11 Correlations-family monthly income of the respondents and frequency of visiting a restaurant

		Family income	*Frq. visit a restaurant*
Family monthly income	Pearson correlation	1	0.063
	Sig. (two-tailed)		0.358
	N	214	214
Visit a restaurant	Pearson correlation	0.063	1
	Sig. (two-tailed)	0.358	
	N	214	214

Table 12 Correlations – educational status of the respondents and app preference for making an order from a restaurant

		Education	*App preference*
Education	Pearson correlation	1	0.476**
	Sig. (two-tailed)		< 0.001
	N	214	214
App preference	Pearson correlation	0.476**	1
	Sig. (two-tailed)	< 0.001	
	N	214	214

Note: **.Correlation is significant at the 0.01 level (two-tailed).

Table 13 Variables entered/removed

Model	*Variables entered*	*Variables removed*	*Method*
1	Social media platform, family income, app preference, accompany, gender, education		Enter
2		Accompany	Backward (criterion: probability of F-to-remove >= 0.100)
3		Social media platform	Backward (criterion: probability of F-to-remove >= 0.100)
4		Education	Backward (criterion: probability of F-to-remove >= 0.100)

Notes: a. Dependent variable: reviews. b. All requested variables were entered.

Table 14 Model summary

Model	*R*	*R Square*	*Adjusted R square*	*Std. error of the estimate*
1	0.388[a]	0.150	0.126	0.835
2	0.387[b]	0.150	0.129	0.833
3	0.385[c]	0.148	0.132	0.832
4	0.377[d]	0.142	0.130	0.833

Notes: [a]Predictors: (constant), social media platform, family monthly income, app preference, accompany, gender, education.
[b]Predictors: (constant), social media platform, family monthly income, app preference, gender, education.
[c]Predictors: (constant), family monthly income, app preference, gender, education.
[d]Predictors: (constant), family income, app preference, gender.

Table 15 ANOVA[a]

Model		*Sum of squares*	*df*	*Mean square*	*F*	*Sig.*
1	Regression	25.533	6	4.255	6.100	< 0.001[b]
	Residual	144.416	207	0.698		
	Total	169.949	213			
2	Regression	25.447	5	5.089	7.326	< 0.001[c]
	Residual	144.502	208	0.695		
	Total	169.949	213			
3	Regression	25.221	4	6.305	9.105	< 0.001[d]
	Residual	144.728	209	0.692		
	Total	169.949	213			
4	Regression	24.111	3	8.037	11.573	< 0.001[e]
	Residual	145.837	210	0.694		
	Total	169.949	213			

Notes: [a]Dependent variable: reviews.
[b]Predictors: (constant), social media platform, family monthly income, app preference, accompany, gender, education.
[c]Predictors: (constant), social media platform, family monthly income, app preference, gender, education.
[d]Predictors: (constant), family monthly income, app preference, gender, education.
[e]Predictors: (constant), family monthly income, app preference, gender.

Table 16 Coefficients[a]

Model		*Unstandardised coefficients*		*Standardised coefficients*	*t*	*Sig.*
		B	*Std. error*	*Beta*		
1	(Constant)	4.283	0.426		10.043	< 0.001
	Family income	0.166	0.074	0.155	2.241	0.026
	Gender	–0.233	0.155	–0.122	–1.505	0.134
	Education	0.059	0.050	–0.095	–1.168	0.244
	Accompany	0.040	0.113	0.025	0.351	0.726
	App preference	–0.191	0.067	–0.218	–2.839	0.005
	Social media platform	0.046	0.097	0.033	0.472	0.638
2	(Constant)	4.352	0.378		11.523	< 0.001
	Family income	0.163	0.074	0.152	2.220	0.027
	Gender	–0.236	0.154	–0.124	–1.530	0.128
	Education	–0.060	0.050	–0.097	–1.197	0.233
	App preference	–0.194	0.067	–0.221	–2.910	0.004
	Social media platform	0.054	0.095	0.038	0.570	0.569
3	(Constant)	4.529	0.216		20.982	< 0.001
	Family income	0.161	0.073	0.150	2.195	0.029
	Gender	–0.246	0.153	–0.129	–1.605	0.110
	Education	–0.063	0.050	–0.102	–1.266	0.207
	App preference	–0.198	0.066	–0.225	–2.982	0.003
4	(Constant)	4.577	0.213		21.514	< 0.001
	Family income	0.156	0.073	0.146	2.129	0.034
	Gender	–0.322	0.141	–0.169	–2.291	0.023
	App preference	–0.227	0.062	–0.259	–3.653	< 0.001

Note: [a]Dependent variable: reviews.

