

“Theoretical foundations of algorithmic pricing in the short-term rental market”

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THEORETICAL FOUNDATIONS OF ALGORITHMIC PRICING IN THE SHORT-TERM RENTAL MARKET

Abstract

The shift towards the “product as a service” paradigm requires adaptive pricing tools. The article aims to conceptualize AI-driven algorithmic pricing methods for short-term rentals and to validate them through simulation modelling as a synthetic proof of concept. The methodology distinguishes conceptual evaluation – structural-functional and SWOT analyses – from empirical simulation. The proposed framework of the actual demand-probability model uses a logistic function as a deep learning-based predictive model (MLP) within an explicit revenue-maximization procedure. While the MLP is trained to minimize prediction error in latent demand, the forecast WTP serves as a critical input to a bounded search module that calculates the revenue-maximising price. The algorithmic model demonstrates a significant uplift in simulated gross booking revenue relative to the Static, Rule-Based, and Random Forest benchmarks, based on 100 Monte Carlo repetitions. A deep learning-based predictive model with an average cumulative revenue of USD 7,307.42 outperforms the Random Forest model with high statistical significance and achieves a high win rate across simulated scenarios. Probability-based algorithmic pricing mitigates the risks of resource downtime. The sensitivity analysis confirms MLP model stability across varying consumer price elasticities. AI-driven pricing is positioned as a scalable, systemic digital technology for coordinating economic processes in modern platform industries.

Keywords

algorithmic marketing model, dynamic pricing,
reactivity, predictability, revenue management, product
as a service, deep learning, rental

JEL Classification

D40, M31, L11

INTRODUCTION

Considering a “product as a service” (PaaS) system that ensures the maximum involvement of economic agents in achieving the goals of sustainable development and the formation of a circular economy. It should also be noted that the development of the digital economy creates the necessary prerequisites for implementing these relations. The digitalization of economic systems offers an opportunity to embrace the dynamic nature of pricing. At the same time, price parameters are derived from a complex information and analytical process. Digital technologies, AI, and machine learning algorithms require adaptive regulation in response to changes in demand, supply, and the behaviour of economic agents (Davenport et al., 2020; Huang & Rust, 2021; Mustak et al., 2021). The use of AI for pricing management is gaining systemic importance in the development of modern industries, as it serves not only as a tool for maximizing enterprise revenues but also as a driver of structural changes in the competitive environment.

Despite growing interest, the systemic role of algorithmic pricing in industry development in the context of digital technologies remains underexplored. As a theoretical article, this study addresses the scien-

tific problem of the need for a systematic analysis of algorithmic pricing, accounting for its economic effects and managerial consequences, without relying on unsupported assumptions about institutions or market structure. In this context, an important issue is the need for a systematic scientific analysis of algorithmic pricing as a digital technology of industrial development, accounting for its economic effects, managerial consequences, and potential regulatory risks.

The paper aims to conceptualize AI-driven algorithmic pricing methods for short-term rentals and validate them through simulation modelling as a synthetic proof of concept.

1. THEORETICAL BASIS

The issue of algorithmic and dynamic pricing in marketing emerged at the intersection of the theory of the firm, microeconomics, revenue management theory, and information economics. According to Ezrachi and Stucke (2020), automated pricing can significantly increase resource efficiency while also creating new challenges for regulating competition and protecting consumers. Classic works on revenue management (Talluri & Van Ryzin, 2004) laid the methodological foundations for price optimisation under constraints and stochastic demand. According to Talluri and van Ryzin (2004), Kimes (2017), Yeoman and McMahonBeattie (2017), further development of these approaches is associated with the spread of digital platforms and the ability to process real-time data.

Current research focuses on analyzing AI-based algorithmic pricing as a strategic management tool in digital markets. For example, Goldfarb and Tucker (2019) emphasize that digital technologies significantly reduce the costs of data collection and processing. This creates the prerequisites for new forms of price discrimination and personalised pricing based on consumer behavior (Hinz et al., 2011; Fisher et al., 2017). Spann et al. (2024) emphasize that automated pricing enables firms to adjust prices in real time in response to changing market conditions. This increases both management efficiency and regulatory challenges, particularly regarding the potential impact on competition and consumer behavior.

A separate area of research is devoted to the risks of algorithmic coordination and reduced market transparency. The market is interpreted as a dynamic system of interaction between economic entities, whose interests are coordinated through

information mechanisms, competition and pricing. It is constantly changing in accordance with the concept of markets as holistic systems (Vargo et al., 2017). As Ezrachi and Stucke (2020) point out, algorithms can contribute to the emergence of anticompetitive behavior without direct collusion among economic entities, thereby complicating the application of traditional antitrust policy instruments.

Price is not only an indicator of value or a regulator of the balance between supply and demand, but also a tool for coordinating economic behavior and ensuring the system's adaptation to changes in the external and internal environments. Similarly, in classical marketing works, price is considered an information signal that coordinates agents' interactions, supporting the coordination of economic decisions in a changing environment (Den Boer, 2015). In the digital economy, there is a qualitative shift towards procedural and adaptive pricing that can respond to data in real time (Spann et al., 2024). Modern algorithmic pricing is based on digital data analysis, demand forecasting and optimisation of management decisions. It integrates classical economic models with machine learning algorithms, enabling continuous price adjustments based on consumer behavior and market conditions. Thus, the price ceases to be a fixed management decision and becomes the result of a complex information and analytical circuit that quickly adapts to new conditions (Spann et al., 2024; Nowak & Pawłowska-Nowak, 2024).

Algorithmic pricing integrates fundamental principles of microeconomic theory (in particular, the concepts of supply and demand, price elasticity, and marginal utility) with optimization methods and machine learning. Unlike traditional approaches, in which responses to changing market conditions are often delayed (Den Boer, 2015), algorithmic mechanisms can quickly identify weak

Source: Summarized based on Gallego and Topaloglu (2019), Talón-Ballester and González-Serrano (2013).

