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Hospitality Business Analytics: Understanding Analytics Knowledge in Hotel Management

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The main aim of this study was to investigate the effect of integration and infrastructures, business adaptation, business knowledge, organizational culture, and costs on business analytics and whether the status of the participants moderates this relationship. This is an exploratory, cross-sectional study. A quantitative and correlational methodology was used. The sample of this study is made up of 482 participants, all of whom work in the hotel industry in Portugal. Organizational culture and costs' positive and significant effect on business analytics was proven. Integration and infrastructure also positively and significantly affected knowledge and adaptation to the business. Status moderates the relationship between integration and infrastructure, business adaptation, organizational culture, costs, and business analytics. This study points us in new directions for the hotel industry. Organizational culture is one of the most important factors, as it is the variable with the strongest effect on business analytics.

Keywords: business analytics, integration and infrastructure, business knowledge, business adaptation, organizational culture, costs

1. INTRODUCTION

The travel and hotel industries kept up with the many diverse information technologies. Everything has increased due to the Internet's rapid growth, and new applications of every kind and genre are constantly being released. Computer engineers and hotel managers are interested in this digital economy because of the challenges involved in selecting new operating systems and figuring out how to integrate them all so that information can be extracted holistically, and the volume of data these systems generate. Significant developments have occurred in recent years, such as the shift from non-digital to digital services [1]. Additionally, photos, audio, video, and social media content – unstructured data – have replaced text-structured data as the primary data type [2]. New data types and sophisticated analytical tools brought forth by modern technology present businesses with benefits and challenges [3].

The difficulty hotel managers face is how to store these massive amounts of data in a way that, when combined with analytics tools, yields insights that improve the company

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and aid in improved decision-making based on analyzed patterns and the best understanding of their industry. Hotels must use information well to compete with other hotels and improve hotel performance because they operate in a dynamic and competitive environment [4]. The hotel industry has started recognizing the usefulness and significance of analytical tools in discovering usage trends and decision making, while not being one of the industries that use them most [5]. Hotels and their management must have a thorough awareness of the business they operate to make this feasible. The engagement of the entire organization and the suitability of internal, external, or recent graduates' human resources in terms of training and qualifications to comprehend the business and analyze the insights obtained from implementing decision support analytical systems are also critical.

The primary objective of this research study is to examine and explore the knowledge and behavioral intentions of hotel industry users regarding the usage and acceptance of analytics technology. The study also aims to explore whether young graduates are aware of these challenges and whether their integration into the workforce can have any impact on addressing these issues within hotels.

Furthermore, the study intends to illuminate the potential value and return on investment associated with implementing such systems in the hotel industry. By addressing these objectives, the research aims to provide valuable insights for decision-makers regarding the importance and feasibility of investing in analytics technology in the hotel industry.

2. LITERATURE REVIEW

In the past decade, particularly in the last five years, the tourism and hospitality industries have experienced a rise in using Big Data and Analytics (BDA). This trend has increased emphasis on research in these domains [6]. According to the authors, the literature on big data and analytics in the hospitality and tourism sector is expanding but remains fragmented.

In the hotel industry, there is a significant increase in data generated by all the systems involved in hotel operations, and terms like Business Intelligence (BI), Big Data (BD), and Business Analytics (BA) are gaining importance. Business analytics can be a valuable tool for top management in the hospitality industry, enabling them to improve their understanding of the business and make more informed decisions [7]. Managers can derive tangible and significant organizational benefits when accessing and effectively utilizing the appropriate technology. This enables top managers to drive company growth in alignment with market developments, fostering a competitive advantage [8].

2.1 Business Intelligence

Business Intelligence (BI) has evolved through various generations, emphasizing different functionalities. Earlier generations of BI focused primarily on reporting, visualization, and scorecards. The initial Business Intelligence (BI) system generation primarily focused on basic reporting capabilities. However, subsequent generations introduced self-service BI, allowing users to perform analysis tasks independently and have more control over decision-making processes [9].

The term "Business Intelligence" was introduced by the Gartner Group, a prominent research and advisory firm, in the mid-1990s. However, the underlying concept of BI can

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be traced back to the management information systems (MIS) reporting systems in the 1970s. These early systems focused on collecting and presenting data as reports to support organizational managerial decision-making. Over time, the concept evolved and expanded, incorporating technological advancements, data analysis techniques, and integrating various data sources. The term BI, coined by Gartner, helped crystallize and popularize this concept, leading to the development and widespread adoption of more sophisticated BI methodologies and technologies [10].

2.2 Business Analytics

"If you can't measure it, you can't manage it". [11] state that this well-known Peter Drucker expression is full of wisdom, which explains why the recent explosion of digital data is so important nowadays. The authors argue that, thanks to big data, managers can measure and, therefore, know much more about their companies and directly translate that knowledge into better decision-making and performance.

According to [12], Business Intelligence and Business Analytics have drawn attention to academic and business communities over the past decades. [13] reinforce this statement by saying that Business analytics has emerged as a rapidly growing term, garnering significant attention and recognition in both business and academic spheres like never before. However, the main aim of this study was to investigate the effect of integration and infrastructures, business adaptation, business knowledge, organizational culture, and costs on business analytics and whether the status of the participants moderates this relationship. The growing recognition of the importance of knowledge orientation and business analytics capabilities in driving business model innovation, empirical research on their relationship remains limited [14].

In the past, information was regarded as a source of power. However, a significant shift has occurred in recent decades, fundamentally altering our perception of information and its significance. The exponential growth of data has outpaced our ability to thoroughly explore and analyze it, presenting a new challenge in effectively harnessing its full potential [15]. Significant progress and advancements have occurred in various fields in recent decades. Technological innovations, scientific discoveries, and socio-economic changes have shaped our world during this period. The rapid evolution of technology, such as the rise of the internet, mobile devices, and artificial intelligence, has revolutionized how we communicate, work, and access information. The emergence of Big Data has made data readily available and inexpensive. However, the true value of data lies in its utilization to extract valuable and meaningful information. The key lies in effectively harnessing and analyzing data to derive actionable insights that can drive.

