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ORIGINAL RESEARCH

Restaurant revenue management through combinatorial auctions

Martina Luzzi[1] · Francesca Guerriero[1] · Giusy Macrina[1] · Chefi Triki[2]

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Abstract
Booking a table in some popular restaurants, particularly in certain big cities, is becoming increasingly challenging. The number of requests to eat in those restaurants exceeds the available supply, resulting in a shortage of seating capacity. In recent years, the market for resale of restaurant reservations has emerged as possible solution to this problem. However, this practice does not offer to restaurateurs any protection on the certainty of booking, is unfair to customers, and can lead to a high no-show rate. This work presents an innovative framework for restaurant revenue management, which aims to optimise revenues by managing bookings at restaurants. Particularly, the concept of combinatorial auction is applied to allocate tables and menus to the customers who participate in the auction through a web platform. The winner determination problem is solved in order to assign requests to the bidding customers. Furthermore, a procedure to address the bid generation problem, based on realistic data, is also proposed. The scalability of the model is addressed with an extensive test phase. The applicability of this novel approach is also tested on a real Michelin-starred restaurant. Results of computational experiments suggest that the profitability of this practice has the potential to revolutionize the restaurant reservations sector in the near future.

Keywords Auction · Winner Determination · Bid Generation · Restaurant Revenue Management

✉ Martina Luzzi
martina.luzzi@unical.it

Francesca Guerriero
francesca.guerriero@unical.it

Giusy Macrina
giusy.macrina@unical.it

Chefi Triki
C.Triki@kent.ac.uk

1 Department of Mechanical, Energy and Management Engineering, University of Calabria, Rende (CS), Italy

2 Centre for Logistics and Sustainability Analytics, Kent Business School, University of Kent, Canterbury, UK

1 Introduction

Nowadays, especially in renowned cities such as New York, Rome, London, Paris, and Los Angeles, securing a reservation for a table at a fine dining, Michelin-starred, or a popular restaurants can be challenging. More often than not, the demand from customers exceeds the supply from restaurateurs, making it almost impossible to secure a table at the desired time and date without booking well in advance, enduring long waiting lists or queuing outside the restaurant hoping that a table becomes available. In Table 1 we have reported the average waiting times for a reservation at three different Michelin-starred restaurants as examples among many others.

Looking at Table 1 it is clear that the waiting lists are excessively long, thereby increasing the risk that people's plans change in the meantime, or becoming discouraged from attending. Trying to avoid this problem, several companies have started to propose innovative solutions for booking management. For example, *Appointment Trader* (appointmenttrader.com) is a successful website that was launched in 2021. It helps people to secure a reservation at their desired places in a short time, by facilitating the purchase and sale of restaurant reservations.

The logic of this business model is simple: new users are required to create an account in order to either purchase or sell reservations. Sellers make reservations at famous restaurants and subsequently resell them on the platform. From the buyer perspective, an individual who is unable to book a table at a specific restaurant on a particular date and time due to high demand can purchase the reservation directly through a platform. The platform levies a commission of between 20 and 30 percent on each successful transaction. Some users have achieved impressive earning, with one seller generating $26,697 from reservation trading in a single month (see https://leonardo.it/news/appointment-trader-cos-e-come-funziona-sito-guadagnare-prenotazioni-ristoranti/ (Last accessed on 27th January 2026).

1.1 The problem

It is important to note that the above mentioned secondary market can lead to several issues. One such issue is that large numbers of reservations, often made via automated software, i.e., bots, result in restaurants always appearing to be fully booked, forcing customers to resort to purchasing reservations. Secondly, if reservations made by people who only intend to resell them and therefore do not attend the restaurant, are not resold, there is a high no-show rate, which results in financial losses for restaurateurs. Furthermore, it becomes practically impossible for restaurateurs to verify if the person who made the reservation is the one who will actually dine, which makes it difficult to create customers' profile and may result in a reduction in the quality of the offered service. These factors contribute to an environment that is perceived as unfair by restaurateurs and customers alike. Additionally, although deposits or prepayments can partially mitigate the economic impact of no-shows, they do not fully address the broader inefficiencies caused by automated bot bookings and speculative secondary markets. Automated reservations made by bots are not only an unfair and often illegal practice, but they also result in a loss of valuable customer knowledge, as the actual diner is not the one who booked the table. Furthermore, bot activity may lead to lost revenues for the restaurant. Since no auction takes place, high-demand tables are not allocated efficiently, and the high no-show rate can leave tables empty despite having collected penalties. In many cases, the collected fee may not be sufficient to cover the fixed costs of the restaurant, particularly for high-end establishments with substantial staffing and preparation expenses. Finally, from the customer;s perspective, speculative reselling reduces

Table 1 Average waiting times for reservations at three different Michelin-starred restaurants. https://www.finedininglovers.it

Restaurant	Michelin Stars	Average Waiting Time	Location
De Librije	***	>6 months	Netherlands
Osteria Francescana	***	4 months	Italy
Core	**	2-3 months	England

satisfaction: fewer diners are served, while those who do access tables through unofficial channels may end up paying more than they would in a transparent auction and still face uncertainty about whether their reservation is valid.

While automated booking tools and bots can operate under any online allocation mechanism, including auctions, the proposed approach does not aim to technically eliminate such activity. Instead, by internalizing the value of scarce reservation slots within a transparent, restaurant-controlled auction framework, it reduces the economic incentives that sustain secondary markets. The auction mechanism should therefore be regarded as complementary to standard technical safeguards, such as user verification or payment authentication. From a regulatory perspective, although restaurant reservations are not currently subject to specific anti-secondary-market legislation, existing legal frameworks such as the Italian regulation on unauthorized ticket resale introduced by Law No. 145/2018, highlight a growing policy concern regarding automated purchasing and commercial resale of access rights. These developments suggest that market-based mechanisms capable of reallocating scarcity in a transparent and controlled manner may play an important role alongside legal and technical interventions.

From this analysis, it can be concluded that there is a significant market for customers willing

to pay a premium to secure a reservation at their desired restaurant on their desired date and time.

It is evident that Restaurant Revenue Management (RRM) could play a significant role in assisting restaurant managers in making decisions regarding the acceptance or rejection of reservations, the optimization of revenues, and the avoidance of the risk of no-shows. RRM is a critical aspect of the hospitality industry, especially for high-demand dining establishments (Bertsimas & Shioda, 2003). The aim is to manage the availability and pricing of restaurant tables in a strategic manner in order to maximize the restaurateurs' revenue. This is because traditional reservation systems often fall short in addressing the dynamic nature of customer demand, which can result in inefficiencies and lost revenue opportunities. The emergence of secondary markets for reservations, like those facilitated by *Appointment Trader*, has highlighted significant inefficiencies in the existing reservation systems. The dynamics of this market highlight the necessity for innovative solutions in RRM. By understanding and addressing these challenges, the industry can enhance customer satisfaction and optimize revenue streams.

1.2 Proposed solution

Given the aforementioned premises, this research proposes an innovative approach based on the employment of the Combinatorial Auction (CA) mechanism to manage restaurant reservations. The main purpose of this work is to provide an alternative system that can assist restaurants in addressing the limitations of traditional booking systems. Auctions represent a more robust alternative, as they allocate high-demand tables transparently and directly to genuine diners, thereby reducing the incentive for fraudulent intermediaries and ensuring that revenues remain within the restaurant.This mechanism also improves transparency and trust by reallocating reservations within a restaurant-controlled framework, rather than through opaque secondary markets.

Current secondary markets for high-end restaurant reservations are frequently characterized by unauthorized resale practices, which operate outside the control of restaurants and existing platform rules. In such settings, diners may face inflated prices and uncertainty regarding the effective validity of their reservation, while restaurants lose access to customer information and control over the allocation of their capacity. By contrast, the proposed auction mechanism provides a legitimate and transparent restaurant-managed framework, in which customers with a higher Willingness To Pay (WTP) can compete for reservation slots according to predefined and observable rules. Although this mechanism does not aim to equalize prices across all diners, it avoids the inefficiencies and risks of the black market and therefore represents a fairer and more controlled alternative to the current situation. In this work, fairness is not interpreted in a distributive or egalitarian sense, nor is willingness-to-pay assumed to be a universally fair allocation criterion. Rather, fairness is understood in procedural and market-based terms, referring to an allocation process that limits opaque intermediation and unauthorized value extraction while preserving control and information at the restaurant level. In particular, the proposed mechanism aims to ensure that reservation rights are allocated and monetized directly by the restaurant, that payment is made *ex ante* by the actual diner, and that no secondary resale of reservations occurs outside the restaurant;s control. Under this interpretation, fairness relates to the alignment between payment, consumption, and ownership of the service, rather than to equality of outcomes across customers. More generally, fairness in allocation problems admits multiple interpretations depending on the normative criterion adopted, including distributive equity, equality of opportunity, or procedural fairness (Moulin, 2003; & Young, 1994). As extensively discussed in the market design literature, no allocation mechanism can be considered fair in an absolute sense, since each rule implements different trade-offs among efficiency, transparency, and equity objectives (Roth, 2002). In line with this perspective, the present work adopts a procedural notion of fairness, focusing on the alignment between allocation rules, payment, and control over reservation rights. Specifically, the novelty and originality of this research are best illustrated by the following:

- a novel framework for restaurant revenue management, an area not extensively explored for dynamic booking management is developed;
- the concept of combinatorial auctions to allocate tables and menus is applied, offering a unique solution for optimizing restaurant bookings;
- a procedure to address the bid generation problem, based on realistic data is presented;
- the practical application and validation of the framework have been made in a Michelin-starred restaurant, providing concrete proof of concept for the effectiveness of the proposed solution.

