FairPlay$^+$: A Certified-Fair Hotel Rooms Recommendations Framework

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Abstract

Over the past decade, *overtourism* has emerged as a major threat to the quality of life in popular tourist destinations. Overtourism poses multiple challenges to the local communities. Among others, overpricing and profiteering harm local societies and economies deeply. On the other hand, uncontrolled overpricing makes such popular destinations inaccessible to a large portion of the populace, undermining the UN-sanctioned *right to tourism*. In this work, we put forward *FairPlay*$^+$, a framework for hotel room recommendations with *certified-fair* prices. Our framework *(a)* can incorporate any mechanism that guarantees *fair* hotel room prices, according to any corresponding definition of fairness; *(b)* ascertains that the providers receive *fair exposition* by the system; and *(c)* importantly, guarantees that the providers are appropriately *incentivised* to *accept the fair price proposed by the mechanism for their rooms* instead of setting that price themselves. Specifically, we prove that providers are in expectation (weakly) better-off to accept the pricing policy proposed by the platform. Moreover, our simulation experiments demonstrate that (a) the platform-proposed fair policy is indeed the most profitable choice for the providers; while (b) providers adhering to the FairPlay$^+$ proposed policy can better serve customer demand, considering customers of various budgets: in particular, FairPlay$^+$ allows low-budget visitors to find accommodation that would be inaccessible to them without the use of fair pricing policies.

1 Introduction

An emerging problem with significant impacts on society is that of *overtourism*. Overtourism describes the phenomenon of overpopulation due to excessive numbers of tourists, usually referring to the side-effects it brings on local communities. According to the UN World Tourism Organisation (UNWTO),[2] overtourism is defined as “the impact of tourism on a destination, or parts thereof, that

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[2]https://www.unwto.org/

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excessively influences perceived quality of life of citizens and/or quality of visitor experiences in a negative way" [1]. Along similar lines, the Responsible Tourism Partnership[3] refers to overtourism as "destinations where hosts or guests, locals or visitors, feel that there are too many visitors and that the quality of life in the area or the quality of the experience has deteriorated unacceptably" [1].

On the other hand, tourists themselves experience unpleasant consequences. The excessive demand on popular tourist destinations often fosters profiteering and overpricing. This effect harms and challenges not only the local communities, but it incommodes tourists, as well. In particular, overpricing may come in conflict with the *right to tourism* as defined by the World Tourism Organisation in the "Global Code of Ethics for Tourism" [17]. That is, overpricing can result in prohibitive prices for a large portion of the populace, undermining the tourists' accessibility to many popular destinations suffering from overtourism. Looking closely at Article 7 ("Right to tourism"), we discern:

> Article 7.1: "The prospect of direct and personal access to the discovery and enjoyment of the planet's resources constitutes a right equally open to all the world's inhabitants."

In other words, everyone has a right to equal access to tourist destinations, while local authorities bear the responsibility to support accessibility. Hence, allowing uncontrolled overpricing and profiteering undermines the right to tourism, as it limits accessibility to a large number of tourists.

In an attempt to overcome overtourism, many popular tourist destinations employ relevant regulations, among them, cities such as Barcelona, Venice, Dubrovnik, Kyoto, etc. These regulations include high tourist taxation [8], access fees [7], and limitations to the number of tourists that can visit the destination at hand [6]. However, profit growth (occupancy rates, average daily rate) has been rising in some regions despite overtourism regulation, which suggests that many tourist professionals (such as hotel owners) are still benefiting financially [16]. This implies that the adopted regulations have little effect and indicates the need for more appropriate and effective solutions.

Here, we focus on tourist accommodation, and specifically, on providing fair and affordable hotel rooms. Data shows that hotels and similar accommodations account for a large share of guest nights in many overcrowded tourist areas. For example, a report by Airbnb claims that hotels comprise $\sim 80\%$ of guest nights in EU destinations, and $\sim 75\%$ of the increase in guest nights between 2021-2023 in the top-10 EU cities; despite the rapid emergence of short-term home rentals [2]. As such, with the understanding that the hotel industry is the pivotal player in providing accommodation to tourists, we opt to address the problem of hotel room overpricing. [4]

Notably, literature offers technical solutions that address this problem. These solutions mainly propose adjusting the room prices based on time-relevant features, i.e., employing dynamic pricing. For example, Aziz et al. [4] presented a dynamic pricing model exploiting booking patterns, time, and market conditions to adjust room rates in real time. Bayoumi et al. [5] proposed a dynamic pricing approach using price multipliers to adjust hotel room rates efficiently based on demand and market conditions. More recently, Streviniotis et al. [15] put forward a multi-sided fair dynamic pricing policy for hotels that balances revenue optimisation with fairness toward both hotels and their guests. However, it is doubtful that hotel owners would opt to use such solutions in practice, as this would mean that they relinquish control of the pricing of their rooms to an algorithm. To do so, appropriate *incentives* have to be put in place.