2.3 Technology Integration in Hospitality Industry

According to [16], software vendors in the hospitality industry are increasingly offering integrated information systems that meet the functional requirements of hotel operators. These systems also incorporate digital technology advancements, improving data capture, processing, and reporting capabilities. Integrated systems play a crucial role in the efficient operation of a hotel. They combine various components and functions within the hotel, allowing for seamless communication, data sharing, and process automation [17].

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According to [16], the hotel industry is witnessing a growing integration of digital technologies alongside core information systems, often hosted in the Cloud. These information systems serve as central databases for storing and retrieving transaction data generated within the system and through additional digital technology applications. However, standalone devices and technologies, including robotics and the Internet of Things (IoT), require connectivity and integration. Hotel operators face the challenge of aligning their evolving business needs with the most suitable combination of these technologies in a fast-paced technology and business environment. They must navigate this landscape effectively to stay competitive and meet customer expectations [17].

(A) Infrastructures for a Business Analytics Thinking

Infrastructure for business analytics implementation encompasses various components, including hardware, software, and data management systems. These components work together to provide a reliable and scalable foundation for implementing business analytics, enabling organizations to collect, process, analyze, and visualize data for actionable insights and informed decision-making [18].

(B) Business Adaption

The tourism industry has demonstrated remarkable adoption of the latest technologies. However, the pace of adoption varies among organizations, and many have struggled to implement business intelligence and analytics strategies and embrace digital listening initiatives at the same level as others [19].

To deliver valuable insights and support decision-making, professionals in Business Intelligence and Analytics need to comprehend business challenges and develop suitable analytical solutions. Their expertise lies in understanding the intricacies of the business environment and utilizing analytical techniques to address the specific needs of the organization [20]. This requires careful planning and organization to integrate various internal and external data sources effectively [14].

Conducting an analytics readiness assessment can be advantageous in gauging the organizational culture and level of preparedness for Business Analytics technologies and strategies [21]. This comprehensive approach thoroughly explains the organization's readiness to implement BI initiatives.

BI goes beyond mere technology; it encompasses understanding how various organizational, technological, and people-oriented processes interact within an organization [21]. The field of business analytics is constantly evolving, leading to an expansion of its applications [22].

(C) Business Knowledge

According to [23], knowledge exploration involves acquiring or creating new knowledge, sharing it with others, and storing it for future use. It encompasses research, experimentation, information gathering, collaboration, and knowledge management. [24] argue that business analytics enables organizations to generate detailed reports on various subjects, including market trends. By leveraging BA, organizations gain valuable insights into market dynamics, consumer preferences, and emerging trends, enabling them to align their product strategies with market demands and capitalize on opportunities for growth and competitive advantage [25].

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According to [26], various technological infrastructures such as social media, forums, blogs, and virtual networks are commonly used for knowledge management. [23] states that the presence of social media capability within firms can facilitate the exploration and exploitation of knowledge. According to [14], organizations that foster a knowledge-oriented culture, characterized by a questioning attitude and a willingness to challenge existing ideas and models, are well-positioned to leverage the benefits of business analytics.

(D) Organizational Culture

Organizational culture definitions often highlight its influence on an organization's behavior, values, and norms [27]. Upadhyay *et al.* [28], one of the most cited authors in multidisciplinary studies, defines Organizational Culture (OC) as the organizational norms, expectations, and shared behavioral patterns that shape how people behave and carry out tasks within an organization. For the author, it includes both explicit and implicit norms, values, and assumptions that guide the actions of individuals and work units.

The charter of principles and values is the key element of an organizational culture [29]. Effective management of these values fosters emotional commitment by aligning employees with the organization's brand when they identify with its values. Also, their perception and acceptance of organizational culture significantly influence their behavior. [30], state that to achieve positive outcomes, firms should prioritize aspects such as organizational culture and the alignment of business processes. The authors pointed out that to ensure competitive and sustainable financial performance, firms must focus on developing and incorporating analytical capabilities within their internal resources, particularly among employees.

Knowledge orientation plays a vital role in developing a knowledge-based organizational culture. By fostering an environment that values and promotes knowledge creation, sharing, and utilization, companies can effectively harness knowledge as a key driver of growth. A knowledge-based organizational culture empowers employees to continuously learn, collaborate, and contribute expertise, enhancing performance and sustainable growth [14].

(E) Business Analytics and Organizational Culture

Business analytics (BA) should not be viewed solely as a technical development but as a component of organizational culture. By proactively utilizing BA insights, organizations can make informed decisions, implement changes, and ultimately gain a competitive advantage. The ability to leverage BA findings effectively demonstrates an organization's commitment to leveraging data-driven insights for strategic decision-making and achieving positive outcomes [31]. They state that it is evident that a data-driven culture plays a crucial role in the era of Big Data. This emerging organizational culture enables leaders to rely less on intuition and more on leveraging data-driven insights. By cultivating a data-driven culture, organizations can make informed decisions and harness the power of data to drive innovation and success.

Adequate and competent human resources are crucial in preparing technology and data for effective utilization. They ensure the necessary technology infrastructure is available and ready to support data analysis and management. This includes assessing data availability, ensuring data is properly prepared and cleaned, verifying data completeness, implementing security measures to protect data, and establishing governance frameworks

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for data management. By having skilled professionals in place, organizations can optimize the use of technology and data, leading to more accurate and reliable insights for decision-making [32].

According to [14], establishing a knowledge-oriented organizational culture is essential for companies to recognize the value of Business Analytics. A knowledge-oriented culture fosters an environment where employees are encouraged to acquire, create, and share knowledge, enabling them to effectively leverage BA tools and insights. By embracing a knowledge-oriented culture, companies can fully harness the potential of BA and drive innovation and growth in their organizations.

