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The Impact of Statistical Data Analytics on Decision Making Process in Hotels

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Keywords

Statistical Data Analytics;
Decision Making Process;
Hotels.

Abstract

Understanding the role of statistical data analytics in enhancing the effectiveness of hotel decision making is a vital to improve operational performance and enhance customer satisfaction. Although previous studies have focused on explaining statistical data analytics, there is a lack in these studies that have focused on exploring the impact of statistical data analytics on decision making in the Egyptian hospitality contexts. Therefore, this research intends to uncover the impact of statistical data analytics dimensions (analytical skills, data quality, domain knowledge, big data, and tool sophistication) on the decision making process in hotels. The research methodology is analytical; the population consists of managers and employees from four- and five-star hotels in Hurghada and Sharm El-Sheikh, and the sample is randomly stratified. As a result, the researchers obtained data from 405 respondents. SPSS V. 22 was used to analyze the data and test the research hypotheses. The findings indicate that each dimension of statistical data analytics (analytical skills, data quality, domain knowledge, big data, and tool sophistication) has a statistically significant positive impact on the decision making process in hotels. The research recommends that hotels prioritize developing analytical skills through targeted training programs. This investment in human capital enables employees to interpret complex data and derive actionable insights, ultimately leading to better decision making. Moreover, this research contributes to filling the research gap in previous studies by investigating statistical data analytics and providing important practical implications for the hospitality sector.

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1. Introduction

Statistical data analytics has become a cornerstone for decision making process in the hotel industry, enhancing operational efficiency, optimizing revenue management, and improving customer satisfaction (Kitchens et al., 2018; Tuboalabo et al., 2024; Ibeh et al., 2024). Gudivada (2017) described data analytics as the integration of diverse data sources to enable innovation and strategic decisions, while Black (2023) defined statistics as the systematic collection, analysis, interpretation, presentation, and arrangement of data. Statistical data analytics transforms large volumes of data into valuable information that supports strategic planning and informed decision making process (Nguyen et al., 2020; Prakash et al., 2022). Moreover, effective data analytics competency includes deploying these tools, supported by data quality, domain knowledge, and analytical skills (Ghasemaghaei et al., 2018; Cao, 2017). Therefore, hotels leverage statistical models to forecast demand, optimize pricing strategies, and allocate resources effectively by analyzing historical booking data, market trends, and customer preferences (Jones & Brown, 2019).

Organizations that process and utilize information effectively show improved performance and operational outcomes (Mithas et al., 2011; Chen et al., 2014). Particularly in the hospitality industry, the decision making process is an essential managerial function that has a big impact on organizational effectiveness (Shet et al., 2021; Elgendy et al., 2022; Tuboalabo et al., 2024). Moreover, effective decision making process in the contemporary hospitality sector relies heavily on robust data management and analytics systems (Obi & Agwu, 2017; Lassoued et al., 2020). Therefore, decision making process ranges from routine responses to complex problem-solving scenarios (Solomon et al., 2006). Furthermore, the process of making decisions is characterized as a cognitive one in which people select from a range of possibilities in order to accomplish particular objectives (Adam & Humphreys, 2008; Eisenfuhr, 2011). In hotels, data-driven decision making is crucial for forecasting and operational optimization, allowing better anticipation of market trends, resource management, and pricing strategies (Wang & Zhang, 2018; Garcia et al., 2020). This approach fosters a culture of evidence-based decision making process and supports continuous improvement and adaptability (Chen et al., 2022; Haugland et al., 2007). Moreover, it ensures that decisions are well-informed and balanced (Hunink et al., 2014; Davidson et al., 2018; Elsawah et al., 2020).

Based on a pilot study conducted by the researchers, 50 questionnaire forms were distributed to professional hotel managers and experts. The analysis of the collected data revealed two significant knowledge gaps in the hospitality industry in Egypt that motivated the researchers to pursue this topic: (1) the direct impact of statistical data analytics on the quality of decision making process and operational outcomes within hotels is inadequately assessed. This gap necessitates further research to understand how these processes enhance decision making (Davidson et al., 2018; Elsawah et al., 2020); (2) there is a need for practical recommendations derived from empirical findings to address the benefits, challenges, implementation levels, and impact of statistical data analytics on decision making process in hotels in Egypt.
Thus, the research aims to investigate the impact of statistical data analytics on decision making process in hotels. Moreover, the research intents to achieve five objectives: (1) examine the effect of analytical skills on decision making process in hotels in Egypt; (2) explain the impact of data quality on decision making process in hotels in Egypt; (3) uncover the effect of domain knowledge on decision making

process in hotels in Egypt; (4) investigate the impact of big data on decision making process in hotels in Egypt; (5) explain the effect of tool sophistication on decision making process in hotels in Egypt.

2. Literature Review

2.1. Concept of Statistical Data Analytics

To fully appreciate the role of statistical data analytics, it is essential to understand the core concepts of statistics (Black, 2023). Nisbet et al. (2009) defined statistics as a mathematical science focused on the systematic collection, analysis, interpretation, presentation, and arrangement of data. Gudivada (2017) defined data analytics as the science of integrating diverse data sources to enable innovation and strategic decision making. Moreover, data analytics is described as a blend of art and science (Fitz-enz and Mattox, 2014; King, 2016 Mohamed et al., 2020).

2.2. Importance of Statistical Data Analytics in the Hospitality Industry

The significance of data analytics in the hotel industry cannot be overstated, Cooper (2006) and Rodrigues et al. (2020) emphasized that having timely and accurate data provides valuable insights into client behavior and market trends. Analytical tools range from basic spreadsheet programs like Microsoft Excel, suitable for smaller datasets, to advanced business intelligence tools and statistical computing and data visualization programming language such as R and Python, which handle larger datasets and complex analyses (Braun & Murdoch, 2021; Elhalid et al., 2023). According to Jones and Brown (2019), hotels leverage statistical models to forecast demand, optimize pricing strategies, and allocate resources effectively by analyzing historical booking data, market trends, and customer preferences. Effective data analytics competency includes deploying these tools, supported by data quality, domain knowledge, and analytical skills (Ghasemaghaei et al., 2018; Cao, 2017). Analytics tools improve customer relationship management, marketing strategies, financial performance, and operational efficiency (Urbinati et al., 2019; Selvan & Balasundaram, 2021). Additionally, data analytics facilitates understanding and adapting to market scenarios, driving business intelligence efforts (Cattaneo et al., 2018). The significance of data analytics in the hotel industry is highlighted by its ability to provide timely and accurate insights into client behavior and market trends, thereby enhancing performance and maintaining competitiveness (Cooper, 2006; Rodrigues et al., 2020). Phillips-Wren and Hoskisson (2015) and Notz et al. (2022) suggested that data analytics provides value through descriptive, predictive, and prescriptive methods, ultimately improving decision making process and organizational performance.

2.3. Statistical Data Analytics Dimensions

Data analytics dimensions are defined as a firm's ability to deploy and combine data analytics resources for rigorous and action-oriented analyses of data (Ghasemaghaei et al., 2018; Anton et al., 2023). The identification of data analytics competency is based on the interaction of data volume, data quality, analytical skills, domain knowledge, and tool sophistication (Cao, 2017; Persaud, 2021). This study uses Ghasemaghaei's (2018) framework to classify statistical data analytics dimensions into five areas: analytical skills, data quality, domain knowledge, big data, and tool sophistication.

