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Disentangling the impact of bidding price on advertising performance in E-commerce search advertising: The moderating role of product competitiveness

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ABSTRACT

Though E-commerce search advertising has become an increasingly prevalent approach for online retailers to promote their products, it is nontrivial for online retailers to use search advertising effectively, particularly without a comprehensive understanding of the effect of bidding price. This research investigates the effect of bidding price on product click-through rate and conversion rate, with a focus on the moderating role of product competitiveness. We collected data consisting of 10,734 search advertising records of 421 advertised stock keeping units and 206 keywords from a retailer operating on a leading e-commerce platform. This dataset was matched with data of 39,066 rival products to construct the indexes of product competitiveness in terms of mouth and product competitiveness in terms of sale price. Contradictory to the wisdom that there is a monotone relationship between bidding price and click-through/conversion rate, our result reveals an inverted U-shaped relationship between bidding price and click-through/conversion rate. Moreover, product competitiveness in terms of word-of-mouth weakens the inverted U-shaped relationship between bidding price and click-through/conversion rate, while product competitiveness in terms of sale price only weakens the inverted U-shaped relationship between bidding price and click-through rate, but not conversion rate. This research enriches the literature on search advertising by untangling the impact of bidding price and the moderating role of product competitiveness.

1. Introduction

E-commerce search advertising refers to a promotion model in which e-commerce search engines allocate limited advertisement space to retailers through auction and prioritize the display of the product information of successful bidders [1]. On e-commerce platforms, search advertising is crucial for retailers to promote their products and services to consumers [2,3]. The traffic and sales generated by e-commerce search advertising have been documented as the main source of revenue for many e-commerce retailers [4]. According to Statista, the global search advertisement spending is forecasted to reach 304.90 billion dollars in 2024 and anticipated to demonstrate an annual growth rate of 7.97 %, leading to a projected market volume of 414.40 billion dollars by 2028 [5].

E-commerce search advertising requires retailers to set their bidding price to participate in search advertising auctions [6]. It has been claimed by scholars that the role of bidding price is particularly prominent in influencing advertising performance [7]. On the one hand, bidding price determines whether the target advertised product can gain exposure and favorable position on the search result page [8,9], while favorable positions typically result in higher click-through rate (CTR, the probability of clicking an advertisement to view details) and conversion rate (CR, the probability of making an order after viewing the detailed page) [10–12]. On the other hand, bidding price directly relates to retailers' advertising cost, with higher bidding price implying increased investment [13]. Therefore, it is important for retailers to determine appropriate bidding prices for advertised products to attain favorable advertising performance.

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Prior studies have yielded fruitful findings on bidding price in search advertising in two streams. One stream takes a behavioral perspective by identifying behavioral patterns such as bidding inflation and cyclical patterns performed by retailers in bidding search advertisement for products [14,15]. The other stream of literature leverages analytical models or machine learning methods to investigate the optimization problem of bidding, trying to find the optimal bidding price to maximize retailers' revenue [16–19]. Most past studies assumed that higher bidding prices necessarily result in better advertising performance [16,17,20]. However, this assumption is challenged by scholars who found that top positions can have worse CR and profit because consumers are more likely to choose recently viewed products which located at the bottom based on their browsing behavior [10]. Given the questionable assumption adopted by past studies, it is imperative to investigate the impact of bidding price on advertising performance. As such, the first research question (RQ) is proposed below.

RQ1. *How does bidding price influence advertising performance (*i.e.*, CTR and CR) in e-commerce search advertising?*

Nevertheless, merely considering the bid price is insufficient; the product's inherent competitiveness will also affect the advertising performance. E-commerce platforms are highly competitive, which makes the role of bidding price hinges on the competitiveness of the advertised product in comparison with its rival products [21]. Although a favorable bidding price could secure a product appearing in an attractive position on webpage, the advertised product is subject to the influence exerted by rival products displayed around in the search result [22–24]. Consumers' attention and willingness to click in and purchase would be dependent on the competitive advantage of the advertised product compared with other rival products. Product competitiveness, defined as a set of qualitative and price characteristics of products, meeting market demands and outperforming similar offerings [25], can capture the comparison with rival products. Existing literature has advocated the necessity of considering rival products. For example, [11] demonstrated that the effectiveness of sponsored search advertisements is contingent upon the organic search result displayed on the same page. [22] further revealed that the presence of other advertised products on the result page also impacts advertising performance. Although past studies have alluded to the importance of considering rival products in search advertisement, it remains unclear regarding how product competitiveness effectuates the relationship between bidding price and advertising performance. To bridge this gap, this research aims to investigate the moderating role of product competitiveness by disentangling the RQ below.

RQ2. *How does product competitiveness moderate the relationship between bidding price and advertising performance (*i.e.*, CTR and CR) in e-commerce search advertising?*

To address the RQs, we collected 10,734 search advertising records of 421 stock keeping units (SKUs) from a retailer operating on a leading e-commerce platform. Data on rival products were collected to operationalize product competitiveness in terms of sale price and word-of-mouth. This study contributes to literature in two ways. First, this study contributes to bidding strategy literature in the search advertising context by investigating the effect of bidding price on CTR and CR. Interestingly, our results show that there is an inverted U-shaped relationship between bidding price and CTR, CR. Although past literature provides invaluable insights into the analysis of bidding behavior and optimization of bidding, it has largely overlooked the performance implications of bidding price and assumed that higher bidding prices inevitably lead to better advertising performance. However, this study has demonstrated that this assumption is incorrect. Second, this research investigates the moderating role of product competitiveness on the relationship between bidding price and CTR, CR. Previous research has suggested the significance of taking rival products into account in search advertising [26,27]. However, it is not yet clear how the competitiveness of products influences the connection between bidding price and advertising performance. Practically, our findings provide guidance for online retailers in optimizing their bidding price for search advertising. Specifically, our results suggest that retailers need to find the optimal bidding price that can maximize CTR and CR, while considering the competitiveness of their products.

In the subsequent sections, we conduct a comprehensive review of relevant literature and identify research gaps in the second section. The third section formulates four hypotheses, followed by a detailed methodology discussion section. Section 5 presents the analytical results. Finally, there are the discussion, implications, and limitations.

2. Theoretical background and literature review

2.1. Search advertising

Search advertising typically operates on a pay-per-click basis, in which retailers pay the search engine for each click on their advertisements [28]. Retailers compete by setting bidding price for each click, and the search engine determines advertisement rankings based on bidding price and other factors, such as advertisement quality. Advertisement quality includes factors such as advertisement relevance, landing page quality, and advertisement performance history [29,30]. The pay-per-click model allows retailers to better control their advertising budgets [3], while considering advertisement quality in determining rankings can encourage retailers to offer higher-quality and more relevant advertisements [31].

The rapid development of search engine promotion is closely related to the numerous advantages it has over traditional advertising methods. Search advertising allows for precise targeting and placement of advertisement based on users' search keywords and histories, thereby improving advertisement CTR and CR (Hosanagar and Cherapanov 2008). Search advertising is characterized by immediacy, allowing retailers to make real-time adjustments and optimize their advertising strategies based on real-time data [32,33]. Stanton (2002) also noted that search advertising can achieve the same advertising performance as traditional advertising methods at a lower cost.

In the realm of search advertising, previous scholarly research has predominantly concentrated on three key perspectives: the retailer's viewpoint, the e-commerce platform's viewpoint, and the consumer's viewpoint. From the retailer's perspective, the literature has been focused on advertising strategies, encompassing aspects like keyword selection [34], match type configuration (Yang 2021), bidding price determination [35], and budget allocation [36]. Research from the e-commerce platform's perspective has revolved around revenue models. Pay-per-click and pay-per-impression are two common pricing models that have been investigated in search advertising literature [37]. Moreover, sponsored search auction mechanism is also a key focus for e-commerce platforms [38]. Many scholars explore whether the allocation of advertising space should be based solely on bids or if relevance indicators like quality score should also be factored in [12]. Literature from the consumer's perspective delves into consumer behavior such as search activity between organic and sponsored listings [39], spillover effects across related keywords [40], the effect of word-of-mouth and other factors on consumers' decision making [41].

2.2. Attention theory in search advertising

Attention theory is a cognitive psychological theory that aims to explain how people allocate their limited cognitive resources to process information in the environment [42,43]. It defines attention as the process of selectively concentrating cognitive capabilities on specific aspects of the environment [44]. Attention theory has been widely applied in various domains, such as education, marketing, and human-computer interaction, helping to understand how people acquire and process information [45,46]. The key principles of this theory include: attention is a limited resource; attention can be divided into different types (e.g., selective attention and divided attention); attention is influenced by underlying mechanisms (e.g., perceptual salience and working memory capacity); and attention allocation is guided by top-down processes (e.g., motivation and expectations) [47–49]. Overall, attention theory provides a framework for understanding how humans selectively focus on and process information.

