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Predictive Modelling Techniques for Airbnb Rental Pricing: A Systematic Review of Algorithmic Approaches

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Abstract. The paper provides a comprehensive literature review of pricing prediction modelling techniques for Airbnb short-term rentals. The primary focus of this study is on high-calibre academic outputs from 2015 to 2024 within the domains of hotel management, information science, and pricing forecasting. The author conducts a comprehensive review of existing pricing strategies. The study identifies the core pricing determinants, i.e. the factors that have the most significant impact on pricing strategy. These determinants include property attributes, host reputation, geographical location, temporal patterns, and market competition. It is important to note that research has demonstrated that machine learning methods exhibit significant advantages in capturing complex interactions among multidimensional factors. The efficacy of ensemble learning frameworks and deep neural network architectures has been demonstrated. However, contemporary approaches are confronted with critical challenges that necessitate resolution, including inadequate cross-domain generalisation capabilities, persistent algorithmic biases, and the absence of real-time dynamic pricing mechanisms. The present paper proposes an innovative business strategy framework integrating circular economy principles. By pursuing three pathways—cultural transformation, process reengineering, and technological advancement—in a synergistic manner, the objective is to transcend the constraints of traditional linear pricing. It is hoped that this review will catalyse the evolution of platform ecosystems towards value co-creation models, thereby actively steering Airbnb's sharing economy platform and its participants towards a shift from profit-driven to ecologically collaborative development trajectories.

Keywords: Airbnb Pricing, Machine Learning Algorithms, Predictive Modelling

1. Introduction

The present literature review focuses on the development of pricing prediction modelling techniques for Airbnb short-term rentals. The author's primary objective is to examine the key mechanisms influencing short-term rental pricing. A review of extant research indicates that machine learning methods excel at handling the complex interactions of multidimensional pricing factors. It is evident that both ensemble learning frameworks and deep neural network architectures have yielded remarkable outcomes with regard to predictive accuracy. It is important to note that current models continue to demonstrate certain deficiencies, particularly with regard to adapting to cross-regional

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markets and identifying algorithmic biases. Numerous studies have explored pricing factors and forecasting methods, yet the literature lacks overall coherence [1]. Empirical work remains largely centred on traditional machine learning approaches. There remains considerable scope for the application of emerging technologies such as deep learning and transfer learning. In the field of price forecasting, Tziridis et al. [2] have conducted a series of experiments utilising multiple machine learning algorithms. Nevertheless, the challenge of rendering these models' decision-making processes transparent and interpretable persists as a significant impediment to their practical implementation.

This paper reviews and analyzes studies on how to predict Airbnb rental prices. It focuses on high-quality academic papers published from 2015 to 2024 in top journals related to hotel management, information science, and machine learning. We use strict criteria to select the literature, giving priority to research that shows new methods, solid analysis, and practical guidance.

2. Literature review

2.1. Property-specific attributes and their price impact

The intrinsic characteristics of a property form the essential dimensions of what we identify as the prevailing pricing model. Factors such as property type, floor area, quality of fit-out, and the availability of facilities significantly influence the price determination process. A large-scale cross-city analysis by Wang and Nicolau [3] indicates that the property type variable has the greatest explanatory power in pricing, with entire flats commanding a substantial premium over single-room units.

2.2. Host credibility and service quality variables

As modern homestays grow in popularity, host credibility and service quality are key factors in setting prices. Trust is essential in the sharing economy. Teubner, Hawlitschek, and Dann [4] developed a model to measure how credibility affects pricing. Their studies show that trust signals like Superhost status, star ratings, and the number of reviews can improve a listing's bargaining power. Achieving Superhost status can allow hosts to charge 15–20% more.

Tools for rating systems serve as instrumental mechanisms in the service quality evaluation process. Researchers, engaging deeply with natural language processing, analyze review texts intricately to refine the precision of measuring metrics related to service quality. Positive rating percentages and cleanliness assessments—among other elements such as responses to communication—influence significantly the accuracy of predictions regarding pricing. Beyond mere identification lies the sophistication of contemporary methodologies. Sentiment analysis entwined with machine learning by Rezazadeh, Kalehbasti, et al [5], formulates an intricate analytical paradigm assessing market competitiveness of hosts, where explicit data does not solely reside but also nuanced service aspects arise—from user reviews' emotional nuances, insights richer for strategies involving prices thereby provided.