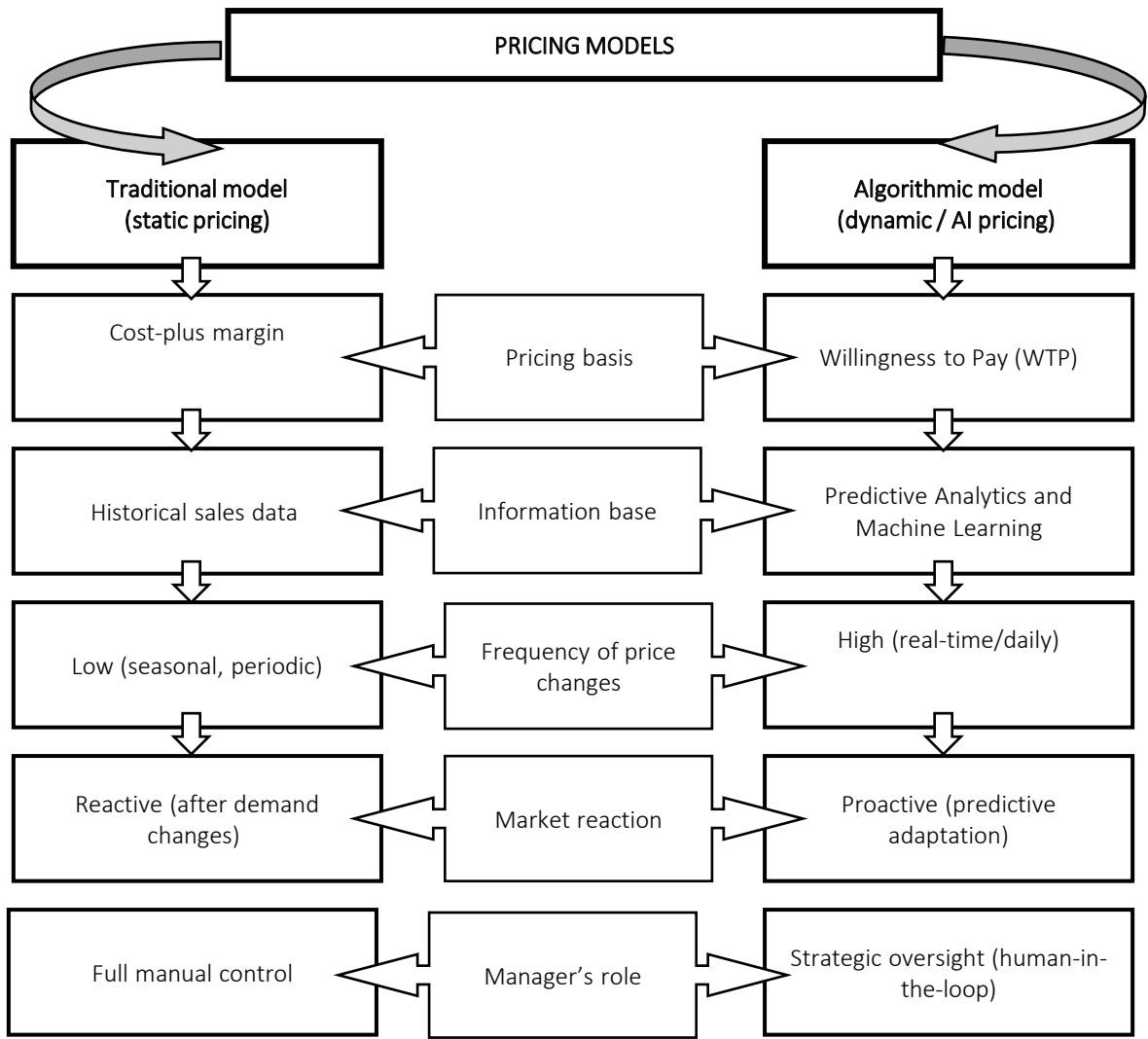


Figure 1. Comparative structure of traditional and algorithmic pricing models

signals of change and translate them into management decisions through demand forecasting based on large datasets.

The summarized key differences between traditional and algorithmic pricing are shown in Figure 1. It demonstrates the methodological and practical advantages of algorithmic models: the high frequency of price corrections and the use of predictive analytics.

Figure 1 shows the fundamental transformation of pricing logic driven by digitalization. The traditional model is based on a cost approach and is characterized by low adaptability to changes in market conditions. In contrast, algorithmic pricing integrates predictive demand models, enabling a tran-

sition from reactive price adjustments to proactive revenue management. This changes the manager's role from an operational to a strategic one.

The evolution of pricing models is depicted in Figure 2.

Phases of evolution:

1. Yield management (1980s): manual adjustment, rigid quotas, retrospective analysis.
2. Rule-based / automation (2000s): reactive systems based on “if-then” logic.
3. Predictive ML (Industry 4.0): proactive systems with demand forecasting.

Source: Build using Boyd and Bilegan (2003), Nowak and Pawłowska-Nowak (2024).

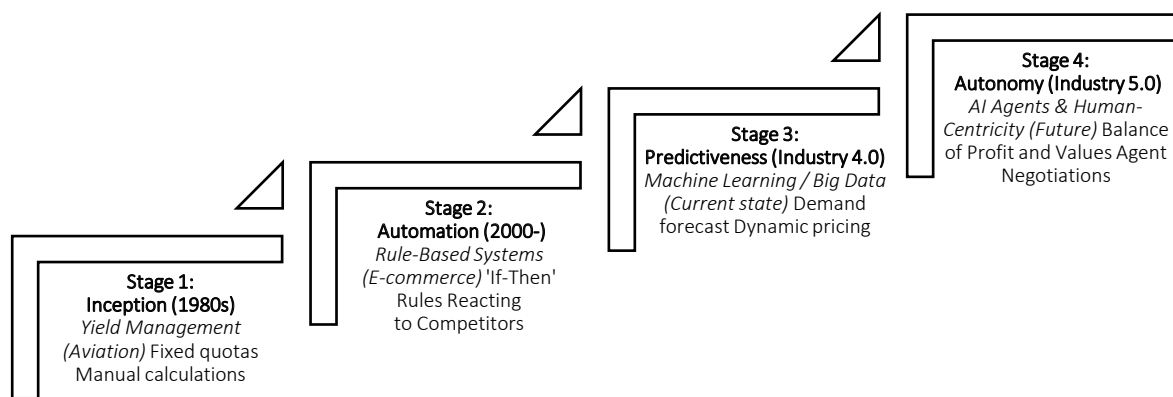


Figure 2. Evolution of revenue management systems: from yield management to AI-driven solutions

4. AI-driven / Industry 5.0: autonomous systems, integration of economic efficiency with human-centric factors (customer loyalty, ethics).

As shown in Figure 2, as technological sophistication increases, the need for manual intervention decreases, thereby improving the accuracy and efficiency of revenue management.

AI-based algorithmic pricing can be interpreted as an economic system evolutionary adaptation to information impulses. At the same time, AI-based algorithmic pricing increases information asymmetry among market participants, raising ethical and regulatory questions regarding the use of digital pricing technologies (Nunan & Di Domenico, 2022; Zhao, 2023).