A. Analytical Skills

Analytical skills give individuals the potential for effective data analysis (Ghasemaghaei et al., 2018; Dingelstad et al., 2022). Analytical skills are critical for generating business insights from data analytics, leading to higher firm decision making process performance (Wong, 2012; Gupta et al., 2020).

B. Data Quality

Data quality is defined as the quality of raw facts that reflect the characteristics of an entity or event (Detlor et al., 2013; Wook et al., 2021). Ghasemaghaei et al. (2018) identified four categories of data quality: intrinsic, contextual, representational, and accessibility. Intrinsic quality ensures accuracy and objectivity, contextual aspects aid in understanding, and accessibility enhances information quality. Data quality is crucial for decision making process and strategic planning, predating computing (Gudivada, 2017). Therefore, high data quality is essential for effective decision making process and competent data analytics (Hazen et al., 2014; Popovič et al., 2014; Li et al., 2022).

C. Domain Knowledge

Domain knowledge is a comprehensive understanding of the procedures, facts, and processes within a specific firm or industry, enabling analysts to effectively solve business problems (Sukumar & Ferrell, 2013; Abu-Salih, 2021). Analytical skills are critical for generating business insights from data analytics, leading to higher firm decision making process performance (Wong, 2012; Gupta et al., 2020).

D. Big Data

Data volume refers to the increasing availability of data that provides the impetus for the use of data analytics (Lycett, 2013; Ekbia et al., 2015; Iqbal et al., 2020). The concept of "big data" is often defined by the "three Vs": volume, variety, and velocity (Ghasemaghaei, 2021; Pramanik & Bandyopadhyay, 2023). Volume is the amount of data, which is increasing significantly due to the widespread use of smart devices and the digitization of content (Newell & Marabelli, 2015). Variety refers to the many sources and types of data, including structured, semi-structured, and unstructured data (Abbasi et al., 2016). Velocity is the speed at which data is created, which in the context of big data is almost real-time (Ertemel, 2015). Big data, focusing on volume, variety, and velocity, is a strategic resource for identifying patterns and providing insights for better business decisions (Fernández et al., 2014).

E. Tool Sophistication

Tools sophistication refers to the maturity and complexity of the analytical tools used within the organization (Ghasemaghaei et al., 2018; Król & Zdonek, 2020). Sophisticated analytical tools provide insights about past or current events, help firms understand past occurrences, provide accurate projections of future happenings, and recommend courses of action with likely outcomes; these tools enable firms to generate business insights and improve decision making process performance (Cao & Duan, 2015; Sapountzi & Psannis, 2018). Therefore, advanced analytical tools offer firms valuable insights into past events, accurate projections of future events, and recommended actions, thereby enhancing decision making process performance (Ghasemaghaei et al., 2018; Yalcin et al., 2022).

2.4. Concept of Decision Making Process

Decision making process is a pivotal aspect of managerial functions that underpins organizational effectiveness (Shet et al., 2021; Tuboalabo et al., 2024). Adam and Humphreys (2008) defined decision making as a cognitive process wherein an individual chooses an action plan from multiple options. Moreover, Eisenfuhr (2011) defined decision making as the process of selecting one of the many options for achieving a goal. The process of decision making involves selecting the most appropriate course of action from various alternatives to achieve desired goals (Mailool et al., 2020; Haseli et al., 2020). Additionally, Schoemaker and Russo (2018) stated that decision making is a process by which an individual, group, or organization builds decisions about what future activities to take given a set of goals and constraints on available resources.

2.5. Factors Influencing the Decision Making Process Quality

The quality of decision making process is critical to organizational success and hinges on the effective use of decision making process systems (Obi & Agwu, 2017; Lassoued et al., 2020). Chen et al. (2014) argued that effective decision making process is facilitated by robust information management capabilities, which in turn enhance organizational outcomes. Big data and business intelligence play crucial roles in improving decision quality by providing precise and actionable insights (Visinescu et al., 2017; Shamim et al., 2020). Decision making process quality is also measured by the decision-makers' satisfaction with achieving targeted results (Kaltoft et al., 2014). Factors affecting decision quality include data accuracy, the effectiveness of the data analysis process, the skills of data handlers, and the accessibility of data infrastructure (Ghasemaghaei & Calic, 2019). Collaboration in data analysis and the ability to interpret data contribute to improved decision quality (Hazen et al., 2014).

2.6. The Impact of Statistical Data Analytics on Decision Making Process

In today’s commercial landscape, the sheer volume and diversity of available data underscore the increasing necessity for managers and professionals to embrace data-driven decision making practices (Hossein, 2012). Statistical data analytics has emerged as a cornerstone in effective decision making process within modern organizations (Tuboalabo et al., 2024; Ibeh et al., 2024). Lepri et al. (2017) asserted that high-quality decisions are fundamentally driven by robust data. Elgendy and Elragal (2016) highlighted that the ability to comprehend and leverage data is a critical success factor, significantly influencing the quality of decisions made. Walker and Moran (2019) emphasized that data should be readily available to employees at all levels, fostering an environment where data can actively inform decisions. Kiron (2017) and Mikalef et al. (2020) argued that decision making process should integrate data analytics throughout the organization, promoting a culture where analytics guide strategic choices. Anderson (2015) described the analytics value chain as comprising essential stages: acquiring accurate data, ensuring its reliability, conducting thorough analysis, integrating insights into decision making, and translating these insights into actionable steps (see Figure 1).

Figure 1: Analytics Value Chain
Source: Anderson (2015)

Moreover, data-driven decision making process has emerged as a fundamental component of modern organizational strategies, particularly within the hospitality industry (Elgendy et al., 2022). Smith (2021) highlighted that the utilization of data and statistical analysis enables organizations to make well-informed decisions, enhance operational efficiency, and achieve superior outcomes. Earlier studies found that organizations using data-driven decision making had 5-6% higher production and efficiency than competitors (Brynjolfsson et al., 2011; Ashaari et al., 2021). Hotels are transitioning from intuition-based to data-driven methodologies, enabling them to use empirical information for more objective, strategic, and effective decision making process (Jones & Brown, 2019). Furthermore, decision making process is crucial in hospitality industry for informed, accurate forecasting, accountability, and continuous enhancement, providing a competitive advantage and successful business objectives (Singh, 2023). Employing data analytics allows hotels to remain ahead of market changes and make decisions that support their strategic objectives (Xiang et al., 2015). Hence, hotels using statistical data effectively communicate their decision making process, fostering a culture of openness and responsibility, demonstrating evidence-based decision making process rather than subjective opinions (Chen et al., 2022). The process may involve helping the individual formulate opinions, evaluate alternatives, participate in decision making, and implement the chosen decision (Hunink et al., 2014).

3. Research Methodology

The current research examines the relationship between independent and dependent variables, utilizing empirical data and numerical measures to confirm or reject hypotheses, with post-positivism paradigm deemed the most suitable philosophical worldview (Creswell, 2018; Shields et al., 2019). Moreover, reflecting a positivist perspective prevalent in business and management literature (Neuman, 2014; Creswell, 2018; Saunders et al., 2019). A deductive approach was utilized to investigate the impact of the statistical data analytics on decision making process in hotels in Egypt. Given the quantitative nature of this study, a quantitative research design was adopted, with a questionnaire chosen for its alignment with positivism, its suitability for quantitative research, and its cost and time efficiency.

