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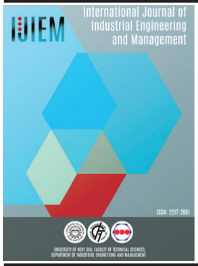

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Original research article

Employee Perceptions of BI and AI Tools for Service Transformation: Evidence from the Serbian Airline and Hotel Industries

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ABSTRACT

This study explores the perception of the transformative impact of Business Intelligence (BI) and Artificial Intelligence (AI) on the service sector by employees in an airline and hotels in Serbia. Four key factors were identified: business optimization (BO), service personalization (PS), efficiency of resource management (ERM), and business transformation (BT). Data were collected through a survey of employees in these sectors, and the results were analyzed using structural modeling. The findings indicate that employees perceive a significant positive impact of BI and AI on business transformation, particularly in terms of improving operational efficiency, increasing customer satisfaction, and enhancing business sustainability. This study highlights the importance of implementing BI and AI technologies in advancing the service sector, providing innovative approaches to optimizing business processes and personalizing services. These findings contribute to a better understanding of how modern tools and technologies can improve the performance and competitiveness of service enterprises in Serbia.

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1. Introduction

Business Intelligence (BI) and Artificial Intelligence (AI) have emerged as transformative technologies in the airline and hotel industries, driving significant advancements in service delivery and operational efficiency [1]. The evolution of tourism technology has progressed from basic Information and Communication Technologies (ICT) through eTourism to smart tourism, ultimately leading to ambient intelligence tourism [2].

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The implementation of BI tools in these sectors serves multiple strategic purposes. In airlines, these tools enable sophisticated data analysis for ticket pricing optimization, flight planning, and capacity management, resulting in enhanced operational efficiency and cost reduction [3]-[6]. BI applications help organizations monitor performance metrics, identify market opportunities, and provide crucial insights into aviation safety [7], [8]. Through analysis of supply and demand data, organizations can optimize routes and pricing strategies to enhance profitability [9].

AI technology has introduced innovative solutions that complement BI capabilities [10]. These solutions excel in processing large volumes of data for applications such as weather prediction and traffic optimization [11], while enabling personalized service delivery to enhance customer experience [12]. The implementation of automated customer support systems, including chatbots, has improved communication efficiency and reduced waiting times [13]. Furthermore, AI's predictive analytics capabilities help identify potential system failures pre-emptively, enhancing both safety measures and operational efficiency [14], [15].

Despite the widespread global adoption of these technologies, there remains a significant gap in understanding their perception and utilization by employees in specific regional contexts, particularly within Serbia's airline and hotel sectors. While existing research has documented the technical capabilities of these technologies, limited attention has been paid to employee perspectives and local market adaptations in developing economies. This gap is particularly significant as the successful implementation of BI and AI systems heavily depends on employee acceptance and effective utilization.

This research aims to examine the perceptions of employees in Serbian airlines and hotels regarding the impact of Business Intelligence (BI) and Artificial Intelligence (AI) on business transformation. Specifically, the study focuses on four key aspects: business process optimization, service personalization capabilities, resource management efficiency, and overall business transformation effectiveness. The significance of this research is reflected in its potential to provide practical recommendations for managers implementing BI and AI solutions in similar contexts, contribute to the local academic literature, and support evidence-based decision-making processes in the tourism sector. The decision to analyze the airline and hotel sectors together stems from the fact that both are part of the broader tourism industry and face similar challenges in implementing BI and AI tools. Both sectors rely heavily on large volumes of data to optimize operations, enhance customer experience, and improve resource management efficiency. Additionally, travelers often use services from both sectors within a unified tourism value chain, creating a need for integrated technological solutions.

The study employs a comprehensive approach that considers local market specificities, making it particularly relevant for developing effective strategies in similar markets. The research framework and hypotheses are developed based on established theoretical foundations in technology adoption and business transformation [13]. The subsequent sections of this paper present a detailed literature review, followed by the research methodology, findings, and implications for theory and practice.

2. Literature Review

The airline industry has leveraged AI capabilities to enhance operational efficiency through weather prediction, flight schedule optimization, and fleet management [16]. Machine learning algorithms have proven particularly effective in predicting flight delays and facilitating proactive schedule adjustments to minimize passenger disruption [17].

The hospitality sector has undergone significant transformation through the implementation of Business Intelligence tools, fundamentally improving service quality and operational efficiency [18]. Hotels employ BI for multiple purposes, including customer satisfaction analysis, performance metric evaluation, and strategic planning [19]. The same study also indicates that, in the airline industry, BI tools are used for route optimization, flight occupancy analysis, real-time ticket price adjustments, and the improvement of safety protocols. For example, Lufthansa uses BI systems to analyze delay data and manage its fleet more efficiently, while American Airlines applies BI tools to optimize its loyalty programs and personalize offers for passengers. Marriott International has implemented BI tools to analyze occupancy data and optimize room pricing, which led to a 10% increase in Revenue per Available Room (RevPAR) in selected hotels. On the other hand, Hilton Hotels uses BI systems to analyze guest reviews and adjust services in real-time, resulting in a 15% increase in customer satisfaction [12].

