

The moderating role of online booking on the effects of digital marketing and dynamic pricing on customer satisfaction and hotel performance: Evidence from three-star hotels in Bali

Ismoyo Sugiarto¹, Ida Aju Brahmasari^{2*}, Ida Aju Brahma Ratih³

^{1,2,3}University 17 Agustus 1945 Surabaya, Indonesia; brahmasari@untag-sby.ac.id (I.A.B.).

Abstract: This study aims to examine the influence of digital marketing and dynamic pricing on customer satisfaction and hotel performance, with customer satisfaction serving as a mediating variable and online booking as a moderating variable. The research focuses on three-star hotels in Bali Province to understand the effectiveness of digital marketing strategies and price flexibility in enhancing customer experience and hotel performance amid increasingly dynamic industry competition. A quantitative approach was employed through a survey of managers of three-star hotels registered with hotel associations in Bali. The data were analyzed using PLS-SEM to test the direct, mediating, and moderating effects within the research model. In addition, IPMA was utilized to identify managerial priorities in improving variables that contribute to hotel performance. The findings reveal that dynamic pricing significantly influences customer satisfaction and hotel performance, while digital marketing does not show a direct effect on satisfaction. Customer satisfaction is confirmed to be an important mediator in improving hotel performance. Furthermore, online booking strengthens the effect of dynamic pricing on satisfaction but does not moderate the impact of digital marketing. These results offer practical implications for hotel management to prioritize customer satisfaction, optimize data-driven dynamic pricing strategies, and ensure effective integration between digital strategies and online booking systems to enhance long-term competitiveness.

Keywords: Bali Three-Star Hotels, Customer satisfaction, Digital marketing, Dynamic pricing, Hotel performance, Online booking, PLS-SEM.

1. Introduction

The tourism industry is one of the main pillars of the global economy, contributing around 10% to global GDP, equivalent to approximately US\$10.9 trillion in 2024, and generating more than 357 million jobs, or one in every ten jobs worldwide [1, 2]. In 2025, its contribution is projected to increase to US\$11.7 trillion, with international tourist spending rising to US\$2.1 trillion [3]. This growth drives the hotel industry to accelerate digital transformation, ranging from contactless self-service and big data analytics to the use of AI and IoT, which have been shown to improve efficiency and guest satisfaction [4, 5]. However, this transformation continues to face challenges such as high technology investment costs, integration complexity, and the need for workforce training [4]. At the same time, digital distribution models through Online Travel Agencies (OTAs) such as Booking.com and Agoda help expand market reach but impose high commission fees and reduce direct interaction with guests [6, 7]. Recent trends indicate a shift toward direct booking, with projections suggesting that by 2030, direct reservations will surpass OTAs as the primary channel, presenting opportunities to strengthen loyalty and improve hotel profitability [8].

Indonesia has shown positive developments in the global tourism industry, reflected in its rise in the Travel and Tourism Development Index (TTDI) to 22nd position globally, up from 32nd, driven by

improvements in safety, accessibility, and digital infrastructure [9]. The tourism sector also contributes significantly to the national economy, with projected growth reaching 12% in 2025 and tourist spending estimated at IDR 344 trillion [9]. Indonesia is listed among the top 20 Asia-Pacific countries with the highest international tourist arrivals, according to the United Nations World Tourism Organization [10] supported by rich cultural and natural attractions and the government's strategic programs under the Indonesia Tourism Development Master Plan [9]. Nevertheless, increasing regional competition requires destination marketing strategies that are more adaptive to shifting post-pandemic tourist preferences.

In the domestic context, Bali remains Indonesia's leading tourist destination, contributing more than 30% of international tourist arrivals and significantly supporting foreign exchange earnings [9]. Its combination of natural beauty, cultural heritage, arts, and high-quality services positions Bali among the world's best destinations according to the Tripadvisor Travelers' Choice Awards 2024. However, this dominance comes with challenges, including pressure on infrastructure and service sustainability. According to Badan Pusat Statistik Provinsi Bali [11], three-star hotels represent the largest segment with 182 hotels and 10,561 rooms, surpassing five-star hotels (129 hotels; 21,287 rooms) and four-star hotels (173 hotels; 21,543 rooms). The large number of three-star hotels reflects highly intense competition in the mid-range segment, creating a strong need for service innovation and optimization of digital marketing strategies.

Despite demonstrating signs of post-pandemic recovery, hotel occupancy performance in Bali remains volatile. The room occupancy rate (TOR) of three-star hotels increased from 10.30% in 2021 to 59.77% in 2024 but declined again to 55.42% in June 2025, a 7% decrease compared to the previous year [11]. This downward trend is consistent with declines in five-star hotels (down 12%) and four-star hotels (down 11%). Monthly trends show that occupancy for three-star hotels peaked in August 2024 (67.60%) and May 2024 (64.15%) but dropped sharply in March 2025 (44.10%) from 50.21% in March 2024. The average length of stay for domestic tourists increased from 1.87 nights (January 2024) to 2.48 nights (January 2025), while foreign tourists experienced a decline from 3.14 nights (January 2024) to 3.02 nights (June 2025), indicating a shift where domestic tourists are becoming an increasingly important segment for the sustainability of three-star hotels [11].

Tourist behavior has shown a strong shift from offline to online booking, driven by increasing preferences for convenience, price transparency, and real-time payment. The value of global offline bookings decreased from US\$729 billion in 2019 to US\$610.5 billion in 2024, marking a major transformation toward digital platforms [12]. A 2024 global survey also reported that 80% of travelers now consider it essential to book their entire trip online, particularly among millennials (86%) and Gen Z (83%), further reinforcing the dominance of digital channels in the modern travel industry [13].

A bibliometric review reveals several key gaps in the hotel marketing literature. First, online booking has never been positioned as a moderating variable, despite the growing attention to booking channels such as OTAs and direct booking [14, 15]. Second, empirical evidence on the impact of dynamic pricing on customer satisfaction remains limited, as most studies focus on revenue management rather than consumer perception [16-18]. Third, no integrative model has incorporated digital marketing and dynamic pricing toward customer satisfaction and hotel performance; these two topics remain in separate clusters in bibliometric mapping, leaving the combined contribution of digital strategies to hotel performance underexplored. Fourth, prior studies are dominated by upscale hotel settings or developed countries, while research on three-star hotels in developing nations such as Indonesia remains scarce [19-21]. Fifth, post-COVID studies on changing booking behavior and its potential moderating role are still limited, even though online booking has emerged as a new topic with weak connectivity to hotel performance in bibliometric networks [22]. Lastly, there is a practical gap due to the absence of operational guidelines for three-star hotel managers on aligning digital marketing strategies and pricing policies with booking channels [23, 24], highlighting the theoretical and practical need addressed by this study.

This study offers several important contributions that remain underexplored in the hotel marketing literature. First, it positions online booking as a moderating variable rather than merely an operational characteristic or control variable, providing new insights into how booking-channel variation strengthens or weakens the effects of marketing strategies on customer satisfaction. Second, it develops an empirical pathway linking dynamic pricing to customer satisfaction through perceived fairness and price transparency, addressing the paucity of empirical evidence that has traditionally focused on revenue and demand aspects. Third, it integrates digital marketing and dynamic pricing into a comprehensive model, leading to customer satisfaction and hotel performance, an approach rarely adopted, as most studies examine these constructs separately. Fourth, the study provides contextual novelty by focusing on three-star hotels in Bali, a segment that is understudied compared to upscale hotels in developed countries, thereby offering relevant contributions for mid-scale hotels in emerging destinations. Fifth, it captures post-COVID-19 dynamics by examining how shifts in booking behavior influence the moderating role within the relationships among the studied variables.

2. Study of Literature

2.1. Organizational Performance Theory

Organizational Performance Theory by Venkatraman and Ramanujam [25] emphasizes that organizational performance should be evaluated not only through financial indicators but also through non-financial dimensions such as operational efficiency, service quality, and customer satisfaction. Performance is classified into three dimensions: financial performance, operational performance, and organizational effectiveness, which collectively reflect the organization's ability to innovate, maintain customer relationships, and adapt to environmental changes [25]. In the modern hospitality context, Busulwa et al. [26] add that digitalization has transformed the way hotels achieve and measure performance, making organizational agility and guest experience essential elements. Technology enables process optimization, resource management, and data-driven decision-making, all of which contribute directly to enhancing customer satisfaction and loyalty.

Building on this framework, Lounsbury and Gehman [27] highlight the importance of organizational identity and strategic responsiveness to market dynamics. In the hotel industry, firms are required to maintain a consistent brand identity while remaining flexible in adopting service innovations and new technologies. Therefore, Organizational Performance Theory provides a comprehensive conceptual foundation for evaluating the performance of three-star hotels in Bali by integrating financial, operational, technological, and customer experience dimensions. This perspective is relevant because digital marketing, dynamic pricing, and customer satisfaction directly influence these dimensions, enabling a more holistic analysis of how hotel performance can be improved amid intensifying industry competition.

2.2. Hotel Performance

Hotel performance reflects the hotel's ability to manage resources to achieve business objectives, measured not only through profitability but also through stability in operations amid market fluctuations [28]. Such stability includes maintaining consistent service quality, cost efficiency, and adaptability to external changes. Managerial factors and organizational culture also play a crucial role in shaping performance, where employee empowerment, quality management practices, and support for innovation distinguish high-performing hotels [29]. Thus, hotel performance is understood as a multidimensional construct encompassing financial outcomes, operational efficiency, innovation, sustainability, and growth strategies, all of which collectively determine competitiveness in the modern hospitality industry [30].