Thus, the primary contribution of this work lies in demonstrating how combinatorial auctions can be used as a revenue management tool to internalize surplus currently captured by secondary markets. While other considerations, such as customer experience or perceived fairness, are relevant, they are treated as secondary aspects and represent directions for future empirical research.

1.3 Paper organization

The paper is structured as follows: section 2 is devoted to the literature review, section 3 reports the mathematical formulation of the problem for the winner determination, in section 4 the bid generation problem is addressed, testing phase and results analysis are reported is section 5, case study is examined in section6 while in section 7 conclusion and future works are summarized.

2 Literature review

Our contributions to this study are rooted in two main streams of research: restaurant revenue management and the employment of CAs as a tool for resources assignment. In the sequel, we will review the most relevant works related to both fields.

2.1 Revenue management in restaurants industry

The application of revenue management techniques is becoming increasingly prevalent in several sectors, particularly those characterised by limited capacity, high fixed costs and intensive demand. The interest in applying revenue management to the restaurant industry started back in 1998 through the seminal work of Kimes et al. (1998). Since then, many studies appeared in the literature, and several approaches have been developed. A recent review analyzing the RRM techniques has been published by Tyagi and Bolia (2021). Additional insights can be also extracted from the review by Subying and Yoopetch (2023) that covers the broader context of tourism and hospitality industries, including restaurants.

Tyagi and Bolia (2021) identified three different levers on which the implementation of RRM relies (see also Kuokkanen (2024)). The first one focuses on capacity management that allows to increase the service capacity during peak periods by optimizing the layout and size of the tables. The most studied problem in this context is known as the “Tables Mix” which deals with identifying the most suitable tables mix to ensure the highest seats occupancy (see Kimes and Thompson (2004) and Guerriero et al. (2014)). One of the recent approaches of capacity management consists in applying the overbooking strategies to the restaurants’ management (Lebaka, 2024).

The second lever is related to duration management and involves predicting the meals duration of customers and developing performance indicators (such as "revenue per available seat hour" or "profit per available square meter") to measure the performance of RRM techniques on the restaurant operations (see (Kimes et al., 1999) and Heo (2017)).

The third and last lever deals with price management to ensure that the most appropriate prices are chosen for the offered menus to maximize the restaurant’s profit. Several techniques have been used in this context, such as demand-based pricing and targeted discounts (Norvell & Horky, 2017; Webb et al., 2023) and (Gómez-Talal et al., 2024), prices fencing and fidelity schemes (Basak Denizci et al., 2018; Kimes & Wirtz, 2003) and unbundling the reservation pricing from the menus charges (Kimes & Wirtz, 2016; Nadia Hanin Nazlan et al., 2018).

A detailed explanation of the basics of the above mentioned techniques goes beyond the scope of this paper, and interested readers are referred to the excellent review by Tyagi and Bolia (2021). However, it is worth noting that our approach covers all three levers through the auction mechanism, as our models help restaurateurs to make the most appropriate decisions regarding the capacity (table mix), duration (turns) and price (bidding) levers of the RRM.

2.2 CAs designs and applications

Auctions have been used since ancient times. Nowadays, auctions are known to be an efficient way to trade items and allocate resources (Felicetti et al., 2025). CAs are multi-item auctions where bidders can define their own combinations of items and can submit bids on the whole bundle rather than on single items.

2.2.1 *Designing CAs*

The design and operation of CAs is more challenging than that of single-item auctions. This is due to the necessity of selecting an optimal design that aligns with the requirements of the specific field of application. The effectiveness and outcomes of CAs can vary considerably when different designs are considered. In particular, the main categories of CAs, which are also relevant in the context of RRM, are:

- forward (one-seller-many-buyers) vs. reverse (many-sellers-one-buyer) auction
- open vs. sealed-bid auction
- single-round vs. multi-round to reach the auction clearing and decide the winning bids
- First-price vs. second-price (called also Vickrey) auction
- static one-shot bidding vs. dynamic bids submission.

The aforementioned categories are sufficiently self-explanatory and interested readers are referred to Palacios-Huerta et al. (2024) for more details. In the sequel, we will examine a forward single-round CA with sealed-price bidding. Our primary focus will be on the static and first-price clearing design, but extensions to cover the dynamic and second-price variants will be also proposed.

2.2.2 *Applications of CAs*

The earliest use of CAs can be attributed to Stephen et al. (1982), who applied this approach to solve the problem of allocating airport time slots to contending airlines. Subsequently, several industries began to increasingly rely on the use of CAs as a tool for trading and resource allocation. A non-exhaustive list of fields of application includes treasury bill trading (Menezes, 1995), telecommunications service obligations (Kelly & Steinberg, 2000), spectrum licenses assignment (Günlük et al., 2005), bus routes assignment (Cantillon & Pesendorfer, 2006; Cramton, 2010)), energy procurement in deregulated electricity markets (Musmanno et al., 2010), public cleaning contracts Lunander and Lundberg (2013), real estate trading (Dries et al., 2014), construction procurement (Salim & Shaqsi, 2018), supplier selection (Abbaas & Ventura, 2024) and drivers assignment in logistics services Triki (2021).

For completeness, it is worth noting that auctions have also been applied within the broader hospitality and travel sectors-for instance, in hotel room reservations (Toh et al., 2011), airline seat upgrades (Matzke et al., 2016), and event ticketing (Budish & Bhave, 2023). Nevertheless, these applications primarily rely on traditional single-item auction formats and do not exploit the potential of bundling or package bidding that characterizes combinatorial auction mechanisms.

The above applications typically involve relatively homogeneous resources (e.g., identical flight seats, standard hotel rooms, delivery slots, etc.) and demand patterns that are comparatively well-structured. In contrast, restaurant table allocation introduces a distinct set of challenges that make the direct application of existing modeling paradigms insufficient. Restaurant resources are highly heterogeneous, as tables differ in size and can often be combined or split to accommodate different customer groups. Also, the existence of several types of menus that can be combined in different ways increases the problem's heterogeneity. Furthermore, the problem is inherently dynamic: reservations overlap across time slots, and turnover times vary depending on party size and dining duration. Additionally, unlike flights or hotel rooms, where customers purchase one unit each, restaurant demand comes in groups of varying sizes, creating significant variability in resource requirements. These unique features necessitate novel adaptations of combinatorial auction mechanisms. Thus, our contribution lies in demonstrating how these mechanisms can be tailored to address the complexities of restaurant operations, offering a new perspective within the broader literature on auction-based allocation and hospitality revenue management.

Finally, it is important to emphasize that the different applications exhibit limited overlap with each other and specifically with the RRM. This is because the predominant drivers of the models are highly application-specific, and the auction mechanism functions only as one component within a much broader decision-making framework. Consequently, the integration of CAs into RRM cannot be viewed as a straightforward extension of previous applications. Instead, the distinctive operational features of restaurants necessitate the development of tailored modeling approaches, where domain-specific elements dominate and the auction mechanism must be carefully adapted. Thus, the application of CAs to RRM represents a novel contribution, rather than a replication of existing auction-based practices in other service industries.

2.2.3 *Applications of CAs in the food industry*

To the best of our knowledge, three studies have been conducted that focus on the application of CAs in the field of the food industry (Triki et al., 2023).

The first application is proposed by Hohner et al. (2003) who developed an iterative CA to support the renowned American multinational, *Mars Incorporated*, in procuring its products and required services in an effective manner. *Mars Incorporated* is a well-known manufacturer in the American market and worldwide, with its core business in selling confectionery items related to food and beverages, pet food and also in providing animal care services. *Mars Incorporated* imposed both an upper and a lower limit on the number of suppliers that could be successful in the auction, as well as on the value to be awarded to each of them. The aim is to avoid relying on a limited number of suppliers while reducing the effort of managing too many suppliers and limiting the exposure effect. Suppliers can submit their bids as a bundle of items they would like to offer, thereby taking advantage of economies of scale through a quantity-discount pricing scheme. Moreover, the iterative nature of the auction allows the suppliers to re-adjust at each round their bids prices if they wish to be more competitive. The authors developed a complex Winner Determination Problem (WDP) which they embedded in an online auctioning portal, namely "Number1traders". The results of the auction mechanism suggest that it has the potential to achieve cost savings and facilitate more effective interactions with suppliers.

Within the same context of procuring foodstuffs, Harris and Biere (2014) proposed another application of the auction mechanism, focusing on sweetener products. The authors implemented two distinct types of auctions, allowing suppliers to select the most suitable option in accordance with their preferences. The first type is based on a single-product auction, with the manufacturer defining 19 bidding scenarios. These scenarios provide the framework within which suppliers can define their bids.

The second type of auction is characterised by a combinatorial nature. However, the auctioneer limited the number of possible bundles to 100 in order to reduce the complexity of the bidding process.