These implementations have yielded substantial improvements in service personalization and resource optimization [20] while enabling more informed strategic decisions through a better understanding of market trends and competitive dynamics [21].

Modern BI systems process extensive data from diverse sources, including customer feedback, reservation systems, and market trends [22], though implementation faces challenges in data integration and storage within big data warehouses [23]. Contemporary BI architectures incorporate sophisticated components for data management, including extraction, transformation, storage, and analysis capabilities, supported by reporting systems, OLAP (Online Analytical Processing), and data mining tools [24].

The integration of AI in hospitality has catalyzed significant operational and customer experience improvements [25]. Predictive analytics has emerged as a cornerstone technology, enabling hotels to anticipate guest needs and optimize operations [26]. AI models excel in forecasting booking patterns and guest consumption behaviors, allowing for refined service offerings [27]. The AI-powered analysis of online reviews has become crucial for understanding guest expectations [28] and developing competitive advantages [29]. The marketing landscape has been transformed through AI-enabled targeted campaigns [30], with continuous technological advancement driving further innovation [31]. Modern hotels increasingly leverage AI for personalized guest experiences, ranging from automated recommendations to adaptive smart room systems [32]. The research framework for understanding these technological implementations builds upon previous work in airline operations [33] and competitive intelligence in hospitality [34].

Despite their benefits, BI and AI implementation faces several challenges. Success depends heavily on ecological and organizational factors affecting competitive advantage [35]. The adoption of robotics and automation raises ethical concerns [36], requiring a careful balance between technological advancement and maintaining human-centric service delivery [37]. Privacy and security concerns have emerged as crucial considerations, as airlines and hotels collect extensive personal data, making them vulnerable to cyberattacks [38]. Security breaches can lead to privacy violations and loss of customer trust [39], while data misuse raises concerns about discrimination and ethical use of information [40]. Furthermore, the potential impact of automation on employment [41] affects various roles across the industry, potentially influencing both individual careers and broader community welfare.

Although BI and AI are distinct technologies, their synergy enables more efficient decision-making and business optimization. BI tools primarily support data analysis and reporting, while AI further contributes through predictive analytics and the automation of business processes. By combining these technologies, organizations can make more accurate strategic decisions, enhance customer experience, and increase operational efficiency [31].

Based on this comprehensive literature review and identified research gaps, this study proposes a research model (Figure 1) examining the relationships between BI and AI implementation and business transformation outcomes. The model builds upon established work in airline operations [33] and hospitality competitive intelligence [34], while incorporating Serbian market considerations. The proposed hypotheses investigate relationships between technology implementation, employee perceptions, and organizational outcomes, providing a framework for understanding the transformation process in the local context:

H1: Employees perceive that business optimization (BO) positively contributes to business transformation (BT).

H2: Employees perceive that effectiveness of resource management (ERM) positively contributes to business transformation (BT).

H3: Employees perceive that personalization of services (PS) positively contributes to business transformation (BT).

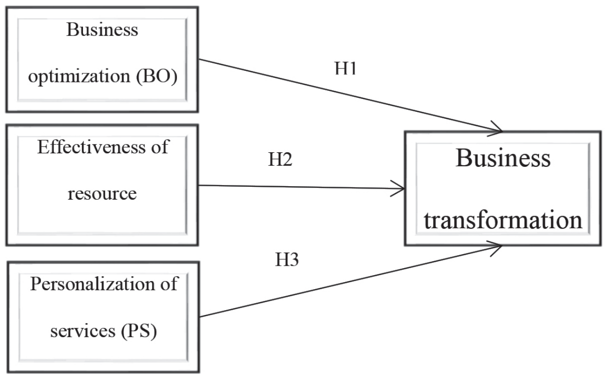


Figure 1. Proposed research model

3. Methodology

3.1 Data collection

Data were collected through a Google Forms survey distributed to airline and hotel employees in Serbia. Contact information was gathered from company websites, LinkedIn, industry events, and through management collaboration. Of 110 distributed surveys, 98 responses were received between December 2023 and May 2024. Special permissions weren't required as data collection relied on publicly available information and voluntary participation, ensuring ethical and transparent research practices. The respondents were selected using stratified sampling to ensure the representation of employees across different hierarchical levels in the airline and hotel industries. The selection criteria included experience in using BI and AI tools, job position, and length of service in the industry. The sample consists of managers, data analysts, and operational staff, providing a comprehensive insight into the perception of these technologies.