Wamba *et al.*, [33] examined the contextual factors such as organizational culture and external pressures that influence BA's successful implementation and utilization. A supportive organizational culture that values data-driven decision-making and fosters a learning mindset can enhance the effectiveness of BA initiatives. According to the authors, organizations that effectively harness these factors are more likely to derive strategic insights, gain a competitive advantage, and achieve positive outcomes from their BA initiatives.

Upadhyay *et al.*, [34] found that organizational culture significantly positively affects the relationship between big data analytics capability and firm performance. They found that in the big data analytics capability (BDAC) model, proposed by [35], the concept of knowledge in business analytics encompasses three dimensions. The first dimension is explicit knowledge, which includes data and technology. It refers to tangible and codified knowledge that can be easily documented, stored, and transferred. The second dimension is tacit knowledge, which involves culture and organizational learning. Tacit knowledge is more intangible and embedded in individuals' experiences, insights, and ways of thinking. It is often acquired through practical experience and is difficult to articulate explicitly. The third dimension is human knowledge, which encompasses the skills and capabilities of individuals within the organization. This includes managerial skills, technical skills, and other expertise that individuals bring. Human knowledge is crucial in effectively utilizing data and technology to derive insights and make informed decisions. By considering all three dimensions of knowledge – explicit, tacit, and human – organizations can develop a comprehensive approach to business analytics. By integrating these dimensions, organizations can harness the full potential of knowledge and drive successful business analytics initiatives [30].

2.4 Theoretical Model of the Study

According to [31], advancements in Business Analytics (BA) in the Big Data era have provided organizations with unprecedented opportunities for innovation and strategic decision-making. BA enables companies to extract actionable insights from data, which can lead to creating or enhancing products, services, and internal processes. The growing importance of BA in the hospitality industry, particularly in hotel management, calls for a deeper understanding of both the organizational and individual-level factors that influence its adoption and effective use.

Drawing on existing literature in Business Analytics, Information Systems, Organizational Culture, and Strategic Management, a theoretical model was developed to examine the key determinants of BA adoption. The model incorporates six core constructs: integration and infrastructure, business adaptation, business knowledge, organizational

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culture, costs, and status (as a moderating variable). These constructs were selected based on their empirical relevance and theoretical significance in shaping data-driven capabilities and organizational readiness for analytics [36-38].

The model is grounded in the Dynamic Capabilities Theory [39], which highlights an organization's ability to integrate, build, and reconfigure internal and external competences in response to rapidly changing environments, and the Technology-Organization-Environment (TOE) Framework [40], which emphasizes how contextual factors drive technological adoption.

(A) Rationale for the Moderating Variable "Status"

The role identity theory theoretically motivates the inclusion of "status" as a moderating variable [41] and is supported by the organizational behavior literature. These frameworks recognize that individuals' perceived status – as students, professionals, or directors – influences how they interpret, evaluate, and act upon technological opportunities and constraints. For example, directors may approach business analytics with a strategic mindset focused on long-term outcomes. At the same time, professionals might emphasize operational efficiency, and students may focus on learning or academic relevance.

Status, therefore, may affect the strength or direction of relationships between organizational/technological factors and BA adoption. This novel inclusion provides analytical depth and accounts for heterogeneous perceptions among stakeholders involved in data-driven transformation in the hotel industry.

(B) Constructs and Operationalization

Each variable was operationalized using validated instruments adapted to the hotel industry context:

- Integration and Infrastructure: Measured through items adapted from [38], this construct captures the degree of system interoperability, data integration, and technological maturity supporting analytics within the organization.
- Business Adaptation: Reflects an organization's flexibility and responsiveness to environmental changes using data insights, based on scales from [36]. This includes the organization's ability to adjust processes or strategies in response to analytical insights.
- Business Knowledge: Assessed using items inspired by [37], this construct measures the availability and use of business-domain knowledge necessary to interpret analytics outcomes and align them with organizational goals.
- Organizational Culture: Captured through adapted scales from [42], this construct reflects the cultural attributes that support or inhibit innovation and data-driven decision-making, including openness to change and leadership commitment.
- Costs: Measured based on perceived financial and resource constraints related to implementing BA tools and processes. This includes both direct (software/hardware) and indirect (training, change management) costs [43].
- Status: This moderating variable is a categorical indicator of the respondent's role (student, professional, director), incorporated into the analysis using the PROCESS macro to explore interaction effects.

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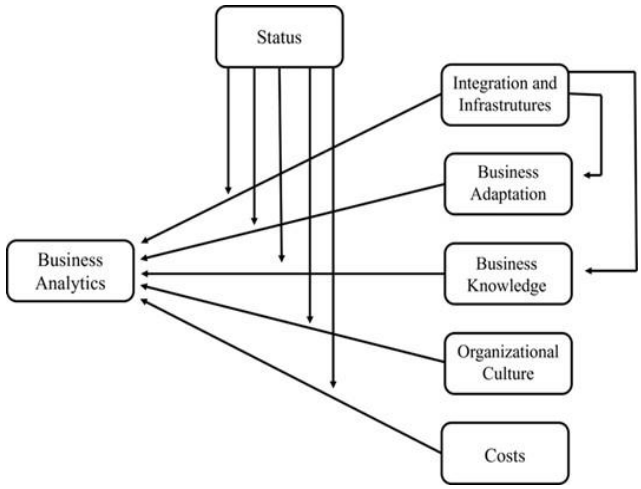


Fig. 1. The proposed theoretical model.

Table 1. Theoretical rationale for each hypothesis.