Despite the aforementioned simplification, all suppliers who wished to participate in the auctions were obliged to attend a training session in order to become familiar with the bidding platform and to learn how to submit meaningful bundles. The authors summarized the outcomes of the auctions employed after one year of operation. They claimed that the CA achieved better results in terms of supplier involvement and cost savings for the manufacturer.

The last application to be reviewed here is related to the distribution of 2.5 million daily meals to school students in Chile, as proposed by Olivares et al. (2012). The governmental agency implemented a single-round CA, allowing the meal suppliers to bid on serving any bundle of a maximum of eight districts among the 100 available school districts. The purpose of such a limitation is to enhance both the economies of scale and the economies of scope of the suppliers, thereby ensuring operational synergy among the selected districts. The auctioneer then solves a WDP, which includes several restrictions on the share to be won by each supplier. The aim is to identify the best set of bids that serves all the districts with the minimum cost and the best reliability of the sellers. Each resulting winner will be required to prepare, distribute, and serve the meals in their designated districts. The authors also proposed a BGP model to provide a decision support tool to assist suppliers in determining the optimal set of bundles to be submitted to the auction.

3 The winner determination problem

In this work, we investigate the use of combinatorial auctions to manage restaurant reservations. Rather than bidding on single items, participants can submit bids in the form of "bundles", which are combinations of items. The customer proposes a bid (an offer) for a certain bundle; hence, the demand is expressed as a demand for a bundle composed of a combination of tables of a particular size. For example, a bidder offers a bid to book a single table for 6 persons, or may offer a bundle composed of two tables: one for 4 people and one for 2, supposing that the group size will not exceed 6. In addition, we consider that the restaurant offers a variety of menu options, which change according to the type of food or the number of courses that compose the menu (i.e., fish menu, meat menu and vegetarian menu or menu with 3, 6 or 8 courses). These menu options have different prices. Thus, a restaurant offers tables of a given size and menus of a given type, which can be considered as auctioned products. The bundle is therefore composed of a combination of tables of certain sizes and different types of menus. From the perspective of the bidders, customers can book a combination of tables and a combination of menus at the restaurant by participating in the CA, which is conducted through a web platform. From the customer's perspective, the auction process works like a standard online booking system. The bidding step is integrated into the reservation flow and provides clear information on minimum bids and available tables. This makes the process intuitive even for customers unfamiliar with auctions, reducing potential entry barriers and improving the booking experience. The possibility of submitting multiple bids is allowed. Furthermore, another feature that we consider in the proposed framework is that the restaurant provides its service over more than one service turn (i.e., for dinner, it works over 2 turns). Thus, when the bidder proposes his offer, he indicates not only the composition of the bundle in terms of the combination of tables and types of menus but also the sequence of turns at which he would prefer to dine at the restaurant. In particular, supposing that the restaurant works on 2 turns for dinner, the bidder may indicate his preference in either of two different ways:

- Soft constraint: the bidder indicates a preference for a specific turn, but if that turn is unavailable, i.e., there is no available capacity, he can be accommodated in a less preferred turn, with a penalty applied to the restaurant.
- Hard constraint: the bidder preference is binding and therefore he can not be shifted to another turn.
  This study considers both types of constraints.

3.1 Problem formulation

This section presents the notation and mathematical formulation of the model. In particular, the proposed framework refers to a combinatorial first-price auction in which the customers who submit the highest bids are declared winners of the auction and are required to pay the amount of their bids. In other words, a first-price auction is an auction in which items are awarded to the highest bidders and winners are required to pay their own bids.

Sets and indices:

- $k = 1, \ldots, K$ indicates the type of menus;
- $c = 1, \ldots, C$ indicates the table capacity;
- $i = 1, \ldots, I$ indicates the turn performed by the restaurant, i.e. $i = \{1, 2, 3, 4\}$;
- $j = 1, \ldots, J$ indicates the bidder (i.e. customer);
- $t = 1, \ldots, T$ indicates the combination of required tables;
- $s = 1, \ldots, S$ indicates the combination of required menus;
- $\theta = 1, \ldots, \Theta$ indicates the turn preference expressed by the bidder;
- Θ_i is a subset of Θ, whose elements are indexed as p;
- $\Theta_{\beta i}$ is a subset of Θ_i, that contains the customer's preference without penalty for the turn i, the elements of $\Theta_{\beta i}$ are indicated by f;
- $\Theta_{\alpha i}$ is a subset of Θ_i, that contains the customer's preference with penalty for the turn i, the elements of $\Theta_{\beta i}$ are indicated by q.

Parameters:

- $b_{jts\theta}$ bid price offered by bidder j for the bundle composed of the combination of tables t and the combination of menus s for the turn θ
- u_{c_i} number of tables of capacity c available at the turn i
- l_{jsk} element that indicates the number of menus of type k required by the bidder j for the bundle of menus s
- $h_{jtc\theta}$ element that indicates the number of tables of capacity c for the combination of tables t required by the bidder j that asks to eat on the turn θ
- u_k indicates the availability of menus of type k (i.e. number of menus of type k that the restaurant can produce in the service time that comprises all turns)
- Ω penalty factor incurred by the restaurant in case of not satisfying the soft constraints turn

Decision variables:

- x_{jtsi} binary variable equal to 1 if the bid offered by bidder j for the bundle (t, s) is satisfied in turn i, 0 otherwise

– $y_{jtc\theta i}$ binary variable equal to 1 if the tables of capacity c are used to satisfy in turn i the combination t required by bidder j with turn preference θ, 0 otherwise
– z_{jsk} binary variable equal to 1 if the menu of type k is used to satisfy the combination s required by bidder j, 0 otherwise

Model formulation:

$$\mathbf{M}ax \quad \sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{i=1}^{I}\sum_{f\in\Theta_{\beta i}} b_{jtsf}x_{jtsi} + \Omega(\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{i=1}^{I}\sum_{q\in\Theta_{\alpha i}} b_{jtsq}x_{jtsi}) \tag{1}$$

$$\sum_{j=1}^{J}\sum_{s=1}^{S} l_{jsk}z_{jsk} \le u_k \quad k = 1,\dots,K \tag{2}$$

$$\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{p\in\Theta_i} h_{jtcp}y_{jtcpi} \le u_{c_i} \quad c = 1,\dots,C \quad i = 1,\dots,I \tag{3}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{i=1}^{I} x_{jtsi} \le 1 \qquad j = 1,\dots,J \tag{4}$$

$$\sum_{c=1}^{C} h_{jtcp}y_{jtcpi} \ge \sum_{c=1}^{C} h_{jtcp}x_{jtsi} \quad j = 1,\dots,J \quad t = 1,\dots,T \quad s = 1\dots,S \quad i = 1,\dots,I \quad p \in \Theta_i; \tag{5}$$

$$\sum_{k=1}^{K} l_{jsk}z_{jsk} \ge \sum_{k=1}^{K}\sum_{i=1}^{I} l_{jsk}x_{jsti} \quad j = 1,\dots,J \quad t = 1,\dots,T\,, \quad s = 1\dots,S \tag{6}$$

$$x_{jtsi} \in \{0,1\} \quad j = 1,\dots,J \quad i = 1,\dots,I \quad s = 1\dots,S \quad t = 1,\dots,T \tag{7}$$

$$y_{jtc\theta i} \in \{0,1\} \quad j = 1,\dots,J \quad t = 1,\dots,T \quad c = 1\dots,C \quad \theta = 1,\dots,\Theta \quad i = 1,\dots,I \tag{8}$$

$$z_{jsk} \in \{0,1\} \quad j = 1,\dots,J \quad s = 1,\dots,S \quad k = 1\dots,K \tag{9}$$

The objective function (1) maximizes the total revenue. It consists of two terms: the first one represents the total revenue obtainable when the preferred turn is assigned to a bidder, whereas the second one considers the penalty incurred when the request is satisfied in a different turn in case of a customer's soft preference. Equations (2) represent the capacity constraints on the menus, ensuring that the menus offered do not exceed the number of available menus. Equations (3) represent the capacity constraints on tables, and they ensure that the tables used do not exceed the number of available tables in any given turn. Equations (4) state that at most one request for each bidder can be satisfied. Constraints (5) and (6) connect variables x, y and z and assure the feasibility of the allocation over the turns. Equations (7)–(9) define variables domain.

As previously stated, the proposed model (1) – (9) implements a first-price auction system. In addition to this, we propose below two further CA design systems, namely second price and dynamic auctions, described in sections 3.1.1 and 3.1.2 .

3.1.1 Second price auction

In the second price, the customer who submits the highest bid is declared the winner of the auction, but the amount that the winner is required to pay is equal to the second-highest bid submitted. The rationale behind this type of design is that bidders are encouraged to bid more aggressively, given that, in the event of winning, they will be required to pay a clearing price that is lower than their submitted bid David et al. (2008).

When a second price strategy is considered, the following procedure is adopted. The auction is open, and bids start arriving; once all the bids have been collected, they are then classified into types. As previously stated, each bid is characterized by several features, in particular: the bidder, i.e., the individual who makes the offer, the combination of the tables and the menus chosen, the preferred turn, and the associated price, i.e., the price offered by the bidder j for the combination (t,s,θ). The classification into classes is carried out by considering the combination (t,s,θ).

Bids in each class are then ranked in descending order of price. The platform assigns to each bidder j (in the ordered class) the bid proposed by the next bidder, and solves the model (1)–(9). The steps for implementing the second price CA are described in Algorithm 1.