The attention theory has been widely applied in the search advertising literature, which has two main streams. The first stream pertains to *selective attention*, which refers to our conscious and selective concentration of attention on certain specific information or objects, while excluding other irrelevant or secondary information [50,51]. Studies on selective attention offer psychological insights into users' attention-allocation dynamics in search advertising [52]. The research suggests that consumers facing multiple options in search advertising tend to exhibit a progressive, non-linear decline in their attention from the top to the bottom of the search results. Specifically, research has found that consumers have a strong tendency to sequentially browse through search results, devoting the majority of their attention to the top-ranked items and paying less attention to the middle- or lower-ranked options [53,54]. Moreover, this attention decay is exponential rather than linear, meaning that consumers' attention decreases more rapidly as they move down the search result page [55].

The other stream of literature discusses *comparative attention*, which refers to the phenomenon where people's attention and perception of an object can be influenced by the comparison raised by surrounding environment [56]. For example, the same object may appear to have different sizes, brightness, or color in diverse backgrounds [57,58]. This effect stems from the brain's mechanisms for analyzing and processing environmental information as a basis for comparison [59,60]. Comparative attention plays a significant role in the search advertising domain because of the limited attention of consumers. An advertised product is exposed to consumers jointly with other products as search results, which indicates competition for attention based on the comparison between the advertised product and other products [11,61]. Literature has shown that the advertising effectiveness of a product can be influenced by the surrounding environment when compared with the focal product. Specifically, some studies found that in search advertising, using visual elements (e.g., color, font, images) that are different from the surrounding products can make the product advertisement more salient (Chris 1998; [62]). Additionally, it is attested that the performance of a target promoted product's advertisement can be influenced by other products on the same search result page due to the comparison among them. For example, Athey and Ellison (2012) found that users may learn about the relevance of a sponsored result from the organic results, so if the quality of the organic search results is higher, the performance of the sponsored result will also be better. Moreover, [22] confirmed that competition from surrounding products on the search result page can directly affect the click performance of the target promoted product.

2.3. Bidding price in search advertising

During the process of search engine advertising, retailers are required to select appropriate keywords and set match types and bidding prices for their products [6]. The various aspects of these bidding strategies have significant implications for the ultimate performance of search engine advertising. One stream of literature has attained fruitful findings on generating, targeting, assigning, and grouping keywords (see [1] for a comprehensive literature review). Bidding price, as another important aspect of search advertising [7], received relatively little attention from extant literature. Previous studies focusing on bidding price mainly concentrate on two aspects: analysis of bidding behavior and optimization of bidding as shown in Table 1. Regarding the analysis of bidding behavior, some scholars explored bidding patterns. For example, [14] observed "bidding inflation" in the search advertising

Table 1
Literature on bidding price in search advertising.

Paper	Methods	Focus	Context	Key findings/ Contribution
[16]	Machine learning	Optimization of bidding	Display advertising; advertisements are sold on a per-impression basis.	This paper designed adaptive bidding algorithms for retailers participating in display advertising to meet impression targets under budget constraint.
[64]	Analytical model	Analysis of bidding behavior	Search engines display both organic search results and sponsored advertisement links on their result pages, where websites bid for positions among the sponsored links.	It reveals the multiple factors that influence websites' bidding behavior when competing for sponsored ad links on search engines, such as website attractiveness, diminishing returns on clicks, and consumer preferences, while also providing normative insights for retailers and search engines.
[15]	Analytical model	Analysis of bidding behavior	Retailers to adjust their bids in real-time to realize payoffs.	Retailers' bids may exhibit cyclical patterns, alternating between phases of price escalation and price collapse, similar to an "Edgeworth cycle."
[65]	Analytical model	Analysis of bidding behavior	Companies with lower product quality bid higher, but companies with higher product quality paradoxically receive more clicks.	Discover and explain the "position paradox" phenomenon in search advertising and argue that this phenomenon will be exacerbated under the pay-per-click pricing model.
[66]	Analytical model	Optimization of bidding	A retailer needs to select keywords and set bid prices for them to maximize expected profit under a given daily budget.	The paper provides an analytical model and optimization framework for keyword selection and bidding strategies in search engine advertising, considering budget constraints and the trade-off between revenue and risk.
[20]	Analytical model, machine learning	Analysis of bidding behavior	The ability to predict how retailers adjust their bids is crucial for search engine.	Considers retailers' bounded rationality and models their bidding strategy prediction accordingly, which is significantly important for

(*continued on next page*)

Table 1 (*continued*)

Paper	Methods	Focus	Context	Key findings/ Contribution
				search engines' revenue forecasting and novel advertising technology evaluation.
[67]	Analytical model	Optimization of bidding	The bidding strategies face challenges such as incentive incompatibility, budget constraints, keyword portfolio effects, and environmental uncertainties.	Presented an analytical model to compute optimal bids in multi-slot advertising auctions under uncertainty
[68]	Analytical model	Optimization of bidding	Adjusting bids under fixed daily budget constraint.	Formulate and solve a new dynamic programming problem to find an optimal dynamic bidding policy for placing online search ads with Google
[63]	Machine learning	Optimization of bidding	Traditionally, retailers allocate the budget at a larger time granularity, overlooking intra-day market dynamics.	Propose a reinforcement learning approach to deal with the problem of adjusting daily bid price for better advertising output.
[69]	Analytical model	Optimization of bidding	Soaring bidding prices is becoming a challenge to the long-term stability, profitability, and effectiveness of the SSA system.	Apply Evolutionary game theory and coevolutionary simulation in analyzing retailers' bidding behavior in repeated SSA auction and find that a group of "nice" and retaliatory strategies can promote stable cooperation among competing retailers.
[14]	Analytical model	Analysis of bidding behavior	In recent years, the search advertising market has seen a phenomenon of "bidding inflation" where retailers continuously raise their bids.	Present a game-theoretic analysis to understand the bid inflation phenomenon in sponsored search and propose the Upper Bound Nash Equilibrium concept to characterize and explain the phenomenon of bid inflation driven by retailers' competitive preferences in sponsored search auctions.
[17]	Analytical model, machine learning	Optimization of bidding	Real-time bidding in sponsored search market.	Formulate the sponsored search advertisement problem as a stochastic optimization problem and test several different automated bidding policies.
[19]	Machine learning	Optimization of bidding	Real-time bidding in sponsored search market.	This paper proposes a novel deep reinforcement learning approach tackling the challenges of environment changing and multi-agent competition faced by real-time bidding optimization and deploys the approach in Alibaba's large-scale practical system.
[18]	Machine learning	Optimization of bidding	An advertising campaign typically includes multiple sub-ad series with different ad creatives and targeting, and they need to be deployed across different channels.	This paper pioneers a combinatorial bandit algorithm for the online joint bid/budget optimization of multi-campaign advertising, validated through simulations and experiments.
[70]	Analytical model	Optimization of bidding	Adjusting bids for multiple keywords under fixed daily budget constraint.	Extend [68]'s research and study the problem of finding a bidding policy for multiple keywords in a general auction setting as a continuous-time optimization problem.

market, referring to the phenomenon that retailers continuously raise their bids. [15] found that retailers' bids may exhibit cyclical patterns similar to an "Edgeworth cycle," alternating between phases of price escalation and price collapse. Moreover, some explored factors that influence retailers' bidding behavior. Katona et al. (2011) found that website attractiveness, diminishing returns on clicks, and consumer preferences would impact retailers' bidding behavior. In terms of the optimization of bidding, studies are concerned with finding the optimal bidding strategy to maximize advertising revenue, with most of them employing analytical models and machine learning methods [16–19, 63]. For example, [19] proposed a novel deep reinforcement learning approach to address the challenges of environmental changes and multi-agent competition in real-time bidding optimization for e-commerce sponsored search advertising systems. This approach was successfully deployed in Alibaba's large-scale practical system.

However, these studies related to bidding price have not fundamentally explored the impact of bidding price on advertising performance metrics such as CTR and CR. During their analysis, some even assumed that higher bidding prices consistently result in improved advertising performance [16,17,20]. Some studies, such as [10], contested this assumption and attested that top positions may have lower CR and profitability because consumers are more inclined to choose recently viewed products located at the bottom based on their browsing behavior. Given the arbitrary assumptions made in previous studies, it is crucial to investigate the impact of bidding price on advertising performance. Therefore, this study essentially examines the impact of bidding price on advertising performance. Using an advertising dataset provided by retailers from e-commerce platforms, we reveal an inverted U-shaped relationship between bidding price and CTR, CR.

2.4. Product competitiveness in search advertising

Product competitiveness refers to the ability of a product to compete effectively in the market relative to similar offerings. It encompasses factors such as quality, price, features, innovation, branding, and consumer satisfaction, all of which contribute to a product's perceived value and desirability compared to alternatives. [25]. A strong product competitiveness typically implies a larger market share and better sales performance for the product [71].

The sponsored search marketplace is an exceedingly dynamic environment with thousands of firms constantly entering the market [21], thus escalating the level of competition, which has been shown to have a direct effect on both sponsored search revenue (Edelman and Ostrovsky 2007; [27]) as well as retailers' bidding strategies ([72]; Lu et al. 2015). Some scholars have tried to investigate the impact of competitiveness on advertising performance. For example, [26] established a game model containing companies with different levels of company competitiveness to explore the value of the top position for retailers in paid search advertising. The results showed that in different competitive situations, companies should formulate different bidding strategies to achieve better paid search advertising results. In addition to analyzing the effects of company competitiveness on paid search advertising, studies focusing on the impact of competitiveness of business environment have also been conducted. [21] analyzed a dataset comprising 500 US retailers and found that for multi-channel retailers, keyword competition intensity has a significant moderating effect on the impact of variables such as advertisement quality on the final placement of advertising products.