Hypothesis	Statement	Theoretical Rationale
H1	Integration and infrastructure are positively and significantly associated with Business Analytics.	Robust IT systems and data integration capabilities facilitate effective data processing and decision-making through Business Analytics [38, 44].
H2	Business adaptation is positively and significantly associated with Business Analytics.	Organizations that can adapt strategically based on analytical insights are better equipped to leverage BA for competitiveness [36, 39].
H3	Business knowledge is positively and significantly associated with Business Analytics.	Domain knowledge enhances the relevance and utility of analytics by enabling interpretation and actionable decision-making [37].
H4	Organizational culture is positively and significantly associated with Business Analytics.	A culture supportive of innovation and data-driven decisions facilitates the integration of analytics in operations [36,42].
H5	Costs are positively and significantly associated with Business Analytics.	High perceived costs may reflect organizational commitment and investment in analytics infrastructure and capabilities [43].
H6	Integration and infrastructure are positively and significantly associated with business adaptation.	Integrated systems support organizational agility and responsiveness to data-driven insights [36].
H7	Integration and infrastructure are positively and significantly associated with business knowledge.	Strong infrastructure enables knowledge sharing and insight generation, enhancing organizational intelligence [38].

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H8	Status moderates the relationship between integration and infrastructure and Business Analytics.	Higher-status individuals may influence or prioritize IT strategies, shaping the effectiveness of infrastructure on analytics outcomes [41].
H9	Status moderates the relationship between business adaptation and Business Analytics.	The role-based ability to act on or initiate strategic change varies, influencing how adaptation supports BA adoption [39].
H10	Status moderates the relationship between business knowledge and Business Analytics.	Knowledge impact varies by status; higher-status roles may wield knowledge with greater strategic influence [37].
H11	Status moderates the relationship between organizational culture and Business Analytics.	Perceptions and influence of culture differ by status, affecting its role in analytics implementation [42].
H12	Status moderates the relationship between costs and Business Analytics.	Cost interpretation is status-dependent; higher roles may perceive cost as investment, lower roles as constraint [43].

3. METHOD

3.1 Data Collection Procedure

The sample procedure for this study will involve a systematic and rigorous process to ensure the selection of appropriate participants [45]. The sample will consist of three main groups: last-year students, recently graduated hotel professionals, and hotel directors/administrators.

First, participating in educational institutions will provide a list of last-year students from relevant hospitality management programs. The students will then be invited to participate voluntarily in this study and provide consent.

Second, a separate list of recently graduated hotel professionals will be compiled. These professionals will be selected based on their employment history in the hotel industry and their availability to participate in the study. They will be contacted and invited to take part in the research.

Third, hotel directors and administrators will be identified through various sources, such as professional networks and industry associations. These individuals will be approached and invited to participate in the study, considering their role and expertise in hotel management.

Due to the size of the target population and different groups, a sampling survey methodology has been chosen for this research. Conducting a comprehensive survey of the entire population is not feasible, so a sampling approach is employed. This involves selecting a representative subset of the population to gather data and draw conclusions about the larger group. The use of sampling allows for efficient data collection while still maintaining a degree of accuracy and generalizability in the findings [45].

The sampling procedure will adhere to scientific principles to ensure the validity and reliability of the study. Participants' confidentiality and anonymity will be strictly maintained, and ethical considerations will be followed throughout the research process.

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3.2 Participants

This study's sample consists of 482 participants, 303 (62.9%) females and 179 (37.1%) males. Regarding age, 171 (35.5%) are up to 24 years old, 144 (29.9%) are between 25 and 34 years old, 82 (17%) are between 35 and 44 years old, 70 (14.5%) are between 45 and 54 years old, and 15 (3.1) are 55 years old or older.

As for status, 177 (36.7%) are students, 216 (44.8%) are professionals, 69 (14.3%) are directors, and 20 (4.1%) are administrators.

Regarding professional experience, 2 (0.4%) participants have no experience, 141 (29.3%) have less than one year of experience, 34 (7.1%) have between one and two years of experience, 81 (16.8%) have between 3- and 5-years' experience, 77 (16%) have between 6- and 10-years' experience, and 146 (30.3%) have more than ten years' experience.

Regarding the geographical zone where the hotel units where the participants work are located, 30 (6.2%) participants work in hotel units in the northern region, 242 (50.2%) in the central region, 200 (41.5%) in the southern region, and 10 (2.1%) in the autonomous region of Madeira.

When we cross the geographic zone where the hotel unit is located, we verify that it is in the southern zone, where we find the highest percentage of younger and older participants. In the autonomous region of Madeira, nine of the 10 participants in this study are between 25 and 34 years old.

Concerning the courses attended or to be attended by the participants of this study, it is found that 245 (50.8%) participants have or are attending the hotel management course, 131 (27.2%) the tourism course, 50 (10.4%) the hotel management and tourism course, 44 (9.1%) another course, and 11 (2.3%) another course.

Finally, 442 (91.7%) of the participants in this study are of Portuguese nationality, and 40 (8.3%) are of foreign nationality.

3.3 Data Analysis Procedure

Data was imported from Google Forms into SPSS Statistics 29 software. An exploratory factor analysis (EFA) was initially performed since this is a new instrument built for this study. After the EFA, a six-factor Confirmatory Factor Analysis (CFA) was performed using the AMOS for Windows 29 software. The procedure was according to a "model generation" logic [46], considering in the analysis of their fit, interactively the results obtained: for the chi-square (χ^2); for the Tucker Lewis index (TLII); for the goodness-of-fit index (GFI); for the comparative fit index (CFI); for the root mean square error o approximation (RMSEA); and the Standardized Root Mean Square (SRMR). After the AFC, construct reliability, convergent validity and discriminant validity were calculated for each instrument.

SPSS Statistics 29 for Windows software was used to analyze the other metric qualities of the instruments used in this study.

Concerning the study of item sensitivity, the different measures of central tendency, dispersion and distribution were calculated for all items.

Subsequently, descriptive statistics of the variables under study were performed using Student's *T*-tests for a sample. The next step was to study the association between the

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variables through Pearson's correlations. Finally, the formulated hypotheses were tested.