Operationally, hotel performance can be assessed through five key indicators: occupancy rate, RevPAR, GOPPAR, total revenue, and market share [31]. Occupancy rate reflects the hotel's ability to manage room demand, while RevPAR combines occupancy and pricing to evaluate revenue optimization. GOPPAR offers insight into operational profitability by accounting for cost efficiency, and

total revenue represents the hotel's overall success across business segments. Market share indicates the hotel's competitive position within the industry. Collectively, these indicators provide a comprehensive measurement basis for understanding and improving the performance of three-star hotels in increasingly competitive environments.

2.3. Customer Satisfaction

Customer satisfaction is an evaluative response that arises when customers compare their expectations with the service performance they receive, generating feelings of pleasure or disappointment that influence repurchase decisions and loyalty [32]. Satisfaction differs from customer experience and loyalty, as experience encompasses the full spectrum of interactions with the brand, while loyalty results from consistent satisfaction and emotional attachment [33]. In service industries such as hospitality, brand experience, which includes sensory, affective, intellectual, and behavioral dimensions, shapes customer satisfaction in a multidimensional manner [34].

The increasing influence of digital technology and social media further strengthens the mechanisms that shape customer satisfaction. Social media marketing activities involving direct interaction, engaging content, and timely responses have been shown to enhance satisfaction and loyalty [35]. The integration of technologies such as IoT also enables real-time service personalization and improved guest comfort, enhancing perceived value and service quality [36]. A consistent and high-quality digital experience fosters strong emotional connections with customers, thereby increasing satisfaction and retention [34].

In terms of measurement, hotel customer satisfaction can be assessed through various indicators such as guest surveys and feedback, complaint ratios and resolution rates, Customer Satisfaction Index (CSI), online ratings, retention levels, digital marketing effectiveness, and responsiveness to dynamic pricing. These indicators provide a comprehensive view of customer perceptions and the effectiveness of hotel service strategies [32, 33]. Online reviews, digital engagement, and the hotel's ability to adjust prices and respond to customer comments are critical factors in maintaining satisfaction amid market competition and digital dynamics [35, 37, 38].

2.4. Digital Marketing

Digital marketing is a marketing strategy that leverages digital technologies and various online platforms to reach, attract, and retain customers more effectively and measurably [39]. Within the perspective of Marketing 5.0, digital marketing functions not only as a promotional tool but also integrates AI, big data, and IoT to deliver personalized and relevant customer experiences [40]. Through multiple digital touchpoints such as websites, mobile applications, social media, and third-party reviews, firms can build a consistent and dynamic communication ecosystem that allows marketing strategies to be adjusted in real time in response to changing consumer behavior [41].

In the hospitality industry, digital marketing plays a strategic role because it influences the entire customer journey, from information search to booking and post-stay evaluation. Official websites, paid advertisements, social media activities, and collaborations with OTAs serve as primary channels for hotels to expand market reach and increase booking conversions [42]. Data-driven personalization provides a key competitive advantage, enabling hotels to tailor promotions to guest preferences and strengthen their reputation through responsive management of online reviews [41]. Consequently, digital marketing not only enhances sales performance but also builds long-term relationships and reinforces the hotel brand image.

The effectiveness of digital marketing is measured through indicators such as website traffic, conversion rate, social media engagement rate, cost per acquisition (CPA), return on investment (ROI), brand awareness, and the quality of online reviews [39, 42]. These indicators are highly relevant in the hotel context as they reflect the accuracy of customer acquisition strategies, the quality of digital experiences, and the impact of promotional activities on booking decisions. Kannan and Li [41] emphasize that metrics should be aligned with the firm's strategic goals, while advancements in AI-

driven analytics allow hotels to monitor performance in real time and optimize marketing strategies rapidly [43].

2.5. Dynamic Pricing

Dynamic pricing is a flexible pricing strategy in which prices change in real time based on demand conditions, customer segmentation, timing, and other external factors. This strategy allows hotels to optimize revenue by adjusting prices in response to market fluctuations [38]. In hospitality settings, dynamic pricing is essential due to the seasonal and volatile nature of demand, requiring prices to align with occupancy levels and booking timing [44]. Recent advancements, such as open pricing and one-to-one pricing, enable increasingly personalized and data-driven price adjustments, allowing hotels to offer more relevant rates to guests [45]. Thus, dynamic pricing is not merely a conventional pricing tactic but a technology-enabled analytical strategy designed to enhance efficiency and revenue.

The implementation of dynamic pricing also affects customer satisfaction, particularly through perceptions of price fairness. Non-transparent price fluctuations can create psychological discomfort and diminish satisfaction, especially among guests in higher-rated hotels [46]. Therefore, transparency and clear communication regarding the rationale behind price changes are crucial to ensure that customers understand the context and do not feel disadvantaged [38]. While price personalization can foster loyalty when executed appropriately, it must still consider customer sensitivity toward price discrimination [45]. The effectiveness of dynamic pricing can be evaluated through indicators such as the frequency of price adjustments, demand elasticity, the degree of price personalization, the accuracy of demand forecasting, and the use of automated pricing systems [47, 48]. These indicators help ensure that dynamic pricing strategies operate optimally while remaining acceptable to customers.

2.6. Online Booking

Online booking refers to a digital reservation system that enables customers to independently make reservations through a hotel's official website or third-party platforms, supported by real-time room availability data [42]. The system operates through integration between the Property Management System (PMS) and booking engine, ensuring accurate room inventory and providing a booking experience that is fast, intuitive, and instantaneous [49]. Key advantages of online booking include accessibility, price transparency, and automatic confirmation features that align with modern travelers' preferences for flexible and staff-free booking processes [50]. Additionally, contemporary online booking models emphasize interface quality, navigation design, transaction security, and the effectiveness of post-booking communication as essential components of hotels' digital competence [51].

The effectiveness of online booking can be measured through a range of technical, strategic, and operational indicators. Technically, interface design quality, booking speed, completeness of information, and clarity of policies are major determinants of conversion success [42]. Strategic indicators include the system's ability to personalize recommendations based on guest preferences and its integration with CRM systems, social media, and channel managers to support hotel marketing activities [50]. From an operational perspective, transaction success rate, direct booking ratio, error rate, data security, and the accuracy of real-time information on room availability and pricing serve as critical measures of system effectiveness [49, 52].

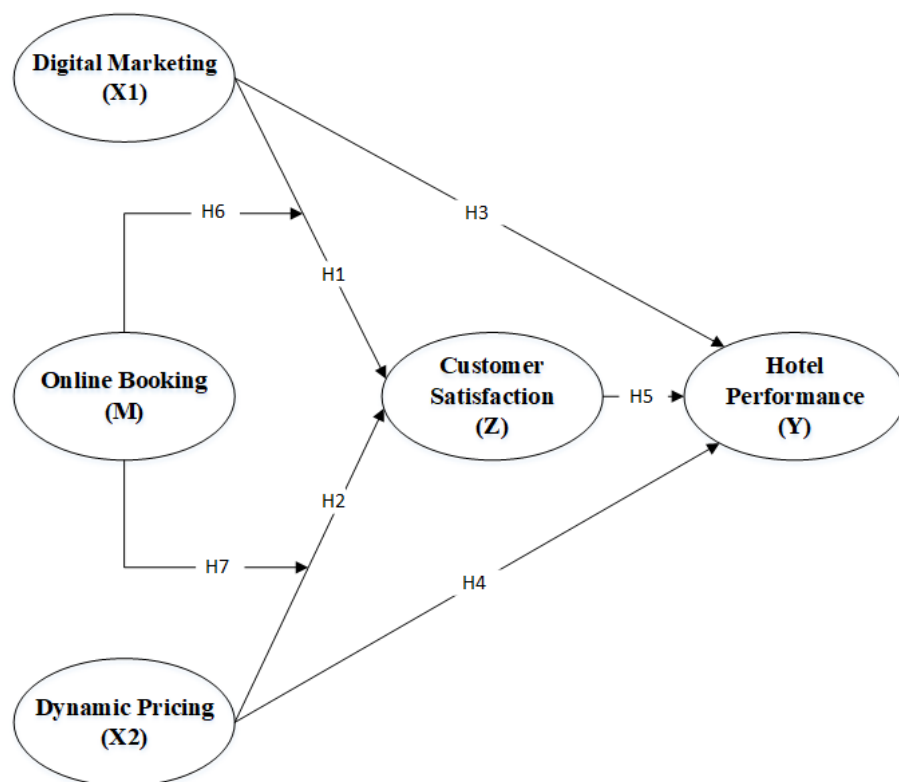


Figure 1.
Conceptual Model.

3. Method

The study employs a quantitative approach using an explanatory (causal) survey design, implemented through a structured questionnaire to examine the causal relationships among Digital Marketing, Dynamic Pricing, Online Booking (as a moderator), Customer Satisfaction, and Hotel Performance. The explanatory design was selected because it enables the measurement of the strength, direction, and statistical significance of causal effects, including moderating influences [53, 54]. The research population consists of all three-star hotels in Bali Province in 2025, totaling 182 hotels according to BPS data. The sample was determined using proportional random sampling and calculated using the Slovin formula with a 5% margin of error, resulting in a minimum required sample size of 126 hotels [53].