3.1. Questionnaire Layout

The questionnaire, designed to test hypotheses and meet research objectives, comprises three sections with a total of 10 questions and 37 statements. The estimated completion time is 10 minutes based on piloting, an informed consent form and screening questions, confirming respondents are 18 years or over, their participation in the survey is voluntary and can terminate participation at any time.

Section (A): The first section comprises eight questions for asking about the respondents' backgrounds and characteristics namely (hotel location, hotel ownership, hotel classification, age, education level, hotel department, administrative level, and years of experience). All the questions are mandatory.

Section (B): The second section comprises two questions with 29 statements addressing the research constructs, which include Statistical Data Analytics in hotels (SDA) and Decision making process in hotels (DMP). A five-point Likert scale, ranging from strongly disagree to strongly agree, was adopted to measure both of the two questions (see Table 1).

Table 1: Questionnaire Layout

Parts	The Questionnaire Layout	No. of Questions	No. of Statements
1	Respondents' Backgrounds and Characteristics	8	1-8
2	The Measurement Items	2	29
	Total	**10**	**37**

Source: prepared by the researchers

3.2. Measurement Items

The research employed a total of 29 items from previous studies. Both variables included in the research, Statistical Data Analytics in hotels (SDA), and Decision Making Process in hotels (DMP) were measured using a five-point Likert scale (1=strongly disagree and 5=strongly agree). For the assessment of SDA, the researchers adopted 22 measurement items from Wang et al. (1996), Olson (2003), Tippins and Sohi (2003), Bassellier and Benbasat (2004), Sharda et al. (2014), and Ghasemaghaei et al. (2018), covering five dimensions: 3 items for Analytical Skills (AS), 6 items for Data Quality (DQ), 4 items for Domain Knowledge (DK), 3 items for Big data (BD), and 6 items for Tools Sophistication (TS). Moreover, for the assessment of DMP, the researchers adopted one-dimensional scale consisting of 7 measurement items from Jarupathirun (2007) and Ghasemaghaei et al. (2018). Items from all scales were slightly modified to fit the study’s context and were presented to respondents with different cover stories.

3.3. Research Population and Sample

The research seeks to identify the most effective sampling strategy while considering constraints related to cost, time, and resources. It highlights the necessity of defining the target sample based on specific factors and incorporates a pilot investigation to establish standards for selecting hotel brands (Mahmoud & Abdelaziz, 2024). The research specifically targets managers and employees in four- and five-star hotels located in Hurghada and Sharm El-Shaikh. To achieve this, stratified random sampling was employed, which involves dividing the population into distinct clusters (Acharya et al., 2013; Sharma, 2017). For large, infinite, or unknown population sizes, Cochran's formula (1977) is used to determine the sample size (Uakarn et al., 2021; Mahmoud & Abdelaziz, 2024). This formula provides a statistical basis for estimating the number of respondents required to obtain reliable results (Hasan & Kumar, 2024), as illustrated (see Figure 2):

$$n = \frac{Z^2 p(1 - p)}{e^2}$$

$$n = \frac{(1.96)^2 \times 0.5 \times (1 - 0.5)}{(0.05)^2}$$

$$n = \frac{3.8414 \times 0.5 \times 0.5}{0.0025} = 384.16$$

Figure 2: Cochran's formula

Source: Uakarn (2021); Mahmoud and Abdelaziz (2024)

The sample size calculation used the formula incorporating a confidence level of 95% (Z = 1.96), an error proportion of 0.05 (e), and a probability of 50% (p). Applying this formula, the ideal sample size (n) was determined to be approximately 385 respondents. However, collecting data from more respondents than the calculated sample size can enhance the robustness of the study and improve the precision of the estimates (Bryman, 2016; Saunders et al., 2019). As result, the researchers were able to distribute and collect data from (405) respondents than initially estimated.

3.4. Data Collection Procedures

The research employed a dual approach to data collection, utilizing both web-based and paper-based questionnaires. Web-based questionnaires, facilitated by Google Forms, provided automated data collection and incorporated visual elements such as images, graphs, and videos. These features enhanced data quality and allowed for the exclusion of unqualified respondents (Roth, 2006; Mei et al., 2014; Abdelaziz et al., 2024). Conversely, paper-based questionnaires facilitated tangible communication and were perceived as more anonymous, which often resulted in higher response rates (Murdoch et al., 2014; Ebert et al., 2018). By integrating both methods, the researchers aimed to ensure a comprehensive and high-quality data collection process. The research targeted a sample of 405 managers and employees of four- and five-star hotels in Hurghada and Sharm El-Shaikh, Egypt. Hurghada and Sharm El-Shaikh were selected for their diverse hotel types and pivotal role in Egypt's tourism, providing a representative and reliable sample for studying data-driven decision making for improving operational efficiency and strategic planning. Moreover, their high-quality hotels ensure consistency and validity in the data collected.

Data collection occurred over three months, from January to March 2024. The questionnaire was initially developed in English and subsequently translated into Arabic. The web-based survey was distributed through invitation link (https://forms.gle/YEPV65g5RC6kK1qHA) and messaged the respondents through their email addresses. This provided various functionalities to tailor the survey to specific objectives. A total of 211 respondents completed the online survey, resulted in a 100% response rate for valid questionnaires. Additionally, 250 paper-based questionnaires were distributed, with 194 valid responses, resulting in a response rate of 77.6% (see Table 2).

Table 2: Number of Questionnaire Forms and the Response Rate

Questionnaire Types	N. of Forms	N. of The Valid Forms	N. of invalid Forms	Response Rate
Hard copy	250	194	56	77.6 %
Online	211	211	-	100 %
Total	**461**	**405**	**56**	**87.6 %**

Source: prepared by the researchers.

3.5. Data Analysis Techniques

The data was processed and analyzed, which involved editing, coding, grouping, tabulating, and performing statistical calculations to ensure the formulation of conclusions based on questionnaire responses. In the data analysis phase of the current research, the Statistical Package for the Social Sciences (SPSS) version 22 was used to compute frequencies, percentages, means, standard deviations, and regression tests between variables.

3.6. Data Validity and Reliability

3.6.1. Data Validity

Validity refers to the extent to which a measurement instrument accurately reflects the intended outcome and can be categorized into several types, including concurrent, content, internal, external, criterion-related, concept, and face validity (Surucu & Maslakci, 2020; Noby et al., 2021; Abdelaziz et al., 2024). In the current research, face validity was employed to evaluate the validity of the data gathering techniques. Hotel managers and professional academic in hospitality industry reviewed the questionnaire and provided feedback, leading to modifications that enhanced the instrument. Content validity was established as all measurement items were adapted from prior research with confirmed content validity. Moreover, a pilot study was conducted by the researchers, 50 questionnaire forms were distributed to professional hotel managers and experts. Additionally, exploratory validity was assessed through factor analysis, which is instrumental in identifying underlying factors within a set of variables and understanding the data structure (Beavers et al., 2019). According to Matsunaga (2010), items with a factor loading of 0.40 or higher are retained, while those with loadings above 0.60 are considered practically relevant (Fabrigar & Wegener, 2011). The factor analysis results indicated that the extraction values for all variables and dimensions exceeded the recommended benchmark of 0.60 (see Table 3), suggesting that the latent variables are statistically valid and significantly contribute to the study's constructs.