The hypotheses formulated in this study were tested by performing linear regressions after the respective assumptions were verified. [47] developed the Macro Process to test the hypotheses that assume a moderating effect.

3.4 Instrument

The instrument used in this study to measure business analytics and associated variables were explicitly built for this study. It consists of 22 items rated on a five-point Likert rating scale (from "1" strongly disagrees to "5" strongly agree). As mentioned earlier, an EFA was initially performed.

We obtained a KMO value of .77 which can be considered acceptable [48], and Bartlett's test of sphericity was significant at $p < .001$, being an acceptable value to continue the analysis, as well as an indicator that the data came from a multivariate normal population [49]. It was found that the structure of this scale is based on six factors, which explain 67% of the total variability of the scale. Item 14 was removed because it had a low factor weight. The remaining items have factor weights above .50.

After semantic analysis of the items, it was decided to assign the following names to the respective dimensions: (1) business analytics (items 17, 18, 19, 20, 21 and 22); (2) integration and infrastructures (items 9, 10, 11 and 13); (3) business adaptation (items 3, 4 and 8); (4) business knowledge (items 1, 2 and 5); (5) organizational culture (items 12, 15 and 16); (6) costs (items 6 and 7).

Next, a six-factor AFC was performed. The values obtained in the three-factor model indicate an acceptable adjustment since the adjustment indexes are within or very close to acceptable values: $\chi^2/gl = 4.23$; GFI = .89; CFI = .91; TLI = .87; RMSEA = .082; SRMR = .051. As for construct reliability, the following values were obtained: .89 for the business analytics dimension; .65 for integration and infrastructures; .70 for business adaptation; .72 for business knowledge; .69 for organizational culture; .60 for costs. Only the costs dimension presents low construct reliability. Concerning convergent validity (AVE), the following values were obtained: .63 for the business analytics dimension; .37 for integration and infrastructures; .46 for business adaptation; .47 for business knowledge; .45 for organizational culture; .45 for costs. The integration and infrastructure dimension shows poor convergent validity. As for divergent validity, the square root of the AVE of each factor is lower than the correlation between them, so we can say that the dimensions diverge from each other.

As for the sensitivity of the items, none of the items has a median close to one of the extremes. All items have absolute skewness values and kurtosis below 3 and 7, respectively, so they do not grossly violate normality [50].

4. RESULTS

4.1 Descriptive Statistics of the Variables Under Study

The first step was to perform descriptive statistics on the variables under study to understand the position of the answers given by the study participants. For this purpose, we performed several *t*-tests for one sample.

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Table 2. Descriptive statistics of variables.

Variable	*t*	*df*	*p*	Mean	SD
Business Analytics	33.88***	481	< .001	3.93	.60
Integration and Infrastructures	2.11*	481	.018	3.06	.65
Business Adaptation	7.33***	481	< .001	3.22	.64
Business Knowledge	5.65***	481	< .001	3.18	.70
Organizational Culture	34.92***	481	< .001	3.97	.61
Costs	21.70***	481	< .001	3.55	.56

Note: * $p < .05$; *** $p < .001$

The participants have a high perception of the variables under study since the average of all of them is significantly above the central point (3) in Table 2. The variable in which participants had the highest perception was organisational culture, and the lowest perception was integration and infrastructure in Table 2.

4.2 Association Between the Variables Under Study

The next step was to study the association between the variables under study using Pearson's correlations.

The results indicate that business analytics is only positively and significantly associated with organizational culture and costs in Table 3. Business adaptation is positively and significantly associated with business knowledge in Table 3. Integration and infrastructure are positively and significantly associated with business adaptation and knowledge in Table 3. Finally, organizational culture is positively and significantly associated with costs in Table 3.

Table 3. Association between variables.

	1	2	3	4	5	6
1. Business Analytics	–					
2. Integration and Infrastructures	–.07	–				
3. Business Adaptation	–.07	.46***	–			
4. Business Knowledge	.02	.41***	.47**	–		
5. Organizational Culture	.56***	.06	.03	.07	–	
6. Costs	.41***	.01	.06	.03	.29***	–

Note: * $p < .05$; *** $p < .001$

4.3 Hypothesis Tests

Finally, the hypotheses formulated in this study were tested. Hypotheses 1, 2, 3, 4, 5, 6 and 7 were tested through multiple linear regressions. As control variables, we considered the age group, the participant's status and the geographic area of the hotel unit.

The results indicate to us that only the control variables, status ($\beta = .13$; $p = .048$) and the geographical area where the hotel unit is located ($\beta = .09$; $p = .042$), have a positive and significant effect on business analytics in Table 4. Both model 1 ($F(3, 478) = 6.41$; $p < .001$) and model 2 ($F(3, 478) = 4.80$; $p < .001$) are statistically significant (Table 4). The model explains 3% of the variability in the dependent variable (Table 4). The results do not support hypothesis 1.

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Table 4. Results of multiple linear regression (H1).

Independent Variable	Business Analytics	
	β Step 1	β Step 2
Age	.07	.07
Status	.13*	.13*
Geographic Area	.09*	.09*
Integration and Infrastructures		.01
F	6.41***	4.80***
R^2_a	.03	.03

Note: * $p < .05$; *** $p < .001$

The results indicate that only one control variable, the geographical area of the hotel unit ($\beta = .13$; $p = .047$), has a positive and significant effect on business analytics in Table 5. Both model 1 ($F(3, 478) = 6.41$; $p < .001$) and model 2 ($F(3, 478) = 4.96$; $p < .001$) are statistically significant in Table 5. The model explains 3% of the variability in the dependent variable in Table 5. The results do not support hypothesis 2.

Table 5. Results of multiple linear regression (H2).