In the context of modern economic transformation, algorithmic pricing serves as the technological foundation for implementing the “product as a service” (PaaS) business model. In the real estate sector, this paradigm transforms an asset (for example, housing) from an object of ownership into a source of service flow (access to accommodation). For the effective functioning of such a model, espe-

cially in a circular economy, a real-time mechanism to balance supply and demand is critical. It is AI algorithms that ensure the maximisation of the asset utilisation rate, which is the main key performance indicator (KPI) for implementing PaaS models. Differences in pricing approaches during changing economic paradigms are systematized in Table 1.

In general, algorithmic pricing is considered a systemic digital technology that changes the logic of market functioning and contributes to the development of modern and

At the same time, the literature analysis shows that a significant portion of publications is fragmentary, focusing either on the technical aspects of algorithms or on regulatory issues. The systemic role of algorithmic pricing in industry development in the context of digital technologies remains insufficiently explored, thereby determining the scientific relevance of this study.

AI-based algorithmic pricing is a digital technology for coordinating economic processes in modern industries, particularly in the short-term rental (STR) segment.

Table 1. Transformation of the cost model: from linear economy to algorithmic economy based on AI PaaS

Model characteristics	Traditional model (linear economy)	Product as a service model	Algorithmic PaaS (AI-driven)
Transaction object	Transfer of ownership (real estate as a commodity)	Temporary access (rental/sharing)	Optimised access time slot (smart slot)
Pricing objective	Coverage of construction costs + profit	Maximising gross booking revenue	Maximising gross simulated revenue over the asset lifecycle
The role of price	Static cost indicator	Contractual amount (fixed rate)	Dynamic asset utilisation controller

To empirically validate the algorithmic pricing model, a synthetic 365-day time series was generated. The use of synthetic data is a methodological necessity in pricing research, as the true marginal willingness to pay (WTP) is inherently latent and unobservable in historical transaction logs (Varian, 2014; Shiller, 2020). The data generation process simulates realistic economic conditions of the short-term rental market for a conventional urban centre (Skift Research, 2024; Cox, 2024; Gibbs et al., 2017; Magno et al., 2018). The daily unobservable demand curve (WTP) is formally defined by the following additive deterministic-stochastic model:

$$WTP_t = \beta_0 + \beta_1 \sin\left(\frac{2\pi t}{365}\right) + \beta_2 t + \beta_3 W_t + E_t + \varepsilon_t, \quad (1)$$

where WTP is the daily unobservable demand curve, W_t is a binary weekend indicator, E_t is a binary event-shock indicator, and ε_t is the error term.

The parameters of the synthetic data generator were specified to reflect stylised market characteristics of urban short-term rental markets, drawing on aggregated descriptive evidence from publicly available sources. The latent willingness-to-pay process was generated as:

$$WTP_t = 120 + 25 \sin\left(\frac{2\pi t}{365}\right) + 15W_t + 15W_t \sin\left(\frac{2\pi t}{365}\right) + 45E_t + \varepsilon_t,$$

where W_t is a binary weekend indicator, E_t is a binary event-shock indicator, and $\varepsilon_t \sim \mathcal{N}(0, 5^2)$.

The weekend component is specified as a seasonal weekend premium, allowing the magnitude of weekend pricing effects to vary over the annual demand cycle. The methodology explicitly distinguishes four concepts: latent willingness to pay, booking probability, market price, and optimal rental price. Consumer willingness to pay is considered a hidden variable generated exclusively within the simulation and is never observed directly by the pricing algorithm. The forecasting model estimates this latent variable using historical data, after which the optimization module de-

termines the rental price to maximize expected booking revenue. The daily optimization module independently determines the specific rental price that maximises expected booking revenue for that day. Thus, for each observation t , the pricing decision is formulated as the following discrete search optimisation problem:

$$p^* = \arg \max_{p \in \mathcal{P}} R(p), \quad (2)$$

where p^* denotes the optimal rental price selected from the feasible pricing interval $\mathcal{P}$ (evaluated between USD 50 and USD 400 with one-dollar increments). The expected revenue $R(p)$ corresponding to every candidate price is calculated as:

$$R(p) = p \cdot P(\text{booking} | p). \quad (3)$$

Here, reservation acceptance is modelled probabilistically through a logistic demand-response function:

$$P(\text{booking} | p) = \frac{1}{1 + \exp(k(p - WTP))}, \quad (4)$$

where k denotes the price-sensitivity coefficient controlling demand elasticity. This sequential formulation transforms the pricing task from a pure forecasting problem into an explicit one.

Taking into account the recommendations from the peer-review process, the experimental study is needed as a synthetic proof of concept. Actually, the reported performance indicators do not represent empirical estimates from an operational rental platform but rather simulated outcomes based on predefined market assumptions. This controlled environment enables an objective comparison of alternative pricing strategies because every model is evaluated under identical market conditions, demand realisations, and booking rules.

2. RESULTS

To ensure a fair comparison, all forecasting models employ the same optimization routine, booking-probability model, feasible pricing interval, and reservation-simulation procedure. Consequently, differences in financial performance originate

primarily from differences in demand estimation rather than from different optimisation algorithms or evaluation rules.

Several pricing strategies representing different levels of pricing sophistication were evaluated. Actually, the first benchmark corresponds to a Static pricing strategy, in which a single rental price equal to the historical average over the training period is applied throughout the entire forecasting horizon. Although intentionally simplified, this benchmark provides a lower reference level illustrating the consequences of ignoring temporal variation in market demand. The second benchmark represents a Rule-Based pricing strategy, which incorporates deterministic managerial pricing rules. The model estimates consumers' latent willingness to pay using the same explanatory variables available to the neural network. Importantly, after forecasting willingness to pay, the identical revenue-maximization procedure is applied. Therefore, differences between the Random Forest and the proposed neural network can be attributed solely to forecasting performance, not to differences in pricing logic.

Unlike standard econometric approaches, the authors' development is based on deep learning methods, specifically the Multi-Layer Perceptron (MLP) Regressor architecture. Unlike Kwok and Xie (2019), in which price positioning and dynamic pricing positively affect a listing's revenue, the neural network can approximate a nonlinear demand function. The proposed MLP employed two hidden layers, each containing 64 neurons, with ReLU activation and the Adam optimisation algorithm. Model training was performed with a maximum of 2,000 iterations, using L2 regularization to reduce the risk of overfitting. Prior to model training, the explanatory variables – including the day of the year, calendar month, and weekend indicator – were standardised using Z-score normalisation (StandardScaler). To preserve the temporal structure of the simulated time series, avoid data leakage, and more closely reflect operational revenue-management practice (where decisions must always rely on previously available information), the 365-day dataset was divided chronologically into a 75% training period (273 days) and a 25% testing period (92 days). This testing phase was implemented through a 4-step rolling valida-

tion procedure (with a 23-day test size per split), using predetermined random seeds to ensure reproducibility.