3.2 Sample

Sample selection included employees from various sectors within the airline and hotel industries, using simple random sampling to ensure fair representation and minimize bias. In social sciences and applied research, the aim is not to cover the entire population but to ensure that the sample is representative and allows for generalization of the findings. Representativeness is not achieved through sample size alone, but rather through its structure specifically by including the key characteristics of the target population. In this study, the sample was designed to reflect various professional roles, levels of responsibility, industry experience, and exposure to BI and AI tools, ensuring that the collected data accurately represents the perceptions of employees in these sectors. Although the exact size of the target population in the Serbian airline and hotel industries is not publicly available, it is estimated to include approximately 1,500 employees directly involved in business processes relevant to BI and AI technologies. The sample was structured to mirror this population. To confirm the adequacy of the sample for analyzing relationships between the studied constructs, an a priori power analysis was conducted using G*Power software (version 3.1.9.7). The analysis was performed under the linear multiple regression fixed model (R^2 deviation from zero), with a medium expected effect size ($f^2 = 0.15$), a standard alpha level ($\alpha = 0.05$), and statistical power of 80% ($1-\beta = 0.80$), including three predictors (business optimization, service personalization, and resource management efficiency). The results showed that the minimum required sample size was 77, indicating that the obtained sample of 98 respondents is statistically sufficient for reliable analysis and valid findings. To further ensure representativeness, the sample includes employees from different types of hotels (ranging from mid-scale to high-category establishments) and airline companies with varying business models. Additionally, respondents were drawn from different hierarchical levels, including managers, data analysts, and operational staff, providing a comprehensive perspective on the perception of BI and AI tools in these sectors. Accessing respondents was challenging due to limited publicly available contact information for employees in the analyzed industries. To ensure a representative sample, participants were contacted through professional networks (LinkedIn), industry events, and direct collaboration with companies. This approach enabled us to collect responses from employees actively involved in the use of BI and AI technologies, further reinforcing the relevance and reliability of the results.

The study comprised 98 respondents from Serbian airlines (51.0%) and hotels (49.0%). The sample was well-distributed across gender (45.9% male, 54.1% female), age groups (predominantly 26-45 years), education levels (majority holding bachelor's or master's degrees), and years of service (most having 6-15 years of experience). Detailed demographic characteristics are presented in Table 1.

Table 1. Sociodemographic characteristics of the respondents

Characteristic	Categories	Percentage
Gender	Male	45.9%
	Female	54.1%
Age	18-25	10.2%
	26-35	28.6%
	36-45	35.7%
	46-55	20.4%
	56+	5.1%
Education Level	High School	20.4%
	Bachelor	40.8%
	Master	30.6%
	PhD	8.2%
Years of Service	1-5 years	20.4%
	6-10 years	30.6%
	11-15 years	25.5%
	16-20 years	15.3%
	21+ years	8.2%
Sector	Airlines	51.0%
	Hotels	49.0%

3.3 Questinaire design

The research examined employee perceptions of BI and AI's impact on business transformation in airlines and hotels through carefully designed questions assessing business optimization, service personalization, and resource management efficiency. The questionnaire design was based on several key studies, Andronie [33] on BI tools for data analysis, price optimization, and flight planning in airlines, Mariani et al. [20] on BI's role in improving service quality and operational efficiency in hotels, Guerra-Montenegro et al. [26] on predictive analytics in hospitality, Koseoglu et al. [42] on analyzing online reviews for service quality improvement, and Casado Salguero et al. [34] on ecological and organizational factors affecting BI initiatives. To avoid moral hazard and leading questions, questions were neutrally formulated, and respondent anonymity was guaranteed to ensure unbiased responses.

A pilot study conducted in December 2023 with 15 randomly selected participants from various airline and hotel sectors assessed question clarity, completion time (approximately 12 minutes), and technical aspects. Based on feedback, questions were refined for clarity, and technical issues, including slow page loading, were resolved. Statistical analysis confirmed satisfactory reliability (Cronbach's alpha > 0.7) and validity (factor loadings > 0.5) for all scales. The final questionnaire was optimized based on these pilot study results to ensure precise and clear questions. The questionnaire used a 5-point Likert scale (1 – strongly disagree, 5 – strongly agree). This type of scale was selected due to its wide application in perception-based research and its reliability in measuring subjective attitudes. All items were formulated as declarative statements, and respondents were asked to indicate their level of agreement with each statement. Additionally, the statistical analysis employed methods compatible with ordinal data, including normality testing of response distributions to ensure accurate interpretation of the results.