The inclusion criteria required hotels to be three-star properties that were operational in 2025, equipped with an online booking system, engaged in digital marketing activities, and maintained documented performance data. The unit of analysis is the hotel manager with at least one year of tenure, as these individuals possess strategic knowledge related to hotel operations, digital marketing initiatives, and booking system management. Data were collected through a five-point Likert-scale questionnaire, chosen for its ability to generate structured, consistent, and easily analyzable data within a quantitative research framework [54, 55].

Data were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM), which is appropriate for complex models involving multiple constructs, indicators, and data that may not meet normality assumptions or involve relatively small sample sizes. PLS-SEM emphasizes predictive capability and is suitable for theory development as well as for examining relationships involving both reflective and formative constructs. Model evaluation was conducted in two stages: the outer model to assess indicator validity and reliability, and the inner model to test structural relationships among latent

constructs [56].

4. Results

4.1. Preliminary Analysis

In the preliminary analysis stage, the researcher conducted two assessments: first, a validity and reliability test of the questionnaire, and second, a bias evaluation to ensure that the data were free from systematic errors.

4.1.1. Testing for Validity and Reliability

The results of the validity and reliability tests, presented in Table 1, show that all questionnaire items achieved Corrected Item–Total Correlation values ranging from 0.402 to 0.908, exceeding the recommended threshold of >0.30 [57]. This indicates that each item is sufficiently correlated with the total score of its corresponding construct, demonstrating that all items accurately represent the variables being measured. Furthermore, the Exploratory Factor Analysis (EFA) results reveal factor loadings between 0.455 and 0.927, all surpassing the minimum threshold of 0.50 recommended by Hair et al. [58], with values above 0.40 still considered acceptable in measurement assessment. Accordingly, both criterion validity and convergent validity are satisfied, confirming that all indicators are valid and adequately capture their respective constructs.

Table 1.
Validity and reliability test.

Variables	Indicators	Items	Corrected Item–Total Correlation	Factor Loadings EFA	Decision
Digital Marketing (X1)	Website Traffic (X1.1)	X1.1.1	0.542	0.563	Valid
		X1.1.2	0.589	0.654	Valid
		X1.1.3	0.250	-	Invalid
	Conversion Rate (X1.2)	X1.2.1	0.722	0.691	Valid
		X1.2.2	0.466	0.494	Valid
		X1.2.3	0.539	0.563	Valid
	Media Social Engagement (X1.3)	X1.3.1	0.654	0.730	Valid
		X1.3.2	0.497	0.578	Valid
		X1.3.3	0.665	0.760	Valid
	Cost per Acquisition (X1.4)	X1.4.1	0.623	0.621	Valid
		X1.4.2	0.748	0.775	Valid
		X1.4.3	0.402	0.455	Valid
	Digital ROI (X1.5)	X1.5.1	0.578	0.671	Valid
		X1.5.2	0.588	0.629	Valid
		X1.5.3	0.699	0.759	Valid
	Reach & Impressions (X1.6)	X1.6.1	0.699	0.770	Valid
		X1.6.2	0.694	0.763	Valid
		X1.6.3	0.551	0.629	Valid
	Online Reviews (X1.7)	X1.7.1	0.114	-	Invalid
		X1.7.2	0.527	0.635	Valid
		X1.7.3	0.443	0.563	Valid
Dynamic Pricing (X2)	Price Frequency (X2.1)	X2.1.1	0.549	0.657	Valid
		X2.1.2	0.673	0.761	Valid
		X2.1.3	0.491	0.562	Valid
	Price Elasticity (X2.2)	X2.2.1	0.669	0.749	Valid
		X2.2.2	0.439	0.553	Valid
		X2.2.3	0.465	0.542	Valid
	Price Personalization (X2.3)	X2.3.1	0.626	0.675	Valid
		X2.3.2	0.540	0.564	Valid

Variables	Indicators	Items	Corrected Item-Total Correlation	Factor Loadings EFA	Decision
	Demand Accuracy (X2.4)	X2.3.3	0.664	0.716	Valid
		X2.4.1	0.610	0.680	Valid
		X2.4.2	0.634	0.680	Valid
		X2.4.3	0.788	0.850	Valid
	Pricing Automation (X2.5)	X2.5.1	0.612	0.652	Valid
		X2.5.2	0.659	0.688	Valid
		X2.5.3	0.662	0.694	Valid
Customer Satisfaction (Z)	Satisfaction Survey (Z.1)	Z.1.1	0.819	0.862	Valid
		Z.1.2	0.674	0.748	Valid
	Complaint Resolution (Z.2)	Z.2.1	0.686	0.759	Valid
		Z.2.2	0.760	0.822	Valid
	Satisfaction Index (Z.3)	Z.3.1	0.628	0.695	Valid
		Z.3.2	0.761	0.817	Valid
	Online Rating (Z.4)	Z.4.1	0.822	0.870	Valid
		Z.4.2	0.857	0.890	Valid
Hotel Performance (Y)	Occupancy Rate (Y.1)	Y.1.1	0.700	0.758	Valid
		Y.1.2	0.827	0.869	Valid
	RevPAR (Y.2)	Y.2.1	0.693	0.752	Valid
		Y.2.2	0.848	0.891	Valid
	GOPPAR (Y.3)	Y.3.1	0.867	0.908	Valid
		Y.3.2	0.723	0.791	Valid
	Total Revenue (Y.4)	Y.4.1	0.574	0.633	Valid
		Y.4.2	0.662	0.716	Valid
Online Booking (M)	Easy Navigation (M.1)	Y.5.1	0.828	0.869	Valid
		Y.5.2	0.836	0.871	Valid
	Clear Information (M.2)	M.1.1	0.865	0.895	Valid
		M.1.2	0.901	0.920	Valid
	Process Speed (M.3)	M.2.1	0.841	0.872	Valid
		M.2.2	0.685	0.722	Valid
	Transaction Security (M.4)	M.3.1	0.908	0.927	Valid
		M.3.2	0.657	0.700	Valid
	Service Personalization (M.5)	M.4.1	0.737	0.776	Valid
		M.4.2	0.896	0.911	Valid
	System Integration (M.6)	M.5.1	0.810	0.836	Valid
		M.5.2	0.675	0.716	Valid
	Booking Conversion (M.7)	M.6.1	0.827	0.852	Valid
		M.6.2	0.878	0.905	Valid
		M.7.1	0.886	0.901	Valid
		M.7.2	0.783	0.820	Valid

Cronbach's Alpha:

Digital Marketing (X1) 0.916; Dynamic Pricing (X2) 0.906; Customer Satisfaction (Z) 0.929; Hotel Performance (Y) 0.938; Online Booking (M) 0.964

The reliability assessment further shows that all constructs exhibit high Cronbach's Alpha values, ranging from 0.906 to 0.964. Based on reliability criteria, Cronbach's Alpha values ≥ 0.60 indicate acceptable reliability [57] while values above 0.70 suggest good reliability [58]. These results confirm that all constructs in the study demonstrate very strong internal consistency, meaning that the items within each variable generate stable and consistent responses across participants. Thus, the research instrument is deemed trustworthy and suitable for subsequent analysis.

4.1.2. Testing For Common Method Bias (CMB) & Non-Response Bias

Common Method Bias (CMB) was assessed using both procedural and statistical strategies to ensure that the use of a single questionnaire instrument did not compromise data validity. Procedurally, the researcher adapted items from reputable journals to fit the study context, separated items by construct, selected respondents based on strict criteria, ensured anonymity, and engaged in personal communication to facilitate respondents' understanding [59, 60]. These steps were designed to minimize respondents' tendencies toward uniform, lenient, or extreme responses that may arise from psychological factors or questionnaire structure [61].

Statistically, CMB was assessed using Harman's single-factor test via EFA and CFA. The EFA results show that the first factor explains only 34.8% of the total variance, well below the 50% threshold, with a TLI value of 0.055, indicating no dominant factor. The CFA results are consistent, where CFI = 0.099 and TLI = 0.072, both far below the minimum acceptable value of 0.90, while SRMR = 0.114 and RMSEA = 0.333 exceed the maximum threshold of 0.08. The poor fit of the single-factor model indicates that respondents provided differentiated answers across constructs, confirming that CMB is not a serious concern in this study [60].

Non-response bias was evaluated to ensure that respondents adequately represented the study population and that no systematic differences existed between early and late participants. Procedurally, potential bias was minimized through personal communication with prospective respondents prior to the survey, resulting in a high response rate [62, 63]. Statistically, the early-late respondent test using the Armstrong & Overton (1977) method showed no significant differences either univariately or multivariately. The t-test yielded a p-value of 0.995 (>0.05), and Hotelling's Trace produced $F = 1.257$ with a p-value of 0.182 (>0.05). These findings confirm the absence of non-response bias, suggesting that the obtained sample is representative [61].

4.2. Descriptive Statistics

The questionnaire was distributed to 126 three-star hotels operating in Bali Province in 2025, with hotel managers, general managers, marketing managers, or operational managers serving as the units of analysis. The characteristics of respondents show that most managers were male (88 respondents, 69.8%), while females accounted for 38 respondents (30.2%). In terms of age, the majority were older than 44 years (70 respondents, 55.6%), followed by those aged 34–44 years (43 respondents, 34.1%), 25–34 years (11 respondents, 8.7%), and <25 years (2 respondents, 1.6%). General managers accounted for 99 respondents (78.6%), followed by marketing managers (19 respondents, 15.1%) and operational managers (8 respondents, 6.3%). Most respondents had more than nine years of work experience (81 respondents, 64.3%), followed by those with 1–3 years (29 respondents, 23%), 3–6 years (9 respondents, 7.1%), and 6–9 years (7 respondents, 5.6%). Regarding hotel age, hotels operating for more than 10 years dominate (62 hotels, 49.2%), followed by hotels operating for less than 3 years (26 hotels, 20.6%), 3–5 years (22 hotels, 17.5%), and 5–10 years (16 hotels, 12.7%). Overall, these characteristics indicate that respondents and hotels possess substantial experience and capacity to provide credible responses.