Although fruitful findings have been yielded by the previous studies regarding the impact of competitiveness on search advertising, they focus on the competitiveness of firms or business environment, but not competitiveness of individual product. Past studies on search advertising pointed out the importance of rival products which appear near the advertised product. For example, [11] demonstrated that the effectiveness of sponsored search advertisements is contingent upon the organic search result displayed on the same page, and [22] further revealed that the presence of other advertised products on the result page also impacts advertising performance. As such, merely considering firm-level or market-level competitiveness is likely to blur the heterogeneity of products, thereby omitting the nuanced relationship between bidding price and advertising performance at different levels of product competitiveness. This study aims to address this issue by exploring the moderating role of product competitiveness.

3. Hypotheses development

3.1. The impact of bidding price on click-through rate

We first pay attention to the effect of bidding price increases on CTR, which can be broadly classified into two categories, the rank effect and the comparison effect. According to attention theory, consumer's attention is scarce [73,74] and consumers tend to sequentially browse through the search results [53], devoting the majority of their attention to the top-ranked items while paying less attention to the middle- or lower-ranked options [54]. Therefore, advertisements appearing on the upper positions of search result are more likely to be noticed [75,76], leading to increased CTR. When the bidding price is low, the advertisement is typically placed in inferior and less visible positions [21,38]. With restricted time and attention, consumers are unlikely to notice them [77], thus resulting in low CTR. As the bidding price increases, the advertised product can secure better placements, which are more visible and likely to attract consumer attention, resulting in higher CTR. Nonetheless, as the bidding price continues to increase and the advertisement display position approaches the top of the page, the marginal benefit of increasing the bidding price diminishes [38,78]. Consequently, the "rank effect" of bidding price increases may not be linear, but instead, it may exhibit a non-uniform pattern that initially increases rapidly, then slows down, and eventually stabilizes at a certain level.

As for the comparison effect, it refers to the advertising performance of target advertised products on specific display positions could be influenced by rival products displayed around [22,79,24], which corresponds to the comparative attention [22,56]. Search results for keywords generally include both organic (non-sponsored) search results and paid advertisement results, with the latter occupying a small portion and interspersed among the former [80]. Organic search results are ranked based on factors such as relevance to the search term, overall product quality, and user browsing behavior, without any manual intervention or paid promotion [81]. When the bidding price is higher, the target advertised product is placed in more salient positions, which are likely to be surrounded by products meeting consumers' preferences. As such, consumer attention will be distracted by other products, leading to lower CTR.

By overlaying these two effects of bidding price increases, we obtain the overall impact of bidding price increases on the performance of CTR, which ought to be inverted U-shaped. Based on this, we develop the following hypotheses 1.

H1. Bidding price of keywords has an inverted U-shaped impact on CTR of the advertised product, such that CTR increases initially and then declines as bidding price increases.

3.2. The moderating effect of product competitiveness on the relationship between bidding price and click-through rate

We then analyze the moderating effect of product competitiveness on the relationship between bidding price and CTR. The relationship between bidding price and CTR is illustrated by the rank effect and the comparison effect, while the comparison effect may be moderated by product competitiveness.

Product competitiveness refers to a product's ability to effectively compete in the market against similar offerings [25]. This involves several factors, including quality, price, features, innovation, branding, and consumer satisfaction, all of which influence the product's perceived value and attractiveness compared to alternatives. Among all these factors, product selling price and word-of-mouth are likely to profoundly influence product competitiveness [82,83]. Generally, selling price is a key factor influencing consumer purchasing decisions, as consumers tend to favor products that offer good value for money (Wuu et al., 2020). Word-of-mouth refers to the subjective evaluations and perceptions of past consumers regarding a product or service, reflecting consumers' overall impressions and experiences with it [84]. Positive word-of-mouth can enhance consumer trust and thus often elevate product competitiveness [41]. Consequently, we measure the competitiveness of target advertised product from the following two aspects: product competitiveness in terms of word-of-mouth and product competitiveness in terms of sale price.

When the target advertised product has strong product competitiveness, it is more likely to meet consumers' preferences in an e-commerce platform [85]. Products with higher competitiveness, such as those with better word-of-mouth or more attractive sale prices, naturally draw and retain more consumer attention. When being displayed with rival products in search results, highly competitive products can attain consumer attention, avoiding them being distracted by other products. The comparison effect proposed in hypothesis 1, where consumers compare multiple products and potentially divert their interest, is effectively minimized by high product competitiveness. As a result, the presence of strong product competitiveness weakens the adverse comparison effect, leading to a less pronounced inverted U-shaped relationship between bidding price and CTR. In other words, when product competitiveness is high, the negative impact of high bidding price on CTR diminishes. Thus, we propose the following hypotheses 2a and 2b.

H2. (a) Product competitiveness in terms of word-of-mouth and (b) product competitiveness in terms of sale price weaken the inverted U-shaped relationship between bidding price and CTR, such that the curvilinear relationship between bidding price and CTR becomes flatter if the target advertised product has higher product competitiveness in terms of word-of-mouth or product competitiveness in terms of sale price.

3.3. The impact of bidding price on conversion rate

In analyzing the impact of bidding price on CR, it is essential to distinguish between CR and CTR due to their different roles in the purchasing process. While CTR measures the initial consumer interest as they click on an advertisement, CR reflects the final decision-making stage where a user completes a purchase [86].

We break down the effect of bidding price increases on CR into position effect and comparison effect, which differ significantly from those affecting CTR. The position effect refers to the clicks originating from the bottom of page that are more likely from picky consumers who tend to click and browse many products before making a final purchase decision, while clicks on top listings are more likely to come from less picky consumers who make purchase decisions more swiftly and directly [87]. Lower positions bring lower CR. The marginal effect may exist in the position effect of bidding price increases on CR as well, continuing increasing bidding price does not bring significant growth of position effect to the target advertised product when the target advertised product has already secured a top position [38,78]. Therefore, the "position effect" of bidding price increases is not linear but instead increases at a decreasing rate. As for the comparison effect, it is similar to the one in the effect of bidding price increases on CTR. Consumers will compare multiple products before they make their final purchase decisions [88–90]; therefore, products displayed will influence the effect of bidding price increase on CR as well. When bidding price is higher, the target advertised product secures a more prominent position surrounded by better products and the comparison effect on CR will be stronger. Finally, after integrating the two effects of bidding price increases, we get the overall introverted U-shaped effect of bidding price increases on CR. Hypothesis 3 concludes our previous analysis.

H3. Bidding price of keywords has an inverted U-shaped impact on CR of the advertised product, such that CR increase initially and then declines as bidding price increases.

3.4. The moderating effect of product competitiveness on the relationship between bidding price and conversion rate

The relationship between bidding price and CR could be influenced by product competitiveness of the target advertised product, as primarily indicated by the moderating effect of product competitiveness on the comparison effect. When a target-advertised product has strong product competitiveness, it means that it is superior to the surrounding products in certain aspects. As a result, it captures consumer attention more effectively and is less likely to be influenced by products displayed around. Therefore, the comparison effect of bidding price increases on CR will be slighter and the relationship between bidding price and CR may be less inverted U-shaped when product competitiveness is strong. Considering the two kinds of product competitiveness, we then have the following hypotheses 4a and 4b.

H4. (a) Product competitiveness in terms of word-of-mouth and (b) product competitiveness in terms of sale price weaken the inverted U-shaped relationship between bidding price and CR, such that the curvilinear relationship between bidding price and CR becomes flatter if the target advertised product has higher product competitiveness in terms of word-of-mouth or product competitiveness in terms of sale price.

4. Methodology

4.1. Data and sample

The dataset used in this study comprises panel data, which integrates data obtained from three distinct sources. The first source, provided by a fashion retailer selling products on a leading e-commerce platform, includes 10,734 advertising records of 421 advertised SKUs and 206 keywords. These records were obtained from the backend system of the e-commerce platform and encompass various advertising parameters such as advertising types, keywords, match types, target advertised products, cost-per-click, total cost, product sales, and order quantity for each keyword advertisement on a daily basis.

The second source of data pertains to the search results of specific keywords obtained from the leading e-commerce platform, which are used to construct the competitor sets of target advertised products under particular keywords. This data reflects the information that consumers will see after they input keywords into the search box and search on e-commerce platforms. We acquire these data by inputting these keywords into the search box on the e-commerce platform for several consecutive days to retrieve all search results provided by the search engine. The data set contains more than 100,000 parts of records and 39,066 unique products, each of which consists of product ID, product title, product images, and other product-related information.

The third source of data comes from a company specialized in providing data services for retailers on the aforementioned e-commerce platform. We exported the mentioned 39,066 unique products' sale prices, comment scores, and review quantities data from September 14, 2022, to August 30, 2023, by purchasing and invoking their API interface. This portion of data will be used to construct the indexes of product competitiveness of target advertised products in terms of sale price and word-of-mouth. This dataset contains ten million records, mainly including fields such as product ID, product image, sale price, and comment score.