3.4 Data analysis

The data were analyzed using multiple statistical methods. Descriptive analysis describes basic sample characteristics, including means, standard deviations, and response distributions [43]. The normality of data distribution was verified using the Kolmogorov-Smirnov test (K-S = 0.087, $p < 0.05$) and the Shapiro-Wilk test (S-W = 0.942, $p < 0.05$). The results of these tests indicated that certain variables, particularly those related to the perceived effectiveness of BI and AI tools, deviated from a normal distribution. Given that the analysis relies on methods assuming data normality, appropriate transformations (logarithmic and squared transformations) were applied to achieve a more symmetrical distribution and enhance the validity of the results. Exploratory Factor Analysis (EFA) was used to reduce data dimensionality and identify latent constructs [44]. EFA identified four key factors: business optimization (BO), service personalization (PS), resource management efficiency (ERM), and business transformation (BT). Confirmatory Factor Analysis (CFA) tested hypotheses and assessed factor validity [45]. The Kaiser-Meyer-Olkin Measure (KMO = 0.778) indicated satisfactory sample adequacy [46], while Bartlett's test of sphericity (Chi-Square = 1.929, df = 12, $p = 0.000$) confirmed the appropriateness of factor analysis [47].

The data satisfied the normality assumptions needed for factor analysis and SEM. Data transformations were applied where needed to improve distribution normality [44]. SEM was used to test hypotheses and examine factor relationships, enabling the assessment of complex models with multiple variables and latent constructs [43]. In this study, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used to assess the model's fit to the data. However, since AIC and BIC are primarily intended for model comparison rather than absolute model evaluation, additional model fit indicators were included—such as the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI)—to ensure a comprehensive assessment. As the manuscript does not present alternative models for comparison, AIC and BIC were interpreted as relative indicators of the model's fit to the existing data rather than as criteria for identifying the best-fitting model. The Fit Summary results for the saturated and estimated models indicate that the SRMR (Standardized Root Mean Square Residual) is 0.004, well below the acceptable threshold of 0.08 [44], indicating excellent model fit. The values of d_ULS (Squared Euclidean Distance) and d_G (Geodesic Distance) are 1.483 and 0.411, respectively, and do not indicate critical issues. A Chi-Square value of 1.160 further confirms the good model fit, while an NFI (Normed Fit Index) of 0.995, which is above the recommended threshold of 0.90, suggests a high model fit to the data [49]. The path coefficients presented in Figure 4 were estimated using the Maximum Likelihood Estimation (MLE) method, based on covariance matrices and z-tests to assess statistical significance ($p < 0.05$). The model was evaluated using SmartPLS software (version 4.0), with the following criteria: a minimum threshold for latent variable loadings of ≥ 0.70, t-values ≥ 1.96 for significance at the 5% level, and a bootstrapping procedure with 5,000 samples. The statistical significance of the path coefficients was further validated through corresponding p-values and 95% confidence intervals.

The results shown in Table 2 indicate that all constructs have satisfactory reliability, with Cronbach's alpha (α) values above 0.7 [45]. Additionally, Composite Reliability (CR) values for all constructs exceed 0.75, and the Average Variance Extracted (AVE) values are above the recommended threshold of 0.5, confirming the validity and reliability of the measured constructs.

Figure 2 combines the Fornell-Larcker criterion and HTMT (Heterotrait-Monotrait ratio) values to assess the discriminant validity of the constructs.

The diagonal values are Fornell-Larcker Criterion values, while the off-diagonal values include HTMT values. The Fornell-Larcker Criterion shows that all constructs in the model are sufficiently distinct, as the diagonal values are greater than all correlations between constructs [46]. The HTMT values are below the threshold of 0.85, which confirms the discriminant validity of the model [43].

Figure 3 displays the Variance Inflation Factor (VIF) values for the indicators within the constructs of PS, ERM, BT, and BO, with the highest values found in the indicators ERM3 and BT3. These values indicate the significance of each indicator in contributing to the reliability and validity of the corresponding constructs [47].

4. Results

Exploratory factor analysis identified four key factors: Business optimization (BO), Personalization of services (PS), Effectiveness of resource management (ERM), and Business transformation (BT), each with four questions. These factors showed high reliability, with Cronbach alpha (α) values above 0.8. Composite Reliability (CR) values ranged from 0.910 to 0.927, indicating excellent internal consistency. Average Variance Extracted (AVE) values were above 0.7, confirming that a significant part of the variance

Table 2. Construct reliability and validity

Construct	α	rho_A	CR	AVE
Business optimization	0.851	0.786	0.791	0.791
Business transformation	0.807	0.787	0.751	0.673
Effectiveness of resource management	0.810	0.901	0.867	0.625
Personalization of services	0.727	0.710	0.775	0.783

Note: α – cronbach alpha, rho_A - reliability indicator of latent constructs, CR - composite reliability, AVE - average variance extracted