In this work, we put forward *FairPlay*$^+$, a novel framework for *certified-fair* hotel room recommendations. FairPlay$^+$ is a platform that leverages prices and exposition opportunities in order to provide room recommendations in accordance with the notion of fairness of choice. Specifically, our proposed platform can incorporate any pricing policy that yields fair hotel room prices, while it allows each hotel to adopt a pricing policy of its own choosing. At the same time, it incentivises the hotels to adopt the fair pricing policy proposed by the platform. Moreover, FairPlay$^+$ ascertains that the providers receive fair exposition by the system, and guarantees that the visitors observe fair recommendations. In a nutshell, our contributions are the following:

1. We introduce FairPlay$^+$, a novel framework to promote *certified-fair* room recommendations.
2. Our platform can adopt *any fairness notion of choice*, and can incorporate *any pricing policy* that adheres to such a notion to guarantee fair prices.

[3] https://responsibletourismpartnership.org/

[4] Nonetheless, including other types of short-term accommodations is an easy extension.

3. Providers can use *any pricing policy of their choosing*, and receive *fair exposition opportunities* by the platform.
4. We formally show that *providers are incentivised to follow the fair price* proposed by the platform.
5. We empirically demonstrate that *the platform-proposed fair policy is indeed the most profitable choice*, and providers adhering to the FairPlay⁺ proposed policy *can better serve customer demand*.

In what follows, Sec. 2 provides the necessary notation. Sec. 3 introduces FairPlay⁺, our proposed framework, and details its different elements. Specifically, in Sec. 3.2 we discuss the fair-base pricing policy, and in Sec. 3.3 we demonstrate our *fair* exposition mechanism. Then, in Sec. 4, we empirically showcase the effectiveness of FairPlay⁺. Sec. 5 concludes the paper and discusses future directions.

2 Preliminaries

In this paper, we address the problem of overpricing in overtourism by proposing a new platform that recommends hotel rooms with fair prices to the visitors. Before presenting FairPlay⁺, let us discuss the necessary notions and notation that we will be using in this work.

Let $H = \{h_1, \cdots, h_m\}$ be a set of distinct hotels. Each hotel $h \in H$ consists of a set of rooms $h = \{r_{h,1}, r_{h,2}, \cdots, r_{h,|h|}\}$, with $|h|$ indicating the size (in terms of rooms) of the hotel. Finally, each room $r \in h$ is characterised by a set of features, e.g., the room type (single, double, triple), whether it is interior or exterior, the floor it is located, etc.

In a platform such as FairPlay⁺, we consider two key aspects of time. On the one hand, there is the *reservation time*, i.e., the time a visitor contacts the platform in order to make a room reservation. On the other hand, there is the *check-in time*, i.e., the time the visitor wishes to make a reservation for. We denote with $t_{\text{reservation}}$ and $t_{\text{check-in}}$, the reservation time and the check-in time, respectively.

Now, a room $r \in h$ can be either *available* or *occupied* at a specific check-in time; while the room's status (available/occupied) can vary depending on the reservation time. As such, the system's landscape holds information regarding the occupied and the available rooms at given timestamps.

Definition 1 (Platform's Occupancy Landscape)**.** *Given the set of hotels H in the platform, a reservation time $t_{reservation}$, and a check-in time $t_{check\text{-}in}$, the* platform's occupancy landscape *is denoted as $\mathcal{L}_H(t_{reservation}, t_{check\text{-}in})$ and indicates the status (available/occupied) of each room $r \in h$ of each hotel $h \in H$ at check-in time $t_{check\text{-}in}$, when viewing the system at reservation time $t_{reservation}$.*

Any available room can be rented by a visitor at some price. Let π_h denote a *pricing policy* of hotel's h choice. Specifically, π_h determines the price of any available room $r \in h$ upon the check-in time and the reservation time at hand. Notably, the pricing policy π_h may use information from the corresponding platform's landscape and the room's at hand characteristics. Moreover, we assume that for each room there is a *minimum daily maintenance cost*. That is, for each room, there is a minimum price that a visitor should pay in order to cover the room's cost.[5] We denote the minimum daily maintenance cost as $u_r \in \mathbb{R}_+$. Notably, a pricing policy π_h may or may not satisfy the minimum daily cost; i.e., the price computed by the policy may or may not cover the cost u_r. Without loss of generality, we can write the price computed by the pricing policy π_h (denoted as p_{π_h}), with respect to the minimum daily cost:

$$p_{\pi_h}\Big(r, \mathcal{L}(t_{\text{reservation}}, t_{\text{check-in}})\Big) = \begin{cases} (1+\alpha_{\pi_h}) \cdot u_r & \text{if room is available} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Intuitively, quantity α_{π_h} indicates the *profit margin* introduced by pricing policy over the minimum daily cost u_r. As we mentioned, a price covering the minimum daily cost results in a non-negative profit margin, i.e., $\alpha_{\pi_h} \geq 0$. On the contrary, a price falling below the minimum daily cost corresponds to a profit margin in the range $\alpha_{\pi_h} \in (-1, 0)$.

Definition 2 (Individual Rationality)**.** *A pricing policy π_h is* individually rational *if and only if it yields prices such that for any room at any given time, the price covers the room's minimum daily cost, i.e., for every $r \in H$ and any $t_{reservation}$ and $t_{check\text{-}in}$, it holds that $p_{\pi_h}\Big(r, \mathcal{L}(t_{reservation}, t_{check\text{-}in})\Big) \geq u_r$.*

[5]For example, this cost covers cleaning fees or an employee's daily wage, etc. It could also include some minimum profit the hotel desires to make from renting the room.