Geographical location's influence relative to Airbnb's pricing transcends any simplistic approach merely reliant upon coordinate mapping. Into a unified model of pricing, eclectic spatial characteristics coalesce—factors like accessibility to transport, proximity to commercial amenities, and safety levels of neighborhoods included within. Studies reveal that properties situated near core business districts, attractions popularized, or hubs for transportation enjoy often heightened price premiums. However, geographical influences vary immensely across different locales, indicating

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pronounced diversity specific to each region. A strong substantiation is granted through Geographically Weighted Regression (GWR) methods applied successfully. Pricing trends thus unveil regional variations which manifest whereby even under identical geographical traits differing effects emerge distinctively due to variations across urban districts [6,7].

However, the pricing effect of geographical location is not solely rooted in economic rationality. It is deeply embedded within socio-cultural factors. 'Area effects' may mask racial biases. That is, within identical geographical locations, landlords of different ethnicities have significantly different pricing power. This reveals latent discriminatory pricing risks within the sharing economy [8].

2.3. Temporal patterns in demand fluctuations

The time of day is a key factor in how Airbnb sets prices, and it directly affects how much people pay to rent. The prices of food and drink are affected by the time of year and the availability of places to eat in the local area [9]. The importance of the time factor can vary a lot depending on where you are and what kind of property it is. Well-liked vacation spots often see more demand and higher prices at the busiest times of the year. However, urban areas have a steady number of visitors during the week because of people travelling for work [3]. On the other hand, houses in the suburbs are most often rented out at the weekend and on public holidays. Special events, like big conferences, have been shown to successfully increase demand in the local area, making a lot of money for the hosts who are smart about it [10].

So, to successfully use dynamic pricing strategies, it's crucial to understand how consumers behave over time. Landlords with multiple properties have an advantage when it comes to pricing because they can manage their income better [11]. After the pandemic, forecasting models need to include new patterns over time [12] and spot cyclical patterns and sudden changes.

2.4. Market competition and supply-demand

To set the right prices, businesses need to understand what their competitors are doing. Basically, if a market is more competitive, it is more likely that prices will be driven up by substitutes and market concentration [3,13,7]. The way the sharing economy works is very different from traditional models [14]. Airbnb is different from regular hospitality because it creates a competitive ecosystem with many different parts [15]. Individual hosts can be both price takers and setters at the same time. This is because the platform is decentralised. While each host can decide on their own prices, they are still affected by the overall market.

To understand market competition, we need to look at how different businesses are similar and different. Different types of property can compete directly or form different markets that are specialised [16]. The increase in competition is also driven by the fact that customers have more choice. For example, business and leisure travellers have different price sensitivities and service preferences [17]. So, it's really important to understand how markets reach a balance. Platforms use algorithms and price signals to make the best use of resources. But sometimes, information that is not available to everyone, and the cost of searching for it, can make markets not work as well as they should [18]. We should measure competition intensity holistically across dimensions, including property density, price distribution, and service differentiation. Market concentration directly influences hosts' bargaining power [11]. Threats of substitution originate from comparable short-term rentals and traditional hotels.

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3. Algorithmic approaches to airbnb price forecasting

3.1. Regression models and their extensions

Existing literature indicates that, while traditional multiple linear regression possesses a theoretical foundation for Airbnb pricing prediction, its linear assumptions fundamentally conflict with the complexity of real-world pricing mechanisms [3]. A seminal study by Wang [3] employed large-scale empirical analysis across 33 cities to identify key pricing factors. These factors included property type, influenced by time and guest flow. Nevertheless, this approach is inadequate in effectively capturing the non-linear interactions between geographical location and price. In essence, the explanatory power of such models is found to be considerably constrained. It is imperative to note that conventional regression methodologies presuppose parameters to be constant over the entire domain. This assumption of 'spatial homogeneity' has also been demonstrated to be inadequate when confronted with the phenomenon of intra-urban spatial variation [6]. It is evident that geographical factors also exert locational effects on property values. The company is transitioning from a 'global uniformity' approach towards 'localised adaptation'. This foundation paves the way for subsequent scholars to implement spatial enhancements through machine learning methodologies.