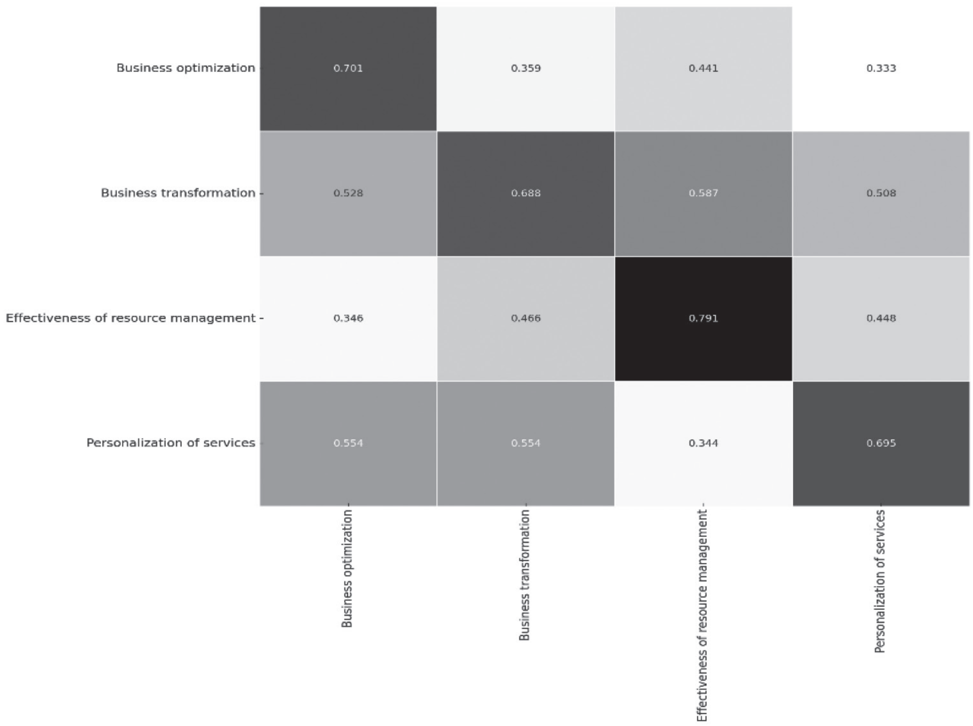
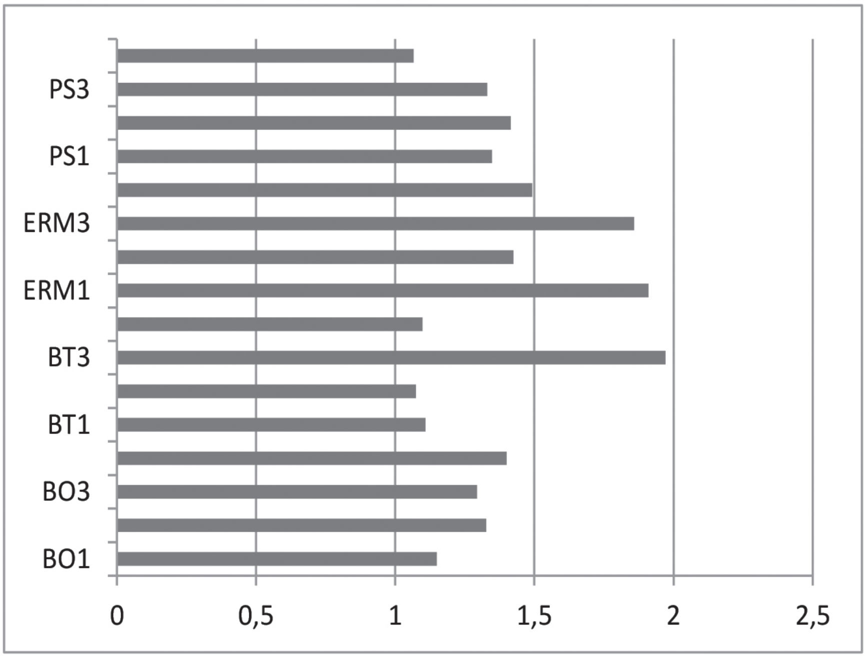


Figure 2. Combined Fornell-Larcker criterion and heterotrait monotrait ratio values



Note: PS - personalization of services, ERM - effectiveness of resource management, BT - business transformation, BO - business optimization.

Figure 3. Collinearity statistics (variance inflation factor - VIF < 3)

is explained by the identified factors. These results indicate the validity and reliability of the measured constructs (Table 3).

The results in Table 4 indicate the high reliability and validity of the measured constructs, with each factor significantly contributing to the explanation of variance in the context of business optimization, service personalization, resource management efficiency, and business transformation.

Business Optimization (BO) includes assessments such as predicting and reducing flight delays using AI, as well as analyzing supply and demand data for optimal planning. This factor has demonstrated high reliability with a Cronbach's alpha (α) value of 0.805 and factor loadings (FL) ranging from 0.824 to 0.881, indicating consistency and reliability of the measurement.