The economic efficiency of each strategy was assessed using a nonlinear revenue function. If the price set by the system exceeded the consumer's marginal solvency, then the transaction was rejected, leaving the asset idle and generating zero cash flow. The final criterion for effectiveness was the cumulative financial result, aggregated over the entire testing period. Comparing the accumulated flows enabled to quantitatively prove the algorithm's ability to eliminate the problem of "double losses": to minimize lost profit during peak loads by capturing additional margin and to prevent irreversible losses from resource downtime during phases of market activity decline.

The final pricing workflow was repeated across 100 independent Monte Carlo simulations, preserving the synthetic market's structural characteristics. For each repetition, the willingness-to-pay process was regenerated, forecasting models were retrained, rental prices were optimised using the proposed revenue-maximization procedure, booking outcomes were simulated using the probabilistic demand model, and the corresponding economic performance indicators were calculated. These key performance indicators included cumulative gross simulated booking revenue, average occupancy rate, Revenue per Available Rental (RevPAR), and Average Daily Rate (ADR). Also, to compare the performance of MLP against the benchmark models, a formal paired Monte Carlo inference was conducted, calculating mean revenue differences, 95% confidence intervals, win rates, paired t-test p-values, and Cohen's d effect sizes.

To ensure metric consistency, all key performance indicators (KPIs) are calculated strictly based on the 92-day testing horizon. The average daily rate (ADR) is derived by dividing total gross revenue by the number of booked nights. In contrast, revenue per available rental (RevPAR) is calculated by dividing total gross revenue by the total available nights in the same testing horizon.

The comparative evaluation focuses on key performance indicators such as cumulative gross

Source: Analysis developed by the authors based on Cox (2024), Gallego and Topaloglu (2019, Chu and Rao (2023).

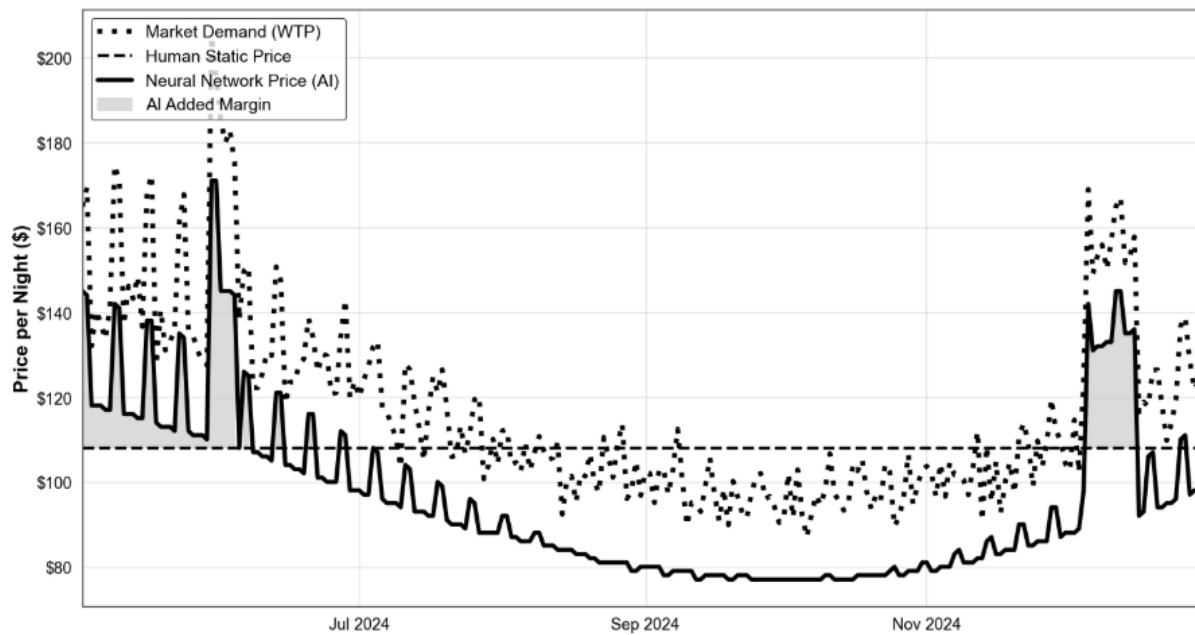


Figure 3. Comparison of static and algorithmic pricing models

simulated booking revenue, average occupancy rate, Revenue per Available Rental (RevPAR), and Average Daily Rate (ADR), along with the corresponding 95% confidence intervals estimated from repeated Monte Carlo simulations.

Having a look at Figure 3, one can see a representative realisation of the simulated pricing process over the testing horizon. The dotted curve represents the latent market willingness to pay generated by the synthetic demand model. At the same time, the dashed line represents the static benchmark, which shows slight step-wise adjustments due to the rolling validation-training splits. The solid curve illustrates the rental prices recommended by the proposed optimization framework, which combines neural-network demand forecasting with explicit revenue maximisation. Crucially, the shaded region between the neural network price and the static benchmark highlights the “AI Added Margin” – the additional revenue premium successfully captured by the algorithmic strategy during demand shocks. The optimized rental price is not a direct output of the forecasting model.

Having a look at Figure 4, one can see the cumulative gross simulated booking revenue ob-

tained during one representative simulation run over the 92-day testing horizon. By the end of the evaluation period, the optimised pricing strategy achieves approximately 48.2% higher cumulative simulated booking revenue than the static pricing benchmark, corresponding to an additional USD 2,293 generated during this illustrative realization. Nevertheless, because this figure represents only a single stochastic experiment, these values should be interpreted solely as an illustrative example of the optimisation process rather than as the principal empirical evidence of model superiority. Statistical evaluation of pricing performance is therefore performed using repeated Monte Carlo simulations.

While Figure 4 illustrates the behaviour of individual pricing trajectories in a single representative simulation, a reliable assessment of pricing performance requires repeated experimentation across different stochastic demand realisations. Therefore, the proposed framework was evaluated using 100 independent Monte Carlo simulations, each generated with a different random seed while preserving the synthetic market’s structural characteristics. The aggregated results across the 92-day testing horizon are summarised in Table 2.

Source: Calculated and constructed by the authors based on the results of simulation modelling based on synthetic data calibrated using aggregated empirical characteristics of the short-term rental market based on Cox (2024), Gallego and Topaloglu (2019), Chu and Rao (2023).