Independent Variable	Business Analytics	
	β Step 1	β Step 2
Age	.07	.07
Status	.13*	.13*
Geographic Area	.09*	.09
Business Adaptation		–.04
F	6.41***	4.96***
R^2_a	.03	.03

Note: * $p < .05$; *** $p < .001$

The results indicate that only the control variables, status ($\beta = .13$; $p = .037$) and the geographical area where the hotel unit is located ($\beta = .10$; $p = .025$), have a positive and significant effect on business knowledge (Table 6). Both model 1 ($F(3, 478) = 6.41$; $p < .001$) and model 2 ($F(3, 478) = 5.16$; $p < .001$) are statistically significant in Table 6. The model explains 3% of the variability in the dependent variable in Table 6. The results do not support hypothesis 3.

Table 6. Results of multiple linear regression (H3).

Independent Variable	Business Analytics	
	β Step 1	β Step 2
Age	.07	.08
Status	.13*	.13*
Geographic Area	.09*	.10*
Business Knowledge		.06
F	6.41***	5.16***
R^2_a	.03	.03

Note: * $p < .05$; *** $p < .001$

The results indicate that, age ($\beta = .14$; $p = .006$), status ($\beta = .10$; $p = .041$) and organizational culture ($\beta = .57$; $p < .001$) have a positive and significant effect on business analytics in Table 7. Both model 1 ($F(3, 478) = 6.41$; $p < .001$) and model 2 ($F(3, 478) = 66.88$;

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$p < .001$) are statistically significant in Table 7. The model explains 35% of the variability in the dependent variable in Table 7. The results support hypothesis 4.

Table 7. Results of multiple linear regression (H4).

Independent Variable	Business Analytics	
	β Step 1	β Step 2
Age	.07	.14**
Status	.13*	.10*
Geographic Area	.09*	.03
Organizational Culture		.57***
F	6.41***	66.88***
R^2_a	.03	.35

Note: * $p < .05$; *** $p < .001$

Table 8. Results of multiple linear regression (H5).

Independent Variable	Business Analytics	
	β Step 1	β Step 2
Age	.07	.07
Status	.13*	.12*
Geographic Area	.09*	.04
Costs		.41***
F	6.41***	29.50***
R^2_a	.03	.19

Note: * $p < .05$; *** $p < .001$

The results indicate that, only status ($\beta = .12$; $p = .032$) and costs ($\beta = .41$; $p < .001$) positively and significantly affect business analytics (Table 8). Both model 1 ($F(3, 478) = 6.41$; $p = .085$) and model 2 ($F(3, 478) = 29.50$; $p < .001$) are statistically significant in Table 8. The model explains 19% of the variability in the dependent variable in Table 8. The results support hypothesis 5.

The results indicate that, in Step 1, age ($\beta = -.13$; $p = .045$) and the geographical area where the hotel unit is located ($\beta = -.14$; $p = .002$) negatively and significantly affect business adaptation (Table 9). In step 2, status ($\beta = .12$; $p = .046$) and integration and infrastructure ($\beta = .48$; $p < .001$) have a positive and significant effect on business adaptation in Table 9. Both model 1 ($F(3, 478) = 6.57$; $p < .001$) and model 2 ($F(3, 478) = 35.94$; $p < .001$) are statistically significant in Table 9. The model explains 23% of the variability in the dependent variable. The results support hypothesis 6.

Table 9. Results of multiple linear regression (H6).

Independent Variable	Business Adaptation	
	β Step 1	β Step 2
Age	–.13*	–.09
Status	–.05	.12*
Geographic Area	–.14**	–.07
Integration and infrastructure		.48***
F	6.57***	35.94***
R^2_a	.03	.23

Note: * $p < .05$; ** $p < .01$; *** $p < .001$

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Table 10. Results of multiple linear regression (H7).

Independent Variable	Business Knowledge	
	β Step 1	β Step 2
Age	–.05	–.02
Status	–.09	–.05
Geographic Area	–.20***	–.14***
Business Analytics		.41***
F	8.74***	28.01***
R^2_a	.05	.18

Note: *** $p < .001$

The results indicate that, in Step 1, only the geographical area where the hotel unit is located ($\beta = –.20$; $p < .001$) negatively and significantly affects business knowledge (Table 10). In Step 2, only the geographical area where the hotel unit is located ($\beta = –.14$; $p < .001$) has a negative and significant effect on organizational culture, while the effect of integration and infrastructure ($\beta = .41$; $p < .001$) is positive and significant (Table 10). Both model 1 ($F(3, 478) = 8.84$; $p = .007$) and model 2 ($F(3, 478) = 28.01$; $p < .001$) are statistically significant (Table 10). The model explains 18% of the variability in the dependent variable (Table 9). The results support hypothesis 7.

We find a moderating effect of status on the relationship between business analytics and integration and infrastructure ($B = –.13$; $p = .009$) in Table 11. The model is statistically significant ($F(3, 478) = 7.01$; $p < .001$) in Table 11. The model explains the variability in integration and infrastructures by 4% in Table 11. For low-status participants, compared to high-status participants, the perception of integration and infrastructure becomes relevant to enhance their perception business analytics. The results support hypothesis 8.

Table 11. Results of moderator effect (H8).

Variable	*B*	SE	*t*	*p*	95% CI
Integration and Infrastructure → Business Analytics ($R^2 = .04$; $p < .001$)					
Constant	3.90***	.02	136.11***	< .001	[3.85,
Integration and Infrastructure	–.01	.05	–.05	.958	[–.09, .09]
Status	.12***	.04	3.29***	.001	[.05, .19]
IInf*Status	–.13*	.05	–2.62*	.009	[–.23,–.03

Note: * $p < .05$; ** $p < .01$; *** $p < .001$

Table 12. Results of moderator effect (H9).