Table 3: Factor Analysis of Study Components

S	Communalities	Initial	Extraction
1	Our data analytics users are knowledgeable when it comes to utilizing such tools.	1.000	0.705
2	Our data analytics users possess a high degree of data Analytics expertise.	1.000	0.705
3	Our data analytics users are skilled at using data analytics tools.	1.000	0.706
4	Data used in data analytics is reliable	1.000	0.811
5	Data used in data analytics has an appropriate level of details	1.000	0.842
6	Data used in data analytics is secure	1.000	0.897
7	Data used in data analytics is timely	1.000	0.781
8	Data used in data analytics is relevant to the task at hand	1.000	0.807
9	Data used in data analytics is accurate	1.000	0.876
10	There is a high level of knowledge of the external environment (government, competitors, suppliers, and customers)	1.000	0.805
11	There is a high level of knowledge of the hotels goals and Objectives	1.000	0.875
12	There is a high level of knowledge of the hotel capabilities.	1.000	0.848
13	There is a high level of knowledge of the Key factors that must go right for the hotel to succeed	1.000	0.803
14	My hotel processes high volumes of data	1.000	0.823
15	My hotel processes real time data.	1.000	0.809
16	My hotel processes different types of data	1.000	0.835
17	My hotel uses tools that provide information processing and retrieval capabilities	1.000	0.688
18	My hotel uses tools that perform modeling and simulation	1.000	0.776
19	My hotel uses tools that perform natural language analytics (extracting information from unstructured	1.000	0.774

	sources such as social media)		
20	My hotel uses tools that provide real-time insight	1.000	0.782
21	My hotel uses tools that identify problems	1.000	0.769
22	My hotel uses tools that evaluate different alternatives.	1.000	0.770
	Overall Statistical Data Analytics in Hotels	**1.000**	**0.998**
1	In my hotel, decision outcomes are often accurate	1.000	0.651
2	In my hotel, decision outcomes are often correct	1.000	0.699
3	In my hotel, decision outcomes are often precise	1.000	0.670
4	In my hotel, decision outcomes are often flawless	1.000	0.645
5	In my hotel, decision outcomes are often error-free	1.000	0.656
6	In my hotel, decision outcomes are often reliable	1.000	0.671
7	In my hotel, the time to arrive at decisions is Fast	1.000	0.736
	Overall Decision Making Process in Hotels	**1.000**	**1.000**

Additionally, the Kaiser-Meyer-Olkin (KMO) test was employed to evaluate the suitability of the data for factor analysis by assessing sample size and sampling adequacy for each variable in the model (Shrestha, 2021). The KMO value ranges from 0 to 1.0, with values between 0.8 and 1.0 indicating that the sampling is adequate. Values between 0.7 and 0.79 are considered middling, while those between 0.6 and 0.69 are deemed mediocre (Pituch & Stevens, 2015). The KMO measure resulted in a value of 0.940, suggesting that the variables in the dataset share a substantial amount of common variance and are suitable for factor analysis (see Table 4).

Table 4: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.940
Bartlett's Test of Sphericity	Approx. Chi-Square	16365.131
	Df	1225
	Sig.	0.000

3.6.2. Data Reliability

A reliability test is essential in research to ensure the consistency and stability of measurements across questionnaires, thereby instilling confidence in the instrument's results over time (Surucu & Maslakci, 2020). This study employed Cronbach's alpha to assess the reliability of the research variables. According to Wetzels et al. (2009) and Hair et al. (2019), a Cronbach's alpha (α) value exceeding 0.7 indicates acceptable internal reliability. The results of the reliability test show Cronbach's alpha values ranging from 0.897 to 0.957, reflecting strong internal reliability. Additionally, the validity coefficient, also known as commonalities or squared multiple effects, is crucial for evaluating the reliability of the research. Bandalos and Finney (2018) suggest that a validity coefficient close to 1 signifies that the common factors identified through factor analysis account for a substantial amount of variance in each variable. The findings show that the common factors explain approximately 95% of the variance, with validity coefficients of 0.962 for all components (see Table 5).

Table 5: Cronbach's Alpha Value of the study components

S	Variables	N	Cronbach's Alpha Value	Validity Coefficient *
4	Statistical Data Analytics	22	0.957	0.978
5	Decision Making Process	7	0.897	0.947
	Total	**29**	**0.927**	**0.962**

* Validity coefficient = √ Reliability coefficient.

4. Results

4.1. Respondents' Backgrounds and Characteristics

The researchers adopted the descriptive analysis for the respondents' backgrounds and characteristics, which includes (hotel location, hotel ownership, hotel classification, age, education level, hotel department, administrative level, and years of experience).

Table 6: Respondents' Backgrounds and Characteristics

Variable	Frequency	Percentage (%)
Hotel Location		
Hurghada	274	67.7
Sharm El Sheikh	131	32.3
Total	**405**	**100.0**
Hotel Ownership		
Independent hotel	197	48.6
Chain hotel	208	51.4
Total	**405**	**100.0**
Hotel Classification		
Five-star hotel	295	72.8
Four-star hotel	110	27.2
Total	**405**	**100.0**
Age		
Less than 25 years	160	39.5
25-35 years	169	41.7
36-45 years	62	15.3
More than 45 years	14	3.5
Total	**405**	**100.0**
Education Level		
Technical education	54	13.3
Secondary education	55	13.6
University education	219	54.1
Postgraduate (Master – Ph.D.)	77	19.0
Total	**405**	**100.0**
Hotel Department		
Human Resources department	99	24.4
Front office department	110	27.2
Food & beverage department	148	36.5
Marketing department	48	11.9
Total	**405**	**100.0**
Administrative Level		
Hotel Manager	20	4.9
Assistant Manager	76	18.8
Department Manager	193	47.7
Department Staff	116	28.6
Total	**405**	**100.0**
Years of Experience		
Less than 5years	193	47.7
From 5-less than10	140	34.6
From 10-15	40	9.9
More than 15 years	32	7.9
Total	**405**	**100.0**

As declared in table (6), the majority of respondents are from Hurghada, representing 67.7%, while from Sharm El Sheikh accounting for 32.3%. The sample is fairly evenly divided between independent hotels, comprising 48.6%, and chain hotels, making up 51.4%. Furthermore, the classification of hotels reveals a predominance of five-star hotels, at 72.8%, in contrast to four-star hotels, which constitute 27.2%. In terms of age distribution, significant proportions fall within less than 25 years and 25 to 35 years, representing 39.5% and 41.7%, respectively. Educational backgrounds vary, with 54.1% of respondents holding university degrees and 19% possessing postgraduate degrees. Additionally, departmental distribution showed that food and beverage department is the most represented, at 36.5%, followed by the front office department at 27.2%, human resources department at 24.4%, and marketing at 11.9%. Furthermore, the distribution of employees across various administrative levels in the hotel reflects a hierarchical structure where the majority of employees occupy the role of department manager for 47.7% of the total staff. Assistant managers make up 18.8%, while department staff constitutes 28.6%, while hotel managers represent the least group at 4.9%. Regarding experience, nearly half of the respondents have less than five years of experience, representing 47.7%, while 34.6% have between five and ten years, and 17.8% have more than ten years.

4.2. Descriptive Analysis for the Study Variables

In this section, descriptive results are presented regarding the study variables (statistical data analytics and decision making process). Moreover, the individual aggregate score indicates their attitude towards the items as follows: Scores below 1.8 indicate "strongly disagree," 1.8 to less than 2.6 indicate "disagree," 2.6 to less than 3.4 indicate "neutral," 3.4 to less than 4.2 indicate "agree," and 4.2 to 5 indicate "strongly agree" (Abdelaziz et al., 2024).