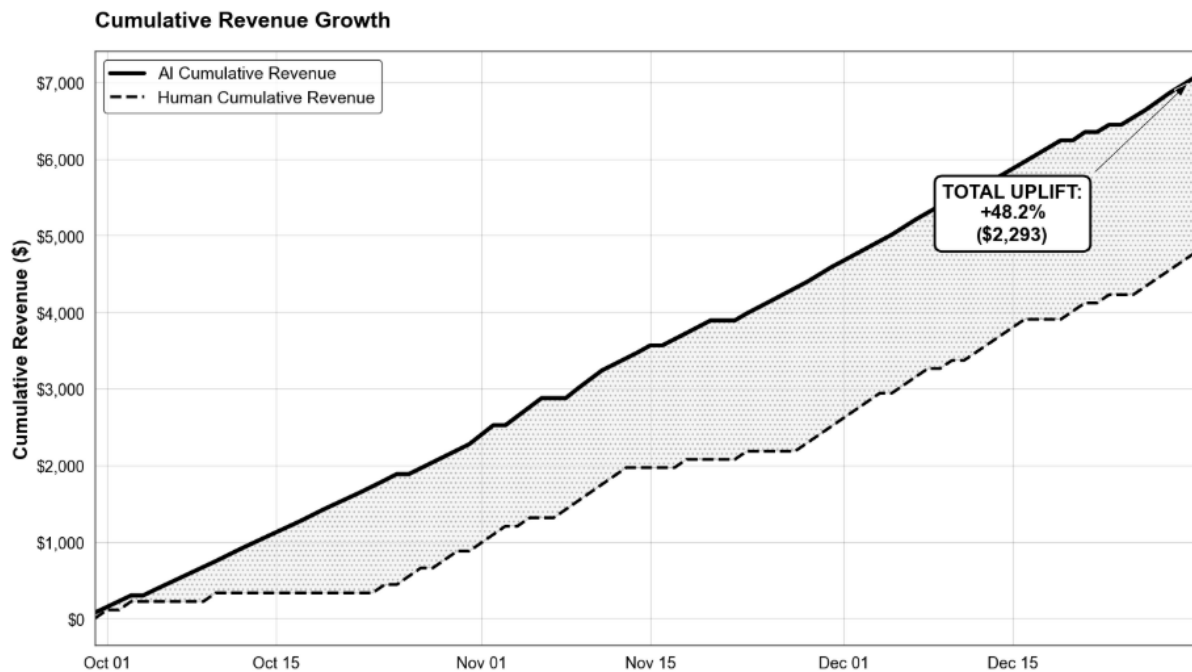


Figure 4. Cumulative revenue under static and algorithmic pricing.

Table 2. Summary of key performance indicators across 100 Monte Carlo simulations (92-day horizon)

Strategy	Mean revenue (\$)	95% CI revenue (\$)	Mean occupancy (%)	Mean ADR (\$)	Mean RevPAR (\$)
Static	5,099.60	[\$4,323, \$5,935]	51.4	\$107.79	\$55.43
Rule-Based	4,792.03	[\$3,681, \$5,849]	46.7	\$111.46	\$52.09
Random Forest	6,972.96	[\$6,361, \$7,402]	89.2	\$84.96	\$75.79
MLP (AI)	7,307.42	[\$6,703, \$7,776]	88.4	\$89.86	\$79.43

The Monte Carlo evaluation demonstrates that machine-learning-based pricing strategies substantially outperform the static and rule-based benchmarks in simulated revenue performance. Among the evaluated approaches, the Static pricing strategy generated an average cumulative booking revenue of USD 5,099.60 (95% confidence interval: USD 4,323–5,935). The corresponding average occupancy reached 51.4%.

Contrary to elementary revenue-management expectations, introducing deterministic pricing adjustments decreased overall performance. The Rule-Based strategy generated an average cumulative revenue of USD 4,792.03, which is lower than the static benchmark, with occupancy at 46.7%, ADR of USD 111.46, and RevPAR of USD 52.09. This demonstrates that rigid, calendar-based heuristics often lead to severe occupancy drops when

they fail to account for the probabilistic nature of consumer demand accurately.

Substantially larger improvements were achieved after introducing machine-learning-based willingness-to-pay estimation. The Random Forest model generated an average cumulative simulated booking revenue of USD 6,972.96 (95% CI: [\$6,361, \$7,402]), with an occupancy rate of 89.2%, an ADR of \$84.96, and a RevPAR of USD 75.79.

The highest overall performance was achieved by the proposed Multi-Layer Perceptron (MLP). To address the similarity in performance among the nonlinear machine learning models, a formal paired Monte Carlo inference was conducted. While the absolute difference in mean revenue between the MLP and Random Forest algorithms appears relatively modest, the paired t-test con-

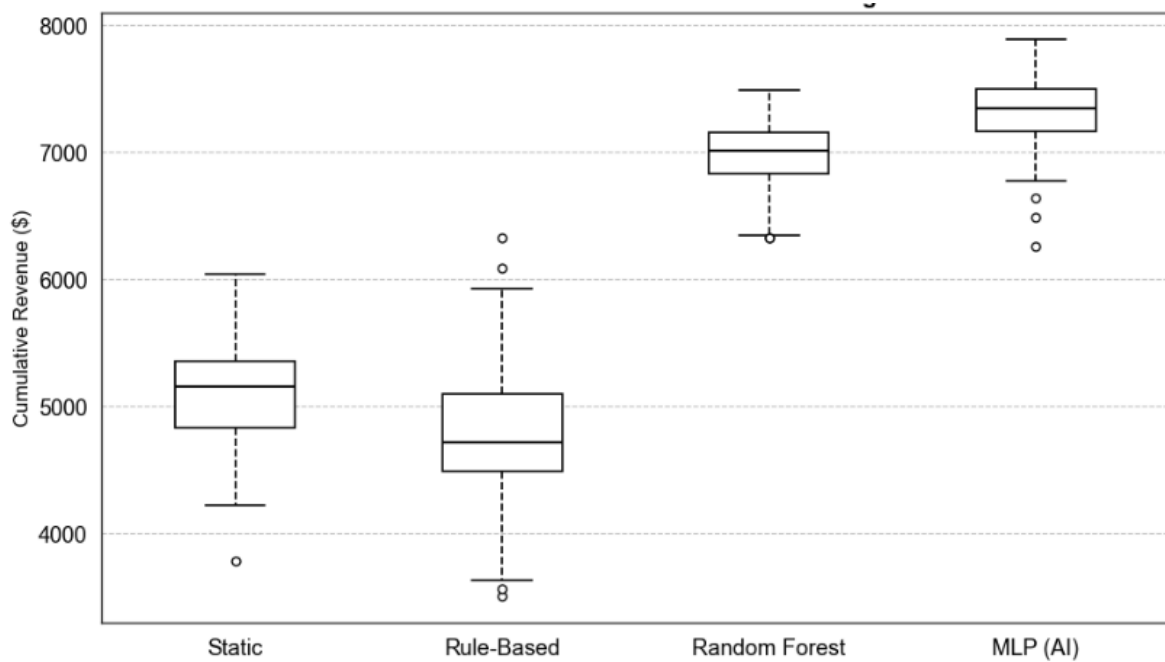


Figure 5. Gross simulated booking revenue (100 Monte Carlo iterations)

firms that the MLP's superiority is highly statistically significant (Mean Diff: \$334.46, 95% CI of Diff: [\$253.49, \$415.43], $p = 1.8232e - 12$, Cohen's $d = 0.810$). Across 100 iterations, the MLP outperformed the Random Forest in 78.0% of the simulated scenarios (Win Rate). Analysis of the expanded KPI metrics reveals that this advantage stems primarily from the MLP's ability to secure a higher Average Daily Rate (\$89.86 vs \$84.96) while maintaining comparable occupancy levels, thereby more precisely approximating peak latent demand.