The subsequent descriptive analysis involves summarizing the assessments provided by respondents for each questionnaire item. The detailed responses for each statement item and variable are presented in Table 2.

Table 2.
Descriptive statistics.

Descriptive statistics:

Indicators	Item number	Item mean	Indicator mean
Digital Marketing (X1)			
Website Traffic (X1.1)	1	3.77	4.11
	2	4.44	
Conversion Rate (X1.2)	3	3.61	4.02
	4	4.29	
	5	4.17	
Media Social Engagement (X1.3)	6	4.14	4.25
	7	4.32	
	8	4.29	
Cost per Acquisition (X1.4)	9	3.61	3.77
	10	4.04	
	11	3.67	
Digital ROI (X1.5)	12	3.88	3.91
	13	3.79	
	14	4.07	
Reach & Impressions (X1.6)	15	4.48	4.38
	16	4.21	
	17	4.46	
Online Reviews (X1.7)	18	4.83	4.76
	19	4.68	
Dynamic Pricing (X2)			
Price Frequency (X2.1)	20	4.48	4.4
	21	4.43	
	22	4.29	
Price Elasticity (X2.2)	23	4.43	4.18
	24	4.44	
	25	3.66	
Price Personalization (X2.3)	26	3.86	3.98
	27	4.15	
	28	3.94	
Demand Accuracy (X2.4)	29	4.2	4.19
	30	4.02	
	31	4.34	
Pricing Automation (X2.5)	32	3.6	3.95
	33	4.05	
	34	4.21	
Customer Satisfaction (Z)			
Satisfaction Survey (Z.1)	35	4.21	4.19
	36	4.16	
Complaint Resolution (Z.2)	37	4.32	4.36
	38	4.39	
Satisfaction Index (Z.3)	39	4.13	4.23
	40	4.33	
Online Rating (Z.4)	41	4.23	4.28
	42	4.33	
Customer Loyalty (Z.5)	43	4.1	4.22
	44	4.34	
Hotel Performance (Y)			
Occupancy Rate (Y.1)	45	4.02	4.07

Indicators	Item number	Item mean	Indicator mean
	46	4.11	
RevPAR (Y.2)	47	4.16	4.15
	48	4.13	
GOPPAR (Y.3)	49	4.06	4.1
	50	4.13	
Total Revenue (Y.4)	51	3.94	4.07
	52	4.19	
Market Share (Y.5)	53	3.87	4.01
	54	4.14	
Online Booking (M)			
Easy Navigation (M.1)	55	4.38	4.38
	56	4.38	
Clear Information (M.2)	57	4.37	4.39
	58	4.4	
Process Speed (M.3)	59	4.42	4.3
	60	4.18	
Transaction Security (M.4)	61	4.42	4.41
	62	4.4	
Service Personalization (M.5)	63	4.25	4.07
	64	3.89	
System Integration (M.6)	65	4.31	4.35
	66	4.39	
Booking Conversion (M.7)	67	4.35	4.29
	68	4.22	
Variable mean: Digital Marketing (X1) 4.17; Dynamic Pricing (X2) 4.14; Customer Satisfaction (Z) 4.25; Hotel Performance (Y) 4.08; Online Booking (M) 4.31			

Descriptive statistics indicate that most variables in this study fall within the high to very high categories. Digital Marketing obtained a mean score of 4.17 (high category), suggesting that three-star hotels in Bali are already effective in utilizing digital promotion and customer interaction, although there remains room for improvement in areas such as conversion optimization and digital performance measurement. Dynamic Pricing achieved a mean score of 4.14 (high category), indicating that pricing strategies are generally adaptive to market demand fluctuations but have not yet reached full optimization, particularly with respect to personalized pricing and the use of automated technologies.

Customer Satisfaction recorded the highest mean score of 4.25 (very high category), reflecting that hotel guests are highly satisfied with the services received. Hotel Performance obtained a mean of 4.08 (high category), demonstrating strong performance in occupancy, revenue, and profitability, although additional revenue streams and market share indicators still offer opportunities for improvement. Meanwhile, Online Booking achieved a mean score of 4.31 (very high category), indicating that the online reservation systems of three-star hotels in Bali are perceived as highly adequate in terms of ease of use, speed, security, and service integration.

4.3. Partial Least Squares

4.3.1. Evaluation of Measurement Model (Outer Model)

The evaluation of the measurement model aims to ensure the quality of the data used in the PLS-SEM analysis by assessing the validity and reliability of the constructs. This step is essential to confirm that each indicator accurately represents its latent construct, allowing the study's findings to reflect empirical reality [56].

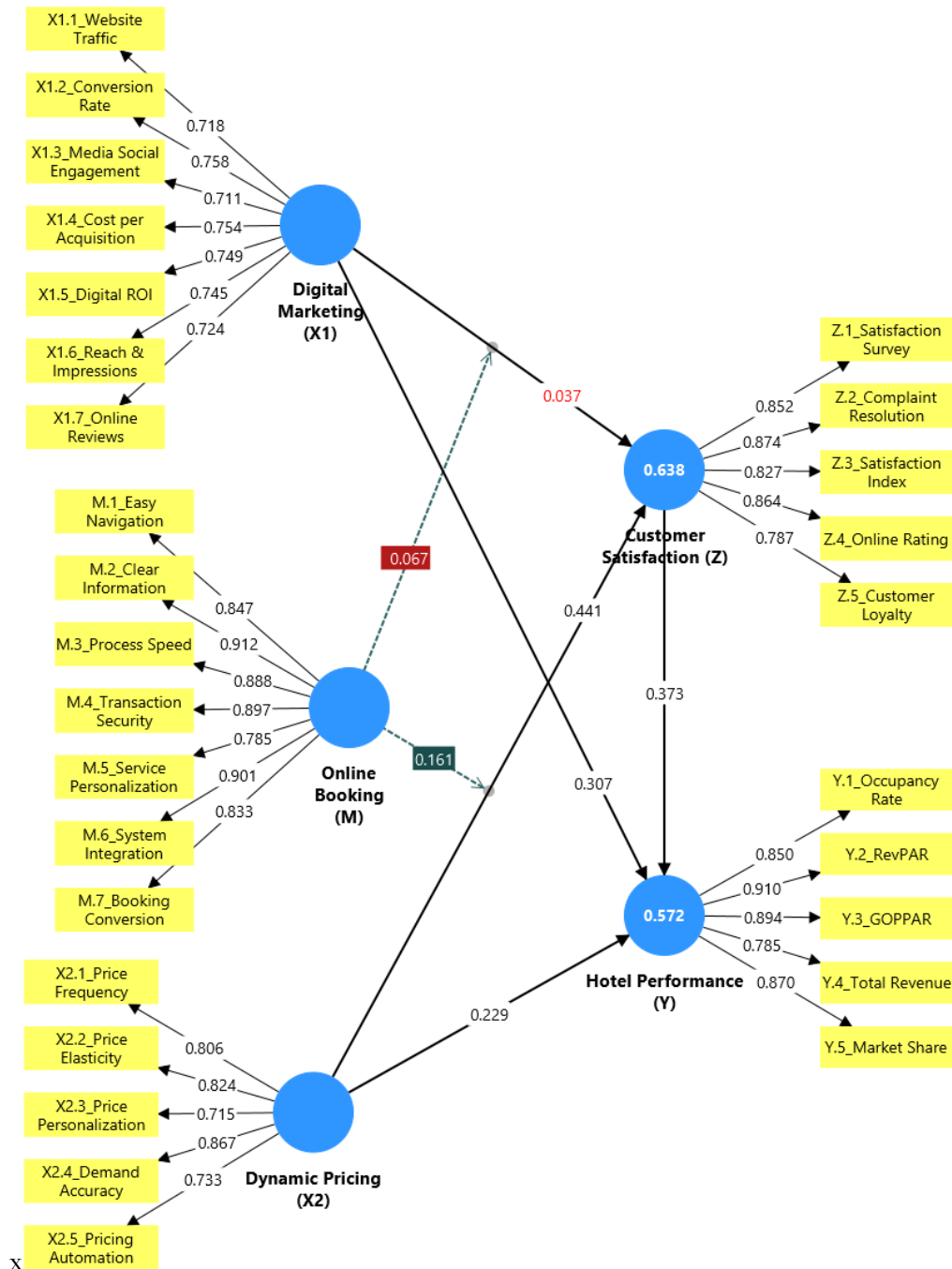


Figure 2.
PLS Algorithm (Embedded Two-Stage).

In this study, the conceptual model incorporates Higher-Order Constructs (HOCs), which are abstract constructs formed from several Lower-Order Components (LOCs). The analysis of HOCs was conducted using the Embedded Two-Stage approach, which is advantageous because it prevents R^2 overestimation and multicollinearity while generating more stable results [56]. This approach involves two steps: first, estimating all constructs (LOCs and HOCs) to obtain Latent Variable Scores (LVS)

from the LOCs; second, using these LVS values as input for re-estimating the model focused on the HOC.