4.2. Measures

We have two dependent variables here, CTR and CR. CTR is defined as the ratio of clicks to impressions for a specific advertisement, while CR is defined as the ratio of sales volume to clicks brought by a specific advertisement.

Bidding price serves as the primary independent variable here and is proxied by the cost-per-click, which denotes the average cost paid for multiple consumer clicks on the same keyword advertisement. Essentially, bidding price is the price level set by retailers, reflecting their willingness to pay for each click, while cost-per-click represents the actual amount paid by retailers. In most cases, these values are closely aligned, subtle differences arise due to e-commerce platforms utilizing a generalized second-price auction mechanism to determine ad placement, where the final payment by retailers corresponds to the bid of the second-highest bidder [91]. The practice of using cost-per-click as a proxy variable for bidding price is not rare, as exemplified by Yang et al. [92].

Product competitiveness in terms of word-of-mouth and product competitiveness in terms of sale price are two moderators, which are constructed based on similar logic. Product competitiveness in terms of word-of-mouth is calculated as the difference between target advertised product's comment score and the weighted average comment score of its competitors, but product competitiveness in terms of sale price is calculated as the difference between the weighted average sale price of competitors and target advertised product's sale price. The identification of competitors relies on the second data source search results of specific keywords obtained from the leading e-commerce platform, products appeared on the first 7 pages of search results were identified as competitors of target advertised product. Given that different competitor products may pose varying levels of competition due to stylistic differences, we use the similarity between each competitors' images and the target advertised product's image to compute weighted average scores and prices. This similarity is computed using the pre-trained ResNet-50 model in TensorFlow, which is developed by Google [93] and based on Residual Network [94,95]. On a specific day, the word-of-mouth competitiveness of target advertised product is calculated by subtracting the weighted average comment score of competing products for a particular keyword from the comment score of target advertised product on that day. Additionally, sale price competitiveness is determined by subtracting target advertised product's sale price from the weighted average sale price of competing product.

Some control variables are included as well. Display quantity (DISPLAY) signifies the number of times the advertised product is shown to consumers and click number (CLICK) represents the number of consumer clicks received by a keyword advertisement in a day. MATCH is related to the matching mechanisms between advertised keywords and search queries entered by users, with three main types: exact match, phrase match, and broad match. Exact match requires user queries to exactly match advertised keywords. Phrase match includes the advertised keyword in user queries, while broad match encompasses terms with similar meanings to the keywords. EXACT and BROAD are two dummy variables of match types, EXACT equals 1 when the keyword match type is exact match, BROAD equals 1 when the keyword match type is broad match, while EXACT and BROAD both equal 0 when the keyword match type is Phrase match.

The influence of time factors should also be considered as control variables. Markets may undergo changes, such as the preference for short sleeves in summer and the popularity of down jackets in winter. To control the impact of such temporal variations on advertising effectiveness, we incorporate dummy variables for each month, denoted as MONTH1, MONTH2, …, MONTH12, to account for differences across the 12 months in a year. The descriptions of those main variables are shown in Table 2 while Table 3 is the correlation matrix of them. Generally, the correlation matrix shows no sign of multicollinearity.

Table 2
Descriptive statistics.

	Mean	SD	Min	Max
Dependent Variables				
CTR	0.012	0.031	0.000	0.750
CR	0.045	0.110	0.000	0.080
Independent Variables				
BP	0.374	0.169	0.020	1.260
WC	−2.411	3.848	−43.113	4.966
PC	−1.749	9.188	−38.279	53.561
Control Variables				
DISPLAY	1758.546	3050.798	2.000	61,428
CLICK	5.730	7.607	1.000	108.000
EXACT	0.322	0.467	0.000	1.000
BROAD	0.144	0.352	0.000	1.000

Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

4.3. Model specification

In this research, we employed a two-way fixed effects regression model with standard errors clustered at the keyword level. This methodological choice was driven by several considerations. First, the two-way fixed effects model effectively controls unobserved heterogeneity at both product and keyword levels, which is crucial given our data structure. Second, the Hausman test yielded significant results ($p < 0.05$), indicating that fixed effects estimation is more efficient and consistent compared to random effects in our context. Additionally, clustering standard errors at the keyword level addresses potential serial correlation and heteroskedasticity in the error terms within keyword groups. This approach allows us to account for time-invariant characteristics that might influence our dependent variable while producing more robust and unbiased estimates.

The regression model we used in the analysis of CTR and CR are:

$$\begin{aligned} Log\_CTR_{i,t} = {} & \beta_i + \beta_1 BP_{i,t} + \beta_2 BP_{i,t}^2 + \beta_3 WC_{i,t} + \beta_4 PC_{i,t} + \beta_5 BP_{i,t} * WC_{i,t} \\ & + \beta_6 BP_{i,t}^2 * WC_{i,t} + \beta_7 BP_{i,t} * PC_{i,t} + \beta_8 BP_{i,t}^2 * PC_{i,t} \\ & + \beta_9 DISPLAY_{i,t} + \beta_{10}\ EXACT_{i,t} + \beta_{11} BROAD_{i,t} \\ & + \beta_{12} MONTH1_{i,t} + \beta_{13} MONTH2_{i,t} \ldots + \beta_{22} MONTH11_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

And

$$\begin{aligned} Log\_CR_{i,t} = {} & \beta_i + \beta_1 BP_{i,t} + \beta_2 BP_{i,t}^2 + \beta_3 WC_{i,t} + \beta_4 PC_{i,t} + \beta_5 BP_{i,t} * WC_{i,t} \\ & + \beta_6 BP_{i,t}^2 * WC_{i,t} + \beta_7 BP_{i,t} * PC_{i,t} + \beta_8 BP_{i,t}^2 * PC_{i,t} + \beta_9 CLICK_{i,t} \\ & + \beta_{10}\ EXACT_{i,t} + \beta_{11} BROAD_{i,t} + \beta_{12} MONTH1_{i,t} \\ & + \beta_{13} MONTH2_{i,t} \ldots + \beta_{22} MONTH11_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

The distribution of dependent variables CTR and CR are severely left-skewed; therefore, we use their logarithm. $Log\_ctr_{i,t}$ is the logarithm of advertising keyword i's CTR at time t, $Log\_CR_{i,t}$ is the logarithm of advertising keyword i's CR at time t. $BP_{i,t}$ and $BP_{i,t}^2$ are bidding price for advertising keyword i at time t and its squared term. $WP_{i,t}$ and $CP_{i,t}$ represent product competitiveness in terms of word-of-mouth and product competitiveness in terms of sale price, respectively. In addition, $BP_{i,t}*WC_{i,t}$, $BP_{i,t}^2*WC_{i,t}$, $BP_{i,t}*PC_{i,t}$ and $BP_{i,t}^2*PC_{i,t}$ are four interaction terms between bidding price, bidding price's squared term, and the two metrics of product competitiveness. The others are control variables. $DISPLAY_{i,t}$ and $CLICK_{i,t}$ are display quantity and click number, $DISPLAY_{i,t}$ only appears in the regression of CTR while $CLICK_{i,t}$ only appears in the regression of CR. $EXACT_{i,t}$ and $BROAD_{i,t}$ are two dummies related to match types. Further, $MONTH1_{i,t}$, $MONTH2_{i,t}$ … $MONTH11_{i,t}$ are dummies signifying different months.

5. Analytical results

5.1. Regression on click-through rate

We first analyzed the results of the regression on CTR. The dependent variable here is the logarithm of CTR. Regression results of models 1–4 are presented in Table 4, but some control variables concerning different keywords and months were omitted. The first model included only control variables related to time effect, individual effect, match types and display quantities. The second model added the bidding price and its squared term to the first model. The third model included the two moderating variables themselves, product competitiveness in terms of word-of-mouth and product competitiveness in terms of sale price, in addition to the second model. Interaction terms related to bidding price, bidding price's squared term and the two moderators were added to the fourth model.

In the regression results of model 2, the coefficient for bidding price is 8.831, and this variable is significant at 0.1 % level. The coefficient for

Table 3
Correlation matrix.

	1	2	3	4	5	6	7	8	9
1. CTR	1.000								
2. CR	0.047	1.000							
3. BP	0.020	0.300	1.000						
4. WC	0.001	−0.215	−0.091	1.000					
5. PC	−0.413	0.023	−0.048	0.044	1.000				
6. DISPLAY	−0.206	−0.052	−0.027	−0.061	0.314	1.000			
7. CLICK	−0.052	−0.205	−0.004	0.036	−0.140	0.126	1.000		
8. EXACT	0.053	0.044	0.166	0.085	0.034	−0.052	−0.104	1.000	
9. BROAD	−0.056	−0.071	−0.057	0.033	0.051	0.092	0.218	−0.284	1.000

Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

Table 4
Regression result of CTR.