The variability of pricing performance across repeated Monte Carlo experiments is illustrated in Figure 5, which presents the distribution of cumulative simulated booking revenue for all evaluated pricing strategies over the 92-day testing horizon. The Static and Rule-Based benchmarks occupy substantially lower revenue ranges, with median revenues around USD 4,700–5,200 and comparatively wide dispersion.

The Random Forest and MLP models also exhibit noticeably smaller relative variability than the simpler pricing strategies. Although several individual outliers are observed for each approach, the interquartile ranges remain comparatively narrow, suggesting that the proposed optimisation

framework maintains stable performance despite stochastic variation in simulated market demand. Furthermore, the considerable separation between the distributions of machine-learning and non-machine-learning strategies indicates that the observed performance improvements cannot be attributed solely to random simulation effects; rather, they remain consistent across repeated experiments.

To further investigate the contribution of the neural network architecture itself, an ablation study was conducted by comparing three alternative Multi-Layer Perceptron configurations that differed in depth and complexity. The results of the ablation study are systematically outlined in Table 3.

Table 3. Architecture comparison and ablation study results

Architecture	R ² score	Mean Absolute Error (MAE) (\$)
Shallow (32)	−9.6635	48.01
Proposed (64, 64)	0.7978	6.00
Deep (100, 50, 25)	0.8125	5.52

The results presented in Table 3 demonstrate that increasing network complexity improves predictive performance, although the gains become

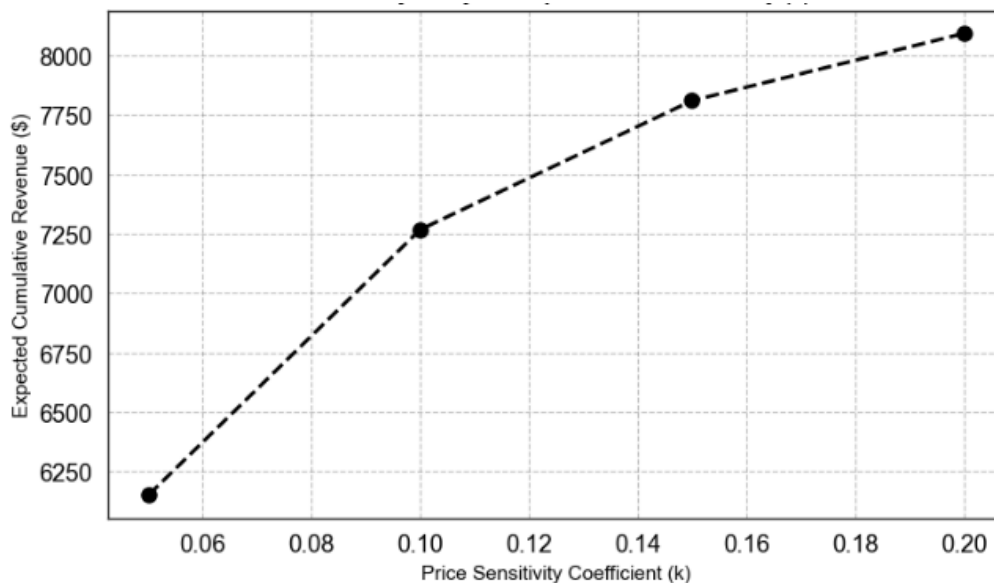


Figure 6. Impact of price elasticity (k)

relatively limited for the deeper architecture. The shallow architecture (32 neurons) fails to adequately capture the underlying nonlinear market dynamics, resulting in a negative score of -9.6635 and a high MAE of \$48.01. Increasing the network capacity substantially improves predictive accuracy: the proposed (64, 64) architecture achieves a score of 0.7978 and an MAE of \$6.00. Although the deeper network achieves a marginally higher forecasting precision, the proposed (64, 64) architecture is selected as the operational standard. It provides an effective balance between predictive performance and architectural complexity, without introducing unnecessary architectural overhead for the downstream revenue-maximisation routine.

The representative pricing trajectories presented in Figures 3-4 illustrate how the optimisation procedure dynamically adapts rental prices to changing market conditions while maintaining a balance between higher daily rates and reservation probability. Rental prices are no longer equated with predicted willingness to pay. The proposed forecasting model estimates latent demand, determining the rental price that maximizes expected booking revenue. The proposed Multi-Layer Perceptron achieved the highest average cumulative simulated booking revenue (USD 7,307.42), the average occupancy (88.4%), and the highest RevPAR (USD 79.43) among all evaluated pricing strategies. The Random Forest benchmark proved

to be better than deterministic rule-based and static pricing approaches. Furthermore, the relatively narrow confidence intervals and compact revenue distributions indicate that the proposed framework remains robust despite stochastic variation in the generated demand process.

Analysis of the training loss curve confirms stable convergence of the optimisation algorithm, with no evidence of numerical instability or overfitting throughout the training process. As seen in Figure 6, the sensitivity analysis indicates that the proposed pricing framework remains stable under different assumptions regarding consumer price elasticity. The sensitivity analysis indicates four alternative values of the price-sensitivity coefficient k (ranging from 0.05 to 0.20), showing that expected cumulative booking revenue increases smoothly from about USD 6,150 to USD 8,100. Although the absolute values of cumulative simulated booking revenue vary as the elasticity coefficient changes, the optimization procedure exhibits consistent behaviour across all investigated parameter values, suggesting that the reported improvements are not dependent on a single parameter configuration.

The experimental findings indicate that combining machine-learning-based willingness-to-pay estimation with an explicit revenue-maximisation procedure provides a consistent improvement over simpler pricing strategies. Nevertheless, the

reported results should be interpreted exclusively as gross simulated booking outcomes generated under the assumptions of the synthetic demand model. Given that the experimental environment does not capture all data related to operational short-term rental markets (including competitor interactions, cancellation behavior, availability constraints, and observed booking data), the resulting numerical values should not be interpreted as direct estimates of the real-world situation. On the contrary, they demonstrate the feasibility and internal consistency of the proposed methodology as a synthetic proof of concept and provide a methodological basis for subsequent validation using empirical short-term rental datasets.