The results of the first-stage PLS algorithm estimation using the embedded two-stage approach are presented in Appendices E, showing that all indicators achieved outer loading values above 0.50, confirming that all indicators are valid in representing their respective constructs and thus included in the LVS calculation. The results of the second-stage model estimation based on these LVS values are displayed in Figure 2.

Based on the second-stage PLS algorithm estimation, the measurement model evaluation was conducted, including assessments of indicator reliability, internal consistency, convergent validity, and discriminant validity [56], as well as confirmatory tetrad analysis serving as a robustness check to ensure that the measurement model aligns with its theoretical specification [56]. The results of the measurement model evaluation are presented in Table 3.

Table 3.
Evaluation of the indicator reliability.

Constructs	Indicators	Outer Loadings
Digital Marketing (X1)	Website Traffic (X1.1)	0.718
	Conversion Rate (X1.2)	0.758
	Media Social Engagement (X1.3)	0.711
	Cost per Acquisition (X1.4)	0.754
	Digital ROI (X1.5)	0.749
	Reach & Impressions (X1.6)	0.745
	Online Reviews (X1.7)	0.724
Dynamic Pricing (X2)	Price Frequency (X2.1)	0.806
	Price Elasticity (X2.2)	0.824
	Price Personalization (X2.3)	0.715
	Demand Accuracy (X2.4)	0.867
	Pricing Automation (X2.5)	0.733
Customer Satisfaction (Z)	Customer Satisfaction (Z.1)	0.852
	Complaint Resolution (Z.2)	0.874
	Satisfaction Index (Z.3)	0.827
	Online Rating (Z.4)	0.864
	Customer Loyalty (Z.5)	0.787
Hotel Performance (Y)	Occupancy Rate (Y.1)	0.850
	RevPAR (Y.2)	0.910
	GOPPAR (Y.3)	0.894
	Total Revenue (Y.4)	0.785
	Market Share (Y.5)	0.870
Online Booking (M)	Easy Navigation (M.1)	0.847
	Clear Information (M.2)	0.912
	Process Speed (M.3)	0.888
	Transaction Security (M.4)	0.897
	Service Personalization (M.5)	0.785
	System Integration (M.6)	0.901
	Booking Conversion (M.7)	0.833

Indicator reliability. The results show that all indicators within each construct have outer loading values above 0.70, indicating a strong and significant representation of their respective latent constructs

in accordance with Hair et al. [56]. Since all indicators meet the minimum threshold, none require elimination. Thus, the indicators used demonstrate a strong representational ability for the constructs they measure.

Table 4.
Evaluation of the validity, reliability, & robustness check.

Discriminant validity	HTMT:					
		X1	X2	Z	Y	M
	Digital Marketing (X1)					
	Dynamic Pricing (X2)	0.452				
	Customer Satisfaction (Z)	0.508	0.807			
	Hotel Performance (Y)	0.628	0.674	0.737		
	Online Booking (M)	0.656	0.679	0.761	0.801	
Reliability	Internal consistency and convergent validity:					
		Cronbach's alpha	rho_c	AVE		
	Digital Marketing (X1)	0.861	0.839	0.544		
	Dynamic Pricing (X2)	0.85	0.839	0.626		
	Customer Satisfaction (Z)	0.869	0.824	0.708		
	Hotel Performance (Y)	0.814	0.836	0.745		
	Online Booking (M)	0.845	0.855	0.752		
Robustness check	Confirmatory tetrad analyses (CTA):					
	Digital Marketing (X1)	p-value CTA 0.097				
	Dynamic Pricing (X2)	p-value CTA 0.419				
	Customer Satisfaction (Z)	p-value CTA 0.244				
	Hotel Performance (Y)	p-value CTA 0.329				
	Online Booking (M)	p-value CTA 0.493				

Discriminant validity. Discriminant validity was assessed using the Heterotrait–Monotrait Ratio (HTMT). The HTMT values for all construct pairs are below the 0.85 threshold [56], indicating no conceptual overlap among constructs. These findings confirm that the five constructs possess strong discriminant validity, with each construct measuring a concept distinct from the others.

Internal consistency. The internal reliability test indicates that all constructs have Cronbach's alpha and composite reliability (ρ_C) values above the 0.70 threshold, signifying excellent reliability. The lowest Cronbach's alpha value is 0.814, and the lowest ρ_C value is 0.824. These results demonstrate that all indicators within each construct consistently measure the same underlying concept and exhibit strong reliability.

Convergent validity. All constructs exhibit Average Variance Extracted (AVE) values greater than 0.50, demonstrating that each construct explains more than half of the variance in its indicators, thereby satisfying convergent validity [56]. Construct M records the highest AVE value (0.752), indicating high indicator homogeneity and strong reflective ability. Overall, these results show that each construct effectively explains the variance of its indicators and that the measurement model aligns well with the underlying theoretical framework.

Robustness check. The Confirmatory Tetrad Analysis (CTA) results show that all constructs have p-values greater than 0.05, indicating that the null hypothesis (H_0 : tetrad = 0) is accepted. This confirms that the measurement model is appropriately specified as reflective. Therefore, changes in the latent constructs are reflected in changes in the indicators. These robustness check results reinforce the theoretical suitability of the measurement model and ensure that the model is free from misspecification errors that could bias the analysis.

4.3.2. Evaluation of Structural Model (Inner Model)

The structural model evaluation in PLS-SEM aims to assess the extent to which the model can theoretically and empirically explain and predict the relationships among latent constructs [56]. The results of the structural model evaluation are presented in Table 5.

Table 5.

Evaluation of the Structural Model.

Path	VIF	f-square	R-square
Digital Marketing (X1) -> Cust. Satisfaction (Z)	1.709	0.002	0.638
Dynamic Pricing (X2) -> Cust. Satisfaction (Z)	1.65	0.326	
Digital Marketing (X1) -> Hotel Performance (Y)	1.298	0.17	0.572
Dynamic Pricing (X2) -> Hotel Performance (Y)	2.031	0.061	
Cust. Satisfaction (Z) -> Hotel Performance (Y)	2.202	0.148	
<u>PLSpredict MV summary</u>			
	PLS RMSE	LM RMSE	IA RMSE
Z.1_Satisfaction Survey	0.316	0.396	0.516
Z.2_Complaint Resolution	0.325	0.393	0.524
Z.3_Satisfaction Index	0.456	0.464	0.578
Z.4_Online Rating	0.372	0.442	0.577
Z.5_Customer Loyalty	0.431	0.492	0.64
Y.1_Occupancy Rate	0.521	0.581	0.715
Y.2_RevPAR	0.33	0.411	0.575
Y.3_GOPPAR	0.415	0.462	0.591
Y.4_Total Revenue	0.462	0.518	0.664
Y.5_Market Share	0.451	0.531	0.651
<u>PLSpredict LV summary</u>			
Customer Satisfaction (Z)	Q ² predict = 0.573		
Hotel Performance (Y)	Q ² predict = 0.528		
<u>CVPAT LV summary (PLS-SEM vs IA)</u>			
	Loss difference	P value	
Customer Satisfaction (Z)	-0.13	0	
Hotel Performance (Y)	-0.158	0	
Overall	-0.144	0	
<u>CVPAT LV summary (PLS-SEM vs LM)</u>			
	Loss difference	P value	
Customer Satisfaction (Z)	-0.046	0.003	
Hotel Performance (Y)	-0.06	0.003	
Overall	-0.053	0	
<u>Model fit measure:</u> SRMR 0.097; GoF 0.639			
<u>Linearity (p-value Anova):</u> Linearity X1 -> Z 0.000; Linearity X2 -> Z 0.000; Linearity X1 -> Y 0.000; Linearity X2 -> Y 0.000; Linearity Z -> Y 0.000.			
<u>Endogeneity:</u> X1 p-value = 1.000; X2 p-value = 1.000; Z p-value = 1.000.			

Collinearity. The collinearity assessment shows that all predictor constructs have VIF values ranging from 1.298 to 2.202, well below the threshold of 5 [56]. This indicates the absence of multicollinearity issues among exogenous constructs in the structural model. These results reinforce the validity of the structural model and demonstrate that each predictor construct contributes uniquely to explaining the endogenous variables, without redundancy or overlapping information among predictors.

Explanatory power. The R-square value for construct Z is 0.638, indicating that approximately 63.8% of the variance in Z is explained by X1 and X2, which falls within the moderate category. Meanwhile, the R-square value for Y is 0.572, suggesting that about 57.2% of the variance in Y is explained by X1, X2, and Z, also classified as moderate. The f-square values, ranging from 0.002 to

0.326, indicate that the relationships among constructs exhibit small to large effect sizes on the respective endogenous variables [56]. Overall, the model demonstrates adequate explanatory power and reveals substantial structural relationships.

Predictive power. The PLSpredict results show that all PLS RMSE values are lower than those of LM and IA, both at the indicator and latent construct levels. Additionally, the Q^2 predict values of 0.572 for Z and 0.528 for Y, both well above zero, indicate that the model possesses positive predictive power and is capable of predicting out-of-sample data effectively. These findings demonstrate that the model not only fits the analyzed data but also exhibits strong generalizability to new data [56].