Table 17 Excluded variables

Model		*Beta in*	*t*	*Sig.*	*Partial correlation*	*Collinearity statistics tolerance*
2	Accompany	0.025[b]	0.351	0.726	0.024	0.844
3	Accompany	0.032[c]	0.475	0.635	0.033	0.893
	Social media platform	0.038[c]	0.570	0.569	0.040	0.904
4	Accompany	0.040[d]	0.587	0.558	0.041	0.900
	Social media platform	0.047[d]	0.698	0.486	0.048	0.914
	Education	–0.102[d]	–1.266	0.207	–0.087	0.627

Notes: [a]Dependent variable: reviews.
[b]Predictors in the model: (constant), social media platform, family monthly income, app preference, gender, education.
[c]Predictors in the model: (constant), family monthly income, app preference, gender, education.
[d]Predictors in the model: (constant), family monthly income, app preference, gender.

Table 18 Gender * preference of mode cross tabulation

			Preference of mode			
			Newspaper	*Social media*	*Word of mouth*	*Total*
Gender	Male	Count	8	108	29	145
		% within a preference of mode	21.6%	82.4%	63.0%	67.8%
	Female	Count	29	23	17	69
		% within a preference of mode	78.4%	17.6%	37.0%	32.2%
Total		Count	37	131	46	214
		% within a preference of mode	100.0%	100.0%	100.0%	100.0%

From Table 14 of the model summary, it is inferred that from the performed regression analysis the adjusted R square value showing the predictability performance of the regression model was increased gradually from 12.6% in the first iteration to 13.0% in the final iteration after the excluded variables.

4.5 ANOVA

ANOVA was used to find the significant variance between the selected variables. From Tables 15 and 16, it is inferred that, since the significance value is less than the hypothetical value of 0.05, there is no significant variance between the dependent variable (online reviews for selecting a restaurant) and independent variables (gender, family monthly income, educational status, person accompanying, app preference and social media platform preference).

From Table 17, it is inferred that the model has excluded the variable with an insignificant value in order. In the second iteration the variable with the highest significant value ‘person accompanying’ was excluded with a significance value of 0.726. In the third iteration the variable with the next highest significant value ‘preference of social media platform’ was excluded with a significance value of 0.569. In the next iteration the variable with the next highest significant value ‘educational status’ was excluded with a significance value of 0.207.

4.6 Chi-square analysis

Pearson Chi-square test was used to find if there is an association between the independent variable (preference of a mode of choosing a restaurant) and the dependent variable (gender).

Table 19 Chi-square tests

	Value	*df*	*Asymptotic significance (2-sided)*
Pearson Chi-square	49.448[a]	2	< 0.001
Likelihood ratio	48.113	2	< 0.001
Linear-by-linear association	12.245	1	< 0.001
N of valid cases	214		

Notes: [a]0 cells (.0%) have an expected count of less than 5. The minimum expected count is 11.93.

From Tables 18 and 19, it is inferred that there is no association between the preference of mode for choosing a restaurant and gender since the Pearson Chi-square value is 0.01, which is less than the hypothetical value of 0.05.

5 Findings and conclusions

5.1 Findings of the study

1 Correlation analysis

- Positive correlation between family monthly income and restaurant visit frequency: This implies that as respondents’ family monthly income increases, there is a corresponding increase in the frequency of their visits to restaurants. For instance, higher-income individuals may have more disposable income to spend on dining out, leading to a higher frequency of restaurant visits.
- High positive correlation between educational status and preferred app for online food ordering: This suggests that respondents with higher levels of education tend to have a stronger preference for specific apps when ordering food online. This correlation could be due to factors such as technological proficiency, awareness of different apps, or preferences for certain features offered by these platforms.

2 Regression analysis

- Dependency of online reviews and ratings on family monthly income, app preference, and gender: The regression analysis indicates that family monthly income, app preference, and gender are the variables that most strongly influence online reviews and ratings. This means that these factors have a significant impact on how consumers perceive and evaluate restaurants and food delivery services based on online feedback.

3 ANOVA (analysis of variance)

- Insignificance variance between online reviews and independent variables: The ANOVA results suggest that gender, family monthly income, app preference, and social media platform preference do not have a statistically significant impact on online reviews. Despite being important factors in consumer behavior, they may not directly influence online ratings and reviews.

4 Chi-square analysis

- The absence of an association between gender and preference of mode for choosing a restaurant suggests that gender does not significantly influence individuals’ choices in selecting a mode for dining out. This finding highlights the importance of considering other factors, such as personal preferences, convenience, and social influences, in understanding consumer behaviour in the restaurant industry.

5 Discriminant analysis

- By assessing the predictability and classification accuracy of family monthly income based on various variables, discriminant analysis provides insights into the demographic characteristics of consumers. The classification accuracy rates indicate the model's effectiveness in predicting respondents' family monthly income levels. However, the varying accuracy rates across income categories suggest that certain income groups may be more accurately classified than others, emphasising the need for further research and refinement of the classification model.
- From the analysis it is found that there is a 65.4% predictability on the family monthly income of the respondents and classified as follows, 90.7% is classified accurately with a family monthly income in the range from Rs.10,000 to Rs.50,000. For respondents who have a family monthly income from Rs. 50,000 to Rs. 100,000 are accurately classified with 67.2%. For respondents who have a family monthly income of more than Rs. 100,000 have classified with an accuracy of 29.7%.

