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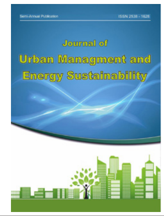


CASE STUDY RESEARCH PAPER

# Validation of the Effective Indicators of Artificial Intelligence with Emphasis on Consumer Behavioral Patterns in Tourism Institutions

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ABSTRACT

The present study was conducted with the aim of validating the effective indicators of artificial intelligence with emphasis on consumer behavioral patterns in tourism institutions. Methodologically, the study adopted a mixed approach and was pursued quantitatively in its final stage. In the qualitative phase, the statistical population comprised 18 professors, specialists, and experts in the fields of information technology, management, and tourism marketing, who were selected purposively and contributed to the design of the initial model. In the quantitative phase, based on the variables extracted from the qualitative phase, a semi-open questionnaire was designed and distributed among 100 respondents. The data were analyzed using SPSS and LISREL software through descriptive statistics, confirmatory factor analysis, and structural equation modelling. The descriptive results showed that the majority of respondents were men, held bachelor's and master's degrees, and were mainly in the 31–35 age range. The inferential findings indicated an appropriate fit of the study's measurement and structural models: the goodness-of-fit indices (GFI and AGFI) were at a desirable level, and the factor loadings of all indicators were significant. The convergent validity and composite reliability of the constructs were also confirmed. The results showed that components such as digital-sales development, prediction of customer purchase behavior, analysis of customer data, the use of data mining, the development of customer-relationship-management systems, and the improvement of service quality play a significant role in the effectiveness of AI in tourism institutions. Overall, the findings indicate that AI can be used as a strategic instrument for improving marketing decisions, personalizing services, and enhancing customer engagement in the tourism industry.

*Running Title: AI Effectiveness Indicators and Consumer Behavior in Tourism*

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## INTRODUCTION

Despite the ever-increasing application of artificial intelligence (AI) in the tourism industry and its growing role in improving marketing, decision-making, and customer-engagement processes, fundamental challenges still remain in identifying and validating the effective indicators of this technology in relation to consumer behavior. Many tourism institutions use AI tools without possessing a scientific and localized framework, and the real capacities of AI in analyzing customer behavior, personalizing services, and increasing the effectiveness of marketing activities are not fully exploited. On the other hand, the complexity and diversity of tourism consumers' behavioral patterns and the rapid changes in their expectations have redoubled the need for a systematic examination of the role of AI in shaping these patterns. Therefore, the absence of a valid and comprehensive model capable of explaining and assessing the effective AI indicators with emphasis on consumer behavioral patterns in tourism institutions is posed as the main problem of this research a problem whose resolution can lead to improvements in competitiveness, marketing efficiency, and service quality in these institutions. In recent years, the remarkable advancement of AI techniques has caused the application of this technology in the field of tourism marketing to expand considerably. The developments arising from the growth of AI have driven the managers and practitioners of tourism institutions to offer a more diverse range of services and have provided the ground for the extensive use of this technology in future products and services. By enabling the design of smarter, more effective marketing methods that are better suited to consumers' needs, AI plays an important role in improving customer engagement; so much so that it is predicted that, in the near future, this technology will turn from a competitive advantage into an inescapable necessity for enhancing the position of tourism institutions in the market. On the other hand, with the increasing attention of researchers to tourism marketing as one of the key instruments for delivering tourism services especially under conditions where the growth of internet users and the ever-increasing online supply of products and services have accelerated, AI has emerged as one of the most important technological achievements of the Fourth Industrial Revolution. This technology is widely employed in the field of electronic marketing by tourism companies and institutions to enhance the efficiency and success of their marketing processes. On this basis, the main problem of this research is to examine the level of awareness of the impact of deploying AI technologies and their varied capabilities on the effectiveness of consumer behavior and on increasing the competitive capacity among tourism institutions, organizations, and companies.

Technological disruptions such as AI, the Internet of Things (IoT), and big-data analytics (BDA) have provided novel digital solutions for attracting, developing, and retaining a customer base (Anshari et al., 2018; Bolton et al., 2018). These emerging technologies, by facilitating the process of delivering products and services to customers, create the conditions for a sustainable competitive advantage for organization. In the current business environment, the intensity of competition and the acceleration of technological developments have transformed the ways in which organizations operate (Gans, 2016). In this context, the customer-centric approach—whose principal focus is identifying and responding to customers' needs plays a decisive role in the growth and survival of organization (Vetterli et al., 2016).