3.2. Decision tree ensemble methods

Decision trees, when employed as a group, have clear advantages when dealing with high-dimensional features and complex interactions. As demonstrated in the extant literature, the random forest algorithm effectively addresses the tendency of individual decision trees to overfit through a dual mechanism of bootstrap resampling and random feature selection [19]. At this juncture in time, sharing economy platforms are enjoying a period of significant growth and development. The quality of the data is subject to significant variation. These frameworks have been shown to work well even when some of the data is missing or unusual. In the early days of machine learning, researchers noticed that using a group of algorithms (a set of rules that work together) was a lot better at predicting prices than using just one algorithm on its own [2]. Gradient boosting is clearly another key group of strategies. The system has been designed to learn in stages. This means it can predict outcomes more accurately. Researchers recently used a special kind of computer program called a particle swarm optimisation-based ensemble framework to study how prices change in places where there's been a pandemic. This system has been shown to be able to accurately predict changes in customer numbers and support pricing decisions. This way of doing things has been shown to be successful in dealing with new market volatility [12]. This paper summarises the results of a series of studies that compared artificial intelligence methods with traditional statistical approaches. Studies show that ensemble learning is technically superior. The model is very good at predicting future outcomes, as shown by many studies [20].

3.3. Neural network architecture for price forecasting

The basic idea of deep learning is to move from the subjective process of manual feature engineering to an objective, data-driven discovery process. The main problem with traditional machine learning methods for predicting prices is that they rely too much on expert knowledge [21]. Researchers often find it hard to identify and weigh up pricing factors because they are subjective [22]. This is especially difficult when dealing with the large, varied sets of data that are common on

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sharing economy platforms. Deep neural networks use a different approach, known as hierarchical abstraction mechanisms. This helps people to learn how to understand complex maps on their own. The substantial daily volumes of transaction data, user behaviour data, and market feedback generated by the platform furnish deep networks with extensive learning samples [23].

Convolutional neural networks boast distinct advantages when it comes to modelling location-based dynamic pricing. The main process is basically turning on-going geospatial data into something you can use on your computer [23]. In Airbnb's pricing, the significance of geographical location extends far beyond simple latitude and longitude coordinates. It's got all these complex ideas about space, like how easy it is to get around, how busy the shops are, and the cultural vibe. The convolutional operations of CNNs automatically extract similarity features from spatially adjacent regions, identifying the 'bubble effect' –a spatial pattern difficult to quantify using traditional methods [24]. Within temporal modelling, recurrent neural networks (LSTM architecture) possess inherent irreplaceability. Their unique technical advantages result in a well-designed gating mechanism, effectively capturing both short-term and long-term dependencies within time series [22].

The formula above clearly shows the different roles of the three gating mechanisms in the LSTM. The forget gate is responsible for selecting which historical information should be discarded, the input gate determines the importance of new information, and the output gate adjusts the weighting of the current state's influence on subsequent predictions. Airbnb's practical application of price forecasting is made possible by this design. It effectively balances long-term market trends with short-term volatility factors [23]. Of pivotal significance, the model eschews the exaggerated emphasis on historical patterns that could diminish responsiveness to sudden market fluctuations, whilst simultaneously forestalling an over-attention on evanescent fluctuations that might obfuscate underlying price regularities. This dynamic equilibrium capability represents a significant advantage over traditional statistical models.