Variable	*B*	SE	*t*	*p*	95% CI
Business adaptation → business analytics ($R^2 = .04$; $p < .001$)					
Constant	3.92***	.03	144.64***	< .001	[3.87, 3.98]
Business Adaptation	–.04	.04	–.88	.379	[–.12, .05]
Status	.13***	.03	3.85***	< .001	[.06, .19]
Badap*Status	–.12*	.05	–2.33*	.020	[–.21, –.02]

Note: * $p < .05$; *** $p < .001$

We find a moderating effect of status on the relationship between business analytics and business adaptation ($B = –.12$; $p = .020$) in Table 12. The model is statistically significant ($F(3, 478) = 6.94$; $p < .001$) in Table 12. The model explains the variability in business adaptation by 4% in Table 12. For low-status participants, compared to high-status

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participants, the perception of business adaptation becomes relevant to enhance their perception of business analytics. The results support hypothesis 9.

Status was found not to moderate the relationship between business analytics and business knowledge (B = .03; p = .751) in Table 13. The model is statistically significant (F(3, 478) = 4.87; p = .002) in Table 13. The results do not support hypothesis 10.

Table 13. Results of moderator effect (H10).

Variable	*B*	SE	*t*	*p*	95% CI
Business knowledge → business analytics (R^2 = .03; p = .002)					
Constant	3.93***	.03	144.23***	< .001	[3.87, 3.98]
Business Knowledge	.03	.04	.74	.458	[–.05, .10]
Status	.13	.03	3.81***	. < .001	[.06, .19]
BK*Status	.02	.05	.32	.713	[–.11, .07]

Note. *** p < .001

We find a moderating effect of status on the relationship between business analytics and organizational culture (B = –.14; p = .006) in Table 14. The model is statistically significant (F(3, 478) = 89.20; p < .001). The model explains the variability in organizational culture by 36% in Table 14. For low-status participants, compared to high-status participants, the perception of organizational culture becomes relevant to enhance their perception of business analytics. The results support hypothesis 11.

Table 14. Results of moderator effect (H11).

Variable	*B*	SE	*t*	*p*	95% CI
Organizational culture → Business Analytics (R^2 = .36; p < .001)					
Constant	3.93***	.02	177.84***	< .001	[3.94, 4.03]
Organizational cul-	.55***	.04	15.21***	< .001	[.51, .66]
Status	.14***	.03	4.98***	< .001	[–.16, –.05]
OC*Status	–.14*	.05	–2.76*	.006	[–.29, –.09]

Note: * p < .05; *** p < .001

We find a moderating effect of status on the relationship between business analytics and costs (B = –.13; p = .022) in Table 15. The model is statistically significant (F(3, 478) = 40.63; p < .001). The model explains the variability in costs by 20% (Table 15). For low-status participants, compared to high-status participants, the perception of costs becomes relevant to enhance their perception of business analytics. The results support hypothesis 12.

Table 15. Results of moderator effect (H12).

Variable	*B*	SE	*t*	*p*	95% CI
Costs → Business Analytics (R^2 = .20; p < .001)					
Constant	3.93***	.02	160.01***	< .001	[3.51, 3.61]
Costs	.44***	.04	9.94***	< .001	[.30, .46]
Status	.12	.03	4.04***	< .001	[–.09, .02]
Costs*Status	–.13*	.05	–2.29*	.022	[–.22, –.02]

Note: * p < .05; *** p < .001

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5. DISCUSSION AND CONCLUSIONS

The main aim of this study was to investigate the effect of integration and infrastructures, business adaptation, business knowledge, organizational culture, and costs on business analytics and whether the status of the participants moderates this relationship.

The hypotheses formulated in this study were then tested.

Table 16. Hypotheses testing.

Hypothesis	Statement	Supported	Explanation
H1	Integration and infrastructure → Business Analytics	No	The expected relationship was not statistically significant, possibly due to insufficient perceived impact of infrastructure alone on analytics adoption without complementary capabilities or strategic alignment.
H2	Business adaptation → Business Analytics	No	Although theoretically linked, business adaptation may not directly influence analytics usage unless supported by cultural or leadership drivers. Contextual factors such as organizational rigidity or external pressures could explain the lack of significance.
H3	Business knowledge → Business Analytics	No	The hypothesized association was not supported, suggesting that knowledge alone, without an analytics-driven mindset or enabling systems, may not translate into actual usage. This could also point to a gap in knowledge application rather than knowledge possession.
H4	Organizational culture → Business Analytics	Yes	Supported, indicating that a culture that promotes data-driven decision-making significantly enhances the adoption and effective use of Business Analytics.
H5	Costs → Business Analytics	Yes	Supported, showing that cost perceptions are an important consideration – potentially as a proxy for commitment and resource allocation towards analytics initiatives.
H6	Integration and infrastructure → Business adaptation	Yes	Supported, suggesting that technological readiness plays a key role in facilitating strategic and operational agility in the organization.
H7	Integration and infrastructure → Business knowledge	Yes	Supported, highlighting that effective infrastructure contributes to improved access, sharing, and generation of knowledge relevant for analytics.
H8	Status moderates: Integration and infrastructure → Business Analytics	No	The moderating effect of status was not statistically significant, possibly because infrastructure benefits may be perceived similarly across roles or because status does not influence how infrastructure is leveraged.

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H9	Status moderates: Business adaptation → Business Analytics	No	Not supported, which may suggest that adaptation strategies are implemented at an organizational level rather than being driven by individual status differences.
H10	Status moderates: Business knowledge → Business Analytics	No	The lack of support may indicate that the role of business knowledge in influencing analytics use is uniform across status levels or overshadowed by other factors like training or organizational policy.
H11	Status moderates: Organizational culture → Business Analytics	Yes	Supported, indicating that the influence of culture on analytics use may differ by status, possibly because higher-status individuals shape or are more attuned to cultural norms.
H12	Status moderates: Costs → Business Analytics	Yes	Supported, suggesting that perceptions of cost as a barrier or enabler may vary depending on hierarchical level and decision-making authority.