This research is an initial exploration of AI-driven pricing within rental frameworks. Future studies can scale these methodological provisions to broader paradigms of sharing and rental, whose relevance will grow as the transition toward a circular economy.

3. DISCUSSION

Unlike prior works (e.g., Den Boer, 2015) that focus primarily on microeconomic efficiency, our conceptual and simulation-based framework shapes the logic of market coordination. The quantitative simulation results are consistent with the paper by Talluri and Van Ryzin (2004), which illustrates the limited adaptability of tra-

ditional pricing strategies. Also, the simulation outcomes are consistent with Spann et al. (2024), indicating that the economic benefits of algorithmic models are cumulative, scaling with predictive accuracy and data availability. Although STR markets exhibit high demand volatility and behavioral complexity, the core mechanisms mirror those of broader platform markets (such as e-commerce, transport, and hospitality), where, as in paper Einav and Levin (2014), real-time pricing coordinates resource allocation.

The key managerial implication of this paper relates to the transformation of the manager’s role, shifting it toward strategic control over algorithm parameters, data quality, and automated decisions. This aligns with research by Nunan D. and Di Domenico, which conceptualizes the ethical challenges raised by the contemporary use of dynamic pricing while introducing new challenges related to algorithmic trust, automated error risks, and vendor dependence.

From a broader theoretical and institutional perspective, our framework highlights a dual effect of algorithmic pricing. Firstly, algorithms enhance micro-level market coordination and reduce supply-demand mismatches. Secondly, they also introduce the risk of information asymmetry, as discussed in the paper by Ezrachi and Stucke (2020). This underscores the necessity of coupling economic analysis with regulatory and ethical considerations. The first block of results concerns the

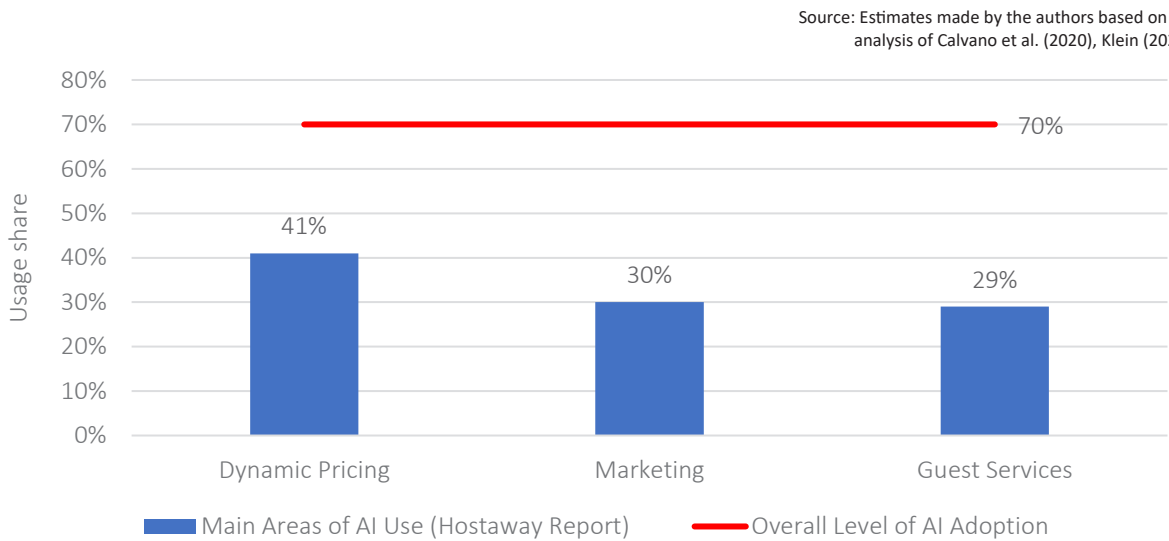


Figure 7. Functional structure of the application of artificial intelligence in algorithmic pricing

functional implementation of algorithmic pricing within digital platforms. As shown in Figure 7, the functional structure of the application of artificial intelligence in algorithmic pricing indicates that the key areas of use are demand forecasting, optimisation of price parameters, and consumer segmentation.

This structure indicates the dominance of a proactive management logic, in which the price is formed not based on retrospective data but rather through the continuous processing of market information. The result confirms the theoretical proposition that the price shifts from a passive indicator of market equilibrium to an active tool of systemic adaptation.

The second block of results is devoted to the analysis of behavioral mechanisms of algorithmic pricing. The data are summarised in Table 2. Types of price discrimination in algorithmic pricing indicate that modern algorithmic models offer a flexible combination of temporal, segment, and behavioural discrimination.

This allows for more accurate alignment of prices with consumers' willingness to pay and minimises potential revenue losses. Combined with the strategies of digital platforms, systematised in Table 4, algorithmic pricing forms a new model of market coordination, within which platforms act as central nodes for managing price flows. In particular, Table 5 specifies this based on publications, using the example of short-term rental (STR) implementation.

An important result of the study is the identification and formalisation of the risks and limitations of algorithmic pricing. The primary information for the analysis consisted of a set of recent scientific publications in revenue management, as well as industry reports and technical specifications from leading digital short-term rental platforms (Wang, 2024; Cervera et al., 2024; Klein, 2021; Calvano et al., 2020). Based on the analysis of these publications, the authors performed their own expert assessment of the benefits and risks of using algorithmic pricing in rental business management (Figure 4).

Table 4. Types of price discrimination in algorithmic pricing

Source: Summarised based on Zervas et al. (2017), Einav and Levin (2014).