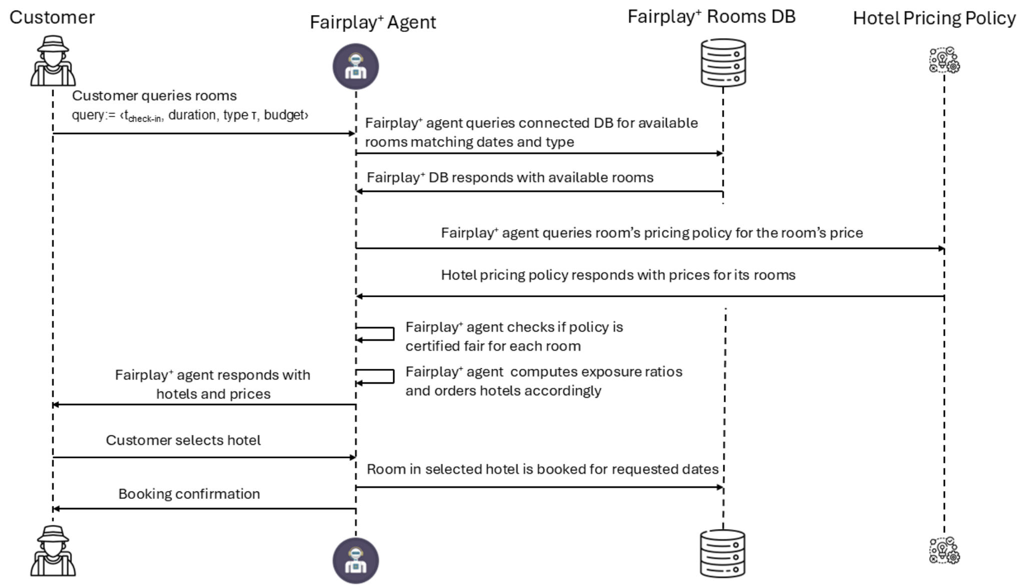

Figure 1: FairPlay⁺ Framework

Moreover, we highlight that a profit margin of $\alpha_{\pi_h} < -1$ is counter-intuitive, as it suggests a negative price for the room; therefore, it shall always hold that $\alpha_{\pi_h} > -1$.

Regarding the *fairness* of a room price, the literature offers several definitions. In particular, according to Jiang and Erdem [9] visitors' perception of fairness depends on how pricing strategies align with what the visitors expect is reasonable and transparent. Alderighi et al. [3] measures price fairness via how close the paid price is to a reference price, the degree of transparency of the pricing process, and whether differences in rates are seen as justified by visitors. Finally, Streviniotis et al. [15] define fair price as prices that allow a fair profit margin, computed via a by-design fair power index.

Additionally, [15] also addresses fairness on the provider's side. Specifically, they consider fair exposition opportunities. A hotel is *exposed* to a visitor whenever this hotel is displayed as a recommendation to the visitor. As such, by the term *exposition opportunity*, we refer to the probability of a hotel being recommended to a visitor. Following the notation of [15], let ϱ_h be a metric that measures a hotel's exposition ratio considering the hotel's past expositions and the platform's landscape. The exposition ratio is used to determine the exposition opportunity, and specifically, we assume that $Pr(h \text{ is exposed given query } q) \propto 1/\varrho_h$.

3 The FairPlay⁺ Framework

In this section, we introduce the FairPlay⁺ framework. FairPlay⁺ constitutes a hotel room booking platform that leverages rooms' prices and hotels' exposition opportunities to deliver *certified-fair* hotel room recommendations. Specifically, FairPlay⁺ is designed to accommodate any pricing policy that ensures fair room rates, while granting individual hotels the flexibility to implement their preferred pricing policies (that are not necessarily fair). Figure 1 illustrates the FairPlay⁺ framework, and, in particular, it depicts the interactions between a visitor and the proposed platform during the reservation process. In some detail, FairPlay⁺ employs a *fair-base pricing policy* and uses it to compute room prices. At the same time, it allows hotels to use the pricing policy of their choice. Notably, FairPlay⁺ aims to deliver *certified-fair* room prices. To do so, we propose to adjust the hotel's exposition opportunity so that it would be more beneficial (in expectation) if the hotel followed the fair-base policy. Hence, FairPlay⁺ adjusts the hotel's exposition opportunity (taking into account both the price computed by the hotel's policy and the one internally computed) in order to promote rooms with fair prices. Next, we detail each component of the proposed framework.

3.1 The Reservation process

We begin with describing the reservation process (see Figure 1). We consider a visitor (or "customer", or "guest") who seeks to make a room reservation. To do so, the guest visits the FairPlay⁺ platform and submits a *room query*. The room query conveys information regarding the guest's preferences. Specifically, the query consists of *(a)* the desired check-in time, *(b)* the duration of the stay, *(c)* the room's desired features and *(d)* the visitor's budget. Formally, we denote a room query as $q = \langle t_{\text{check-in}}, d, F, b\rangle$, where $d \in \mathbb{N}$ is the duration of the stay in days, F contains the desired room features, and $b \in \mathbb{R}_+$ is the visitor's daily budget. Note, that the time the visitor submits their query corresponds to the reservation time $t_{\text{reservation}}$.