4.2.1. Descriptive Statistics for the Statistical Data Analytics

The objective of this variable was to assess the statistical data analytics in hotels, as illustrated in the table below:

Table 7: The Assessment of Statistical Data Analytics

Statements		M	SD	Rank	Attitude
Analytical Skills	Our data analytics users are knowledgeable when it comes to utilizing such tools.	3.74	1.003	2	Agree
	Our data analytics users possess a high degree of data Analytics expertise.	3.71	.989	3	Agree
	Our data analytics users are skilled at using data analytics tools.	3.79	.955	1	Agree
Overall mean		**3.7481**	**.86599**		**Agree**
Data Quality	Data used in data analytics is reliable	3.80	1.022	6	Agree
	Data used in data analytics has an appropriate level of details	3.82	.970	3	Agree
	Data used in data analytics is secure	3.82	1.025	5	Agree
	Data used in data analytics is timely	3.74	.977	2	Agree
	Data used in data analytics is relevant to the task at hand	3.87	.970	1	Agree
	Data used in data analytics is accurate	3.82	.945	4	Agree
Overall mean		**3.8107**	**.83298**		**Agree**
Domain	There is a high level of knowledge of the external environment	3.84	1.023	4	Agree

Knowledge	(government, competitors, suppliers, and customers)				
	There is a high level of knowledge of the hotels goals and Objectives	3.87	.896	3	Agree
	There is a high level of knowledge of the hotel capabilities.	3.89	.993	2	Agree
	There is a high level of knowledge of the Key factors that must go right for the hotel to succeed	3.90	.933	1	Agree
	Overall mean	**3.8759**	**.82403**		**Agree**
Big Data	My hotel processes high volumes of data	3.70	1.016	3	Agree
	My hotel processes real time data.	3.73	.954	2	Agree
	My hotel processes different types of data	3.82	.938	1	Agree
	Overall mean	**3.7531**	**.84298**		**Agree**
Tools Sophistication	My hotel uses tools that provide information processing and retrieval capabilities	3.73	.982	5	Agree
	My hotel uses tools that perform modeling and simulation	3.80	1.012	3	Agree
	My hotel uses tools that perform natural language analytics (extracting information from unstructured sources such as social media)	3.73	.990	6	Agree
	My hotel uses tools that provide real-time insight	3.76	.961	4	Agree
	My hotel uses tools that identify problems	3.80	.940	2	Agree
	My hotel uses tools that evaluate different alternatives.	3.87	.966	1	Agree
	Overall mean	**3.7798**	**.79906**		**Agree**
Overall Mean of Statistical Data Analytics		**3.7935**	**.70796**		**Agree**

M = Mean. SD = Standard Deviation
Source: prepared by the researchers

As illustrated in table (7), the assessment of data analytics in hotels reveals a generally positive attitude towards the dimensions of analytical skills, data quality, domain knowledge, big data, and tool sophistication, with overall means indicating agreement across all dimensions. Specifically, hotels demonstrate a high level of user knowledge and skill in utilizing data analytics tools, as well as confidence in the reliability, relevance, and accuracy of the data utilized. Furthermore, there is a strong recognition of the importance of domain knowledge concerning external factors and key operational objectives. Additionally, hotels are seen to process various types of data and utilize sophisticated tools for modeling, real-time insights, and problem identification. Specifically, hotels demonstrate a high level of user knowledge and skill in utilizing data analytics tools, as well as confidence in the reliability, relevance, and accuracy of the data utilized. This finding aligned with research by Wong (2012) and Sukumar & Ferrell (2013), which emphasizes the importance of analytical skills and domain knowledge in effective data analysis. Furthermore, hotels process various types of data and utilize sophisticated tools for modeling, real-time insights, and problem identification on the impact of tool sophistication on decision making process performance (Davenport, 2014; Ghasemaghaei et al., 2018). Additionally, the importance of data quality and trust in data sources is highlighted, consistent with the findings of Hazen et al. (2014) and Lycett (2013), who stress the critical role of high-quality data in deriving valuable business insights.

4.2.2. Descriptive Statistics for Decision Making Process

The objective of this variable was to evaluate the decision making process in hotels, as illustrated in the table below:

Table 8: The Assessment of Decision Making Process

Statements	M	SD	Rank	Attitude
In my hotel, decision outcomes are often accurate	3.81	.944	4	Agree
In my hotel, decision outcomes are often correct	3.80	.822	5	Agree
In my hotel, decision outcomes are often precise	3.78	.947	6	Agree
In my hotel, decision outcomes are often flawless	3.73	.997	7	Agree
In my hotel, decision outcomes are often error-free	3.82	.927	3	Agree
In my hotel, decision outcomes are often reliable	3.85	.988	2	Agree
In my hotel, the time to arrive at decisions is Fast	3.89	.896	1	Agree
Overall Mean of Decision Making Process	**3.8120**	**.73380**		**Agree**

M = Mean. SD = Standard Deviation
Source: prepared by the researchers

As clarified in table (8), the evaluation of the decision making process in hotels indicates a positive perception among respondents regarding the accuracy, reliability, and speed of decision outcomes, with an overall mean score reflecting agreement across all statements. Notably, the highest-ranking statement pertains to the rapidity of decision making, suggesting that hotels prioritize efficiency in reaching conclusions. Additionally, respondents express confidence in the reliability and error-free nature of decisions, with scores indicating that outcomes are frequently deemed accurate and precise. This result aligns with previous research highlighting the significance of decision making in the hotel industry. The ability to forecast and adapt based on historical data enhances operational efficiency and customer satisfaction (Wang & Zhang, 2018; Garcia et al., 2020). Furthermore, data-driven decision making fosters accountability and transparency, reinforcing the importance of grounding decisions in reliable information (Chen et al., 2022). Moreover, this prioritization of efficiency aligned with the conceptualization of decision making process as a critical managerial function (Forman & Selly, 2001). Decision making, characterized as a process of selecting among alternatives to achieve objectives (Adam, 2008; Eisenfuhr, 2011), is central to management practice and involves both automatic and in-depth problem-solving approaches (Solomon et al., 2006; Schoemaker & Russo, 2016).

4.3. Test of Hypothesis

Based on analysis of the literature, the researchers developed the hypothesized model, which consist of one main hypothesis, divided into five sub-hypotheses to assess the impact of statistical data analytics dimensions (analytical skills, data quality, domain knowledge, big data, and tool sophistication) on the decision making process in hotels in Egypt (see figure 3). The hypotheses are framed in a null format, positing that there is no statistically significant effect of these variables on decision making process.