Personalization of Services (PS) focuses on personalizing services through AI, including recommendations for travelers and creating personalized marketing campaigns for hotel guests. This factor has an α value of 0.796, with FL values ranging from 0.836 to 0.889, confirming the high reliability and relevance of the items.

Effectiveness of Resource Management (ERM) covers aspects such as fuel consumption optimization and resource analysis in hotels to identify savings. The reliability of this factor is exceptional, with an α value of 0.810 and FL values between 0.861 and 0.889, indicating the effectiveness of measuring resource efficiency. Business Transformation (BT) encompasses the impact of BI and AI on operational efficiency, client satisfaction, security, and business sustainability. This factor shows an α value of 0.788 and FL values ranging from 0.809 to 0.899, suggesting that the items are well-constructed and reliable for measuring business transformation.

Table 3. Descriptive values, reliability, and validity of the factors

Factor	IEV	%V	C%	EAE	%VAE	C%AE	EAR	m	sd	α	CR	AVE
BO	4.855	30.347	30.347	4.855	30.347	30.347	4.325	2.48	1.026	0.863	0.915	0.721
PS	2.028	12.674	43.021	2.028	12.674	43.021	3.034	2.37	1.049	0.874	0.910	0.702
ERM	1.359	8.496	51.517	1.359	8.496	51.517	2.216	3.41	1.504	0.882	0.927	0.759
BT	1.241	7.756	59.273	1.241	7.756	59.273	1.370	3.22	1.752	0.895	0.921	0.744

Note: IEV - initial eigenvalues, %V - % of variance, C% - cumulative %, EAE - eigenvalues after extraction, %VAE -% of variance after extraction, C%AE - cumulative % after extraction, EAR - eigenvalues after rotation, m – arithmetic mean, sd – standard deviation, α - cronbach alpha, CR - composite reliability, AVE - average variance extracted

Table 4. Descriptive statistics of statements and factor loadings

Factor	Statements	m	sd	α	FL
Business Optimization (BO)	AI predicts and reduces flight delays by analyzing weather conditions.	2.30	1.439	0.805	0.863
	BI analyzes supply and demand data for optimal planning.	2.72	1.487	0.793	0.824
	AI automates guest check-in and reception, reducing wait times.	2.29	1.446	0.803	0.881
	BI analyzes hotel occupancy, helping to optimize room rates.	2.63	1.494	0.803	0.847
Personalization of Services (PS)	AI provides personalized recommendations to travelers.	2.11	1.411	0.796	0.836
	BI creates personalized marketing campaigns for hotel guests.	2.29	1.470	0.797	0.837
	AI chatbots provide 24/7 support.	2.17	1.351	0.798	0.836
	BI analyzes guest preferences to customize services.	2.91	1.945	0.819	0.889
Effectiveness of Resource Management (ERM)	AI optimizes fuel usage, reducing costs.	2.90	2.079	0.810	0.874
	BI analyzes resource consumption in hotels to identify savings.	4.01	2.377	0.833	0.861
	AI predicts equipment maintenance needs, reducing downtime.	3.46	2.169	0.786	0.861
	BI monitors energy and water consumption, reducing costs.	3.29	2.251	0.779	0.889
Business Transformation (BT)	BI and AI impact operational efficiency and cost reduction.	2.85	2.110	0.788	0.892
	BI and AI influence the increase of customer satisfaction through the personalization of services.	3.32	2.209	0.791	0.809
	BI and AI influence the improvement of security.	3.81	2.343	0.800	0.859
	BI and AI influence the optimization of the use of resources and the improvement of business sustainability.	2.90	2.101	0.808	0.899

Note: m – arithmetic mean, sd – standard deviation, α - cronbach alpha, FL – factor loading.

Table 5 presents the criteria for model selection for the construct of Business Transformation. The Akaike Information Criterion (AIC) value is -91.342, while the unbiased Akaike Information Criterion (AICu) is -87.295. The sample size-corrected Akaike Information Criterion (AICc) provides a value of -82.021. The Bayesian Information Criterion (BIC) is -78.776, the Hannan-Quinn Criterion (HQ) is -86.243, and the corrected Hannan-Quinn Criterion (HQc) is -85.767. The results indicate a relatively good fit of the model, suggesting a better fit of the model to the data.

The research results confirm all proposed hypotheses regarding the influence of different business aspects on business transformation (Table 6).

Hypothesis H1, which posits that employees perceive Business Optimization (BO) as positively contributing to Business Transformation (BT), was supported by the model with an estimated path coefficient of 0.259 ($t = 3.114$, $p = 0.002$). This suggests that respondents believe improvements in business optimization are associated with positive changes in business transformation processes. Hypothesis H2, indicating that employees perceive the Effectiveness

Table 5. Model selection criteria

	AIC	AICu	AICc	BIC	HQ	HQc
Business transformation	-91.342	-87.295	-82.021	-78.776	-86.243	-85.767

Note: AIC - akaike's information criteria, AICu - unbiased akaikes information criteria, BIC - bayesian information criteria, HQ - hannan quinn criteria, HQc - corrected hannan-quinn criteria.