On the platform's side, we consider the FairPlay⁺ agent, which is responsible for processing the guests' room queries and deliver the room recommendations. First, the FairPlay⁺ agent consults the platform's landscape $\mathcal{L}(t_{\text{reservation}}, t_{\text{check-in}})$, and identifies the rooms that are possible matches to the query. We note that the relevant hotels can be selected for potential exposition to the visitor via any (e.g., a top-k, or Bayesian) recommender algorithm of choice [12, 13, 14]. As soon as the FairPlay⁺ agent identifies the matching rooms, it requests from the corresponding hotels' pricing policies to compute the room's price. At the same time, the FairPlay⁺ agent uses the internal fair-base pricing policy to compute the fair room's price. Given the two prices, the FairPlay⁺ agent computes the exposition ratios, and adjusts accordingly the exposition opportunities if necessary, i.e., if the hotel uses a pricing policy different to the internal fair-base one. In particular, we do so if the profit margin suggested by the hotel's pricing policy exceeds the fair-base one. Finally, the FairPlay⁺ agent responds to the visitor's query based on the computed exposition opportunities.

In a nutshell, the reservation process in the FairPlay⁺ platform follows the steps below:

1. The visitor poses a room query.
2. The FairPlay⁺ agent identifies the available rooms in the platform that match the query.
3. For each identified room,
   - the FairPlay⁺ internal fair-base pricing policy computes the room's fair price;
   - the hotel's pricing policy computes the room's price.
4. The FairPlay⁺ agent computes exposition opportunities based on the exposition ratios.
5. The FairPlay⁺ agent displays the recommended hotel rooms.
6. The visitor reviews the recommendations (with prices computed by the hotel's pricing policy) and selected their room of choice.
7. Finally, the FairPlay⁺ agent completes the room reservation, and charges the visitor with the corresponding price computed by the hotel's pricing policy.

3.2 The fair-base pricing policy

In this section, we briefly describe the fair-base pricing policy used by our platform to compute reference-fair prices for the hotel rooms. Specifically, we adopt *FairPlay*, the double-sided fair pricing policy introduced by Streviniotis et al. [15], as the fair-base pricing policy of choice; and thus we named our platform FairPlay⁺.

The *FairPlay* pricing policy computes a *fair* profit margin over the minimum daily cost (which[15] refers to as "Minimum Expected Price"). In some detail, *FairPlay* considers the several interdependencies among the different rooms and hotels to compute a profit margin. First, it builds a Dynamic Hotel-Rooms Game (DHRG) based on the system's landscape, capturing relations based on room's features—the authors consider only the feature of room type for illustrative purposes, however as they mention, more features can be used as well. Specifically, the DHRG captures the popularity of the different hotels, and the different room features. Then, it computes the power of each room, exploiting a fair-by-design game theoretic solution concept, namely the Owen values[11]. Finally, the room's Owen value is therefore used as the room's profit margin.

Here, we would like to highlight that despite that here we assume *FairPlay* as the fair-base pricing policy, one could replace it with any fair pricing policy of choice. For example, an alternative choice could be the pricing policy presented in [10]. In that WWW'25 work, Abachi et al. extend the *FairPlay* policy and enhance it with a combined competitive/cooperative algorithmic scheme to further align provider revenue goals with fairness constraints across a marketplace. Across similar lines, Zhu et al. in [18] propose a pricing mechanisms that explicitly incorporate similarity and competitive context—a technical idea often used in fairness-by-comparison approaches. As such, even if here we consider *FairPlay* as the fair-base pricing policy, the FairPlay⁺ framework can incorporate *any* pricing policy that serves some notion of fairness; and therefore provide *certified-fair* room prices in accordance to the chosen notion of fairness.

3.3 Adjusted Exposition Opportunities

As we mentioned earlier, FairPlay⁺ aims to recommend hotel rooms that are offered in fair prices. Notably, despite the guarantees provided to hotels that they receive not only fair exposition opportunities but also a fair profit margin—since the computed margins reassembles the rooms' power perceived through popularity—it is conceivable that hotel owners may be reluctant to allow the platform to itself set the final price for their rooms. In this section, we act upon such concerns in two ways. First, we allow the hotels to participate in the FairPlay⁺ platform while choosing their own pricing policy. Second, and more importantly, we put forward a (mathematical/financial) incentivisation mechanism that provides hotel owners with the incentives to adopt the fair-base pricing policy. The hotels that choose the fair-base pricing policy (here the FairPlay policy) are labelled by the platform as *certified-fair (CF)* ones. Moreover, we argue that *it is not in expectation beneficial to hotels to not participate in our double-side fairness-guaranteeing platform*—a claim that we empirically observe in our experiments discussed in Section 4.

The intuition behind our incentivisation mechanism is that it adjusts the exposition opportunities so that, if the hotel is not *certified-fair*, these are always lower than the fair exposition opportunities that would have been provided by the system if the hotel had followed the fair-base policy. Specifically, the exposition opportunities are lowered to the extent appropriate so that the expected value from not being *Certified-Fair* and setting a room price to an (arbitrarily) high amount, will be lower than the expected value from accepting the system price. In other words, a non-CF will have their probability of exposition lowered by some factor depending on their artificially high profit margin, so that if they pursue that margin, they will not, in expectation, be making more profit than the profit they would make by just using the prescribed price by the system. On the other hand, if a non-CF hotel offers a lower price than the corresponding fair price, then they exhibit the same exposition opportunities; however, in expectation, they observe a lower value (in comparison to the one if they had opted for the fair-base price). That being said, note that our mechanism should not and *does not* completely "starve" non-CF hotels—otherwise, it would be as if FairPlay⁺ platform refused hotels to choose their own pricing policy. As such, non-CF hotels always receive a non-zero probability to be exposed.