DV: Log_CTR	Model 1	Model 2	Model 3	Model 4
EXACT	0.153	0.040	−0.391	−0.024
BROAD	0.048	0.155	−0.601	−0.038
DISPLAY	−2.6e-05***	−2.4e-05***	−1.9e-05***	−1.7e-05***
BP	–	8.831***	8.523***	7.470***
BP^2	–	−7.838***	−7.648***	−5.282***
WC	–	–	−0.220***	0.377***
PC	–	–	−0.178***	−0.187***
BP *WC	–	–	–	−1.078***
BP^2*WC	–	–	–	1.445***
BP *PC	–	–	–	−0.263***
BP^2*PC	–	–	–	0.627***
Month FE	YES	YES	YES	YES
Constant	−3.815***	−5.884***	−5.709***	−5.823***
Observations	10,734	10,734	10,734	10,734
Overall R^2	0.100	0.115	0.440	0.475
Within R^2	0.135	0.170	0.254	0.326
U shape test	–	$p = 0.001$**	$p = 0.002$**	–
95 % Fieller interval for extreme point	–	[0.495, 0.768]	[0.491, 0.754]	–
Extreme point	–	0.563	0.557	–
Slopes when BP=0.02	–	8.518***	8.217***	–
Slopes when BP=1.26	–	−10.520**	−10.749**	–

Notes:.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

the squared term of bidding price is −7.838, and this variable is significant at 0.1 % level as well. The significance of bidding price and its squared term, together with the negative coefficient of the squared term, signifies a non-linear relationship between bidding price and CTR. To rigorously validate the hypothesized non-linear relationship, we employed the systematic three-step testing approach for U-shaped relationships as proposed by [96]. This methodology provides more stringent validation standards compared to conventional approaches that rely solely on the significance of quadratic terms. First, we checked whether the extreme point is within the range of the independent variable. We found the extreme point to be 0.563, with a 95 % confidence interval of [0.495 - 0.768]. This is within the 0.020–1.260 range of the independent variable. Second, we assessed the slopes at the lower and upper ends of the distribution, which should be sufficiently deep and have different signs. We found that when bidding price is 0.020, the slope is 8.518 and significant ($p = 0.000$), while when bidding price is 1.260, the slope is −10.520 and significant ($p = 0.001$). Third, the p value of the overall test of presence of an inverted U-shape is 0.002. The satisfaction of all three criteria not only validates the existence of the inverted U-shaped relationship but also ensures its statistical and substantive reliability, thereby providing robust support for Hypothesis 1, which posits that CTR exhibits a U-shaped relationship with bidding price. When the bidding price is relatively low, the rank effect of attention predominantly comes into play. Increasing the bidding price can elevate the target advertised product from a lower position to a more prominent one, thereby gaining more consumers' attention and enhancing its CTR. However, if the bidding price continues to increase, the comparison effect may become more significant. As the target advertised product advances in position, the competition from surrounding products intensifies, which can distract consumers' attention. Consequently, the CTR of the target advertised product may decline. The precise form of this inverted U-shape association is depicted in Fig. 1.

Next, we examine the moderating effect of product competitiveness on the above relationship. In model 4, the coefficients for the interaction term between product competitiveness in terms of word-of-mouth and bidding price's squared term is 1.445 and significant at 0.1 % level, indicating that product competitiveness in terms of word-of-mouth significantly influences the relationship between bidding price and CTR. More specifically, the positive coefficient of the interaction term implies that product competitiveness in terms of word-of-mouth weakens the inverted U-shaped relationship between bidding price and CTR. In other words, when product competitiveness in terms of word-of-mouth is stronger, the relationship between bidding price and CTR will be less inverted U-shaped. Therefore, hypothesis 3a is supported. As for the moderating effect of product competitiveness in terms of sale price, it shows a similar pattern. The interaction term between product competitiveness in terms of sale price and the squared bidding price is significant and positive as well, meaning that product competitiveness in terms of sale price weakens the inverted U-shaped relationship between bidding price and CTR, hypothesis 3b is supported. The moderating role of product competitiveness in the relationship between bidding price and CTR can be understood from this perspective: When the target advertised product has stronger competitiveness, it

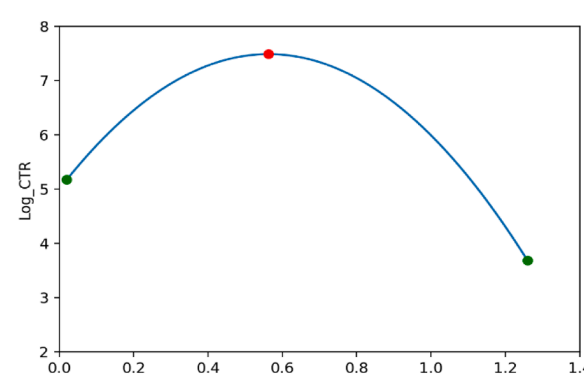

Fig. 1. Inverted U-shaped relationship between bidding price and CTR.

holds an advantage over surrounding competing products. Consequently, it is less affected by the comparison effect, allowing the rank effect to remain dominant for a longer duration. Therefore, the relationship between bidding price and CTR becomes less inverted U-shaped.

The previous analysis demonstrates that product competitiveness can flatten the inverted U-shaped relationship between bidding price and CTR. Additionally, the turning point of the inverted U-shaped curve between bidding price and CTR may also be moderated by product competitiveness. From the results presented in model 4 of Table 4, we can observe that not only the two interaction terms between the squared bidding price and product competitiveness are significant, but also the two interaction terms between the linear term of bidding price and the two kinds of product competitiveness, which collectively affect the shift direction of turning point as product competitiveness changes. According to [96]'s description, in a regression model in the form of formula (3), the direction of the shift in the turning point is determined by the sign of the numerator (4). If the numerator is positive, the turning point will shift to the right as the moderator increases. Conversely, if the numerator is negative, the turning point will shift to the left. According to the regression result of model 4, we calculate the numerators of the two moderators, word-of-mouth competitiveness and sales price competitiveness, which both turn out to be positive. Therefore, the turning point of the inverted U-shaped curve between bidding price and CTR will shift to right as word-of-mouth competitiveness or sales price competitiveness increases.

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 XZ + \beta_4 X^2 Z + \beta_5 Z \tag{3}$$

$$\beta_1 \beta_4 - \beta_2 \beta_3 \tag{4}$$

To gain a more intuitive understanding of the moderating effect of product competitiveness in terms of word-of-mouth and product competitiveness in terms of sale price on the relationship between bidding price and CTR, we have depicted the graphical relationships between bidding price and CTR with different levels of the two moderators in Figs. 2 and 3, respectively. Fig. 2 concerns the moderating effect of product competitiveness in terms of word-of-mouth and Fig. 3 refers to the moderating effect of product competitiveness in terms of sale price. Blue line represents the relationship between bidding price and CTR for products with strong product competitiveness, which is one standard deviation above the sample mean. Orange line represents the relationship for products with moderate product competitiveness in terms of word-of-mouth, the value of product competitiveness is the sample mean. Moreover, green line represents the relationship for products with weak product competitiveness, one unit of standard deviation below the mean. It can be observed that when product competitiveness in terms of word-of-mouth or product competitiveness in terms of sale price is relatively large, the inverted U-shaped relationship between bidding price and CTR becomes less pronounced, and the peak of the curve shifts more to the right, compared to when product competitiveness is moderate or low.

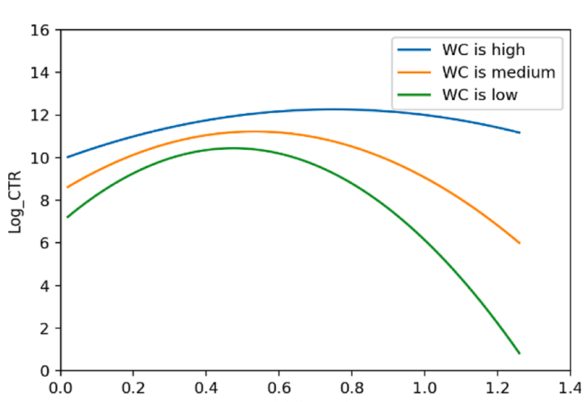

Fig. 2. Moderating effect of product competitiveness in terms of word-of-mouth on the impact of bidding price on CTR.

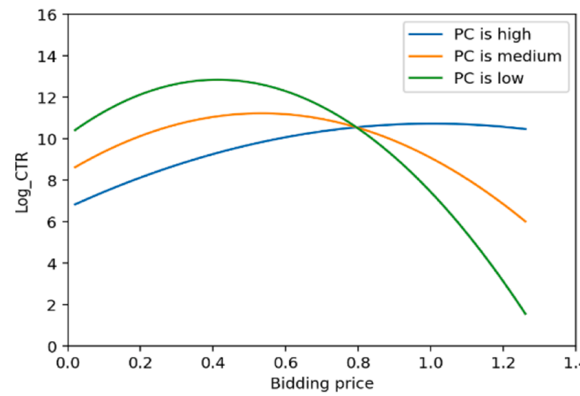

Fig. 3. Moderating effect of product competitiveness in terms of sale price on the impact of bidding price on CTR.

For retailers participating in search advertising, including those leveraging AI systems for dynamic pricing and bidding, the previous analytical results have great practical significance. The observed relationship between bidding price and CTR is an inverted U-shape, indicating that higher bidding price do not necessarily lead to higher CTR. Rather, increasing the bidding price can result in diminishing returns in terms of CTR and an escalation in advertising expenditure for retailers. For retailers focused on optimizing CTR, it is crucial to identify the optimal bidding price. Our study on the moderating effect of product competitiveness offers insights into how retailers can find this optimal bidding price. Specifically, when word-of-mouth competitiveness or sale price competitiveness is strong, the optimal bidding price tends to be higher. Furthermore, as product competitiveness weakens, the inverted U-shaped relationship between bidding price and CTR becomes more pronounced, underscoring the importance for retailers to determine the optimal bidding price.