Model fit measure. The SRMR value of 0.097 indicates that the model exhibits a good fit, as it falls below the recommended maximum threshold of 0.10. Furthermore, the Goodness-of-Fit (GoF) value of 0.639 is classified as high (>0.36), confirming strong model adequacy and alignment between the structural model and empirical data. These findings affirm that the proposed model accurately represents the relationships among constructs and does not suffer from model misspecification.

Model comparison. The model comparison results between PLS-SEM vs. IA and PLS-SEM vs. LM show negative loss difference values. This indicates that the PLS-SEM model yields smaller prediction errors compared to the alternative models (IA and LM). Consequently, it can be concluded that the PLS-SEM model possesses superior predictive performance and efficiency over competing model alternatives, thereby strengthening the reliability of the structural model.

Robustness check. The robustness check results indicate that all relationships among constructs satisfy the linearity assumption, with ANOVA p-value = 0.000, confirming significant and linear associations among variables in the model. Moreover, the endogeneity test yielded a p-value of 1.000, indicating no causal bias arising from correlations between predictor variables and the error terms of endogenous constructs. Accordingly, the structural model can be considered stable, free from endogeneity and non-linearity issues, and produces reliable estimates to support the study's conclusions [56].

4.4. Hypothesis Testing

The results of the direct, mediating, and moderating effects were analyzed using the PLS bootstrapping procedure.

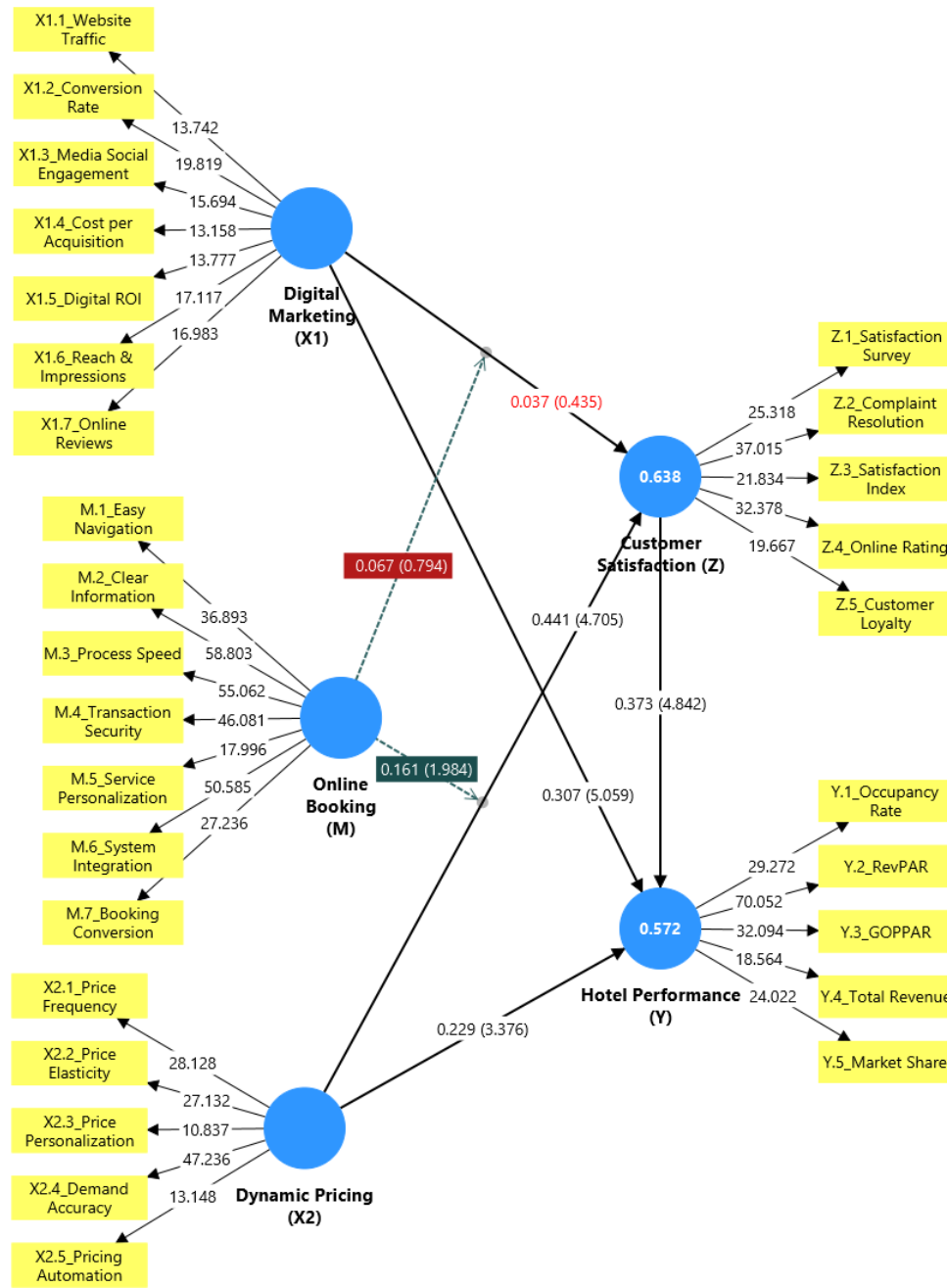


Figure 3.
PLS Bootstrapping.

4.4.1. Analysis of the Direct Effect

The following presents the path coefficients (original sample estimates), t-statistics, and p-values for the direct effect tests.

Table 6.

Summary of the direct effect analysis.

No	Direct Effects	Estimate	T-Stat	P-Values	Decision
1	Digital Marketing (X1) -> Customer Satisfaction (Z)	0.037	0.435	0.664	H ₁ rejected
2	Dynamic Pricing (X2) -> Customer Satisfaction (Z)	0.441	4.705	0.000	H ₂ accepted
3	Digital Marketing (X1) -> Hotel Performance (Y)	0.307	5.059	0.000	H ₃ accepted
4	Dynamic Pricing (X2) -> Hotel Performance (Y)	0.229	3.376	0.001	H ₄ accepted
5	Customer Satisfaction (Z) -> Hotel Performance (Y)	0.373	4.842	0.000	H ₅ accepted

The findings indicate that out of the five hypotheses tested, four were supported, and one was rejected based on the criteria of a t-statistic ≥ 1.96 and a p-value < 0.05 . The relationship between Digital Marketing and Customer Satisfaction (H1) yielded an estimate of 0.037 with a t-value of 0.435 and a p-value of 0.664, indicating insignificance and leading to the rejection of the hypothesis. Conversely, Dynamic Pricing significantly influenced Customer Satisfaction (H2), with an estimate of 0.441, a t-value of 4.705, and a p-value of 0.000. Regarding Hotel Performance, Digital Marketing (H3) showed a significant effect, with an estimate of 0.307, a t-value of 5.059, and a p-value of 0.000. Dynamic Pricing (H4) was also significant, with an estimate of 0.229, a t-value of 3.376, and a p-value of 0.001. Lastly, Customer Satisfaction significantly affected Hotel Performance (H5), with an estimate of 0.373, a t-value of 4.842, and a p-value of 0.000.

These results indicate that dynamic pricing exerts a strong influence on customer satisfaction, whereas digital marketing does not directly enhance satisfaction in three-star hotels in Bali. However, both digital marketing and dynamic pricing significantly improve hotel performance, highlighting their strategic importance. The substantial effect of customer satisfaction on hotel performance reinforces that guest experience remains a critical determinant of both operational and financial success. These findings emphasize the need for hotels to balance digital marketing initiatives, adaptive pricing strategies, and service quality improvements to achieve sustainable performance gains.

4.4.2. Analysis of the Mediation Effect

The following summarizes the results of the mediation analysis and the classification of mediation types.

Table 7.

Summary of the mediating effect analysis.

Mediating effect	Estimate	T-Stat	P-Values	Type of mediation
X1 -> Z -> Y	0.014	0.431	0.666	-
X2 -> Z -> Y	0.165	3.970	0.000	Partially mediation

The mediation test results indicate that only one of the two mediation paths was significant. The path Digital Marketing -> Customer Satisfaction -> Hotel Performance produced an estimate of 0.014 with $t = 0.431$ and $p = 0.666$, indicating insignificance and the absence of mediation. Conversely, the path Dynamic Pricing -> Customer Satisfaction -> Hotel Performance yielded an estimate of 0.165 with $t = 3.970$ and $p = 0.000$, confirming significance at the 5% level. Because both the direct and indirect effects of X2 on Y are significant, this relationship qualifies as partial mediation.

These findings show that customer satisfaction does not mediate the effect of digital marketing on hotel performance, suggesting that improvements in hotel performance driven by digital marketing occur directly rather than through enhanced customer satisfaction. In contrast, customer satisfaction serves as a partial mediator between dynamic pricing and hotel performance, meaning that adaptive pricing strategies improve performance both directly and through increased guest satisfaction.

4.4.3. Analysis of the Moderating Effect

Moderation analysis was performed to assess whether online booking strengthens or weakens the effects of digital marketing and dynamic pricing on customer satisfaction, with results presented in Table 8.

Table 8.

Summary of the moderating effect analysis.