In more detail, the FairPlay⁺ agent computes the exposition ratio ϱ_h for each hotel in the platform—here we again follow [15] in order to compute the ratio, where it is defined as the number of past exposition over the hotel's Owen value, i.e., $\varrho_h = \frac{\#\text{expositions}}{Ow_h}$. Let us assume that hotel $h \in H$ is a non-certified fair hotel, i.e., the hotel's pricing policy differs from the fair-base one. Then the hotel's exposition opportunity shall be lowered according to the non-CF profit margin posed by the non-CF pricing policy. First, we compute the hotel's exposition opportunity, i.e, the probability of the hotel being exposed to the visitor, as if the hotel had opted for the fair-base policy:

$$Pr(\pi_{h,CF}; q) \triangleq \gamma \cdot \frac{1}{\varrho_h} \tag{2}$$

where $\pi_{h,CF}$ denotes the fair-base pricing policy and $\gamma = \left(\sum_{h \in H} \frac{1}{\varrho_h}\right)^{-1}$ is a normalisation factor—given that hotel h contains at least one room relevant to the visitor's query. Note that in case $\varrho_h = 0$, i.e., the hotel has never been exposed so far, we arbitrarily set the exposition opportunity as $Pr(\pi_{h,CF}; q) = 1/2$, i.e., we provide 50% of chances to be exposed.

Then, we lower the fair exposition opportunity by a factor $\lambda \leq 1$:

$$Pr(\pi_h; q) = \lambda \cdot Pr(\pi_{h,CF}; q)$$

Specifically, we define the lowering factor as the ratio of the fair profit margin over the profit margin suggested by the non-CF policy, i.e.,: $\lambda \triangleq \frac{1+\alpha_{\pi_{h,CF}}}{1+\alpha_{\pi_h}}$. Now, as mentioned earlier, we only adjust the exposition opportunity if the offered price *exceeds* the fair price computed by the fair-base policy. As such, we define the exposition probability for non-CF hotels as:

$$Pr(\pi_h; q) = \min\{\lambda, 1\} \cdot Pr(\pi_{h,CF}; q) \tag{3}$$

Intuitively, the closer the artificially high profit margin is to the fair one (to the one computed via the fair-base policy), the less we lower the hotel's exposition probability.

Proposition 1. *A non-CF hotel receives a zero exposition opportunity if and only if the corresponding certified-fair exposition opportunity is zero.*

The proof is derived from the definition of the lowering factor since $\lambda > 0$ for any individually rational pricing policy (see Definition 2).

Proposition 2. *Each hotel h is exposed at least once in the first x queries, given that the hotel can offer at least one relevant to the query room, with probability* $(1/2)^{x+1}$.

Notice that each hotel, before its very first exposition to a visitor it exhibits a zero exposition ratio ($\varrho_h = 0$). Hence, until the first exposition, the hotel is being exposed with probability $Pr(\pi_h; q) = 1/2$, regardless of its chosen pricing policy; and, therefore, being exposed in the first x queries results in a Bernoulli trial—with the understanding that the hotel has at least one room relevant to the queries.

Theorem 1. *Providers are in expectation (weakly) better-off when using the fair-base pricing policy.*

Proof. We compute the expected value of a non-CF hotel as:

$$\begin{aligned}\mathbb{E}[(\text{value}(\pi_h; q)] &\triangleq Pr(h \text{ be selected}) \cdot Pr(\pi_h; q) \cdot p_{\pi_h}\Big(r, \mathcal{L}(t_{\text{reservation}}, t_{\text{check-in}})\Big) \\ &= Pr(h \text{ be selected}) \cdot Pr(\pi_h; q) \cdot (1 + \alpha_{\pi_h}) \cdot u_r\end{aligned}$$

where $Pr(h \text{ be selected})$ is the probability it is actually selected by the guest if presented to them. In the worst case scenario (best-case scenario for the hotel), we assume that $Pr(h \text{ be selected}) = 1$, i.e., the non-CF hotel will for sure be selected if it is exposed. Then, the expected value becomes:

$$\mathbb{E}[(\text{value}(\pi_h; q)] = Pr(\pi_h; q) \cdot (1 + \alpha_{\pi_h}) \cdot u_r = \min\{1, \lambda\} \cdot Pr(\pi_{h,CF}; q) \cdot (1 + \alpha_{\pi_h}) \cdot u_r \tag{5}$$

Assume the case where $\alpha_{\pi_h} \geq \alpha_{\pi_{h,CF}}$, i.e., the hotel's pricing policy allows for a larger profit margin than the fair one. Then, Equation (5) becomes

$$\begin{aligned}\mathbb{E}[(\text{value}(\pi_h; q)] &= \frac{1 + \alpha_{\pi_{h,CF}}}{1 + \alpha_{\pi_h}} \cdot Pr(\pi_{h,CF}) \cdot (1 + a_{\pi_h}) \cdot u_r \\ &= (1 + \alpha_{\pi_{h,CF}}) \cdot Pr(\pi_{h,CF}) \cdot u_r = \mathbb{E}[(\text{value}(\pi_{h,CF}; q)]\end{aligned} \tag{6}$$