5.2. *Regression on conversion rate*

We then analyze the results of the regression on CR and the dependent variable here is the logarithm of CR. Similarly, four regression models with the same settings were presented in Table 5, though display quantity was replaced by click number. Model 5 included control variables only, model 6 included bidding price and its squared term. Product competitiveness in terms of word-of-mouth and product competitiveness in terms of sale price were added into the regression model 7, while model 8 further incorporated interaction terms between bidding price's squared term and two kinds of product competitiveness.

In model 6′s regression result, the coefficient of bidding price is 1.342 and significant at 0.1 % level. Meanwhile, the coefficient for the squared term of bidding price is −0.970, significant at 0.1 % level. The two variables are statistically significant and the negative coefficient for the squared term signaled a non-linear relationship between bidding price and CR. Again, we tried to test the non-linear relationship further. Firstly, the extreme point, 0.692, is within the range of the independent variable. Secondly, we evaluated the slopes at the lower and upper ends of the distribution. When bidding price is 0.020, the slope is 1.304 and significant ($p = 0.000$), while when it is 1.260, the slope is −1.101 and significant ($p = 0.000$). Last, the p-value of the overall test of the inverse U-shape's presence is 0.000. These findings support Hypothesis 3, which suggests that CR initially decreases and subsequently increases as the bidding price increases. The exact form of this inverted U-shape relationship is illustrated in Fig. 4. As we discussed in the hypothesis formulation section, when the bidding price is low, increasing the

Table 5
Regression result of CR.

DV: Log_CR	Model 5	Model 6	Model 7	Model 8
EXACT	9.2e-05	−0.014	−0.015	−0.014
BROAD	0.026	0.029	−0.028	−0.028
CLICK	−0.003***	−0.003***	−0.003***	−0.003***
BP	–	1.342***	1.338***	0.918***
BP^2	–	−0.970***	−0.965***	−0.552***
WC	–	–	0.001	0.044***
PC	–	–	−0.001	−0.003
BP *WC	–	–	–	−0.206***
BP^2*WC	–	–	–	0.206***
BP *PC	–	–	–	0.008
BP^2*PC	–	–	–	−0.010
Month FE	YES	YES	YES	YES
Constant	0.157***	−0.186***	−0.187***	−0.097**
Observations	10,734	10,734	10,734	10,734
Overall R^2	0.048	0.176	0.160	0.183
Within R^2	0.028	0.102	0.103	0.115
U shape test	–	$p =$ 0.000****	$p =$ 0.000***	–
95 % Fieller interval for extreme point	–	[0.650, 0.747]	[0.650, 0.748]	–
Extreme point	–	0.692	0.693	–
Slopes when BP=0.02	–	1.304***	1.300***	–
Slopes when BP=1.26	–	−1.101***	−1.059**	–

Notes.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

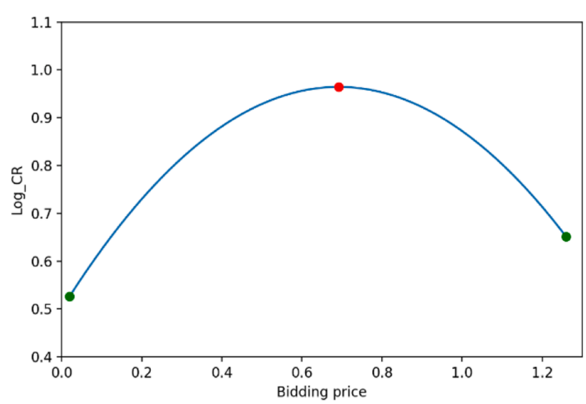

Fig. 4. Inverted U-shaped relationship between bidding price and CR.

bidding price primarily enhances the position effect, leading to an increase in the CR of the target advertised product. However, as the bidding price continues to rise, the comparison effect begins to dominate, causing a decline in CR due to the intensified competition from surrounding products.

Then, it is the moderating effect of product competitiveness on the relationship between bidding price and CR. From model 8, it can be seen that the interaction term between the squared bidding price and product competitiveness in terms of word-of-mouth is significant at 0.1 % level and its parameter is 0.206, which has the opposite sign with the parameter of the squared bidding price. Therefore, product competitiveness in terms of word-of-mouth flattens the inverted U-shaped curve between bidding price and CR as well, hypothesis 4a is supported. However, the interaction terms between product competitiveness in terms of sale price and bidding price, the squared bidding price are insignificant in model 8. Therefore, we know that product competitiveness in terms of sale price does not moderate the relationship between bidding price and CR, hypothesis 4b is unsupported. The moderating effect of word-of-mouth competitiveness on the relationship between bidding price and CR can be understood through its influence on the comparison effect. When a target advertised product has strong word-of-mouth competitiveness, it holds an advantage over competing products, resulting in less competition from surrounding products. Consequently, the negative effect is reduced, making the relationship between bidding price and CR less inverted U-shaped. The reason why product competitiveness in terms of sale price does not moderate the impact of bidding price on CR may be that consumers in this field are not that price-sensitive.

The turning point of the inverted U-shaped curve between bidding price and CR is also influenced by word-of-mouth competitiveness. The interaction terms between word-of-mouth competitiveness and the linear term of bidding price, the squared term of bidding rice, are both significant. Similarly, here based on the regression result of model 8, we calculated the numerator (4) of word-of-mouth competitiveness and got a positive value. Therefore, with the increase of word-of-mouth competitiveness, the turning point of the inverted U-shaped curve between bidding price and CR will shift to the right.

To gain a more intuitive understanding of the moderating effect of product competitiveness in terms of word-of-mouth, a graph depicting the relationship between bidding price and CR with various levels of product competitiveness in terms of word-of-mouth is presented in Fig. 5. The blue line, orange line and green line represent the relationship between bidding price and CR for products with strong, moderate, and weak product competitiveness in terms of word-of-mouth, respectively. The blue line, which refers to higher product competitiveness in terms of word-of-mouth, is flatter and higher than the other two lines, while its peak shifts more to the right.

For retailers focused on optimizing CR, including those leveraging AI systems for dynamic pricing and bidding, the findings of the aforementioned analysis provide strategic guidance for enhancing their CR performance. The observed curvilinear relationship between bidding price and CR indicates that retailers need to identify the optimal bidding price that can maximize their CR. Importantly, the analysis reveals that word-of-mouth competitiveness moderates this inverted U-shaped relationship between bidding price and CR. Specifically, higher levels of word-of-mouth competitiveness tend to weaken the inverted U-shaped effect. This suggests that as a product's word-of-mouth competitiveness increases, retailers should consider proactively adjusting their bidding prices upwards. Furthermore, for products with weaker word-of-mouth competitiveness, the importance of precisely determining the optimal bidding price is amplified. Interestingly, in contrast to the findings regarding CTR, sale price competitiveness does not appear to moderate the relationship between bidding price and CR. This insight implies that if retailers solely focus on conversion optimization, adjusting sale prices may not be an effective lever for improving performance in this regard. Overall, the analysis provides retailers focused on CR optimization with valuable guidance on calibrating their bidding strategies. Specifically,

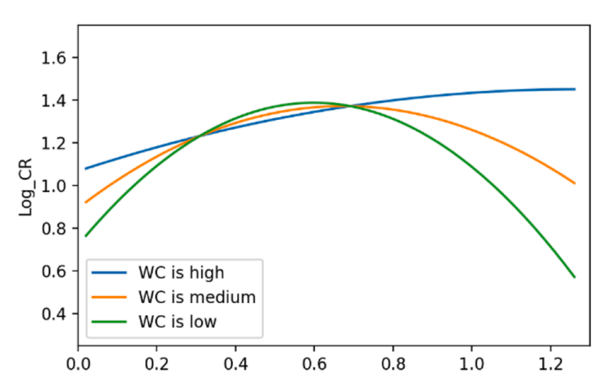

Fig. 5. Moderating effect of WC on the impact of bidding price on CR.

they should seek to identify the profit-maximizing bidding price, while also accounting for changes in a product's word-of-mouth competitiveness over time.

5.3. Robustness checks

Ensuring the reliability and validity of empirical findings is crucial for drawing solid conclusions. To this end, we carried out a series of robustness checks to verify the stability and generalizability of our results.

Firstly, there might be issues related to autocorrelation and heteroskedasticity in the data. The method developed by Driscoll and Kraay (1998) for estimating standard errors allows for the presence of both heteroskedasticity and autocorrelation in the error terms of panel data. It also remains robust in the face of potential cross-sectional correlation. To address concerns of autocorrelation and heteroskedasticity, we utilized the "xtscc" command in Stata, introduced by Hoechle (2007), to implement the standard errors proposed by Driscoll and Kraay (1998). The regression results for CTR and CR were presented in model 9 and model 10 of Table 6, respectively. Compared with our main regression result in model 4 and model 8, minimal differences can be observed in model 9 and model 10. Consequently, we can confidently assert that our regression results are robust and not influenced by autocorrelation and heteroskedasticity.