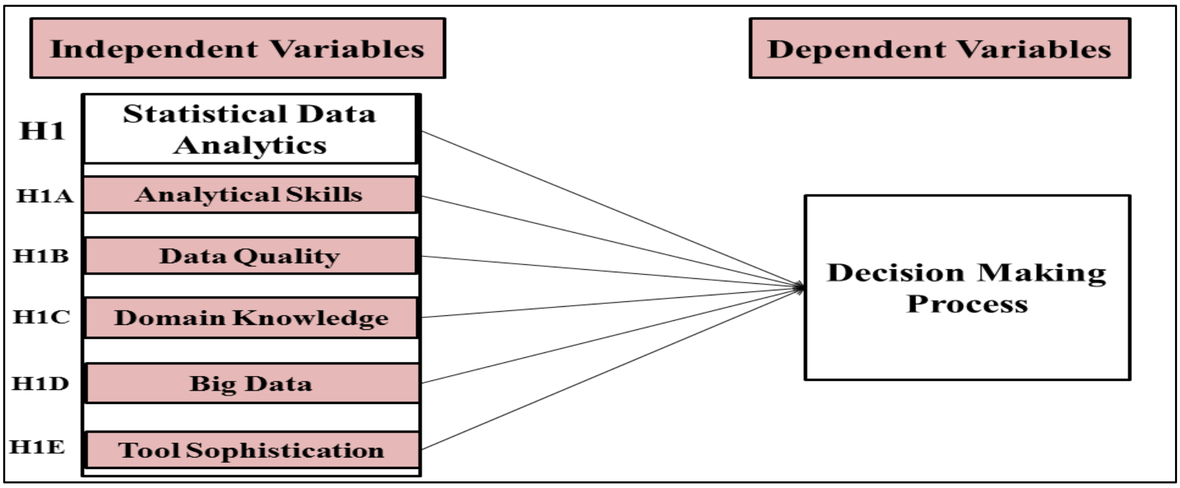

Figure 3: Hypothesized Model

To test H_1, the researchers adopt the linear regression coefficients to test the impact of statistical data analytics on decision making process. The results presented as follows:

Table 9: Linear Regression Coefficients for the Impact of Statistical Data Analytics on Decision Making Process

Variables		Decision Making Process
Statistical Data Analytics	Pearson Effect (R)	0.643*
	Sig. (2-tailed)	0.000
	R Square	0.413
	Constant (α)	1.284
	B	0.666
	N	**405**

As illustrated in table (9), there is a significant and positive impact of statistical data analytics on decision making process effectiveness in hotels, with a Pearson effect coefficient of 0.643, an R-squared value of 0.413, and a P-value of 0.000 indicating substantial impact. The regression equation indicates that enhancing data analytics capabilities improves decision making process effectiveness by 0.666 units and concludes that enhancing data analytics capabilities is likely to improve decision making process in hotel management, thereby providing a compelling rationale for investment in data analytics systems and training. Based on the findings, h_1 was not accepted. Therefore, the researchers rejected the null hypothesis and accepted the alternative hypothesis. Hence, there is a statistically significant effect of statistical data analytics on decision making. This result concurred with Ghasemaghaei et al. (2018) that enhancing data analytics capabilities is likely to improve the decision making process in hotel management, underscoring the importance of investing in data analytics systems and training. Moreover, Wu et al. (2016) argued that the effectiveness of data analytics depends on various factors, including data quality and analytical skills.

To test H_{1A}, the researchers adopt the linear regression coefficients to test the impact of analytical skills on decision making process. The results presented as follows:

Table 10: Linear Regression Coefficients for the Impact of Analytical Skills on Decision Making Process

Variables		Decision Making Process
Analytical skills	Pearson Effect (R)	0.502*
	Sig. (2-tailed)	0.000
	R Square	0.252
	Constant (α)	2.219
	B	0.425
	N	**405**

As shown in table (10), there is a significant and positive impact of analytical skills on decision making process, with a Pearson effect coefficient (R) of 0.502 and a P-value of 0.000. This indicates a strong relationship where higher levels of analytical skills are associated with more effective decision making process in hotels. The R-squared value of 0.252 suggests that approximately 25.2% of the variance in decision making process can be explained by variations in analytical skills. The regression equation includes a constant (α) of 2.219 and a coefficient (b) of 0.425 for analytical skills, indicating that for every unit increase in analytical skills, decision making effectiveness increases by 0.425 units. Based on the findings, H_{1A} was not accepted. Therefore, the researchers rejected the null hypothesis and accepted the alternative hypothesis. Hence, there is a statistically significant effect of analytical skills on decision making process. This is consistent with Draganidis and Mentzas (2006), who emphasized the importance of combining domain knowledge with analytical skills for effective data analysis. Wong (2012) also noted that having the right talent and skills is crucial for deriving valuable business insights. Conversely, Ghasemaghaei et al. (2018) highlighted that inadequate analytical skills can lead to delays and errors, reinforcing the need for strategic investments in staff training.

To test H_{1B}, the researchers adopt the linear regression coefficients to test the impact of data quality on decision making process. The results presented as follows:

Table 11: Linear Regression Coefficients for the Impact of Data Quality on Decision Making Process

Variables		Decision Making Process
Data Quality	Pearson Effect (R)	0.558*
	Sig. (2-tailed)	0.000
	R Square	0.312
	Constant (α)	1.937
	B	0.492
	N	**405**

As shown in table (11), there is a significant and positive impact of data quality on decision making process, with a Pearson effect coefficient (R) of 0.558 and a p-value of 0.000. This indicates a moderate to strong relationship, suggesting that higher data quality is associated with improved decision making process in hotels. The R-squared value of 0.312 implies that approximately 31.2% of the variance in decision making process can be attributed to variations in data quality. The regression equation includes a constant (α) of 1.937 and a coefficient (B) of 0.492 for data quality, indicating that for every unit increase in data quality, decision making process effectiveness increases by 0.492 units. These highlight the critical role that data quality plays in enhancing decision making process within the hotel sector. Based on the findings, H_{1B} was not accepted. Therefore, the researchers rejected the null hypothesis and accepted the alternative hypothesis. Hence, there is a statistically significant effect of data quality on decision making process. Lycett (2013) and Popovič et al. (2014) supported this by emphasizing that the ultimate value of data analytics is contingent on the quality of the data used, reinforcing the need for high-quality data to improve decision making performance.

To test H_{1C}, the researchers adopt the linear regression coefficients to test the impact of domain knowledge on decision making process. The results presented as follows:

Table 12: Linear Regression Coefficients for the Impact of Domain Knowledge on Decision Making Process

Variables		Decision Making Process
Domain Knowledge	Pearson Effect (R)	0.492*
	Sig. (2-tailed)	0.000
	R Square	0. 242
	Constant (α)	2.114
	B	0.438
	N	**405**

As seen in table (12), there is a significant and positive impact of domain knowledge on decision making process, with a Pearson effect coefficient of 0.492 and a p-value of 0.000. This suggests a moderate relationship, signifying that enhanced domain knowledge is associated with improved decision making process capabilities in the hotel sector. The R-squared value of 0.242 indicates that approximately 24.2% of the variance in decision making process can be explained by variations in domain knowledge. The regression equation features a constant (α) of 2.114 and a coefficient (B) of 0.438 for domain knowledge, implying that for each unit increase in domain knowledge, decision making process effectiveness increases by 0.438 units. These findings support the importance of domain knowledge in bolstering decision making process within hotels. Based on the findings, H_{1C} was not accepted. Therefore, the researchers rejected the null hypothesis and accepted the alternative hypothesis. Hence, there is a statistically significant effect of domain knowledge on decision making process. This underscored previous research by Sukumar and Ferrell (2013) highlighted that deep domain knowledge enables better identification of key attributes and more effective problem-solving. Wong (2012) further supported this by stressing that the right talent and skills are essential for generating valuable insights.