Moderating effect	Estimate	T-Stat	P-Values	Decision
X1*M -> Z	0.067	0.794	0.427	H ₆ rejected
X2*M -> Z	0.161	1.984	0.048	H ₇ accepted

The moderation test indicates that only one of the two moderation hypotheses was supported. For the moderation path Digital Marketing x Online Booking -> Customer Satisfaction, the estimate was 0.067 with $t = 0.794$ and $p = 0.427$, which are below the required thresholds ($t \geq 1.96$; $p \leq 0.05$), resulting in the rejection of H₆. Meanwhile, the moderation path Dynamic Pricing x Online Booking -> Customer Satisfaction produced an estimate of 0.161 with $t = 1.984$ and $p = 0.048$, meeting the 5% significance level and supporting H₇.

These results indicate that online booking does not strengthen the relationship between digital marketing and customer satisfaction; thus, the effectiveness of digital marketing in enhancing guest satisfaction does not depend on the quality of the online booking system. However, online booking significantly strengthens the effect of dynamic pricing on customer satisfaction, meaning that adaptive pricing strategies become more effective in enhancing guest satisfaction when supported by a user-friendly, fast, and well-integrated online booking platform. In other words, the quality of the online booking system is a critical factor in maximizing the benefits of dynamic pricing for guest experience in three-star hotels in Bali.

4.4.4. Analysis of the Total Effect

The analysis of total effects or dominant influences in PLS-SEM can be conducted using the Importance–Performance Map Analysis (IPMA). IPMA is a technique used to identify exogenous variables that exert the greatest influence (importance) but demonstrate relatively low performance toward an endogenous variable. This analysis simultaneously considers the total effects and average performance scores of each variable, enabling researchers to determine priority areas for improvement and develop more effective strategies [56]. IPMA provides practical guidance for decision-makers in allocating resources to the elements that contribute most significantly to enhancing the targeted endogenous construct.

The IPMA results show that the variable with the highest total effect (importance) on hotel performance is Dynamic Pricing (0.394), followed by Customer Satisfaction (0.373) and Digital Marketing (0.321), while Online Booking exhibits the lowest influence (0.154). However, in terms of performance, Online Booking also has the lowest score (59.445), followed by Customer Satisfaction (64.359), Dynamic Pricing (67.303), and Digital Marketing (69.585). The combination of these findings indicates that Dynamic Pricing is the most dominant factor in improving hotel performance, although its performance score is not the highest and therefore still requires strengthening. Additionally, the low performance of Online Booking, despite its relatively small influence, highlights a critical area that still needs improvement due to its role as an enabler of marketing strategies. Thus, strategic improvement priorities for three-star hotels in Bali should primarily focus on enhancing the effectiveness of Dynamic Pricing and improving the quality of Online Booking, while maintaining strong performance in digital marketing and customer satisfaction to maximize overall hotel performance.

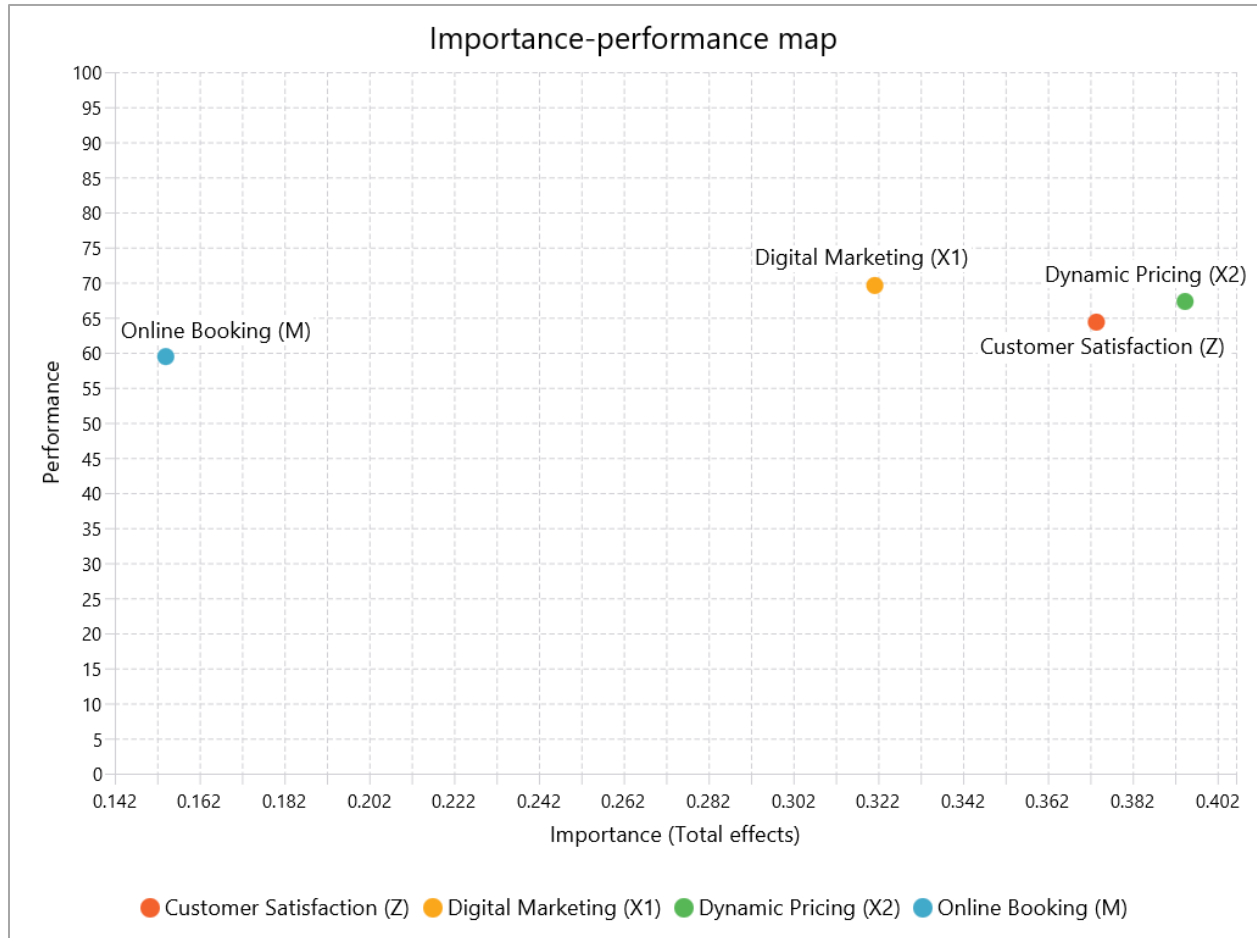


Figure 4.
PLS IPMA.

4.5. Discussion

The findings indicate that digital marketing does not have a significant effect on customer satisfaction, suggesting that the digital strategies implemented by three-star hotels in Bali have not succeeded in creating meaningful added value for guests. This result contrasts with numerous previous studies that underscore the importance of digital marketing in enhancing customer satisfaction, such as Aljumah et al. [20], Clara et al. [64], and Ferreira et al. [65], who highlight the roles of interactivity, visual content quality, and information transparency. The insignificant effect suggests that digital marketing efforts in three-star hotels remain basic and predominantly one-directional, lacking personalization and emotional engagement with customers. This condition also reflects the suboptimal fulfillment of principles related to accurate, transparent, and non-misleading information mandated by the Electronic Information and Transactions Law (UU ITE) and the Regulation on Electronic Commerce (Permen PMSE). Consequently, current digital strategies fail to meet the expectations of digital-savvy travelers who demand fast, accurate, and personalized experiences.

In the operational context of hotels, the managerial characteristics, where most managers possess extensive experience and prioritize operational stability, also help explain the slow pace of digital innovation. Additionally, descriptive results of the digital marketing indicators show that although visibility-related aspects such as promotional reach, engagement, and online reviews are relatively strong, more critical performance-oriented indicators, including conversion rates, cost per acquisition,

and digital ROI, remain low. This condition implies that digital marketing functions more as an exposure tool rather than a driver of meaningful customer experiences. Thus, three-star hotels in Bali should shift their focus from merely increasing digital presence to strengthening transaction effectiveness and enhancing the digital customer experience to ensure that their strategies directly contribute to customer satisfaction.

The findings show that dynamic pricing has a positive and significant effect on customer satisfaction, indicating that the more effectively price adjustments are implemented, the higher the level of customer satisfaction. This result is consistent with Qi et al. [18], who emphasize that customers accept price fluctuations as long as the mechanism is transparent and reasonable. Studies by Wilson et al. [66] and Viglia et al. [67] further highlight that perceived value and price fairness greatly influence satisfaction, suggesting that pricing strategies aligned with customers' psychological expectations can enhance perceived value and foster loyalty. Within the competitive environment of Bali's three-star hotel segment, characterized by hundreds of hotels and fluctuating occupancy rates, dynamic pricing becomes a crucial strategy for managing demand without compromising service quality. Moreover, changing traveler behavior and heightened price sensitivity reinforce the need for flexible pricing practices perceived as fair by customers.

This finding is also in line with the Consumer Protection Law (UUPK) and the Regulation on Electronic Commerce (Permen PMSE), which emphasize fairness, transparency, and honesty in the disclosure of price information to consumers. The positive evaluation of dynamic pricing practices indicates that hotels have applied ethical principles consistent with Article 7 of UUPK and the transparency requirements of Permen PMSE No. 50/2020. Indicator-level analysis further shows that price adjustment frequency, demand-based sensitivity, and the use of technology are rated positively, although price personalization remains low and offers room for improvement. Overall, dynamic pricing enhances customer satisfaction as long as hotel management maintains a balance between price flexibility, fairness perceptions, and clarity of information provided to guests.