Intrinsic to the endeavor of forecasting Airbnb's pricing is its inherently complex and dynamic nature, manifesting across fluctuating temporal and spatial dimensions. The demanding intricacy herein arises from dual foundational pillars. It can be observed that first, a remarkably heterogeneous corpus of data is aggregated by the platform, encompassing information such as characteristics of properties, consumer behavior patterns, prevailing market trends, alongside exogenous factors. This conglomerate synthesis of disparate datasets presents formidable obstacles. Moreover, models rooted in deep learning necessitate pristine training sets; fluctuations caused by noise, absent values, or inconsistencies critically compromise their efficacy. Consequently, an observance of rigorous data governance architecture becomes paramount. Controlling each phase of the data lifecycle—initial capture, stringent cleansing, annotation, through to storage—is essential for ensuring the integrity and comprehensiveness indispensable for accurate model input processing. Such discipline embodies a fundamental technical mandate. Evidently, triumphant harnessing of deep learning methodologies in the forecast realm pivots on proficient amelioration of these pivotal technical impediments.

Within the operational forefront resides the real-time dynamic pricing algorithm, established as the cornerstone element of Airbnb's prognostication mechanization, thereby epitomizing avant-garde advancements within this sector. Its quintessential challenge lies in adeptly discerning fluxes within the marketplace amidst constraints concerning finite computational assets, facilitating expeditious yet sagacious price strategy calibrations. Clearly translating into a Markov Decision Process (MDP), this formulation navigates the quest for viable solutions efficiently.

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Technical infrastructure reveals a state space encapsulating multifarious market intelligence variables; specifics encompass instantaneous interplays between supply and demand, competitor-influenced strategic pricing articulations, coupled with historic booking variability insights. These elements constitute the essential framework informing perceptual understanding of market ambiance via algorithmic mechanisms. Concurrently, deliberate construction of action spaces incorporates judicious assessments of feasible price range boundaries, ensuring both competitive adaptability and preservation of rational profitability margins.

Integral to this algorithmic architecture is the intricately formulated reward construct, oriented toward revenue maximization as its quintessential objective. Embedded in a framework epitomized by Markov Decision Processes, model selection allows adept navigation of sequential pricing decisions. Feedback assimilation from evolving market conditions continually refines decision-making strategy; thus emerges optimal pricing amidst fluctuating contexts. Observably, such technological progress accentuates system's pricing efficiency, setting a standard for intelligent price modeling within sharing economies' purview.

In contextual reference, V*(s) delineates the supreme value function each state corresponds with, while notation therein denotes an influence factor applied to antecedent valuations. Iterated computation methods elucidate said optimum policy valuation.

Online learning algorithm incorporation proves pivotal for facilitating immediate price modulation. In particular, the multi-armed bandit scenario advocates a visualization where potential prices emulate selectable 'arms,' inherently grasping expected performance metrics grounded on exploration-exploitation equilibriums. The Upper Confidence Bound (UCB) mechanism proficiently orchestrates this equilibrium via given criteria:

(Should specific elaborations or illustrations pertinent to the UCB be essential, they warrant thorough inclusion at this juncture.)

Empirical mean estimation, indicative of action representation, and selection count designation are presented amidst this analysis. A compulsion toward exploratory actions within high-uncertainty contexts is visible through the confidence interval construct.

Rooted in the technological edifice that forms stream processing, profound capabilities emerge in arranging rapid data streams for voluminous real-time assimilation. Distinctive pathways manifest as expansive pipelines when distributed processing formations come into play, allowing instantaneous multi-source data aggregation—featuring reservation particulars, comparative pricing modulations, alongside market demand indicators—and facilitating prompt execution encompassing feature distillation, inferential modeling, and dynamic price alteration tasks executed within mere milliseconds.

Within an innovative economic proposition aimed at refining Airbnb's property pricing structures, one discerns encapsulated insights drawn from circular economy doctrines. An imperative emerges from these models' optimization themes underpinning sharing economies—a structure underlain by a value loop infusing perpetual self-renewal. Highlighted in considerable scholarly inquiry is the central hindrance: capturing sustained viability amid turbulent competitive climates, notably observed across shared platform paradigms. Departing from purely profit-focused trajectories with inherent shortcomings often leading to shortsighted decisions, substantial shifts become recognizable — derived from circular economic epistemes — yielding novel schemas for generating value anew. It reveals a paradigm shift engendered away from simple linear consumptive practices, repurposing towards 'resource reclaim-invest-return'. Geo-specific strategic approaches anchoring valuation methodologies on properties find application via operators like Airbnb – transformative ideas here playing pivotal roles unravel latent dichotomies festering within shared settings, aligning

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various stakeholder priorities whilst perpetuating enduring equilibrium. Through adopting rounded frameworks, one expects improved resource utilization plus framework support conducive towards nurturing sustainable ecological systems.