Retailers dynamically adjust their advertising keywords, and such adjustments may affect our analysis. Some keywords were advertised for only a few days. To examine the robustness of our research findings considering this issue, we conducted additional analyses. Specifically, we excluded keywords with a duration of less than 15 days and re-conducted the regression analysis. Regression results for CTR and CR were presented in model 11 and model 12. We found that regression results remained largely unchanged in terms of significance and sign of coefficients, except for changes in their magnitude.

Further, one may express doubts that the relationship between bidding price and CTR, CR may follow an S-shaped pattern, as opposed to the previously hypothesized inverted U-shaped pattern. To address this concern, the cubic term of bidding price has been added into regression models. In model 13, we added the cubic term of bidding price into the regression of CTR, while in model 14, we added the cubic term of bidding price into the regression of CR. The cubic terms of bidding price in model 13 and model 14 were not significant. Therefore, our findings suggest that the influence of bidding price on CTR and CR is more likely to follow an inverted U-shaped pattern, rather than an S-shaped pattern.

Currently, we consider the products appearing in the first seven pages of keyword search results as competitors for the target advertised products, based on the fact that the e-commerce platform displays only seven pages of search results for each keyword search. Some might argue that using such an extensive range of competitors to construct the competitors set is unreasonable and that the competitors set should be narrowed, given the limited attention span of consumers. Therefore, we attempt to reduce the scope of competitors and conduct further analysis. Table 7 presents the regression results after narrowing the scope of competitors. Models 15, 16, and 17 show the regression results on CTR after narrowing the scope to five pages, three pages, and one page, respectively. Models 18, 19, and 20 show the regression results on CR after narrowing the scope to five pages, three pages, and one page, respectively. A comparative analysis of the results indicates that, overall, the reduction in the scope of competitors does not significantly impact the outcomes, although the significance of certain interaction terms decreases. Notably, when the scope is narrowed to one page, the significance of the interaction term between the quadratic term of bidding price and the product's word-of-mouth competitiveness is substantially reduced in the regression on CTR, though it remains significant at the 10 % level ($p = 0.066$). The decrease in the significance level of some variables after narrowing the competitors set may be attributed to the limited scope of competitors, which might not adequately capture the competitive influence.

Consumers might search for different keywords multiple times during their purchasing process, and retailers may set multiple advertised keywords for the same product. Currently, our unit of analysis is at the product-keyword level. A potential concern is whether assigning multiple keywords to the same product might affect the robustness of our results. To address this, we aggregated the advertising data at the product level, summarizing data for products with multiple keywords. Table 8 presents the regression results after aggregating the data at the product level. Models 21 and 22 show the regression results for CTR, with model 22 including the product competitiveness indexes and related interaction terms. Models 23 and 24 show the regression results

Table 6
Regression results with Driscoll and Kraay standard errors.

DV	Model 9 Log_CTR	Model 10 Log_CR	Model 11 Log_CTR	Model 12 Log_CR	Model 13 Log_CTR	Model 14 Log_CR
EXACT	−0.024	−0.014	−0.061	−0.018	0.037	−0.013
BROAD	−0.038	0.028	−0.026	0.064	0.142	0.031
DISPLAY	−1.7e-05***	–	−1.6e-05***	–	−2.4e-05***	–
CLICK	–	−0.003***	–	−0.003***	–	−0.003***
BP	7.470***	0.918***	7.654***	0.810***	10.859***	1.017***
BP^2	−5.282***	−0.552***	−5.254***	−0.510***	−11.883*	−0.342
BP^3	–	–	–	–	2.315	−0.353
WC	0.377***	0.044***	0.344**	0.054***	–	–
PC	−0.187***	−0.003	−0.194***	−0.004	–	–
BP *WC	−1.078*	−0.206***	−0.974*	−0.241***	–	–
BP^2*WC	1.445**	0.206***	1.436***	0.222***	–	–
BP *PC	−0.263**	0.008	−0.210*	0.014	–	–
BP^2*PC	0.627***	−0.010	0.578***	−0.013	–	–
Month FE	YES	YES	YES	YES	YES	YES
Constant	−5.823***	−0.097***	−6.042***	−0.073	−6.175***	−0.137**
Observation	10,734	10,734	8646	8646	10,734	10,745
Overall R^2	–	–	0.504	0.176	0.117	0.172
Within R^2	0.326	0.115	0.353	0.120	0.170	0.101

Notes.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

Table 7
Regression result with various competitors scope.

DV	Log_CTR			Log_CR		
Model	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
EXACT	0.043	0.027	0.049	−0.013	−0.014	−0.014
BROAD	0.189	0.155	0.160	0.029	0.029	0.028
DISPLAY	−2.3e-05***	−2.3e-05***	−2.3e-05***	–	–	–
CLICK	–	–	–	−0.003***	−0.003***	−0.003***
BP	8.169***	8.145***	8.687***	1.233***	1.285***	1.316***
BP^2	−6.746***	−6.876***	−7.563***	−0.852***	−0.913***	−0.943***
WC	0.061	0.045*	0.013	0.010***	0.005**	0.003*
PC	−0.003	−0.002	0.006	−1.2e-04	6.0e-04	−6.7e-04
BP *WC	−0.360*	−0.228*	−0.075	−0.053***	−0.023**	−0.014*
BP^2*WC	0.498**	0.284**	0.101	0.056***	0.023**	0.014*
BP *PC	−0.219*	−0.132*	−0.128*	6.1e-04	−0.004	0.002
BP^2*PC	0.357**	0.238**	0.198**	8.5e-04	0.004	−8.4e-04
YES	YES	YES	YES	YES	YES	YES
Constant	−5.901***	−5.782***	−5.887***	−0.166***	−0.174***	−0.182***
Observations	10,734	10,734	10,734	10,734	10,734	10,734
Overall R^2	0.257	0.184	0.163	0.188	0.182	0.178
Within R^2	0.207	0.194	0.185	0.107	0.104	0.103

Notes.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

Table 8
Regression result aggregated at product level.

DV	Log_CTR		Log_CR	
Model	Model 21	Model 22	Model 23	Model 24
EXACT	−0.411	−0.290	−0.008	0.004
BROAD	−0.321	−0.385	−0.021	−0.025
DISPLAY	−2.5e-05***	−2.0e-05***	–	–
CLICK	–	–	−0.002***	−0.002***
BP	8.355***	5.651**	1.167***	1.037***
BP^2	−8.560***	−4.609**	−0.858***	−0.698***
WC	–	0.110*	–	0.009*
PC	–	0.075***	–	−0.002*
BP *WC	–	−0.608**	–	−0.047*
BP^2*WC	–	0.920***	–	0.056**
BP *PC	–	−0.498***	–	0.013*
BP^2*PC	–	0.582***	–	−0.017**
Month FE	YES	YES	YES	YES
Constant	−5.748***	−5.400***	−0.161**	−0.145**
Observations	4636	4636	4641	4641
Overall R^2	0.241	0.345	0.163	0.151
Within R^2	0.296	0.360	0.127	0.136
U shape test	4.65***	–	5.49***	–
95 % Fieller interval for extreme point	[0.414,0.573]	–	[0.626,0.748]	–
Extreme point	0.488	–	0.680	–
Slopes when BP=0.02	4.889***	–	6.904***	–
Slopes when BP=1.26	−4.646***	–	−5.485***	–

Notes.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

for CR, with model 24 including the product competitiveness indexes and related interaction terms. The results indicate that after shifting the unit of analysis to the product level, there are no substantial changes in the regression outcomes. The signs and significance levels of the variables remain largely unchanged, except for the interaction term between sale price competitiveness and the quadratic term of the bidding price in the regression for CR, which becomes significant after previously being insignificant. This suggests that our results are robust even when the data are aggregated at the product level.

Although various methods and many kinds of robustness checks have been employed, it is possible that we have not entirely resolved the potential endogeneity concern between bidding price and advertising performance. For instance, numerous confounding factors may simultaneously influence both bidding price and advertising performance. To further address this endogeneity concern, we identified an instrumental variable: budget of advertising campaign. On this e-commerce platform, the budget is set at the campaign level, while keywords and bidding prices are set at the advertising group level, with a single campaign potentially encompassing multiple advertising groups. In addition, based on feedback from companies, advertising budget allocation does not correlate with product quality. Indeed, products of inferior quality often require more substantial advertising support to maintain market presence. Therefore, the campaign budget does not relate to the CTR or CR of individual keywords. Conversely, the campaign budget is related to bidding prices because retailers with ample funds may simultaneously increase both the campaign budget and the bidding price for keywords within various advertising groups. Thus, theoretically, the campaign budget serves as an appropriate instrumental variable for bidding price. Evidence in Table 9 supports this argument, showing that the chosen instrumental variable (BUDGET) positively correlates with bidding price while having no significant impact on CTR and CR. This implies that the instrumental variable (BUDGET) is valid. In model 25, we regress bidding price on the instrumental variable (BUDGET) and other control variables, then use the fitted values of bidding price obtained from the regression to regress on CTR and CR, yielding the results presented in Table 10. From Table 10, we observe that the regression results do not substantially differ from previous findings. In model 29, where CTR is regressed, the significance of the interaction term between sale price competitiveness and the quadratic term of bidding price decreases but remains significant at the 10 % level ($p = 0.084$). Similarly, in model 31, where CR is regressed, the significance of the interaction term between word-of-mouth competitiveness and the quadratic term of bidding price decreases but remains significant at the 10 % level ($p = 0.056$). Overall, the results from the instrumental variable regression indicate that the

Table 9
The results of the falsification test on the instrumental variable.