5.2 Limitations and future work

The major limitation of the study is that the majority of the respondents in this study were in and around the state of Tamil Nadu; future researchers can increase the scope of respondents in various geographical regions in their research. Another limitation is that the study concerns only some of the variables impacting the business of restaurants/hotels, further research can be done by analysing more variables. Future researchers can also continue this study by increasing the sample size to a larger level.

5.2.1 Limitations

1 Sample size and representativeness: the study's findings may be constrained by the size and representativeness of the sample. A small sample size can limit the generalisability of the results to the broader population. Additionally, if the sample is not representative of the target population in terms of demographics (such as age, income, education level, etc.), the findings may not accurately reflect the behavior of the entire population.

2 Generalisability: the study's findings may be context-specific and may not be generalisable to other populations or geographical regions. Cultural, economic, and social differences across regions can significantly influence consumer behaviour. Therefore, caution should be exercised when extrapolating the findings to different contexts without considering these variations.

3 Data collection methods: the reliance on self-reported data from respondents may introduce biases and limitations. For instance, respondents may provide socially desirable responses or may have difficulty accurately recalling past behaviours. Incorporating multiple data collection methods, such as observations or behavioural data, could enhance the validity and reliability of the findings.

4 Temporal factors: the study's findings may be influenced by temporal factors such as changes in technology, economic conditions, or consumer trends. For example, consumer preferences for online food ordering platforms or social media channels may evolve. Therefore, the findings may not remain applicable or relevant in future contexts without considering these temporal dynamics.

5 Variable measurement: the operationalisation and measurement of variables in the study may have limitations. For instance, the definition of 'online reviews and ratings' or the criteria used to classify respondents' 'preferred app' may vary across studies. Ensuring clarity and consistency in variable measurement can enhance the reliability and comparability of the findings.

5.2.2 Future directions

1 Longitudinal studies: conducting longitudinal studies over an extended period can provide insights into how consumer behaviour evolves. Tracking changes in behaviour, preferences, and attitudes longitudinally can reveal trends and patterns that may not be apparent in cross-sectional studies.

2 Cross-cultural comparisons: comparing consumer behaviour across different cultural contexts or countries can shed light on how cultural factors influence preferences and decision-making processes. Understanding cross-cultural variations in consumer behaviour is essential for businesses operating in diverse markets.

3 Qualitative research: supplementing quantitative analyses with qualitative research methods, such as interviews or focus groups, can provide deeper insights into the underlying motivations, perceptions, and experiences driving consumer behaviour. Qualitative research can uncover nuances and contextual factors that may not be captured through quantitative surveys alone.

4 Exploring new variables: investigating additional variables, such as environmental sustainability preferences, food quality perceptions, or convenience factors, can enrich our understanding of consumer decision-making processes in the hospitality industry. Exploring emerging trends and novel factors influencing consumer behaviour can help businesses stay ahead of evolving consumer preferences.

5 Experimental designs: implementing experimental designs or intervention studies allows researchers to

assess causal relationships between variables and test the effectiveness of specific interventions or strategies in influencing consumer behaviour. Experimental designs provide a rigorous approach to identifying causal mechanisms and informing evidence-based business decisions.

5.3 Conclusions

In conclusion, this research underscores the significant impact of social media on the decision-making process when it comes to choosing a restaurant. The study reveals that factors such as family monthly income, educational status, app preferences, and social media platform usage play pivotal roles in influencing consumers' restaurant choices. Moreover, it suggests that the influence of social media on restaurant selection is poised to grow in the future, paralleling the rapid advancements in technology. By leveraging insights from statistical analyses including correlation analysis, regression analysis, ANOVA, chi-square analysis, and discriminant analysis, this study elucidates the intricate relationships between various factors, providing a comprehensive understanding of how social media shapes consumer behaviour in the restaurant industry. The findings of this research offer actionable insights for restaurant managers and marketers to tailor their strategies effectively. By understanding the nuances of consumer preferences and the influence of social media, restaurant establishments can optimise their online presence, enhance customer engagement, and tailor offerings to meet the evolving demands of their target audience. Moreover, recognising the significance of factors such as family income, educational background, and app preferences allows for targeted marketing efforts, ensuring that restaurants can effectively cater to the diverse needs and preferences of their clientele. Overall, this study underscores the pivotal role of social media in shaping consumer decisions in the restaurant sector and highlights the importance of adapting strategies to capitalise on this evolving landscape.

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