In recent years, the rapid advancement of technology has had extensive effects on the global economy and has caused a significant shift of activities from traditional offline channels to digital platforms, in such a way that an integrated, end-to-end experience is created for customers. AI as a form of machine-based intelligence capable of performing in a manner similar to, or even superior to, humans is widely employed in various technologies and has today transformed numerous industries, including the marketing industry. By drawing on AI, marketers are able to carry out more precise advertising targeting, generate more sales leads, improve website design, and deliver higher-quality services to customers. The application of AI in marketing makes it possible to establish more effective communication with customers and to gain a deeper understanding of their behavior and preferences. Integrating AI into marketing strategies facilitates the identification of the most effective content suited to customers' behavioral patterns and allows organization to benefit from targeted, results-oriented content-marketing strategies.

## MATERIALS AND METHODS

The research method is quantitative. A statistical population refers to a set of individuals or phenomena to which the results of the research are generalized and whose members share one or more common characteristics. The statistical population at this stage comprised 18 professors, specialists, and experts in the fields of information technology, management, and tourism marketing. Sampling was carried out purposively, and individuals with experience and knowledge in these fields were drawn upon for consultation and for designing the model. In this study, after the research method was determined, the data-collection techniques were selected on the basis of the topic, objectives, and limitations of the research, and two approaches library-based and field-based were employed. In the quantitative phase, after the variables were extracted from the qualitative phase, a semi-open questionnaire was designed and administered to measure them. The data were analyzed using SPSS and LISREL through descriptive statistics, confirmatory factor analysis (CFA), and structural equation modelling (SEM).

## FINDINGS AND DISCUSSION

*Gender of respondents*

Based on the first part of the questionnaire and the information completed by the participants, the descriptive statistics for gender were obtained. Table 1. presents the frequency and percentage of the data by respondents' gender. The results showed that, of the total of 100 participants in this study, 32 respondents (32%) were women and 68 respondents (68%) were men (Tab. 1 and Fig. 1).

Table 1: Frequency of the data by respondents' gender (source: author).

| Gender | Frequency | Percent | Valid percent | Cumulative percent |
|---|---|---|---|---|
| Female | 32 | 32.0 | 32.0 | 32.0 |
| Male | 68 | 68.0 | 68.0 | 100.0 |
| Total | 100 | 100.0 | 100.0 | |

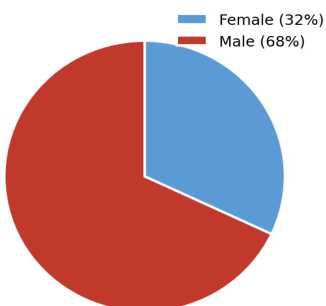

Figure 1: Distribution of respondents by gender (source: author).

*Educational level of respondents*

Based on the second part of the questionnaire, the descriptive statistics for educational level were obtained. Table 2 presents the frequency and percentage of the data by respondents' educational level. The results showed that, of the total of 100 participants, 18 (18%) held an associate degree, 39 (39%) a bachelor's degree, 33 (33%) a master's degree, and 10 (10%) a doctoral degree. (Tab. 2).

Table 2: Frequency of the data by respondents' educational level (Source: Authors).

| Educational level | Frequency | Percent | Valid percent | Cumulative percent |
|---|---|---|---|---|
| Associate degree | 18 | 18.0 | 18.0 | 18.0 |
| Bachelor's degree | 39 | 39.0 | 39.0 | 57.0 |
| Master's degree | 33 | 33.0 | 33.0 | 90.0 |
| Doctorate | 10 | 10.0 | 10.0 | 100.0 |
| Total | 100 | 100.0 | 100.0 | |

*Age of respondents*

Based on the relevant part of the questionnaire, the descriptive statistics for age were obtained. Table 3 presents the frequency and percentage of the data by respondents' age. The data show that 11 respondents (11%) were in the 25–30 age group, 32 (32%) in the 31–35 group, 22 (22%) in the 36–40 group, 28 (28%) in the 41–45 group, and 7 (7%) were 46 years of age or older. Accordingly, the largest frequency group is that of respondents aged 31–35 (32%) and the smallest is that of those aged 46 and above (7%) (Figure-related data). (Tab. 3).