Algorithm 1 Procedure for the second price auction:

```
Auction starts: collect the bids;
Classify the bids into classes;
for bid class do
    Classify bids in a descending order of price;
    Assign to the each bidder j the bid proposed by the next bidder;
    Solve the model (1) – (9);
end for
```

3.1.2 Dynamic auction

In the dynamic auction, multiple rounds are performed, during which bidding takes place. In particular, at each round r the platform receives bids from N groups of customers dynamically over time. When the round r has been concluded, the platform collects all the bids and determines the winners, solving the model (1)–(9). Then, a new round takes place, considering the remaining capacity. The auction terminates when the number of accepted requests has saturated the capacity or when a maximum number of rounds R_{max} is reached.

The dynamic combinatorial auction follows the steps reported in Algorithm 2.

Algorithm 2 Procedure for the dynamic auction:

```
while r <= R_max && Maximum capacity criterion not met do
    Auction round r starts: collect the bids;
    Solve the model (1)–(9);
    Update capacity;
end while
```

4 The bid generation problem

The bid generation process is a challenging phase of the auction mechanism that dictates the success and efficiency of the auction itself Klemperer (1999). It involves the formulation of bids by participants, based on their valuation of the auctioned items or services (in this case, tables and menus), their knowledge of the market, and their willingness to compete Milgrom (1989). In economic theory, bid generation is typically modelled under the assumption that bidders act rationally, aiming to maximize their utility or profit (Vickrey, 1961). However, in practice, the complexity of human behaviour and the uncertainty inherent in the valuation of items make bid generation a challenging problem.

Bid generation is not a monolithic process; it varies widely across different types of auctions, each of which requires different strategies and considerations. To make an example, in English auctions, bid increments and the timing of bids play a crucial role, whereas in sealed-bid auctions the emphasis is on valuation and prediction of other bidders valuations and behaviour (Cassady, 1967) (Preston McAfee et al., 1987). With the advent of online auctions and electronic marketplaces, bid generation has also embraced computational approaches. Algorithms and artificial intelligence are increasingly employed to automate and optimize bid generation, particularly in complex scenarios like spectrum auctions, ad placements, and financial markets, where the sheer volume of data and the speed of decision-making surpass human capabilities (Borissov et al., 2010).

Moreover, the interplay between bid generation and market dynamics raises important questions about market design, bidder behaviour, information asymmetry, and the potential for collusion or gaming of the system (Rothkopf & Harstad, 1994). Thus, the study of bid generation lies at the intersection of economics, game theory, psychology, optimization and computer science, making it a vast and multidisciplinary field of investigation.

In this study, to address the bid generation problem and develop a bidding strategy, we consider a mechanism of sealed bid independent truthful auction. This involves the following properties:

- bidders submit their bids such that the value of their own bid is not revealed to other bidders. The bids are kept confidential until the end of the bidding process;
- the bids of each participant are independent of each other, so the valuations of other bidders have no impact on the value that each bidder assigns to the items or bundles being auctioned. This assumes that there is no collusion or sharing of valuation information between bidders;
- the best strategy for each bidder is to bid an amount equal to their true private valuation of the items. In other words, bidders have a dominant strategy to bid truthfully. In this context, the term "truthful" or "incentive-compatible" denotes that the optimal strategy for each bidder is to submit a bid that reflects their true valuation of the items. This characteristic is designed to prevent bidders from trying to game the system by overbidding or underbidding, thereby ensuring that items are allocated to those who value them the most. It is worth highlighting that bidders know, or at least have an idea, of the mean price of the tasting menus offered by restaurants. These values, namely atomic prices, are used as a reference point for the bidders to decide how much to bid.

Therefore, the bid price $b_{jts\theta}$ proposed by bidder j for the bundle composed by the combination t of tables, combination s of menus, and turn preference θ can be estimated as an atomic price multiplied by the group size associated to the bundle, indicated as n, minus a potential discount factor linked to the bundle's size, plus a markup linked to the customers' characteristics. For ease of notation, we refer to t, s, θ as m.

$$b_{jm} = (atomicprice_m * n) - discount_m + markup \tag{10}$$

The atomic price can be calculated by taking the average of the restaurant menu prices. In practice, the atomic price corresponds to the base price of the tasting menu and is used as the starting point of the auction. Since this price is publicly available, as it reflects the standard menu price, it provides bidders a clear and familiar reference when placing their bids, helping to prevent unrealistic underbidding or overbidding. Bids below the atomic price are not accepted, ensuring that the restaurant covers its basic costs while keeping the process transparent for participants. Concerning the discount factor, the realistic hypothesis is that the discount is greater during the less targeted turns. For example, if for the dinner service, a restaurant has four turns (18:00-19:30; 19:30-21:00; 21:00-22:30 and 22:30-00:00), the discount will be greater during the less popular turns, typically the first and the last turns. This decision helps to incentivize customers to choose a slot that is less required in order to improve the load factor of the restaurant. It is worth highlighting that discounts are a common practice that is already applied by many booking platforms. To estimate the average discount amount, we considered the values scraped from the well-known application The Fork (https://www.thefork.co.uk/).

The value of the markup is calculated as follows:

$$mark\ up = (atomic\ price_m * n) * M\% \tag{11}$$

where $M\%$ is a percentage that depends on the characteristics of the customer. In fact, different clusters of customers can be considered, and the markup value is strictly related to the customer's WTP (i.e., the bidder in this case). Several works have examined different cluster types according to various characteristics. In Adomavicius et al. (2012) and Adomavicius et al. (2020), customers differ according to their bidding strategy and are classified as "analyzers", "explorers" and "participators". The study Park and Hwang (2023) identifies fine-dining behavioural intentions, segmenting the market according to consumption needs. The authors conduct a cluster analysis, and three clusters have been categorized in "self-oriented needs", "high needs" and "low needs".

According to the context under consideration, in our work, the bidders are clustered considering three categories based on income, perceived value, and urgency of need.

The income-based category identifies three distinct groups: high-income customers with a high WTP for premium or luxury products, medium-income customers with a moderate WTP seeking a balance between quality and price, and low-income customers with a low WTP inclined towards the most economical options available. The perceived value-based cluster categorizes customers into deal seekers with a low WTP and price-insensitive customers with a high WTP, who prioritize factors other than price, like convenience or quality. Lastly, the need urgency-based category distinguishes between customers with an immediate need, who are willing to pay a premium for quick access or delivery, and those with a non-urgent need, who have a low to moderate WTP and can afford to wait for the product or service.

It is crucial to remember that these groups are not mutually exclusive; indeed, a single customer may belong to multiple categories. This overlap reflects the dynamic nature of consumer behaviour, whereby individual bidding decisions are influenced by a complex interplay of factors, including but not limited to income, perceived value, and the immediacy of their needs. The details of the numerical values adopted are reported in Section 5, which is devoted to the validation and testing phase.

5 Testing phase and numerical results

This section presents a computational study carried out on ad hoc generated instance sets to validate and assess the scalability of the proposed approach. The experiments are carried out using the software AIMMS 4.75.3.6 and the commercial solver Cplex 10.1, on an Intel Core i7-10610U CPU 1.80 GHz 16,0 GB of RAM PC, under Windows 10 Pro operating system.

Table 2 Estimation of the atomic price.

Restaurant name	*menu 1* (*e*)	*menu 2* (*e*)	*menu 3* (*e*)
Francescana Group (IT)	350	220	140
Cannavacciuolo Group (IT)	300	280	95
Hyle (IT)	170	150	130
Core (UK)	290	275	260
De Librije (NL)	299	289	279
Mean value	281.8	242.8	180.8
Atomic Price	255.13		

5.1 Instances generation and parameters setting

For the instance setting we consider 3 different types of menus (k=1,2,3); 3 different table sizes (c=2,4,6); 4 turns and 8 possible choices ($\theta = 1, 2, 3, 4, 5, 6, 7, 8$). In particular:

- $\theta = 1$ is associated with the bidder who wants to eat in turn 1;
- $\theta = 2$ is associated with the bidder who wants to eat in turn 2;
- $\theta = 3$ is associated with the bidder who wants to eat in turn 3;
- $\theta = 4$ is associated with the bidder who wants to eat in turn 4;
- $\theta = 5$ is associated with the bidder who prefers to eat in turn 1;
- $\theta = 6$ is associated with the bidder who prefers to eat in turn 2;
- $\theta = 7$ is associated with the bidder who prefers to eat in turn 3;
- $\theta = 8$ is associated with the bidder who prefers to eat in turn 4;

Bids are generated considering equation (10), introduced in Section 4. In particular, the value of the atomic price is given by the mean values of the prices applied to the menus of five different restaurants. These prices, presented in table 2, have been gathered directly from the websites of the restaurants.

The combinations of the attributes of the different customer categories introduced in Section 4 result in 12 possible customer types. Each customer type represents a potential cluster. Table 3 reports the possible customer types according to the different WTP for each category, i.e., income, perceived value, and urgency of need.

To estimate the possible relevant values of the markup factor, we have conducted a sensitivity analysis. This consists of three phases. Firstly, we looked at the impact of different feature values on the markup. Secondly, we looked at the impact of different markup values on the bid. Thirdly, we looked at the impact of different bids on the objective function.