Now assume the case where $\alpha_{\pi_h} < \alpha_{\pi_{h,CF}}$, i.e., the hotel's pricing policy allows a smaller profit margin than the fair one. Then Equation (5) becomes

$$\begin{aligned}\mathbb{E}[(\text{value}(\pi_h; q)] &= 1 \cdot Pr(\pi_{h,CF}) \cdot (1 + a_{\pi_h}) \cdot u_r \\ &< (1 + \alpha_{\pi_{h,CF}}) \cdot Pr(\pi_{h,CF}) \cdot u_r = \mathbb{E}[(\text{value}(\pi_{h,CF}; q)]\end{aligned} \tag{7}$$

Therefore, from Equations 6 and 7 we obtain that the expected value of a non-CF hotel is always lower than the corresponding expected utility if the hotel had opted for the fair-base pricing policy. □

3.4 Explainable by design

Finally, in this section, we discuss an inherent property of our proposed framework. Specifically, the FairPlay⁺ platform is designed to be inherently explainable and transparent, allowing even non-expert users to understand its core functioning. The key components of our platform can easily provide a step-by-step view of how pricing and exposition decisions are made. For example, one could illustrate the rationale of the platform's decisions similarly to Figure 1 in [15]; and provide a transparent overview of each decision of the platform. This structure ensures that end-users can trace how inputs—such as hotels' popularity and the demand for the rooms' several features—influence outcomes, and rationalise the resulting prices and exposition metrics. Because the system's logic can be presented concretely, users are not required to rely on black-box reasoning, which enhances both trust and interpretability.

A central element of this transparency is the fair-base pricing policy, which relies on a fair-by-design game theoretic power index. The power index captures two main dimensions: *(i)* the popularity of the hotel; and *(ii)* the popularity of the room's features based on the platform's landscape. By combining these factors, the FairPlay+ using the *FairPlay* pricing policy, determines a fair and explainable price baseline. Furthermore, this approach allows for meaningful comparisons against non-fair prices, making deviations easy to identify and justify. When unfair pricing is detected via artificially high profit margins, FairPlay+ adjusts the hotel's exposition opportunities by a lowering factor λ. In this way, the platform ensures that hotels maintain balanced visibility according to their adherence to fair-pricing principles. This creates a self-regulating ecosystem that promotes fairness, accountability, and transparency throughout the platform.

4 Empirical Evaluation

In this section, we empirically investigate the behaviour of our platform across three directions: *(a)* the total (monetary) income accumulated by the hotels, *(b)* the daily occupancy rate of the hotels, and *(c)* the guest satisfaction in the means of finding a room within the customers' budget. Specifically, we pitch the fair-base pricing policy (*FairPlay*), against three static pricing policies which constantly allow a profit margin of 17%, 40% and 50% over the rooms' minimum daily cost (u_r).

4.1 Experimental Setup & Datasets

For our experiments, we followed a similar setup to the one used in [15]. Specifically, we consider a 30-day period where visitors can make room reservations through the FairPlay+ platform. In our simulations, we assume that a visitor seeks to make a room reservation within a time window of 7 days, i.e., $t_{\text{reservation}} \leq t_{\text{check-in}} \leq t_{\text{reservation}} + 7$ days. We do so to retain a balanced number of reservations on a daily basis, and avoid overloading the final days of the simulation. However, we do place the higher demand over weekends; that is, the days Friday to Sunday have a higher probability of being booked (with 95% probability, while Thursdays are booked with 60% and Mondays to Wednesdays with 10%). We perform up to 750 room queries per day (the exact number is drawn from a uniform distribution). For each room query, we randomly select the check-in time and the room's features (here, we only assume as a feature the type of room, similarly to [15]). Moreover, we randomly choose the visitor's profile across six budget profiles: Very Low (up to 45 MU),[6] Low (up to 65 MU), Medium (up to 80 MU), High (up to 100 MU), Very High (up to 200) and Unlimited. The visitor reserves the room that exhibits the lowest price that falls within their budget. Finally, we allow reservation cancellations, that is, for each simulated day we randomly cancel one future reservation with probability $p = 0.1$.

We synthetically built two datasets, based on the datasets used in [15]. In Table 1 we describe the synthetic datasets. Briefly, the first dataset (referred to as 'Dataset 1') contains identical hotels, all offering the very same number of rooms and the very same (a single) type of rooms. Notably, the room's minimum daily cost is selected to be in the low budget profile. The second dataset (referred to as 'Dataset 2') contains hotels with various numbers and types of rooms, and hotels that offer rooms in different budget profiles. In each dataset, there are a total of 48 hotels, while each pricing policy (FairPlay, Static+17%, Static+40%, Static+50%) is the policy of choise of 12 hotels.

Our experiments were coded in Python 3.12. The FairPlay+ framework, the code for the experiments, and datasets are available in `https://github.com/ageorgara/CertifiedFairPlay.git`

4.2 Results

We explore FairPlay+ platform's behaviour across three directions, while we compare three different pricing policies against the fair-base policy. In this section, we discuss our observations and findings.

4.2.1 Cumulative Income

First, we study the income of the hotels per pricing policy. Figure 2 shows the average accumulative income of the hotels per pricing policy for Dataset 1 (the average is over 50 simulations). As we can see, in the case where all the hotels offer equivalent services (the very same room) at different

[6] MU stands for monetary units.