Table 6. SEM analysis results and hypothesis testing

Hypothesis	Path	Estimate	m	sd	t	p	Confirmation
H1	BO →BT	0.259	0.266	0.083	3.114	0.002	Confirmed
H2	ERM → BT	0.267	0.274	0.079	3.384	0.001	Confirmed
H3	PS → BT	0.318	0.312	0.083	3.851	0.000	Confirmed

Note: m – arithmetic mean, sd – standard deviation, t – t statistic, p – statistical significance of Resource Management (ERM) as positively influencing Business Transformation (BT), was also supported, with an estimated value of 0.267 ($t = 3.384$, $p = 0.001$). According to participants, more efficient management of resources may contribute to greater organizational adaptability and transformation. The strongest perceived effect was observed in Hypothesis H3, which suggests that employees believe Personalization of Services (PS) plays a crucial role in supporting Business Transformation (BT). This hypothesis was supported with a path coefficient of 0.318 ($t = 3.851$, $p < 0.001$), indicating that service personalization is viewed by respondents as a key driver of transformation. All three hypotheses are confirmed with high levels of statistical significance, indicating the robustness of the model and the significant impact of business optimization, resource management, and service personalization on business transformation.

The factor loadings presented in Table 4 are the result of Exploratory Factor Analysis (EFA), which was used to identify latent constructs based on correlations among observed variables. In contrast, Figure 4 shows the results of Confirmatory Factor Analysis (CFA) obtained through the SEM model, which confirms the proposed factor structure by modeling structural equations. Differences between the factor loadings in Table 4 and Figure 4 are expected, as CFA estimates loadings within a theoretically defined model (confirming hypothesized relationships), while EFA freely explores underlying structures and associations among indicators. To ensure model consistency, the CFA analysis demonstrated that all factor loadings were statistically significant ($p < 0.05$) and within an acceptable range (> 0.50), confirming the validity of the measured constructs.

The results shown in Figure 4 illustrate that Business Optimization (BO), Effectiveness of Resource Management (ERM), and Personalization of Services (PS) have a significant positive impact on Business Transformation (BT). Business Optimization has an estimated effect of 0.259, Effectiveness of Resource Management is 0.267, and Personalization of Services is 0.318, all with high levels of statistical significance ($p < 0.05$).

5. Discussion

The findings of this study reflect employees' perceptions rather than direct measurements of BI and AI implementation outcomes. Our results suggest that employees perceive Business Optimization (BO), Effectiveness of Resource Management (ERM), and Personalization of Services (PS) as influential elements that may contribute to Business Transformation in Serbian airlines and hotels. Although all fac-