In particular, the markup is calculated using equation (11). To understand the impact of the features on the markup, several values of markup are computed. Specifically, it is assumed that the maximum value of $M\%$ can vary among values 15%, 20% and 25%. Table 4 shows a possible combination of values adopted to compute the $M\%$ and to perform the sensitivity analysis considering the values of the maximum markup. The first column shows the name of the customer type associated with the WPT values; the second, third, and fourth columns show the different levels of WTP associated with the bidder's categories (i.e., Income, Perceived value, and Urgency of need, respectively). Whereas the fifth column, namely "sum", contains the sum of the WTP values associated with each category, this term is used to calculate the values of $\%M$ reported in the last column. In particular, to calculate $\%M$, the values of the

Table 3 Customer types and attributes.

Customer type	Income			Perceived value		Urgency of need	
WTP	High	Medium	Low	High	Low	High	Low
a1	x			x		x	
a2	x				x	x	
a3	x			x			x
a4	x				x		x
a5		x		x		x	
a6		x			x	x	
a7		x			x		x
a8		x					x
a9			x	x		x	
a10			x		x	x	
a11			x		x		x
a12			x	x			x

column sum are used as a proportional factor (e.g., $1.00 : 25\% = 0.85 : x$, $x = 21.25\%$). The last three columns report the values of $M\%$.

The value of the discount factor, as already mentioned in Section 4, is selected based on the discount applied by The Fork. In particular, a discount of 10% is applied for the first and the last turn (e.g. 18:00-19:30 and 22:30-00.00). Five customer types are considered across 12 categories. In particular, for each instance, the distribution of bidders may be as follows: they may be distributed equally among the bidders types, randomly distributed, the majority of bidders may belong to the first 4 categories (e.g. a_1, a_2, a_3 and a_4), the majority of bidders may belong to the second 4 categories (e.g. a_5, a_6, a_7 and a_8) and the majority of bidders may belong to the last 4 categories (e.g. a_9, a_{10}, a_{11} and a_{12}). For the sake of simplicity, the aforementioned distributions are indexed with the numbers 1, 2, 3, 4, and 5, respectively. To generate the instances, we consider an increasing number of place settings and bidders. In particular, considering the realistic dimension of restaurants, the number of place settings varies between 20, 50, and 100. The place settings are distributed among tables of sizes with 2, 4, and 6 seats, respectively. Table 5 shows the number of tables of each size considered for the different restaurant capacities.

The total number of available menus is four times greater than the number of place settings, and it is distributed equally among the 3 categories. The number of bidders taking part in the auction varies between half, equal, or 50% more than the number of places available. The instances are denoted with an alphanumeric id code, e.g. $T\_n1\_n2\_n3$ where:

- T refers to the instance name;
- $n1$ refers to the number of place settings of the restaurant;
- $n2$ refers to the number of bidders and can take three values: 1 is associated with a number of bidders equal to half the number of seats, 2 is associated with a number of bidders equal to the number of seats, and 3 is associated with a number of bidders that is 50% more than the number of seats;
- $n3$ is associated with the customer distribution.

Table 4 Values distribution and $M\%$ computation assuming a maximum $M\%$ of 25%, 20% and 15%.

Customer type	Income			Perceived value		Urgency of need		Sum	$M\%$		
WTP	High	Medium	Low	High	Low	High	Low		25%	20%	15%
a1	0.50			0.25		0.25		1.00	25.00%	20.00%	15.00%
a2	0.50				0.10	0.25		0.85	21.25%	17.00 %	12.75 %
a3	0.50			0.25			0.10	0.85	21.25%	17.00 %	12.75 %
a4	0.50				0.10		0.10	0.70	17.50%	14.00%	10.50%
a5		0.30		0.25		0.25		0.80	20.00%	16.00%	12.00%
a6		0.30			0.10	0.25		0.65	16.25%	13.00%	9.75%
a7		0.30			0.10		0.10	0.50	12.50%	10.00%	7.50%
a8		0.30		0.25			0.10	0.65	16.25%	13.00%	9.75%
a9			0.20	0.25		0.25		0.70	17.50%	14.00%	10.50%
a10			0.20		0.10	0.25		0.55	13.75%	11.00%	8.25%
a11			0.20		0.10		0.10	0.40	10%	8.00%	6.00%
a12			0.20	0.25			0.10	0.55	13.75%	11.00%	8.25%

Table 5 Configurations of tables for different restaurant capacities.

Restaurant capacity (# seats)	20	50	100
# tables of size 2	2	8	16
# tables of size 4	3	4	8
# tables of size 6	1	3	6

Table 6 Average revenues (in Euro) over the customer distributions ($n3$)

Test name	CA_c	CA_s	CA_d	$FCFS$	CO
T_20_1	16923.72	13539.26	17008.36	11527.37	15518.58
T_20_2	15206.33	14151.06	16079.13	9640.33	14342.93
T_20_3	18744.56	17468.28	18838.62	14107.80	16929.36
T_50_1	47705.06	42783.31	48132.99	33388.46	43734.18
T_50_2	51948.68	50470.18	51948.68	34564.11	47026.00
T_50_3	52405.77	49726.23	52405.77	28920.99	47026.00
T_100_1	101862.08	95218.24	101862.08	73125.43	93111.48
T_100_2	103201.38	96637.02	103201.38	63014.84	93581.74
T_100_3	105245.13	101784.49	105245.13	62779.71	94052.00

Table 11in Appendix A reports a detailed description of the generated instances, providing all the information related to the name, the number of place settings, the total number of menus available, the number of bidders and their distributions.

5.2 Computational results

To assess the solution quality of the proposed approach, we compare the results obtained by applying the first-price combinatorial auction (that we denoted as CA_c here), the second price combinatorial auction (CA_s), and the dynamic combinatorial auction (CA_d), with the two classical allocation strategies:

- $FCFS$ (First Come First Served), which simply allocates customer requests according to the order of arrival without any type of optimization
- CO (Capacity Optimization), which only optimizes the capacity in terms of tables in the restaurant.

For the $FCFS$ and CO, we calculated the revenue associated with each request, considering the average expense of the customer in the restaurant,i.e., the atomic price. For the CA_d we considered three rounds. Tables 6 and 7 summarize our results.

Tables 6 shows, for each instance T, the average revenues over the customer distributions ($n3$), given by fixing the values $n1$ and $n2$, for each approach, i.e., CA_c, CA_s, CA_d, $FCFC$, and CO. Hence, the first column of Table 6 contains the names of the "aggregated" instances in the form T_n1_n2. Similarly, Table 7 summarizes the average total arriving requests and the average accepted requests over the customer distribution for each approach. As far as CA_d is concerned, the value of total requests refers to the maximum number of total requests for each round. The detailed results considering a markup of 20% are reported in tables 12 and 13 of Appendix A. We decided not to report the execution times of the proposed methods,

Table 7 Average Accepted requests over the customer distributions ($n3$)

Test name	Total requests	CA_c	CA_s	CA_d	$FCFS$	CO
T_20_1	26	4	4.2	4.2	4	4
T_20_2	47	7	6	7.8	6	7
T_20_3	70	7	8.6	7.2	6	7
T_50_1	58	12.6	12	13.2	12	12
T_50_2	112	15.6	16.2	15.6	15	16
T_50_3	164	15.2	16	15.2	10	16
T_100_1	112	30	28.4	29.8	24	30
T_100_2	211	29.4	26.4	29.4	21	30
T_100_3	322	30.6	34.4	30.6	19	31

given that the instances are solved to the optimum in a short computing time, i.e., less than one second, and the comparison will be focused, thus, on the solution quality.

To provide a more comprehensive overview of the results, we have plotted them in the graphs 1 and 2. Graph 1 depicts the revenues for each method across different tests, whereas the bar chart 2 shows the average number of accepted requests for each method across the various tests. Each group of bars represents a test (e.g. T_20_1, T_20_2, etc.), and the different colours indicate the various methods.

Looking at graphs 1 and 2, it is clear that the CA_d outperforms all the other strategies, allowing to obtain the highest revenues for each instance type. In terms of performance, the gap between the policies rises when the instances dimension increases. Specifically, $FCFS$ has the worst performance both in terms of revenues and accepted requests. The revenue trend is very similar for CA_c, CA_s, CO and CA_d. Instead, $FCFS$ shows a different revenue trend, especially when the instance size increases. In fact, the revenue values for all policies are only comparable for small instances. In particular, the results for instances with 20 seats indicate that CA_d, CA_c, CA_s and CO are, on average, 32%, 31%, 22% and 25% higher than $FCFS$, respectively. Whereas, for instances with 50 seats, the revenues are 36%, 36%, 32% and 30% higher than $FCFS$, respectively; and 36%, 36%, 32% and 29% higher than $FCFS$, respectively, for instances with 100 seats. Concerning CA_d, it can be observed that, on average across all restaurant capacities considered, it is 0.7%, 8.2%, 34.8% and 9.7% higher than CA_c, CA_s, $FCFS$ and CO, respectively.

Focusing on the number of accepted requests, hence, on the capacity exploitation, it is worth noticing that the accepted requests are comparable among the five proposed approaches for small-sized restaurants (e.g. T_20_1). Whereas, for large-sized restaurants, especially when there are a large number of requests, the $FCFS$ results in performing worse. In particular, in terms of accepted requests, CA_c, CA_s, CA_d and CO exceed $FCFS$ by 11%, 14%, 16% and 11%, respectively, for instances with a capacity of 20 seats; 14%, 16%, 15% and 15%, respectively, for instances with a capacity of 50 seats, and 29%, 28%, 29% and 30%, respectively, for instances with a capacity of 100 seats.