Form of price discrimination	Theoretical characteristics	Implementation through AI	Economic effect
First degree (ideal)	Individual price for each consumer	Partial implementation through personalised demand signals and behavioural data	Maximum extraction of consumer surplus
Second degree	Differentiation by volume or conditions	Discounts for length of stay, minimum nights	Stimulating demand volume
Third degree	Consumer segmentation by groups	Booking time, traveller type, seasonality	Revenue optimisation with different elasticities
Intertemporal discrimination	Prices depend on the time of purchase	Last-minute prices, early booking	Reducing losses from vacancy

Table 5. Pricing strategies of short-term rental platforms

Characteristic	Airbnb	Booking.com
Business model	Peer-to-peer marketplace for housing and unique offers	Global OTA connecting hotels and STRs
Volume of active offers	~8 million in 2025	~2.9 million apartments/houses + 475,000 hotels (over 3.4 million properties in total) (Booking Holdings, 2023)
Level of use of algorithmic pricing	Smart pricing / automatic recommendations (Airbnb, 2024)	Integrated algorithmic modules in OTA booking
Market share dynamics (2019–2024)	Growth from ~28% to ~44% (Skift Research, 2024)	Growth from ~14% to ~18% (Skift Research, 2024)
Competitive advantages	Large database of unique STRs	Strong integration with hotel and OTA products
Price competition	Automatic adaptation to demand	Algorithmic recommendations in the broader context of bookings

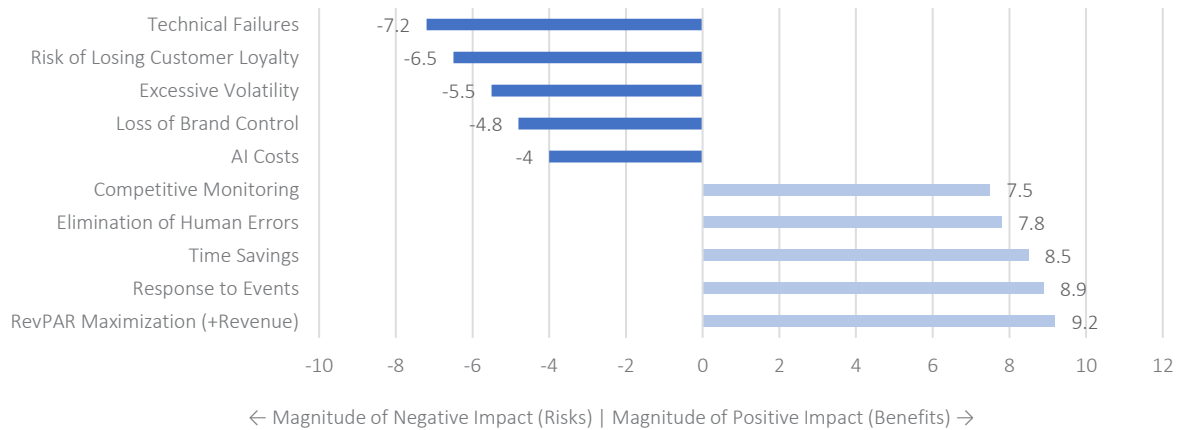


Figure 8. Benefits and risks of algorithmic pricing

The criteria for expert evaluation were formed according to three key vectors:

- **Microeconomic and operational efficiency.** The ability of AI algorithms to maximise key profitability indicators (in particular, RevPAR) by optimizing price peaks, as well as the extent to which transaction costs and manager time are minimised through the automation of routine processes.
- **Technological stability and algorithmic reliability.** The level of vulnerability of predictive models to anomalies in input data sets (the risk of a “Flash Crash” effect – a disproportionate drop in price due to a failure), the need for complex initial system calibration, and the degree of dependence on external providers of digital solutions.
- **Institutional risks and market transparency.** The likelihood of algorithmic coordination (implicit collusion) without the direct participation of economic entities increased information asymmetry between the platform and the consumer. It raised the risk of increased regulatory pressure due to artificially inflated prices.

The benefits and risks of algorithmic pricing (expert assessment) show that, while increasing economic efficiency, the risks of reduced transparency, algorithmic coordination, and technological dependence on digital solution providers also increase. A summary of the strengths, weaknesses, opportunities, and threats of implementing AI pricing based on Meylahn (2024) is outlined as

follow. **STRENGTHS** include RevPAR Growth 15-30% revenue increase from peak-pricing capture; Automation education of the manager’s routine workload by up to 20 hours per week. **WEAKNESSES** has two points: Commission Costs (Software expenses typically range from 1% of turnover to a fixed fee (\$10-20/property)); Setup Complexity (Requires initial staff training and rigorous strategy calibration). **OPPORTUNITIES** also have two points: Scalability (Ability to effortlessly manage hundreds of properties without expanding staff); Global Expansion (Streamlined entry into new markets facilitated by automated data analysis). **THREATS** also have two points: Algorithmic Errors (Risk of selling at ultra-low prices due to data feed failures (the “Flash Crash” effect)). Regulatory Pressure (Potential government restrictions or antitrust scrutiny due to perceived “artificial price inflation”). SWOT analysis of the implementation of algorithmic pricing shows that the long-term effectiveness of such systems is determined not only by technological maturity but also by the quality of the institutional and regulatory environment. Despite extensive Monte Carlo simulations, this study has several limitations. First, the primary limitation lies in the reliance on a synthetic proof-of-concept simulation rather than empirical transactional data. As previously argued, real-world short-term rental datasets record only realised transactions, leaving the latent willingness to pay unobservable. Second, the performance metrics are strictly restricted to gross simulated booking revenue. Therefore, the demonstrated algorithmic uplift indicates revenue-maximization potential but cannot be directly extrapolated to represent net profitability.

Third, in real life, consumer prices are sensitive and may vary depending on booking lead time, trip purpose (business versus leisure), and behavioural economics factors such as anchoring effects.

A significant challenge in translating this synthetic proof-of-concept into an operational system is the empirical observability of the willingness-to-pay function.

CONCLUSION

This article aimed to conceptualize AI-driven algorithmic pricing methods for short-term rentals and to rigorously validate them through simulation modelling as a synthetic proof of concept for the “product as a service” (PaaS) paradigm. Our research demonstrates that algorithmic pricing functions as a systemic digital technology, transforming the market from a reactive, static environment into an adaptive information circuit in which prices serve as active tools in real time.

The empirical findings were validated through 100 Monte Carlo simulations over a 92-day testing horizon, confirming the superior efficiency of the proposed Multi-Layer Perceptron framework. The Multi-Layer Perceptron model generated an average cumulative booking revenue of USD 7,307.42 and achieved the highest RevPAR (USD 79.43) among all evaluated strategies. Compared to the traditional Static (USD 5,099.60) and Rule-Based (USD 4,792.03) benchmarks. Thus, proactive, probability-based optimisation produced higher simulated revenue. The statistical validation via paired Monte Carlo inference confirmed the Multi-Layer Perceptron revenue advantage over the Random Forest benchmark (with statistical significance ($p < 0.001$) and economic soundness).

Beyond mere operational optimisation, this study positions algorithmic pricing as a transformative factor in the platform economy. Algorithmic pricing shifts managerial focus from manual price-setting to the strategic oversight of algorithmic parameters. While our synthetic proof-of-concept provides a stable methodological basis for understanding these dynamics, the study also highlights significant institutional challenges, including increased information asymmetry and the potential for concentration of market power within platform ecosystems. Ultimately, the integration of these intellectualised decision-making models offers a robust pathway for coordinating economic processes in a circular, service-oriented economy.

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