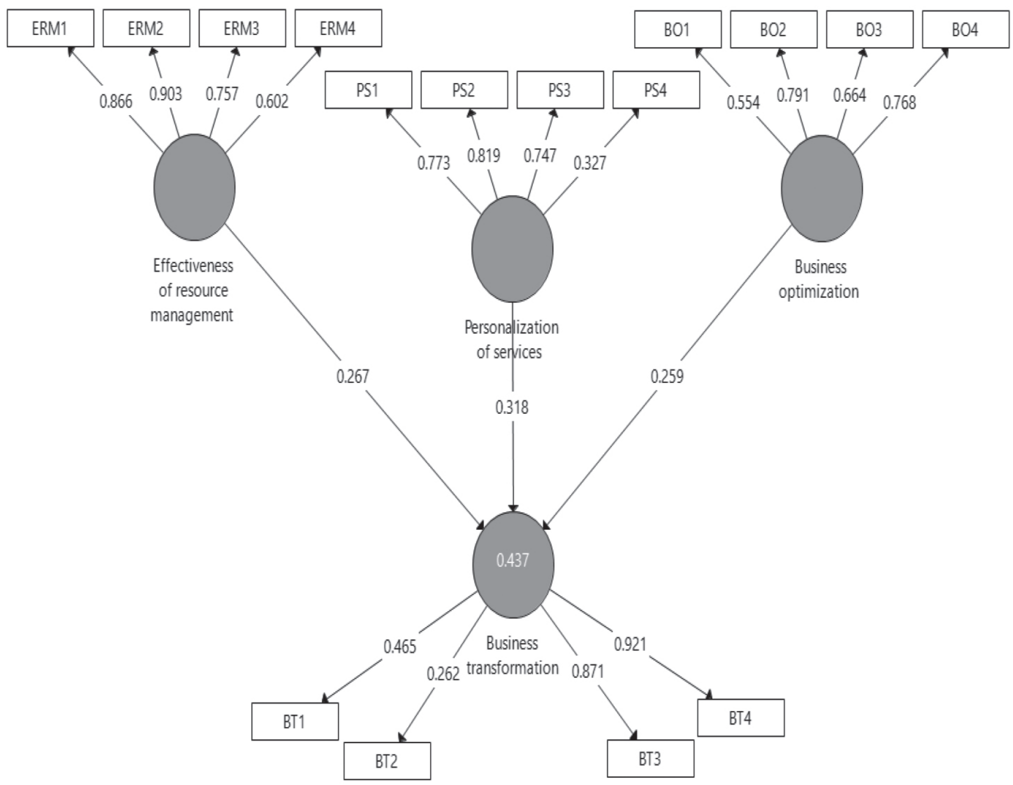


Figure 4. Structural model of business transformation in airlines and hotels

tors demonstrated statistically significant relationships within the structural model, the relatively stronger perceived influence of Personalization of Services (β = 0.48) compared to Business Optimization (β = 0.35) may be interpreted as a reflection of Serbia's relationship-oriented business culture. The application of BI tools in the airline industry, as illustrated by Andronie [33], has shown operational benefits such as optimized flight data analysis, pricing, scheduling, and capacity management. While our study does not measure these effects directly, it confirms that employees in Serbia recognize similar areas where BI may be beneficial. In the hospitality sector, findings by Mariani et al. [20] highlight how BI supports data-driven decision-making, thereby enhancing service quality and operational efficiency. In line with these studies, our respondents expressed the belief that BI tools can assist hotels in analyzing occupancy data and guest preferences, allowing managers to personalize offers and optimize resources. Similarly, the relevance of predictive analytics in hospitality as explored by Guerra-Montenegro et al. [26] resonates with employees' perceptions that AI enables hotels to forecast guest needs and deliver tailored services, potentially leading to better guest experiences and satisfaction. Casado Salguero et al. [34] emphasized the importance of organizational and ecological factors in the success of BI initiatives. Our respondents also perceived that efficient resource management supported by BI and AI tools is crucial for effective business transformation. These perceptions underline the need for improved resource utilization and cost efficiency, especially within the local context. While Christou [50] addressed general risks associated with AI dependence, the participants in our study identified specific challenges relevant to the Serbian context, such as limited access to skilled IT professionals, high implementation costs, and regulatory constraints. These responses suggest that the perceived benefits of BI and AI are balanced by concerns over ethics, data privacy, and human-centric service delivery.

Review studies by Law et al. [51] suggested that AI has significant potential to transform hospitality operations and marketing. Our participants reflected this view, perceiving AI-driven marketing as a way to create personalized campaigns, improve customer targeting, and enhance loyalty. Similarly, while Jabeen et al. [52] raised the issue of job insecurity due to automation, our respondents acknowledged both the efficiency gains and the need for workforce adaptation. Overall, the study finds that employees perceive BI and AI tools as having potential benefits for business transformation, especially in enhancing operational efficiency, customer satisfaction, and business sustainability. However, it is essential to reiterate that these findings represent subjective perceptions rather than objectively verified outcomes. By integrating BI and AI technologies, service providers may be able to achieve greater efficiency and competitiveness. At the same time, ethical and human factors must be carefully managed. Future research should seek to validate these perceptions through longitudinal and implementation-based studies.

The theoretical implications of this research lie in extending existing BI and AI adoption frameworks to the Serbian context. By identifying perceived drivers of transformation, this study contributes to a better understanding of technology acceptance in emerging economies. It highlights the variability in adoption patterns and the need for culturally and economically contextualized models. Additionally, it opens pathways for examining the long-term implications of digital transformation, including ethical concerns and employment dynamics.

From a practical standpoint, the findings suggest that managers should invest in training, communication strategies, and benchmarking processes to support the adoption of BI and AI. While the insights are based on employee perceptions, they offer valuable guidance for planning successful digital transformation efforts.

6. Conclusions

This study provides clear insights into employees' perceptions of the impact of BI and AI technologies on business transformation in airlines and hotels in Serbia. The results demonstrate that business optimization, resource management efficiency, and service personalization have a significant positive effect on business transformation. These findings are crucial for managers and decision-makers in the service sector, as they offer empirical evidence of the benefits associated with integrating BI and AI technologies. Future research should include a larger sample and incorporate comparative analyses with other regions to confirm the generalizability of the results. Additionally, it is recommended to use more objective measurement methods to assess the impact of BI and AI technologies on business transformation. Our results indicate that employees recognize the potential of BI and AI tools for business process optimization. However, although the study provides insight into employees' perceptions, it does not examine the specific methods of BI and AI implementation in Serbian hotels and airline companies. Therefore, further research is needed to empirically validate the identified benefits.

This research has several limitations. First, the relatively small and geographically limited sample may affect generalizability. Second, all findings are based on subjective assessments, which can introduce biases. Third, the study was conducted during a specific period and may not reflect changes over time.

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