In addition, it is easy to notice that it is convenient to adopt the dynamic strategy when it is not possible to saturate the capacity with a single round auction. For instances with 50 and 100 place seats, the accepted requests and the revenues obtained with CA_c and CA_d are on average the same. In particular, it can be stated that the CA_c and CA_d strategies are equivalent when there is a high number of requests and the capacity is saturated within one session. In addition, CA_C and CO exhibit, in many cases, almost the same trend.

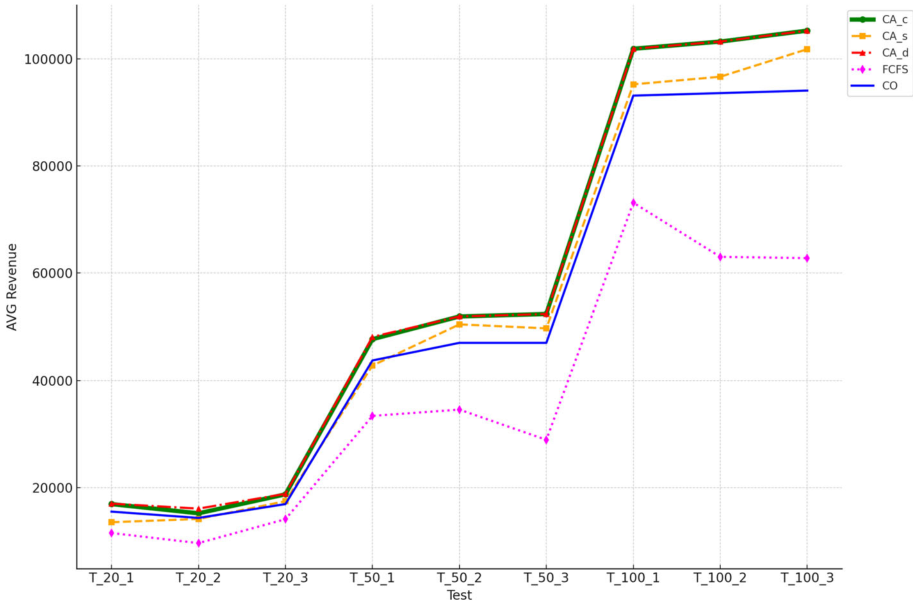

Fig. 1 Average revenue for the five policies.

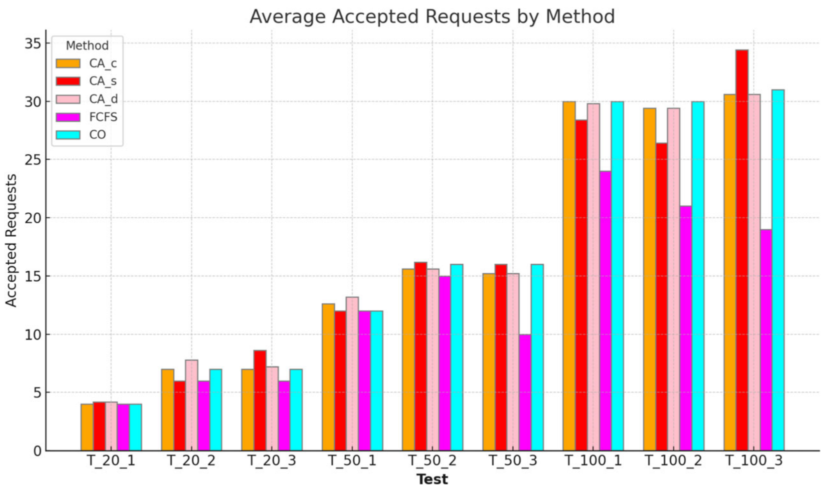

Fig. 2 Average accepted requests for the five policies.

In general, CA_d and CA_c generate more revenue than the other strategies for the same number of accepted requests. Although CA_s allows more requests to be accepted on average for instances with 100 seats, using this method results in lower revenue. Thus, the proposed strategies allow for effectively managing restaurant capacity and maximizing revenue.

Concerning the sensitivity analysis, it can be stated that the markup values are not affected by the use of different values associated with, as different percentages associated with the markups act as scaling factors. Different values of markups, instead, lead to different bids. In particular, a higher percentage of markup results in higher bid values. As a consequence,

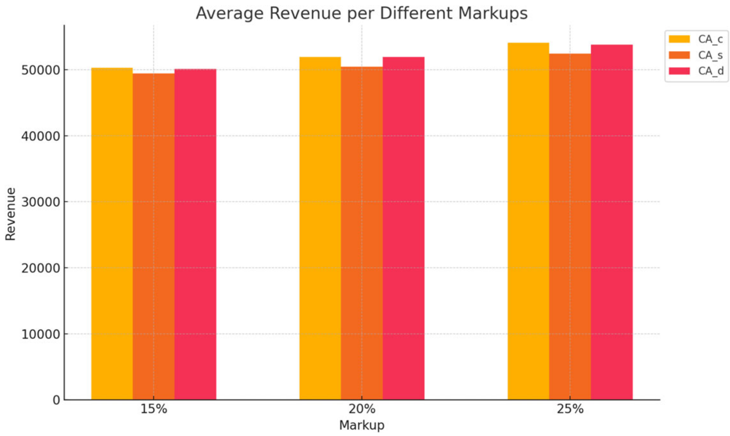

Fig. 3 Average revenues for instances T_50_2 considering different markup values.

regarding the impact of different markup values on the objective function, it can be stated that higher markups lead to increasing values of the objective function. Evidence of this can be viewed in the graph reported in Fig. 3, which plots the average values of the objective function for different values of the markup, for the instance with a capacity of 50 seats and 50 bidders (e.g. T_50_2). However, the trend is the same for all instances.

6 Case study

To test the effectiveness and the potential application of this novel auction-based approach, a series of experiments has been conducted on a real-based case study. The case study is based on real data and managerial insights collected through collaboration with a globally renowned fine-dining group that operates multiple restaurants worldwide, including several with Michelin stars. This partnership made sure that the auction mechanism was designed considering real-world operational constraints and customer expectations. In particular, we considered a famous Michelin-starred Italian restaurant that offers tasting menus in an exclusive location. Due to the restaurant's limited capacity and high popularity, securing a reservation, particularly during certain months of the year, can be challenging. We built a set of real-based instances using the information regarding the capacity, the number and size of available tables, the price of the menu, the mean revenue per bill, and the demand curve provided by the restaurant. In particular, the restaurant has a total of 12 tables, with 3 table sizes (c=2,3,4). There are 2 tables with a capacity of 4 people, 1 table with a capacity of 3 people, and 9 tables with a capacity of 2 people. This results in a total capacity of 29 people per service turn. The restaurant operates on a 2 service turns basis, with one turn dedicated to lunch at 12:30 and another to dinner at 20:00. The average revenue per person is e500 + VAT. Only one type of menu is offered, comprising a 12-course tasting menu priced at e350 per person. Moreover, a wine pairing option is offered at a supplementary cost of e240. Thus, in this case, the atomic price is comprised between e350 (tasting menu without wine pairing) and e590 (tasting menu with wine pairing). This information is public, and the bidders know that it represents the reference point for the auction. As mentioned, the maximum capacity is 29 people, with 29 tasting menus usually served per session. The restaurant presents a high

Table 8 Characteristics of the real instances.

Test name	Place settings	Total menu	Bidders	Bidder distribution
R_1_1	29	29	14	1
R_1_2	29	29	14	2
R_1_3	29	29	14	3
R_1_4	29	29	14	4
R_1_5	29	29	14	5
R_2_1	29	29	29	1
R_2_2	29	29	29	2
R_2_3	29	29	29	3
R_2_4	29	29	29	4
R_2_5	29	29	29	5
R_3_1	29	29	43	1
R_3_2	29	29	43	2
R_3_3	29	29	43	3
R_3_4	29	29	43	4
R_3_5	29	29	43	5

demand for reservations, particularly on weekends (Friday, Saturday, and Sunday). Regarding the size of reservation groups, the maximum group size allowed is 10 people, while the minimum is 2 people. The time between the reservation date and the service date (i.e., the typical advance reservation period) is, on average, 5 months and 29 days. Currently, reservations are made exclusively via the website channel, with a credit card guarantee following a first-come, first-served order. It is the policy of the booking managers to optimize the reservation layout manually in order to reach maximum capacity. It is possible for customers to join a waiting list if the restaurant is unable to accommodate the reservation due to insufficient seating availability. A 7-day cancellation policy is currently adopted; if confirmation is not received within 4 days of the scheduled visit, the reservation is automatically canceled. In the event of a cancellation, the waiting list is contacted.

The information obtained by the restaurant manager was used to develop a series of realistic scenarios, which were then employed to assess the efficacy of the proposed approach. Table 8 summarizes the characteristics of the instances. The first column reports the name of the instance, the second and the third columns report the number of seats and available menus, whereas the fourth one reports the number of bidders; the last column shows the bidder distribution. Focusing on the names of the instances, i.e., R_m1_m2, R refers to the instance name, $m1$ is the number of bidders, and $m2$ is the customer distribution as in Section 5.1.