Table 3: Frequency of the data by respondents' age (Source: Authors).

| Age group | Frequency | Percent | Valid percent | Cumulative percent |
|---|---|---|---|---|
| 25–30 years | 11 | 11.0 | 11.0 | 11.0 |
| 31–35 years | 32 | 32.0 | 32.0 | 43.0 |
| 36–40 years | 22 | 22.0 | 22.0 | 65.0 |
| 41–45 years | 28 | 28.0 | 28.0 | 93.0 |
| 46 years and above | 7 | 7.0 | 7.0 | 100.0 |
| Total | 100 | 100.0 | 100.0 | |

The data in the table above shows the age variable of the people in the research sample, which shows that 11 people (11%) of them are in the age group between 25 and 30 years, 32 people (32%) are in the age group between 31 and 35 years, 22 people (22%) are in the age group between 36 and 40 years, 28 people (28%) are in the age group between 41 and 45 years, and 7 people (7%) are over 50 years old. According to these data, the most frequent group is among people aged 31 to 35 years (32%) and the least frequent group is among people aged 46 and over (7%) (Fig. 2).

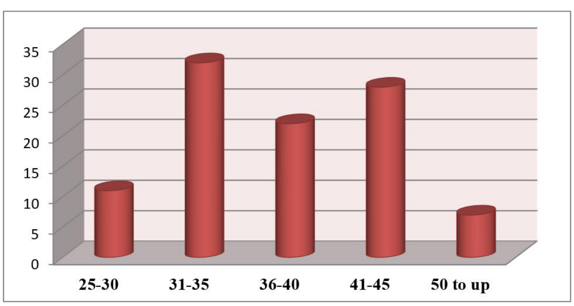


Figure 2: Frequency of the data by respondents' age (Source: Authors).

*Inferential statistics*

The correlation coefficient and structural equation modelling, using LISREL software, were employed to analyses the data. Before examining the structural model of the research variables, a confirmatory factor analysis of the model's variables was carried out. Since the AI variable has two dimensions, it is a two-stage variable and therefore has two confirmatory factor analyses: a first-order CFA, which examines the relationship of the observed variables (indicators) in tourism institutions, and a second-order CFA, which examines the relationship between consumer behavioral patterns and the AI variable in tourism institutions. The results of the first- and second-order factor analyses are reflected in Table 4. (Tab. 4)

Table 4: Results of the first- and second-order confirmatory factor analysis of AI effectiveness with emphasis on consumer behavioral patterns (Source: Authors).

| Variable | Components (indicators) | Standard coefficient | t-value |
|---|---|---|---|
| Effectiveness of artificial intelligence with emphasis on consumer behavioral patterns in tourism institutions | Digital-sales development | 0.71 | 8.23 |
| | Use of novel and emulative technologies (AI) | 0.72 | 8.68 |
| | Application of new technologies | 0.72 | 8.88 |
| | Developing customer-communication capabilities | 0.67 | 7.51 |
| | Dynamic structure for responding to the customer | 0.64 | 5.52 |
| | Tracking a customer's online behavior | 0.43 | 5.21 |
| | Predicting customer purchase behavior | 0.70 | 9.10 |
| | Estimating customer lifetime value | 0.55 | 5.92 |
| | Model simulation for developing the decision-making process | 0.77 | 9.13 |
| | Capturing customer engagement (customer journey) | 0.57 | 4.93 |
| | Using data-mining techniques | 0.77 | 8.51 |
| | Analysing and interpreting customer data | 0.60 | 7.86 |
| | Intelligent advice on marketing-strategy formulation | 0.78 | 7.83 |
| | Developing intelligent systems supporting marketing strategies | 0.80 | 8.62 |
| | Improving service quality and operational efficiency | 0.69 | 7.91 |
| | Respecting personal-data privacy | 0.67 | 8.61 |
| | Familiarity with customer behavioral patterns | 0.73 | 7.87 |
| | Developing customer-relationship-management (CRM) systems | 0.68 | 7.52 |
| | Understanding the customer-journey process | 0.52 | 4.34 |

To assess the measurement quality of the model's variables, convergent validity and construct (composite) reliability were examined. Convergent validity indicates the extent to which the indicators of each construct contribute to explaining the shared variance of that construct, and its assessment requires simultaneous attention to two main criteria. First, the factor loadings, which—as a precondition of convergent validity should be greater than 0.5 and, ideally, greater than 0.7. Second, the average variance extracted (AVE), which expresses the proportion of the variance of the observed variables explained by the latent variable and is calculated as the sum of the squared factor loadings divided by their number; the AVE value should exceed 0.5. The results obtained from the study's tables showed that the factor loadings of all five dimensions of the model exceeded 0.5 and that the AVE values for all dimensions were above the 0.5 threshold; it can therefore be concluded that the research variables possess a desirable convergent validity.