The findings indicate that digital marketing has a positive and significant effect on hotel performance, meaning that stronger digital strategies lead to higher occupancy levels, increased revenue, and improved competitiveness. This supports the findings of Aljumah et al. [20] and De Pelsmacker et al. [14] who affirm that integrated digital marketing can strengthen brand image, accelerate reservation processes, and increase promotional campaign effectiveness. Studies by Kanaan et al. [24] and Freihat [68] similarly highlight that consistent digital interactions enhance brand engagement and loyalty, which in turn drive performance outcomes. However, Serra et al. [69] caution that digital marketing yields optimal results only when supported by robust digital infrastructure and quality service management, ensuring alignment between digital expectations and actual customer experiences.

In the highly competitive hospitality industry of Bali, these findings have strong practical relevance. Given that millions of tourists rely on online platforms for bookings and product evaluation, three-star hotels must optimize digital marketing strategies to maintain occupancy and increase revenue. Effective management of social media, website optimization, strengthening online reviews, and integrating digital marketing with reservation systems are essential to ensure consistency between digital image and customer experience. Furthermore, evaluating digital campaign effectiveness through real-time analytics is crucial so that implemented strategies enhance not only brand image and customer loyalty but also deliver stronger financial performance for the hotels.

The findings show that dynamic pricing has a positive and significant effect on hotel performance, indicating that pricing strategies based on demand, competition, and market trends can directly enhance financial performance and competitiveness. This aligns with Bandalouski et al. [17], who state that dynamic pricing provides real-time flexibility to adjust prices for optimizing occupancy and revenue. Vives and Jacob [44] and Vives and Jacob [70] also emphasize that prices adjusted fairly in accordance with market conditions increase perceived value and stimulate purchasing decisions. Additionally, studies by Guizzardi et al. [16] and Zhang and Weatherford [71] reinforce that dynamic pricing can

maximize RevPAR and profitability, especially when integrated with online booking platforms as described by Mariello et al. [72] and Zhang et al. [73].

In Bali's competitive and seasonally volatile hospitality sector, dynamic pricing becomes a crucial strategy for maintaining the competitiveness of three-star hotels. During the low season, price reductions help maintain occupancy, while during the high season, optimal price adjustments can significantly increase revenue. However, Zhang et al. [73] and Zhuang et al. [74] caution that excessive price fluctuations and poor data quality may generate perceptions of unfairness and harm the hotel. With more than 70% of bookings occurring through online travel agencies (OTAs), hotels must apply adaptive, data-driven, dynamic pricing to remain competitive and sustain business performance.

The findings indicate that customer satisfaction has a positive and significant effect on hotel performance, meaning that higher levels of customer satisfaction lead to better hotel outcomes in occupancy, revenue, and market share. This finding is consistent with Nazari et al. [75], who state that satisfied customers tend to offer positive recommendations, strengthen loyalty, and contribute to revenue growth. Lee and How [76] affirm that positive perceptions of service and value encourage hotel growth, while Hariandja and Vincent [77] and Domínguez-Falcón et al. [78] note that customer satisfaction serves as a key link between service quality and business performance. Moreover, Aakash and Gupta Aggarwal [79] emphasize that positive reviews written by satisfied guests enhance hotel image and occupancy.

In the context of three-star hotels in Bali facing occupancy fluctuations and intense competition, customer satisfaction emerges as a critical factor for maintaining performance stability. High online ratings build prospective customers' trust and directly influence RevPAR and market share. This is also aligned with the principles of the Consumer Protection Law (UUPK), in which customer satisfaction reflects the fulfillment of rights to comfort, safety, and expected service quality. Therefore, the positive influence of customer satisfaction on hotel performance not only strengthens business sustainability but also reflects hotels' compliance with the principles of fairness, transparency, and accountability mandated by the UUPK.

The findings show that online booking does not moderate the relationship between digital marketing and customer satisfaction. Although digital marketing effectively captures customer attention, online booking channels do not strengthen or weaken its influence. This finding aligns with Osés et al. [80], Myat et al. [15], and Guizzardi et al. [16], who assert that although online booking enhances convenience and accessibility, it does not necessarily amplify the effect of digital marketing on customer satisfaction. This suggests that message quality, consistency of information, and relevance of digital marketing content are more influential than the booking medium itself. Additionally, three-star hotels in Bali rely heavily on OTAs, limiting their control over the customer experience during the booking process, which explains the insignificant moderating role of online booking.

On the other hand, several empirical studies, such as Myat et al. [15] and Guizzardi et al. [16], indicate that when online booking channels are well integrated with digital marketing, for example, through high responsiveness, transactional security, and consistent information, customer experiences may improve, thereby strengthening satisfaction. However, the present findings reveal a gap between the digital marketing practices of three-star hotels in Bali and the quality of the booking channels they use, largely because of heavy reliance on OTAs. Additionally, survey results show that customer satisfaction is primarily influenced by pricing, service quality, and the overall stay experience rather than the booking process itself. This finding also aligns with Permen PMSE No. 50/2020 and SIUPMSE regulations, which emphasize accurate, accessible information and consumer protection in electronic transactions, standards that hotels cannot fully guarantee when using third-party platforms.

The findings indicate that online booking acts as a moderator that strengthens the effect of dynamic pricing on customer satisfaction. When reservations are made through online channels, the impact of price fluctuations becomes more salient to customers, thereby intensifying the effect of pricing on satisfaction. This is consistent with Roma et al. [81], who show that the time interval between booking and check-in affects price perception on online platforms, and with Guizzardi et al. [16], who emphasize

that digital channels increase customers' exposure to price changes. Thus, online booking systems function not only as transaction tools but also as mechanisms that make dynamic pricing more visible to guests, amplifying its effect on satisfaction when prices are perceived as fair and transparent.

Nonetheless, prior research, such as Bolton et al. [82], cautions that extremely high price fluctuations may trigger perceptions of price unfairness, potentially reducing customer satisfaction. This phenomenon is relevant in Bali's hospitality sector, where more than 70% of reservations are made online, and customers are highly sensitive to price changes. In practice, well-managed dynamic pricing delivered through digital platforms can offer added value, especially for domestic tourists and backpackers, by enabling real-time price comparisons and allowing customers to assess the fairness of the price they pay relative to the service quality received.

4.6. Implications

Theoretically, this study demonstrates that hotel performance is not solely determined by financial aspects but is also strongly influenced by customer experience and satisfaction, thereby reinforcing the relevance of the Organizational Performance Theory [25] and the Service-Profit Chain Model [83]. The study confirms that marketing strategies do not exert uniform effects on customer satisfaction or hotel performance; digital marketing shows no significant impact on satisfaction, whereas dynamic pricing demonstrates a strong positive effect. Furthermore, customer satisfaction serves as a key mediating variable that links marketing strategies to improvements in occupancy, revenue, and market share. The discovery of the moderating role of online booking, strengthening the effect of dynamic pricing but not digital marketing, offers a conceptual contribution that enriches the understanding of when and how digital channels effectively enhance customer satisfaction. Overall, this study provides theoretical novelty by integrating marketing strategies and online booking into a comprehensive model explaining their combined effects on satisfaction and performance in three-star hotels.

Practically, the findings indicate that three-star hotels in Bali need to optimize their marketing strategies by balancing the use of digital marketing and dynamic pricing to enhance satisfaction and performance. Maintaining consistency between the digital image and actual service delivery is crucial to ensure that customer expectations align with the on-site experience. The management of online booking systems should also be strengthened through the integration of pricing, promotional activities, and review management to ensure transparency and build a positive reputation. Additionally, performance improvement can be achieved by focusing on key indicators such as occupancy, revenue, and loyalty through consistent service quality and adaptive pricing strategies. Based on the IPMA results, customer satisfaction should be prioritized as the primary target of managerial investment, followed by dynamic pricing and digital marketing, in order to build long-term competitiveness through continuous innovation, digital adaptation, and superior service quality.

5. Conclusion

The findings of this study conclude that dynamic pricing and customer satisfaction play the most dominant roles in enhancing the performance of three-star hotels in Bali. Customer satisfaction exerts a positive and significant influence on hotel performance, affirming its position as a critical factor in improving occupancy, revenue, and guest loyalty. Meanwhile, dynamic pricing significantly affects customer satisfaction and indirectly strengthens hotel performance through improved perceived value. Conversely, digital marketing does not significantly influence customer satisfaction, suggesting that digital information alone is insufficient to enhance customer experience without being supported by consistent service quality.

In addition, online booking functions as a moderator that strengthens the relationship between dynamic pricing and customer satisfaction, yet it does not moderate the effect of digital marketing. This finding demonstrates that online booking channels primarily serve as a contextual factor that clarifies customers' price perceptions rather than enhancing the effectiveness of digital marketing messages. Overall, the model indicates that marketing strategies do not exert uniform effects on satisfaction and

performance, emphasizing the importance of integrating dynamic pricing strategies and service quality improvements to achieve optimal hotel performance.

Based on these conclusions, future research is advised to expand the study context to different hotel categories and tourism destinations in order to compare the consistency of variable relationships across diverse operational environments. Furthermore, longitudinal approaches are recommended to capture the dynamic nature of customer behavior and the evolving effectiveness of digital marketing, dynamic pricing, and online booking over time, thereby offering stronger causal insights. Future studies should also consider incorporating operational hotel data such as occupancy, RevPAR, and ADR to enhance the validity of empirical findings and strengthen the connection between research outcomes and actual performance in hospitality management practice.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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