Results obtained on these instances, in terms of objective functions and accepted requests, are reported in Tables 9 and 10 and shown graphically in Fig.4 and 5.

As depicted in the graph reported in Fig. 4, the application of the CA_d policy also proves to be the most profitable in the context of real cases. In particular, in this case, the application of CA_d has been found to result in average revenues that are 14% higher than those achieved by CA_c, 28% higher than those achieved by CA_s, 38% higher than those achieved by $FCFS$, and 20% higher than those achieved by CO. The adoption of CA_d has also been found to lead not only to higher revenues but also to a higher number of accepted requests.

Table 9 Revenues over the five policies.

Test name	CA_c	CA_s	CA_d	$FCFS$	CO
R_1_1	26526.40	18596.80	32001.60	17700.00	26535.70
R_1_2	26821.40	26538.20	37406.00	17700.00	26535.70
R_1_3	27022.00	18950.80	32686.00	17700.00	26535.70
R_1_4	27800.80	19800.40	33464.80	17700.00	26535.70
R_1_5	27800.80	27800.80	33464.80	17700.00	26535.70
R_2_1	37040.20	29830.40	40509.40	23600.00	33040.00
R_2_2	36155.20	28815.60	40533.00	23600.00	33040.00
R_2_3	36709.80	29500.00	40332.40	23600.00	33040.00
R_2_4	36414.80	29995.60	40651.00	23600.00	33040.00
R_2_5	36108.00	29877.60	40320.60	23600.00	33040.00
R_3_1	33748.00	29783.20	38562.40	29500.00	30680.00
R_3_2	33724.40	29995.60	41488.80	29500.00	30680.00
R_3_3	34043.00	29110.60	38385.40	29500.00	30680.00
R_3_4	33606.40	29806.80	38692.20	29500.00	30680.00
R_3_5	33299.60	29382.00	38432.60	29500.00	30680.00

Table 10 Accepted requests over the five policies.

Test name	Total requests	CA_c	CA_s	CA_d	$FCFS$	CO
R_1_1	35	3	3	4	3	3
R_1_2	35	3	3	6	3	3
R_1_3	35	3	3	4	3	3
R_1_4	35	3	3	4	3	3
R_1_5	35	3	3	4	3	3
R_2_1	68	6	5	7	5	6
R_2_2	68	6	5	6	5	6
R_2_3	68	6	5	6	5	6
R_2_4	68	6	5	6	5	6
R_2_5	68	6	5	6	5	6
R_3_1	126	7	7	7	5	7
R_3_2	126	8	7	9	5	7
R_3_3	126	8	7	8	5	7
R_3_4	126	7	7	8	5	7
R_3_5	126	7	7	8	5	7

Indeed, as can be noticed from the graph plotted in Fig. 5, the number of satisfied requests with the CA_d is always greater than the accepted requests with other policies. In particular, the average number of accepted requests with CA_d is 1.6 times higher with respect to the strategy currently adopted by the restaurant examined, i.e., the $FCFS$. It is interesting to highlight that the revenues obtained with CA_c and CA_d for $m1 = 2$ are higher than those obtained with $m1 = 3$. Therefore, more bidders do not always lead to higher revenues. The choice of auction timing reflects operational considerations and the practical constraints of managing table availability. A daily cycle would create unnecessary complexity and limit the number of

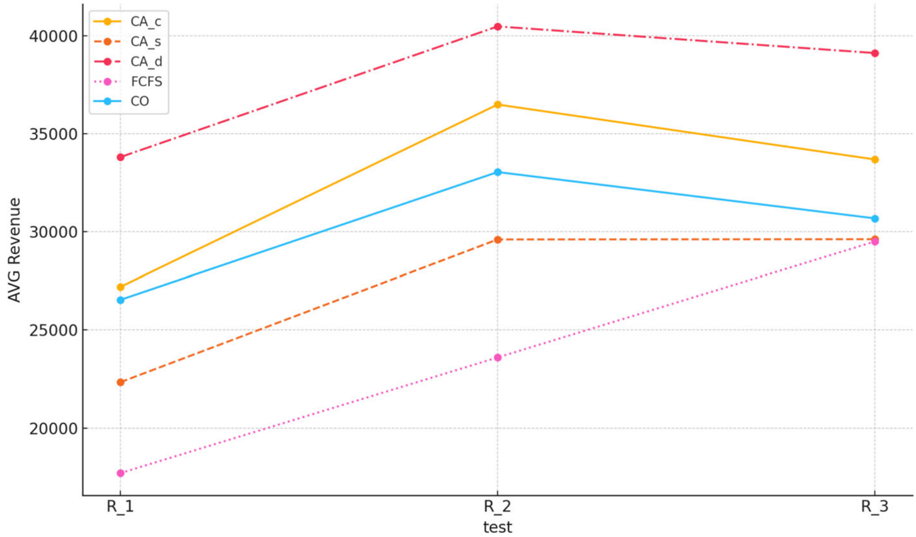

Fig. 4 Average revenue for the five policies for real instances.

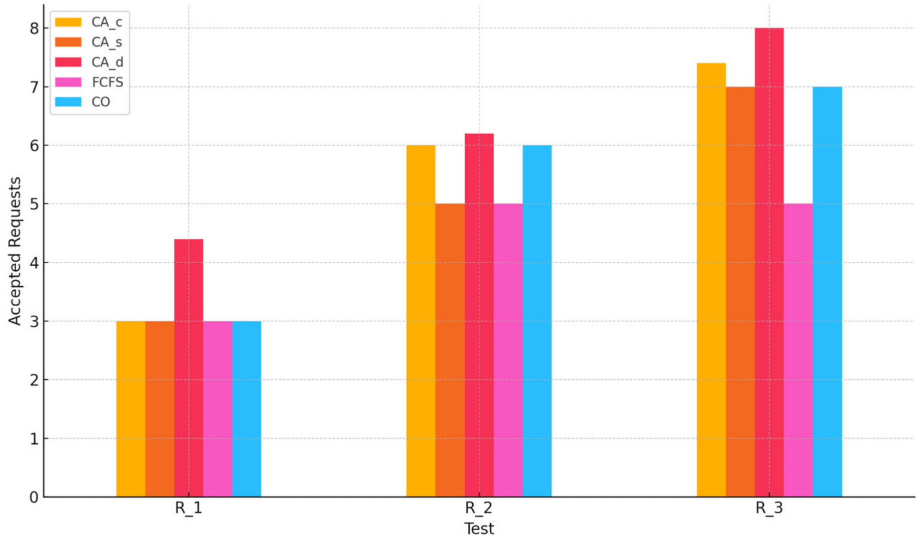

Fig. 5 Average accepted requests for the five policies for real instances.

tables offered, whereas a monthly cycle allows high-demand dates to be grouped and includes a limited number of premium slots. During peak seasons or special events, a weekly cycle may be appropriate. This schedule balances operational feasibility with customer planning needs while preserving the exclusivity and excitement of the auction.

From the customer's perspective, the proposed auction is implemented as a sealed-bid or proxy-based process rather than a real-time dynamic bidding process. Each participant submits bids, and the allocation is determined by the platform at the auction closing time, without requiring bid monitoring or strategic responses to competing offers. This design minimizes cognitive and emotional burden on diners and preserves a smooth booking experience, a feature identified as particularly important by restaurant managers in fine-dining contexts, where anticipation and exclusivity are valued over competitive interaction. The time-limited and structured nature of the auction may also generate positive experiential effects by fostering anticipation and reinforcing perceptions of exclusivity associated with scarce premium slots. At the same time, the absence of continuous participation requirements reduces incentives for intermediation or automated bidding, thereby limiting the reintroduction of opacity into the reservation process.

At the time of writing, the proposed auction-based reservation system has not yet been deployed in an operational environment. The collaboration with the restaurant group focused on model development, access to operational data, and managerial validation, rather than on immediate technological implementation. Customer acceptance was preliminarily assessed through the administration of questionnaires to potential diners, which indicated a generally positive attitude toward auction-based reservations and a willingness to participate in such mechanisms for high-demand restaurants. There was no evidence to suggest an excessive level of complexity for the customers. The transition to a fully operational system requires the development of a dedicated digital platform, the integration of the system with existing reservation infrastructures, and the resolution of legal, regulatory, and brand-related constraints, particularly relevant in fine-dining contexts. These issues are left for future research.

7 Conclusions and future works

This research explores the use of first price, second price and dynamic CAs as a means to manage efficiently and effectively bookings in fine dining restaurants, helping restaurateurs to increase their revenues. Despite this type of auction is relatively classic, this approach has never been used before in the context of RRM. The results show that it is a promising avenue to explore and could be a real innovation in the restaurant business. Moreover, the case study carried out on a real Michelin-starred restaurant helps to support the thesis proposed in this work.

The originality of this work lies not in the abstract application of combinatorial auctions, which have been studied in other domains, but in their tailored integration into restaurant revenue management. In particular, the proposed framework explicitly accounts for heterogeneous table configurations, menu combinations, service turns, and realistic bid generation, and is validated through extensive computational experiments and a real-based case study.