Dataset	Pricing Policy	#Hotels	#Rooms	#Room Types	#Hotels / budget profile		
					Low (30-60 MU)	Medium (65-100 MU)	High (130-250 MU)
Dataset 1 (Identical)	Fairplay	12	276	1	12	-	-
	+17%	12	276	1	12	-	-
	+40%	12	276	1	12	-	-
	+50%	12	276	1	12	-	-
	Total	48	1104	1	48	-	-
Dataset 2 (Non Identical)	Fairplay	12	274	4	4	5	3
	+17%	12	263	4	3	5	4
	+40%	12	267	4	5	5	2
	+50%	12	263	4	2	4	6
	Total	48	1067	4	16	18	14

Table 1: Synthetic Dataset Description. Dataset 1 contains 48 identical hotels that offer a single type of room, while all hotels offer the room with the same minimum daily cost in a low budget profile (i.e., with $u_r \in [30, 60]$ monetary units). Dataset 2 contains 48 hotels that offer rooms of different types at various minimum daily costs. In each dataset, there are 12 hotels that adopt each of the four pricing policies: FairPlay, Static +17%, Static +40%, Static +50%.

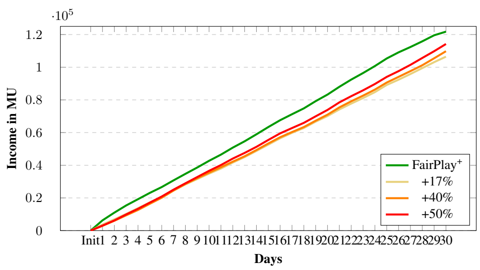

Figure 2: Average cumulative income with fully refundable cancellations. (Dataset 1)

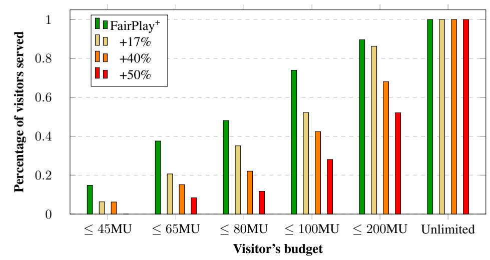

Figure 4: Visitors' satisfaction. (Dataset 2)

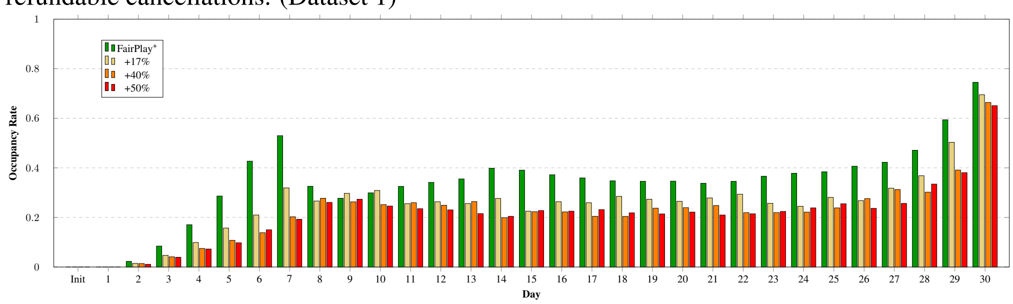

Figure 3: Average occupancy rate. (Dataset 1)

prices (as each hotel has the profit margin suggested by their pricing policy), the hotels following the FairPlay^{+}fair-base pricing policy reach a greater cumulative income. Notably, hotels adopting the FairPlay pricing policy retain greater cumulative income throughout the simulated period of time. This means that, on a daily basis, the FairPlay^{+} fair-base policy offers more appealing prices than the non-CF static policies, hence, the certified-fair hotels are selected by the customers. This results in FairPlay^{+} fair-base policy being more profitable. It is worth noticing that the Static +50% policy is the second most profitable policy (following FairPlay). Such a result is reasonable since they have a constant profit of +50% over the minimum daily cost for each reservation.

Similar results were observed for Dataset 2 as well. In the case where the hotels offer various rooms at various budget profiles, we observe that the FairPlay^{+} fair-base policy is more profitable than the other static policies. However, we notice that, in Dataset 2, FairPlay is comparable to Static +50% and Static +17%. Intuitively, FairPlay and Static +17% offer appealing prices, being selected more often, while Static +50% exhibits a constant high profit for each reservation. Due to space limitations, the corresponding figure is provided in the Supplementary material.

4.2.2 Daily Occupancy rate

Next, we study the *daily occupancy rate*. Essentially, the occupancy rate denotes the percentage of rooms that are occupied per pricing policy, As such, we define the occupancy rate as the ratio of the number of occupied rooms over the total number of rooms (both occupied and available rooms). Figure 3 depicts the average occupancy rates. As we can see, the hotels that adopt the FairPlay^{+} fair-base pricing policy consistently exhibit a higher occupancy rate—with minor exceptions, e.g., days 9 and 10, though even then the occupancy rates are comparable. This observation suggests that hotels offering certified-fair prices are preferred by the visitors on a daily basis. Dataset 2 exhibits similar results, with the certified-fair hotels achieving consistently a clearly higher occupancy rate than the other policies. Due to space limitations, the corresponding figure is provided in the Supplementary material.