To test H_{1D}, the researchers adopt the linear regression coefficients to test the impact of big data on decision making process. The results presented as follows:

Table 13: Linear Regression Coefficients for the Impact of Big Data on Decision Making Process

Variables		Decision Making Process
Big Data	Pearson Effect (R)	0.545*
	Sig. (2-tailed)	0.000
	R Square	0.297
	Constant (α)	2.031
	B	0.474
	N	**405**

As clarified in table (13), there is a significant and positive impact of big data on decision making process, with a Pearson effect coefficient (R) of 0.545 and a p-value of 0.000. This indicates a moderate to strong relationship, suggesting that larger data volumes are positively associated with enhanced decision making process capabilities in the hotel industry. The R-squared value of 0.297 signifies that approximately 29.7% of the variance in decision making process can be attributed to the big data. The regression model presents a constant (α) of 2.031 and a coefficient (B) of 0.474, indicating that for each unit increase in the big data, decision making process increases by 0.474 units. These findings support the critical role that managing large datasets plays in improving decision making process within hotels. Based on the findings, H_{1D} was not accepted. Therefore, the researchers rejected the null hypothesis and accepted the alternative hypothesis. Hence, there is a statistically significant effect of big data on decision making process. This is in consistent with White (2012) and Wamba et al. (2015), who addressed the significance of data veracity and the reliability of data sources. Although Chen et al. (2015), Russom (2011), and Ward and Barker (2013) focused on the core characteristics of big data (volume, variety, and velocity), Lam et al. (2017) emphasized the importance of veracity and value in enhancing accuracy verification.

To test H_{1E}, the researchers adopt the linear regression coefficients to test the impact of tool sophistication on decision making process. The results presented as follows:

Table 14: Linear Regression Coefficients for the Impact of Tool Sophistication on Decision Making Process

Variables		Decision Making Process
Tool Sophistication	Pearson Effect (R)	0.640*
	Sig. (2-tailed)	0.000
	R Square	0.410
	Constant (α)	1.590
	B	0.588
	N	**405**

As seen in table (14), there is a significant and positive impact of tool sophistication on decision making process, with a Pearson effect coefficient (R) of 0.640 and a p-value of 0.000. This strong effect implies that enhanced tool sophistication is positively related to improved decision making process capabilities within hotels. The R-squared value of 0.410 suggests that approximately 41.0% of the variance in decision making process can be explained by the sophistication of the tools employed. The regression model presents a constant (α) of 1.590 and a coefficient (B) of 0.588, indicating that each unit increase in tool sophistication is associated with a 0.588 unit increase in decision making process. These results support the importance of investing in advanced analytical tools and technologies. Based on the findings, H_{1D} was not accepted. Therefore, the researchers rejected the null hypothesis and accepted the alternative hypothesis. Hence, there is a statistically significant effect of tool sophistication on decision making process. This aligned with Raymond and Paré (1992), who emphasized the role of tool sophistication in reflecting an organization's technological maturity, and Chwelos et al. (2001), who noted its impact on analytical depth. Davenport (2014) demonstrated that advanced tools enable detailed analysis and strategic forecasting, supporting the study’s conclusion that investing in advanced tools is crucial for improving decision making process and operational performance.

Based on the results provided, an empirical model can be designed to illustrate the impact of statistical data analytics dimensions (analytical skills, domain knowledge, data quality, big data, and tool sophistication) on decision making process in hotels (see Figure 4).

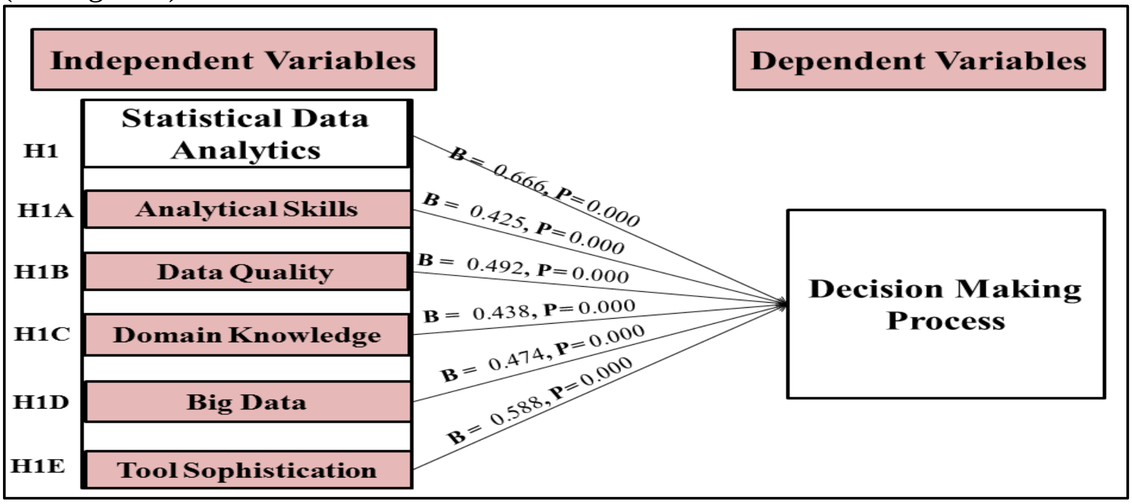

Figure 4: Empirical Model

4.4. Test Hypotheses Summary

The next table indicates to what extent the hypothesis of the research are accepted.

Table 15: Summary of Tested Hypotheses

No.	Research Hypotheses	Testing
H_1	*There is no statistically significant effect of statistical data analytics on decision making process.*	**Rejected**
H_{1A}	*There is no statistically significant effect of analytical skills on decision making process.*	**Rejected**
H_{1B}	*There is no statistically significant effect of data quality on decision making process.*	**Rejected**
H_{1C}	*There is no statistically significant effect of domain knowledge on decision making process.*	**Rejected**
H_{1D}	*There is no statistically significant effect of big data on decision making process.*	**Rejected**
H_{1E}	*There is no statistically significant effect of tool sophistication on decision making process*	**Rejected**

5. Discussion

The findings of this study illuminate the pivotal role of statistical data analytics in enhancing decision making process effectiveness within the hotel industry. The overall positive perception regarding analytical skills, data quality, domain knowledge, big data, and tool sophistication underscores the recognition of these factors' importance in fostering data-driven decision making. However, the results also highlight areas needing improvement, particularly in training and data integration processes, to fully leverage analytics capabilities. The strong belief in the accuracy, reliability, and speed of decisions made within hotels underscores the critical importance of swift decision making process for maintaining competitiveness. Supporting these processes with robust data analytics capabilities is essential for enhancing both operational performance and customer satisfaction.

The hypothesis testing reveals significant insights into the factors influencing decision making process in hotels, underscoring the importance of statistical data analytics and its associated variables. The analysis demonstrates that each examined dimension (analytical skills, data quality, domain knowledge, big data, and tool sophistication) has a statistically significant positive effect on decision making process. Specifically, the strong positive effect between overall statistical data analytics capabilities and decision making process indicates that enhancing these capabilities can significantly improve decision making process. Moreover, improving analytical skills is shown to be crucial, suggesting that better analytical skills for the decision making process. The high quality data indicate that maintaining high standards of data accuracy, consistency, and reliability is paramount. Furthermore, domain knowledge highlights the importance of industry expertise in supporting better decision making process. Additionally, the effect between the big data and decision making process indicates that larger datasets are associated with improved decision making process. This suggests that hotels should invest in advanced data management systems capable of handling large volumes of data efficiently. Finally, the strong effect between tool sophistication and decision making process highlights the significant impact of using advanced analytical tools, which account for 41.0% of the variance.