4. Optimising airbnb property pricing: articulating a novel economic thesis

4.1. Inauguration of cultural dimensions: economic reevaluation cycle of modest cost

Fundamental import assigns itself to the catalytic cultural stratum amid circular economy structures, instituted feasibility asserted herein. Viability surfaces at the current juncture with clear demarcations respective of minimal fiscal requisites yet encompassing expansive influences, wherein palpable gains materialize over accessible spans. From this emerges preferential selection when constrained resources pose limitations. Central to cultural integration within circular domains is nurturing collective axiologies, steering constituents toward re-conceptualizing authentic success parameters. Foundational to subsequent technological advancements become established cognitive progressions. Elaborately discernible are fiscal advantages traceable to trust-laden cultures; landlords' reputation and service calibre steer authority in price settings. Those ascending to "Super Host" echelons frequently command premium margins typifying 15-20%, thus manifesting intangible cultural ingredients into substantive profits realized. Practically unveiled is the transformation at operational crevices via promulgated knowledge-sharing conduits, elaborated communal synergies, and advocation for durable enterprise philosophies. Relative comparisons against procurement investments reveal negligible direct expenditures met by comprehensive positive reverberations—management disbursements on platforms lessened coupled with dispute mitigation efficiencies augmented conspicuously. Naturally confrontive obstacles arise, encountering deeply entrenched vested interests fortifies challenges, necessitating cultivated acquiescence amongst landlord collectivity towards aligned core values.

4.2. The process layer: optimising system efficiency through feedback loops

The process layer is predicated on the premise of leveraging the accumulated benefits of the extant cultural layer, with the objective of standardising pricing decision mechanisms. Investment costs during this phase are moderate. The core task of process optimisation is the translation of value recognition formed in the cultural layer into operational institutional arrangements. The establishment of feedback loop systems facilitates the expeditious dissemination of market intelligence [10]. Multi-unit landlords' demonstrated professional advantages in yield management ultimately enhance the platform's overall operational efficiency [11]. Existing literature on the subject indicates that the implementation of measures such as standardised data collection, the development of decision support systems, enhanced cross-departmental collaboration mechanisms, and the introduction of quality control systems are all viable options for optimising the process layer under review [13].

It's pretty clear that the effect of things like the season and how close something is, on how much rent is charged, has to be thought about at the process level. Optimising a single variable alone often fails to achieve the desired outcome [9]. Process-level improvements require the construction of sustainable price forecasting models. Comprehensive application of machine learning techniques aids in establishing more robust predictive frameworks [5]. As Wang and Nicoulaud [3] note, the diversity of pricing factors in large-scale, multi-city studies demands that process design incorporates sufficient flexibility.

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4.3. Technology layer upgrades: high-investment precision empowerment cycle