Against what was expected, integration and infrastructures do not have a positive and significant association with business analytics, which indicates that the results do not support hypothesis 1. These results go against what the literature tells us because, according to the perspective of [10], organizations, by integrating BIA projects with other IT systems, can harness the full potential of their data assets and create a synergistic ecosystem that supports overall business objectives and strategic initiatives. However, there is much resistance, which may be the case for the participants in this study.

The results also do not support hypothesis 2 since there is no positive and significant association between business adaptation and business analytics. These results are not in line with what the literature tells us. However, some authors, such as [19], state that the pace of technology adoption varies between organizations, with many having difficulty implementing business intelligence and analytics strategies and adopting digital listening initiatives at the same level as other organizations.

As for the association between business knowledge and business analytics, hypothesis 3 was not proven since this association was not significant. Once again, the results are not in line with what the literature tells us because, for [24], business knowledge allows companies to make timely and informed decisions for product development, increasing their ability to commercialize innovative ideas, which will be facilitated by leveraging BA.

On the other hand, the interviews' results are in line with the literature and contradict the results obtained from the previous hypotheses, h1, h2, and h3, as can be seen in Section 5.6.2, which corresponds to the interviews' results. However, a lack of knowledge regarding implementing business analytics systems should still be highlighted.

As expected, hypothesis 4 was proven, *i.e.*, a positive and significant association exists between organizational culture and business analytics. The results of the interviews also reinforce these findings. These results are in line with what the literature suggests. In [14] perspective, organizations that promote a knowledge-oriented culture are well-positioned to take advantage of the benefits of business analytics. In a knowledge-driven culture, there is a strong emphasis on continuous learning, exploration and generating new knowledge. This mindset incentivizes employees to actively seek data-driven solutions,

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adopt innovative approaches and challenge conventional thinking. By cultivating a culture that values knowledge exploration and disruptive innovation, organizations can create an environment that is receptive to the ideas and opportunities that BA provides. Employees are more likely to embrace BA tools and techniques, collaborate across departments, and adopt data-driven decisions. Upadhyay *et al.* [31] state that a data-driven culture plays a crucial role in the era of Big Data.

Hypothesis 5 was proven, as expected, with a positive and significant association between business analytics and costs. The interviews' results also reinforce these findings. These results align with the literature, as costs are significant in implementing BA. According to [51], costs can be high during the formation and application of the model, and the selection of the best model is essential for the company.

A positive and significant association was also found between integration and infrastructure and adaptation to the business, with results that align with literature. The interview results further support these conclusions. Adequate and competent human resources should ensure that technological infrastructure is available to support data analysis and management, address technical challenges, maintain data quality standards, respect ethical and legal considerations, and adapt to the business [32].

There was also a positive and significant association between integration and infrastructure and business knowledge. The results of the interviews further support these conclusions. These results align with what the literature suggests since, according to [26], various technological infrastructures, such as social media, forums, blogs, and virtual networks, are commonly used for knowledge management.

Status moderates the relationship between integration, infrastructure and business analytics. The moderating effect indicated that for low-status participants, when compared to high-status participants, integration and infrastructure become relevant to enhance their perception of business analytics, which is natural as students and professionals (low status) have a higher perception of integration and infrastructure.

According to hypothesis 9, there was a moderating effect of status on the relationship between business adaptation and business analytics, with business adaptation becoming relevant for low-status participants compared to high-status participants in terms of enhancing their business analytics. These results are possible because the students (low status) have a higher perception of business adaptation.

There was no evidence of a moderating effect of status on the relationship between business knowledge and business analytics. Strangely, the moderating effect was not found, but although students (low status) are the participants with a higher perception of business knowledge, professionals (low status) have a lower perception.

As expected, there was a moderating effect of status on the relationship between organizational culture and business analytics. Organizational culture was relevant in enhancing the perception of business analytics in low-status participants compared to high-status participants. These results are also natural since students and professionals (low status) are the participants who have a higher perception of organizational culture.

Finally, a moderate effect was found in the relationship between business analytics and costs. Compared to high-status participants, business analytics becomes relevant for low-status participants to boost their perception of costs. This is strange since low-status and high-status participants have identical perceptions of costs.

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5.1 Research Limitations

Despite this study's strengths, several limitations should be acknowledged. One major limitation is the inherent challenge of accessing proprietary information within the hospitality industry. Another significant limitation is the limited time availability for top hospitality managers and administrations.

Additionally, obtaining enough responses can be challenging despite efforts to gather data through questionnaire surveys. Even with the use of hospitality databases to target potential participants, there may still be difficulties in eliciting questionnaire replies, which can impact the representativeness and reliability of the collected data. Also, when collecting data through self-reporting methods, such as surveys or interviews, there is a risk of response bias. Hospitality professionals may have subjective interpretations or biases when providing information, which can impact the accuracy and reliability of the data. All of this can result in a low response rate, potentially affecting the representative-ness and generalizability of the findings.

The main limitation of this study's quantitative part was that it was a cross-sectional study, and therefore, causal relationships could not be tested. A longitudinal study would have to be conducted to test causal relationships. However, the methodological and statistical recommendations proposed by [52] were followed to reduce the impact of common method variance.

Another limitation of this study was the data collection process and the fact that the questionnaire used consisted of self-report instruments with closed questions, which may have conditioned the participants' answers.

Lastly, while including status as a moderating variable provides novel insights, future studies could further explore the multidimensional nature of status (*e.g.*, formal authority, tenure, expertise) and examine how these dimensions interact with organizational and technological factors in shaping analytics adoption behaviors.

Future research should address these limitations by adopting more diverse methodological approaches, including longitudinal and experimental designs, to strengthen causal inference and track changes over time. Researchers should also aim to include broader and more heterogeneous populations, such as participants from different regions, countries, and hospitality industry segments, to enhance the external validity and generalizability of findings. Additionally, there is a need for further validation and refinement of the measurement tools used in this study, particularly the newly developed scale items, to ensure their reliability, factorial stability, and theoretical alignment across various organizational contexts and cultural settings.

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