6. Conclusion and Practical Implications

The findings from this study underscore the critical role of statistical data analytics in enhancing decision making process in hotels. To capitalize on these insights, hotels should prioritize the development of analytical skills through targeted training programs. This investment in human capital will empower staff to interpret complex data and derive actionable insights, ultimately leading to better decisions. The significant positive effect between analytical skills and decision making process highlights that improving analytical skills can account for 25.2% of the variance in decision making process. Additionally, ensuring the quality of data is paramount. Hotels should implement rigorous data governance frameworks to maintain high standards of data accuracy, consistency, and reliability. The effect between data quality and decision making process indicates that high-quality data explains 31.2% of the variance in decision making. By prioritizing data quality, hotels can enhance the reliability of their decisions, thereby improving overall performance. Fostering domain knowledge within the industry is also essential. By promoting continuous learning and staying abreast of industry trends and best practices, hotel staff can leverage their expertise to make informed decisions. The effect between domain knowledge and decision making process emphasizes that deeper industry knowledge supports better decision-making, explaining 24.2% of the variance. Thus, investing in the continuous education of employees will lead to more informed and effective decisions.

Moreover, embracing big data is another critical step for hotels. Investing in advanced data management systems that can handle large volumes of data efficiently will enable the extraction of valuable insights from extensive datasets. The positive effect between the big data and decision making process effectiveness indicates that larger datasets are associated with improved decision making process, explaining 29.7% of the variance. By leveraging big data, hotels can gain a competitive edge through more comprehensive and informed decision making process. Lastly, the adoption of sophisticated analytical tools is vital. Hotels should explore and integrate state-of-the-art analytics platforms that offer robust functionalities and user-friendly interfaces. The strong effect between tool sophistication and decision making process underscores that more sophisticated analytical tools significantly enhance decision making process. By utilizing advanced tools, hotels can streamline data analysis processes, providing timely and accurate insights that support swift decision making.

7. Theoretical Contribution

This study makes significant theoretical contributions to the field of hospitality management by elucidating the critical role of statistical data analytics in enhancing decision making process effectiveness. The findings demonstrate that various dimensions of statistical data analytics (analytical skills, data quality, domain knowledge, big data, and tool sophistication) each positively impact decision making process. This comprehensive examination expands the theoretical understanding of how statistical data analytics capabilities can be leveraged within the hotel industry to drive informed and effective decisions. First, the study highlights the importance of analytical skills in decision making process, contributing to the existing literature by quantifying this relationship. The effect between analytical skills and decision making process emphasizes the need for targeted training programs to develop these skills, thus providing a theoretical foundation for human capital development strategies in the hospitality sector. This finding supports the theory that skilled analysts can better interpret and utilize complex data, leading to more accurate and reliable decisions.

Second, the study underscores the critical role of data quality in decision making. The strong positive effect between data quality and decision making process affirms the theoretical premise that high-quality data is essential for reliable decision making. This contribution enhances the understanding of data governance and its impact on operational performance, suggesting that hotels should implement rigorous data management practices to maintain data integrity. Third, the effect between domain knowledge and decision making process suggests that deeper industry knowledge supports better decision making. This finding theoretically validates the integration of continuous learning and industry trends into professional development programs, reinforcing the notion that expertise in the hospitality domain is a crucial determinant of decision making process success. Additionally, the study's focus on the big data provides a theoretical framework for understanding the advantages of large datasets in decision making. The positive effect indicates that larger datasets are associated with improved decision making, supporting the theory that comprehensive data can provide more accurate and holistic insights. This contribution suggests that investments in advanced data management systems are theoretically justified to handle extensive datasets efficiently. Finally, the significant impact of tool sophistication on decision making process enriches the theoretical understanding of technological integration in the hospitality industry. This finding supports the theory that advanced analytical tools enhance the ability to process and analyze data quickly and accurately, leading to better decision outcomes.

8. Limitations and Future Research Suggestions

While this research provides valuable insights into the role of statistical data analytics in enhancing decision making process in hotels, it has several limitations. The geographic constraint of data collection may limit the generalizability of the findings to other regions with different market dynamics and technological adoption rates. Future research should aim to include a more diverse sample from various geographic locations to enhance the generalizability of the results. Additionally, the reliance on quantitative methods may not fully capture the qualitative aspects of analytics implementation. The cross-sectional nature of the study offers a snapshot in time but does not account for changes over time, which limits the understanding of long-term impacts. Future research could benefit from a mixed-methods approach, incorporating qualitative interviews or case studies to provide deeper insights into the contextual and experiential factors influencing the use of data analytics in decision making. Furthermore, the study focused on specific dimensions of statistical data analytics (analytical skills, data quality, domain knowledge, big data, and tool sophistication). While these dimensions are critical, future research should explore additional factors that may impact decision making, such as organizational culture, leadership support, and technological infrastructure. Investigating these additional variables could provide a more holistic view of the factors that contribute to effective data-driven decision making process in hotels. Lastly, the study did not consider the potential moderating or mediating effects of variables such as employee engagement, customer feedback mechanisms, and competitive pressures. Future research should examine these moderating and mediating variables to understand better the complex interactions and contextual factors that impact the relationship between data analytics and decision making process. Addressing these limitations through comprehensive, diverse, and longitudinal research will further enrich the theoretical and practical knowledge in this field.

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أثر تحليلات البيانات الإحصائية على عملية إتخاذ القرار في الفنادق

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الكلمات الدالة

تحليلات البيانات الإحصائية؛ عملية إتخاذ القرار؛ الفنادق.

المستخلص

يُعد فهم دور تحليلات البيانات الإحصائية في تعزيز فعالية إتخاذ القرار الفندقي أمر حيوي لتحسين الأداء التشغيلي وتعزيز رضا العملاء. وعلى الرغم من أن الدراسات السابقة ركزت على تحليلات البيانات الإحصائية، إلا أن هناك نقصًا في هذه الدراسات التي ركزت على استكشاف تأثير تحليلات البيانات الإحصائية على عملية اتخاذ القرار في بيئات عمل الضيافة المصرية. لذلك، يهدف هذا البحث إلى الكشف عن تأثير أبعاد تحليلات البيانات الإحصائية (المهارات التحليلية، جودة البيانات، معرفة المجال، البيانات الضخمة، تطور الأدوات) على عملية اتخاذ القرار في الفنادق. وفي ضوء ذلك فإن منهجية البحث تحليلية، ويتكون مجتمع الدراسة من المديرين والعاملين في الفنادق ذات الأربع والخمس نجوم في الغردقة وشرم الشيخ، وعينة الدراسة عشوائية طبقية. ونتيجة لذلك، حصل الباحثون على بيانات من 405 مستجيبًا. تم استخدام برنامج SPSS V.22 لتحليل البيانات واختبار فرضيات البحث. تشير النتائج إلى أن كل بُعد من أبعاد تحليلات البيانات الإحصائية (المهارات التحليلية، جودة البيانات، معرفة المجال، البيانات الضخمة، تطور الأدوات) له تأثير إيجابي ذو دلالة إحصائية على عملية اتخاذ القرار في الفنادق .ويوصي البحث بأن تعطي الفنادق الأولوية لتطوير المهارات التحليلية من خلال برامج تدريبية مخططة. حيث أن الإستثمار في رأس المال البشري يدعم قدرة العاملين على تفسير البيانات المعقدة واستخلاص رؤى قابلة للتنفيذ، مما يؤدي في النهاية إلى اتخاذ قرارات أفضل. علاوة على ذلك، يساهم هذا البحث في سد الفجوة البحثية في الدراسات السابقة من خلال التحقيق في تحليلات البيانات الإحصائية وتقديم توصيات عملية هامة لقطاع الضيافة.

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