*Construct reliability (C.R.)*

Construct reliability is a criterion for determining the internal consistency of the observed variables (indicators); that is, if a large value is computed for it, all the measures consistently and coherently reflect a single subject. This reliability is expressed on the basis of the squared sum of the factor loadings of a construct. According to a rule of thumb, the composite-reliability value should be greater than 0.70 in order to claim that internal consistency exists. The C.R. value for all five dimensions exceeded 0.70, indicating the internal consistency of these dimensions.

*Examining the structural model of the research variables*

The principal question that arises is whether the proposed measurement model is a suitable instrument for assessing the effectiveness of AI with emphasis on consumer behavioral patterns in tourism institutions. To answer this question, the statistical indices and fit criteria of the model must be examined. The results of the analysis showed that the chi-square-to-degrees-of-freedom ratio was 2.33, which is below the threshold of 3; furthermore, the goodness-of-fit index (GFI) was 0.98 and the adjusted goodness-of-fit index (AGFI) was 0.95, both above 90% and at a desirable level. Given the model output at the significance level and the factor loadings of all the items, which are above 0.2, it can be concluded that the measurement model possesses sufficient adequacy and that all the items can be used to test the hypotheses. Figure 3 and 4 presents the model in standard estimation mode, and Figure 3 presents the model in significance (t-value) mode.

In this part, drawing on the interviews conducted in the first stage and employing a grounded-theory approach, the study identified its core phenomenon, namely, the initial model of AI effectiveness in tourism institutions. The data analysis then focused on examining the impact of this model with a focus on consumer behaviors; in the form of an independent study, the initial data were analyzed together with the grounded-theory method and the participation of a focus group. This process paid particular attention to the effectiveness of AI in interaction with consumers' behavioral patterns in tourism institutions, and in the initial stage the related process concepts were extracted and documented through qualitative analysis.

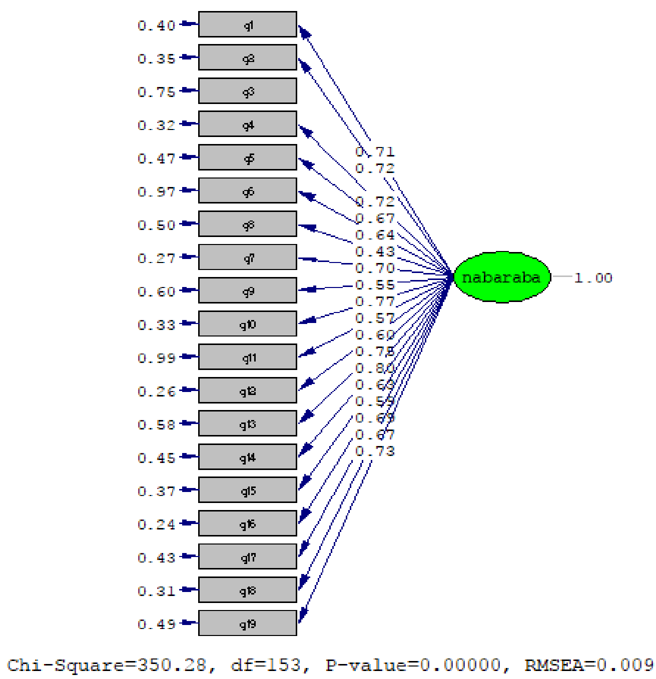


Figure 3: Measurement model in standard estimation mode (Source: LISREL output).