For future research, it could be interesting to define the atomic price and the discount, considering also the number of tables to be booked and the number of menus to be ordered (e.g. fewer menu types mean a larger discount to consider). In addition, to increase the complexity of the system, it could be useful to formulate a multiperiod model that takes into account a wide time horizon for bookings (e.g. one month, six months, one year). Furthermore, investigating how to partition the capacity of the restaurant and the services offered in order to decide the most profitable assortment to allocate to the auctions will be crucial in maximizing revenues and optimizing resource utilization. It will also be relevant to conduct a more detailed survey on potential customers not only limited to better understand whether actual customers are willing to participate in an auction to secure a seat at the restaurant, rather than waiting on a waiting list or buying a reservation on a secondary market, but also how much more than usual customers are willing to pay to secure a seat.

Appendix

Table 11 reports the instance name, the number of place settings, the total number of menus available, the number of bidders and their distributions. Table 12 reports the values of the objective function, thus total revenues obtained by accepting requests, for the five proposed methodologies. Table 13 reports the total number of requests and the number of accepted requests for the five proposed strategies. As concerns the CA_d, the value of total requests refers to the maximum number of total requests for each round.

Table 11 Characteristics of the generated instances.

Test name	Place settings	Total menu	Bidders	Bidder distribution
T_20_1_1	20	80	10	1
T_20_1_2	20	80	10	2
T_20_1_3	20	80	10	3
T_20_1_4	20	80	10	4
T_20_1_5	20	80	10	5
T_20_2_1	20	80	20	1
T_20_2_2	20	80	20	2
T_20_2_3	20	80	20	3
T_20_2_4	20	80	20	4
T_20_2_5	20	80	20	5
T_20_3_1	20	80	30	1
T_20_3_2	20	80	30	2
T_20_3_3	20	80	30	3
T_20_3_4	20	80	30	4
T_20_3_5	20	80	30	5
T_50_1_1	50	200	25	1
T_50_1_2	50	200	25	2
T_50_1_3	50	200	25	3
T_50_1_4	50	200	25	4
T_50_1_5	50	200	25	5
T_50_2_1	50	200	50	1
T_50_2_2	50	200	50	2
T_50_2_3	50	200	50	3
T_50_2_4	50	200	50	4
T_50_2_5	50	200	50	5
T_50_3_1	50	200	75	1
T_50_3_2	50	200	75	2
T_50_3_3	50	200	75	3
T_50_3_4	50	200	75	4
T_50_3_5	50	200	75	5
T_100_1_1	100	400	50	1
T_100_1_2	100	400	50	2
T_100_1_3	100	400	50	3

Table 11 continued

Test name	Place settings	Total menu	Bidders	Bidder distribution
T_100_1_4	100	400	50	4
T_100_1_5	100	400	50	5
T_100_2_1	100	400	100	1
T_100_2_2	100	400	100	2
T_100_2_3	100	400	100	3
T_100_2_4	100	400	100	4
T_100_2_5	100	400	100	5
T_100_3_1	100	400	150	1
T_100_3_2	100	400	150	2
T_100_3_3	100	400	150	3
T_100_3_4	100	400	150	4
T_100_3_5	100	400	150	5

Table 12 Results in terms of objective functions values considering a markup of 20%.

	Revenue				
Test name	CA_c	CA_s	CA_d	$FCFS$	CO
T_20_1_1	16915.25	13722.19	17338.49	11521.37	15518.58
T_20_1_2	16374.45	13052.07	16374.45	11521.37	15518.58
T_20_1_3	17169.19	13835.05	17169.19	11531.37	15518.58
T_20_1_4	17150.38	13609.32	17150.38	11531.37	15518.58
T_20_1_5	17009.30	13477.65	17009.30	11531.37	15518.58
T_20_2_1	15567.96	14107.80	16696.58	9640.33	14342.93
T_20_2_2	15179.99	14164.23	15179.99	9640.33	14342.93
T_20_2_3	15276.40	14474.60	16310.97	9640.33	14342.93
T_20_2_4	15069.48	14098.40	16169.89	9640.33	14342.93
T_20_2_5	14937.81	13910.29	16038.22	9640.33	14342.93
T_20_3_1	19003.21	17719.40	19003.21	14107.80	16929.36
T_20_3_2	18565.87	16847.07	19036.13	14107.80	16929.36
T_20_3_3	18749.27	17510.13	18749.27	14107.80	16929.36
T_20_3_4	18772.78	17686.48	18772.78	14107.80	16929.36
T_20_3_5	18631.70	17578.32	18631.70	14107.80	16929.36
T_50_1_1	48004.14	42337.51	48535.54	33388.46	43734.18
T_50_1_2	47674.96	42535.02	48747.15	33388.46	43734.18
T_50_1_3	48370.94	42986.47	48907.04	33388.46	43734.18
T_50_1_4	47453.94	43188.68	47453.94	33388.46	43734.18
T_50_1_5	47021.30	42868.90	47021.30	33388.46	43734.18
T_50_2_1	51902.60	50458.90	51902.60	34564.11	47026.00
T_50_2_2	52020.16	50270.79	52020.16	34564.11	47026.00

Table 12 continued

	Revenue				
T_50_2_3	52217.67	51089.05	52217.67	34564.11	47026.00
T_50_2_4	51935.51	50703.43	51935.51	34564.11	47026.00
T_50_2_5	51667.47	49828.75	51667.47	34564.11	47026.00
T_50_3_1	52020.16	48937.61	52020.16	28920.99	47026.00
T_50_3_2	52302.32	49812.29	52302.32	28920.99	47026.00
T_50_3_3	52598.58	50299.01	52598.58	28920.99	47026.00
T_50_3_4	52692.63	50007.45	52692.63	28920.99	47026.00
T_50_3_5	52415.18	49574.81	52415.18	28920.99	47026.00
T_100_1_1	102121.66	96558.49	102121.66	73125.43	93111.48
T_100_1_2	101453.89	93779.25	101453.89	73125.43	93111.48
T_100_1_3	102582.52	97198.04	102582.52	73125.43	93111.48
T_100_1_4	101952.37	95119.49	101952.37	73125.43	93111.48
T_100_1_5	101199.95	93435.96	101199.95	73125.43	93111.48
T_100_2_1	103659.41	98260.83	103659.41	63014.84	93581.74
T_100_2_2	103088.05	97230.96	103088.05	63014.84	93581.74
T_100_2_3	103722.90	96556.14	103722.90	63014.84	93581.74
T_100_2_4	103104.51	95801.37	103104.51	63014.84	93581.74
T_100_2_5	102432.03	95335.81	102432.03	63014.84	93581.74
T_100_3_1	105446.40	102126.36	105446.40	62779.71	94052.00
T_100_3_2	104369.50	101832.45	104369.50	62779.71	94052.00
T_100_3_3	106048.33	101980.58	106048.33	62779.71	94052.00
T_100_3_4	105347.65	101994.69	105347.65	62779.71	94052.00
T_100_3_5	105013.76	100988.34	105013.76	62779.71	94052.00

Table 13 Accepted requests per configuration.

		Accepted Requests				
Test name	Total Requests	CA_c	CA_s	CA_d	FCFS	CO
T_20_1_1	26	4	4	5	4	4
T_20_1_2	26	4	5	4	4	4
T_20_1_3	26	4	4	4	4	4
T_20_1_4	26	4	4	4	4	4
T_20_1_5	26	4	4	4	4	4
T_20_2_1	47	7	6	8	6	7
T_20_2_2	47	7	6	7	6	7
T_20_2_3	47	7	6	8	6	7
T_20_2_4	47	7	6	8	6	7
T_20_2_5	47	7	6	8	6	7
T_20_3_1	70	7	9	7	6	7
T_20_3_2	70	7	7	8	6	7
T_20_3_3	70	7	9	7	6	7
T_20_3_4	70	7	9	7	6	7

Table 13 continued

Accepted Requests						
T_20_3_5	70	7	9	7	6	7
T_50_1_1	58	12	12	13	12	12
T_50_1_2	58	13	12	14	12	12
T_50_1_3	58	12	12	13	12	12
T_50_1_4	58	13	12	13	12	12
T_50_1_5	58	13	12	13	12	12
T_50_2_1	112	16	17	16	15	16
T_50_2_2	112	17	16	17	15	16
T_50_2_3	112	17	16	17	15	16
T_50_2_4	112	14	16	14	15	16
T_50_2_5	112	14	16	14	15	16
T_50_3_1	164	15	16	15	10	16
T_50_3_2	164	15	16	15	10	16
T_50_3_3	164	15	16	15	10	16
T_50_3_4	164	16	16	16	10	16
T_50_3_5	164	15	16	15	10	16
T_100_1_1	112	30	29	30	24	30
T_100_1_2	112	31	29	30	24	30
T_100_1_3	112	31	29	31	24	30
T_100_1_4	112	29	27	29	24	30
T_100_1_5	112	29	28	29	24	30
T_100_2_1	211	30	27	30	21	30
T_100_2_2	211	30	25	30	21	30
T_100_2_3	211	28	27	28	21	30
T_100_2_4	211	29	25	29	21	30
T_100_2_5	211	30	28	30	21	30
T_100_3_1	322	30	34	30	19	31
T_100_3_2	322	31	32	31	19	31
T_100_3_3	322	29	33	29	19	31
T_100_3_4	322	32	37	32	19	31
T_100_3_5	322	31	36	31	19	31

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Declarations

Conflicts of Interest Authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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