Ascension within the Technology Stratum: Cycles of Precision Empowerment through High Financial Infusion The apex of cyclical processes finds its representation within the technology stratum, characterized by initial monetary outlays of a substantial nature coupled with promptly beneficial returns. It is apparent from this structuring that triumphant execution relies profoundly upon cultural underpinnings and procedural backing as vested in antecedent layers [25]. Innovations in technological domains channel their energies primarily into capital-heavy undertakings, encompassing algorithm refinement, system amalgamation, and cerebral augmentation enhancements. Resource aggregation serves as the bedrock for these upgrades' architecture. Expenditure notwithstanding, evidence points towards notable accuracies attained in pricing consequent to such investments [26]. Central tenet to the technical hierarchy lies the extrapolation of improvements proliferated from past advancements via algorithmic executions, facilitating conversions of personalized optimization regimes into expansive competitive stature at platform strata. Complexity rides symbiotically with temporal flux in short-term leasing arenas, thus demanding cogent adaptive prowess intrinsically within systems deemed technical. Models borne of machine learning exhibit requisite agility to course-correct per sanguine market vacillations, adjusting predictable maneuvers correspondingly [27]. Concerning accumulated advantages amidst technological ascensions, accruements lend themselves to continuity vis-à-vis benefits discerned. Discourses posited by scholars Li et al. [18] intimate an understanding wherein frameworks robustly engineered lead marginal costs downward near nil, whilst constancy cloaks resultant financial gains. A referential attestation made by Tang [28] highlights integral revenue escalation corollaries emergent from anticipation accuracy subjected to stringent precision metrics. Contemporary challenges exciting technologies subsume deeply tied issues coinciding with algorithm performance; pronounced import is attributed hereupon concerning network-centric commerce's evolutionary prospects henceforth. Strategy formulations within platforms ought shoulder obligations themed around exigencies aligned with enduring commercial ecosystem transfigurations accompanying deliberative technologic expenditure [29].

4.4. Circular mechanisms: the utilisation of self-reinforcing systems with the objective of enhancing resource value.

Mechanisms self-Perpetuating: Resources poised for Value Augmentation Utilising renditions embraced by circular economic paradigms enables dynamically allocatory resource methodologies paired snugly with value fortification principles [15]. Sight clearly discerns a trifold strategem adopting progressive investments coaxing spiralwise progressions. Functions arising, alongside stage-centric resource matrices, undergo redistribution iteratively across cyclic nexuses, each enforced proportionately—thereby earmarking trajectories conducive toward exponential growth. Sharing economy repercussions exposing traditional industry touchstones demonstrate existence where successful platforms imbued with autopoietic sensations landscape transformative adaptability fueled through perpetual critique competition-derived hindrances underscore prerequisites anchoring former cycles herein anticipated references bear necessity in orchestration designs cycling persistence accounting variances phased temporally effectuates slow-evolving cultural redesigns amounting belated resilience [1]. Cognitive musings revolving user conceptualization strategies unfold excavating digital ruptures solidifying entropic dissolutions enterprises ample dynamism adjusts operational reflexively externalities displayed discrepancies adapting intelligently harnesses updates computes commoditized indices predicates proficiencies

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lodging profitability assessment nonetheless optimality measurement presupposes accurately quantified circles calculated enterprise models entrusted permitably transitioning Airbnb standard lineage maturity sustainably revamping organically pathways [30,31].

5. Conclusion

The sharing economy is growing quickly and this is affecting the way traditional accommodation services compete with each other. It is also making Airbnb's pricing more complicated. This review looks at how machine learning can be used to predict prices for short-term rentals. It suggests a business strategy framework guided by circular economy principles. This framework is based on three main parts: changing culture, making processes better and using new technology. All of these parts work together to change pricing systems from being linear and static to being dynamic and circular. This study aims to set out a clear plan to make platforms and hosts better, by encouraging a change from making the most profit for one group of people to working together to create value for everyone.

But there are some real-life problems with putting this plan into action. (1) There is not enough data available to use the model in different markets. (2) Cultural and consumer differences in different regions can make it difficult to apply these ideas, and sometimes they just don't fit. (3) When a system is upgraded, the cost is often high. Small and medium-sized hosts find it hard to implement this because they don't have enough resources.

Future research may focus on: (1) Checking that the framework can be used in different situations in the sharing economy. (2) Making the design of how to combine artificial intelligence and the circular economy even better. (3) Do studies comparing different cultures and regions. (4) Look at how policy instruments like this affect pricing models that use circular pricing, and come up with pricing frameworks that can be used more easily in different regions.

In short, working together more between industry, universities and research teams, and testing out new ideas in real situations, could be the way to turn ideas into solutions that can be used again and again. This will change how platforms set prices, moving from just finding the right price to working together to create value.

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