4.2.3 Visitors' Satisfaction

Finally, we study the visitors' satisfaction. That is, we explore which pricing policy offers the most appealing pricing to visitors, considering different budget profiles. Specifically, we measure the percentage of visitors per budget profile *that are served* by each pricing policy. Figure 4 shows the visitors' satisfaction per pricing policy in Dataset 2. As we can notice, the FairPlay^{+}fair-base pricing policy manages to offer affordable rooms to all budget profiles. Especially when considering the very low (<45 MU) and low (<65 MU), we observe that FairPlay^{+}achieves a significantly greater satisfaction. This observation confirms that our proposed platform works towards providing affordable and accessible rooms to lower budget profiles; supporting in this way the *right to tourism*.

5 Conclusions and Future Work

In this work, we scratch the surface of the overpricing problem due to overtourism, an emerging problem with significant social impact. As a solution to this problem, here we introduced FairPlay^{+}, a novel framework that promotes certified-fair hotel room recommendations. That is, we propose a platform for making hotel room reservations designed to accommodate any chosen fairness notion and seamlessly integrate pricing policies that ensure fair prices across diverse market conditions. Importantly, while providers retain the freedom to employ the pricing policy of their choice, the framework guarantees fair exposition opportunities aligned with their adherence to fairness principles, captured through the FairPlay^{+} fair-base policy. Through formal analysis, we demonstrate that providers are naturally incentivised to adopt the platform's fair pricing policy, as doing so maximises their exposition opportunity. Moreover, we discuss that our framework is an explainable-by-design system, with clear and traceable mechanisms that reveal how pricing and exposition decisions are made, fostering trust and interpretability. Finally, our empirical evaluation confirms that the hotels adhering to the FairPlay^{+} fair-base policy achieve *(i)* higher cumulative income (they offer more appealing prices, and become the visitors' choice), *(ii)* higher daily occupancy rate, and *(iii)* at the same time, they manage to provide affordable room prices for all budget profiles. As such, we show that FairPlay^{+} addresses the problem of overpricing, and offers a double-sided fair solution that is beneficial for both hotel owners (in terms of revenue and occupancy rate) and visitors (in terms of equitable accessibility to affordable room prices).

Regarding future work, a compelling line of research is to integrate the neighbourhood cost of living into the analysis. This would facilitate the establishment of fair pricing for both short-term accommodations and long-term residential properties. The concepts developed can also be in principle applied to other segments of the hospitality sector, such as in restaurant and bar recommendation systems or airline ticket pricing—or beyond, in any domain calling for fair pricing and incentives to willingly adhere to fair policies. As such, hopefully our work in this paper makes a contribution towards an ethical and beneficial Artificial Intelligence for all.

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Supplementary Material

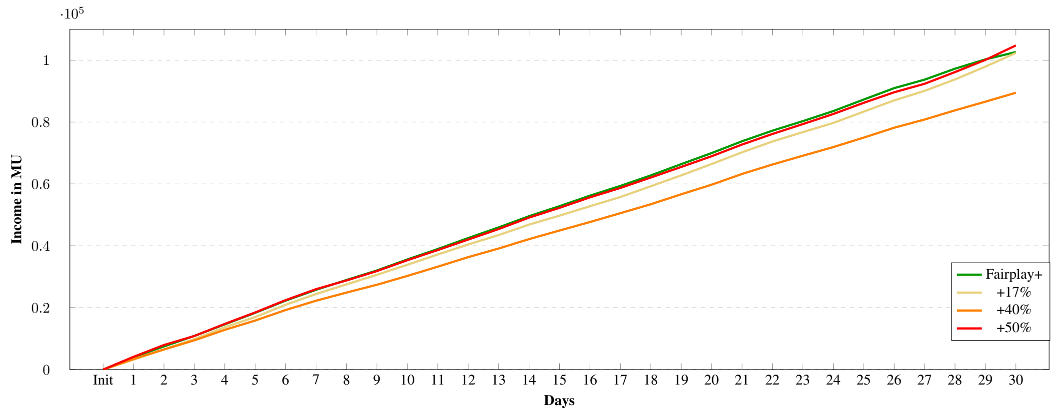

Figure 5: Average cumulative income with fully refundable cancellations. (Dataset 2)

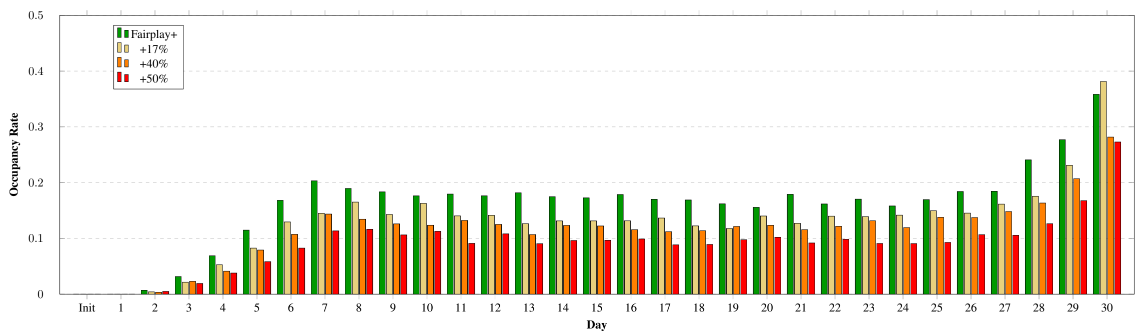

Figure 6: Average occupancy rate. (Dataset 2)