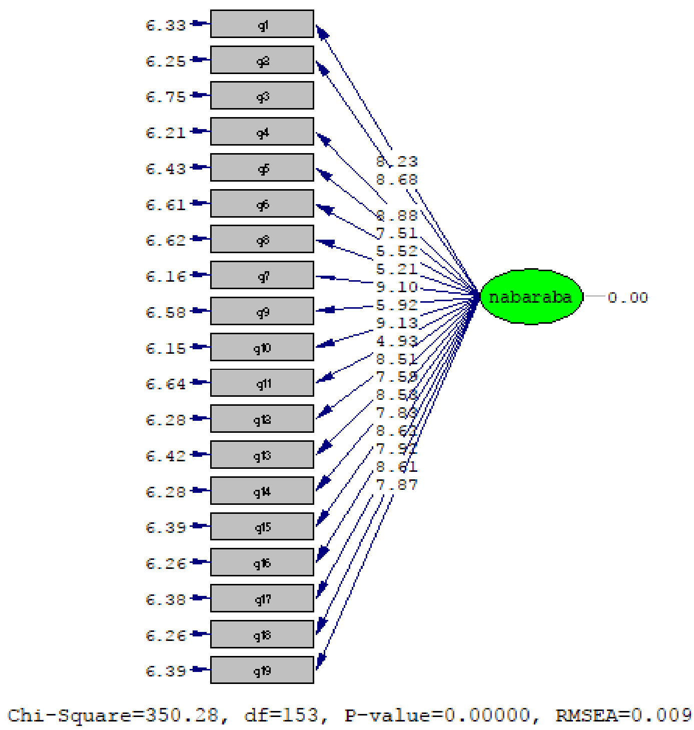


Figure 4: Measurement model in significance (t-value) mode (Source: LISREL output).

## DISCUSSION AND CONCLUSION

According to the findings obtained, the studies of Cook and Zubcsek (2017), Ng and Wakenshaw (2017), Balducci and Marinova (2018), and Kirkpatrick (2020) show that, given the repetitive and routine nature—yet high volume—of market data, AI can collect data efficiently at a large scale (Balducci & Marinova, 2018). Existing studies, such as those of Humphreys and Wang (2023), Berger et al. (2024), Dzyabura and Hauser (2021), Chintagunta et al. (2020), Liu et al. (2018), and Wedel and Kannan (2016), demonstrate various potential applications of intelligent AI for market analysis in areas such as automated text analysis for consumer research and the mapping of market structures for large retail assortments—using a neural-network language model and an analysis of the co-occurrence of products within the shopping basket (Wedel & Kannan, 2016).

The results of this study show that AI has a high capability for market segmentation and customer targeting. For example, search engines can target consumers by analyzing keywords and users' search histories, and social-media platforms make it possible to identify users' interests, content, and communication patterns so that advertisements can be delivered to new audiences with greater precision. In tourism marketing, positioning messages for attractive destinations place greater emphasis on the emotional aspects of users.

Solutions based on AI and machine learning are mainly employed to support brand management, marketing decisions, customer-behavior analysis, and brand and product development, although their role in creating customer equity is more limited. Nevertheless, the use of AI systems across various marketing domains is growing, and this trend is expected to continue as the technology advances. AI can also improve the management and development of new products by providing data-driven recommendations and options. In addition, precise data-driven marketing focusing on specific customer behaviors and predicting their needs and purchase intentions has been identified as an emerging field. This interdisciplinary field, by integrating concepts of marketing, AI/machine learning, and operations-research tools, makes possible accurate modelling in marketing decision-making and the optimization of processes. Finally, AI solutions have the capability to automatically analyses customer behavior, model brands, and determine consumer priorities on the basis of shared behavioral patterns. The results and discussions of this study show that AI, as a strategic instrument, can play a decisive role in improving marketing effectiveness and customer engagement in tourism institutions. The application of AI- and machine-learning-based technologies including big-data analysis, more precise advertising targeting, content personalization, and the prediction of customers' purchase behavior increases the efficiency of marketing activities and enhances the customer experience. AI can also facilitate customer-relationship management and enable the development of data-driven digital-marketing strategies, which helps tourism institutions increase their competitiveness in the market. Moreover, the results show that combining data-driven marketing with AI and advanced customer-behavior-analysis tools improves managerial decision-making, the identification of new market opportunities, and the optimization of product development. In light of these findings, the use of AI not only creates a competitive advantage but will, over time, become a strategic necessity for tourism institutions, enabling them to consolidate their position in the market and to deliver more precise and effective services to customers. This highlights the importance of developing and extensively employing AI technologies in designing tourism-marketing policies and strategies.

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