DV Model	BP Model 25	Log_CTR Model 26	Log_CR Model 27
BUDGET	0.007***	−0.008	9.5e-05
EXACT	0.022**	0.078	0.001
BROAD	−0.028	−0.064	−0.006
DISPLAY	1.37e-07	−2.1e-05***	–
CLICK	−3.3e-04	–	−0.003***
WC	0.001	0.209***	0.002
PC	−0.001	−0.177***	−0.002**
Constant	0.253***	−3.589***	0.153***
Observations	10,263	10,263	10,263
Month FE	YES	YES	YES
F	14.96	16.121	2.77
Overall R^2	0.366	0.221	0.019
Within R^2	0.143	0.430	0.026

Notes: *$p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

Table 10
Regression results with fitted bidding price.

Model DV	Model 28 Log_CTR	Model 29 Log_CTR	Model 30 Log_CR	Model 31 Log_CR
EXACT	0.102	0.035	−0.001	−0.001
BROAD	0.158	−0.190	−0.004	−0.004
DISPLAY	−2.5e-05***	−2.0e-05***	–	–
CLICK	–	–	−0.003***	−0.003***
BP	24.150***	11.564*	1.260*	0.482
BP^2	−31.479***	−15.044*	−1.611*	−0.703
WC	–	0.807*	–	0.075
PC	–	−0.124	–	−0.002
BP *WC	–	−3.261	–	−0.348
BP^2*WC	–	4.409*	–	0.411
BP *PC	–	−0.528	–	0.006
BP^2*PC	–	1.011	–	−0.014
Month FE	YES	YES	YES	YES
Constant	−8.145***	−5.792***	−0.082	0.079
Observations	10,263	10,263	10,263	10,263
Overall R^2	0.055	0.418	0.061	0.024
Within R^2	0.141	0.230	0.026	0.027

Notes.
* $p < 0.05$,
**$p < 0.01$.
*** $p < 0.001$.
Abbreviations: CTR, click-through rate; CR, conversion rate; BP, bidding price; WC: product competitiveness in terms of word-of-mouth; PC, product competitiveness in terms of sale price.

findings from the primary regressions in our previous sections are robust.

6. Discussion, implications, and limitations

6.1. Discussion

This study aims to explore the relationship between bidding price and advertising performance as well as the moderating role of product competitiveness on the previous relationship in e-commerce search advertising. Specifically, we examined the impact of bidding price on CTR, CR, and product competitiveness was further subdivided into two aspects: product competitiveness of word-of-mouth and product competitiveness of sale price.

First, we discovered that the relationship between bidding price and CTR is not monotone but instead exhibits an inverted U-shape, and such U-shaped relationship is weakened by both product competitiveness in terms of word-of-mouth and product competitiveness in terms of sale price. We used the rank effect and the comparison effect to explain the inverted U-shaped relationship between bidding price and CTR. The rank effect suggests that higher bidding price results in better placement of the target advertised product, making it more noticeable [21,38], so initially increasing bids can secure a better position for the product, thereby achieving a higher CTR. The comparison effect refers to that the advertising performance of the target advertised product is influenced by rival products displayed around on the result page [22,79,24], and higher bid can bring more noticeable positions as well as superior surrounding rival products, which may divert consumers' attention away and result in even lower CTR. This explains why CTR starts to drop when the bidding price reaches a point. The moderating effect of product competitiveness on this inverted U-shaped relationship can also be explained through the comparison effect. When product competitiveness of target advertised product is high, it has more advantages over surrounding rival products to some aspects, making it less likely to be influenced by surrounding products, thus weakening the adverse comparison effect. Therefore, stronger product competitiveness brings a less inverted U-shaped relationship between bidding price and CTR.

Second, we attested the inverted U-shaped relationship between bidding price and CR, and it is attenuated by product competitiveness in terms of word-of-mouth. We employed position effect and comparison effect to explain this phenomenon. The position effect posits that clicks obtained from lower positions are more likely to come from fussy consumers [87], thereby leading to lower CR. The comparison effect, consistent with earlier discussions, dictates that consumers engage in comparative analysis among products prior to purchase, and a higher bid securing a noticeable position also subjects the product to comparison with other superior products. Due to the position effect, a moderate increase in bidding price can enhance CR; however, an excessive bidding price invites a potent comparison effect, potentially undercutting CR. Regarding the weakening role of product competitiveness in terms of word-of-mouth, it can be explained as follows: when product competitiveness in terms of word-of-mouth is strong, the target advertised product has a greater advantage over surrounding rival products, reducing the downward pressure of the comparison effect on the CR. Thus, the more pronounced the product's competitiveness in terms of word-of-mouth, the more linear the impact of bidding price on CR appears.

Contrary to our expectations, product competitiveness in terms of sale price does not significantly moderate the relationship between bidding price and CR, although it does moderate the relationship between bidding price and CTR. In fact, the variable of product competitiveness in terms of sale price is not even a significant predictor of CR, which does not affect the CR of the target advertised product. In addition, although sale price competitiveness moderates the relationship between bidding price and CTR, the overall moderating effect exhibits a negative pattern. Fig. 3 depicts that the curve representing higher sale price competitiveness is positioned at a lower level, suggesting that higher sale price competitiveness leads to a reduction in CTR across the spectrum of bidding prices. This above phenomenon may be attributed to the consumer decision-making process wherein price is not the paramount consideration. Previous studies have found that in the context of e-commerce shopping, consumers tend to pay less attention to price and are more concerned with factors such as word-of-mouth [97], which is consistent with our result.

6.2. Theoretical and practical implications

This study contributes to literature on three fronts. First, this research contributes to the existing literature on bidding price in search advertising by unraveling the non-linear relationship between bidding price and advertising performance. Previous research often assumes a linear, positive relationship between bidding price and advertising performance, suggesting that higher bidding price always leads to better outcomes [16,17,20]. We challenge this assumption based on attention theory which indicates the ranking effect and the comparison effect as two underlying mechanisms leading to curvilinear relationships. Our findings attest to the inverted U-shaped relationships between bidding price and both CTR and CR, thereby prompting a reconsideration of basic assumptions when investigating bidding strategies in search advertising research.

Second, this research disentangled the moderating role of product competitiveness in shaping the effectuation of bidding price. While existing studies have examined the impact of competitiveness on search advertising at the firm or market level [21,26], our research shifts focus to product-level competitiveness. Specifically, we identify word-of-mouth and sale price as two product-specific attributes in e-commerce platforms as the basis of measuring product competitiveness in comparison with rival products appearing in search results. It is found that word-of-mouth competitiveness weakens the inverted U-shaped relationship between bidding price and CTR/CR, while sale price competitiveness only weakens the inverted U-shaped relationship between bidding price and CTR, but not conversion rate. This nuanced approach provides an in-depth understanding of how bidding price yields advertising performance under different circumstances where advertised products are exposed with rival products in search results, thereby enriching theoretical models in search advertising.

Third, this study applies attention theory to the context of search advertising in e-commerce platforms, offering a novel lens to understand the effects of bidding price on advertising performance. Attention theory, which addresses how cognitive resources are allocated [42,43], explains the non-linear relationships by underlying mechanisms of the rank effect and the comparison effect. By applying this theory, we provide new insights into how attention allocation impacts CTR and CR and demonstrate how higher bidding prices initially enhance visibility but eventually lead to diminishing returns. We also contribute to attention theory by bridging two streams of literature – selective attention and comparative attention – to be used to interpret the relationship between bidding price and advertising performance in search advertising of e-commerce platforms.

Practically, our study has significant importance to retailers advertising on e-commerce platforms. Our research reveals an inverted U-shaped relationship between bidding price and CTR, CR, indicating that increases in bidding price do not always lead to higher CTR and CR. Beyond a certain point, increasing bidding price can actually decrease CTR and CR, underscoring the importance of identifying the optimal point of bidding price for better CTR and CR to achieve more efficient advertising. From our previous analysis, we can also observe that the bidding price corresponding to the maximum CTR is 0.563, while the bidding price associated with the maximum CR is 0.692, which is 23 % higher. This implies that if retailers are more concerned with conversions during their advertising activity, they need to set a higher bidding price. Furthermore, our findings suggest that product competitiveness in terms of word-of-mouth plays a moderating role in the relationship between bidding price and CTR, CR, while product competitiveness in terms of sale price moderates the impact of bidding price on CR. When making bidding decisions in search advertising, retailers need to consider their product's competitiveness if they value CTR and CR of their advertisement.

For retailers employing AI-driven dynamic pricing models and real-time bidding adjustment strategies, our study can provide valuable guidance as well. The uncovered non-linear relationship between bidding price and advertising performance, coupled with the moderating effects of product competitiveness, can inform the algorithms and decision rules powering these AI systems. By incorporating our findings, dynamic pricing models and bidding adjustment strategies can be optimized to set prices and modify bidding price intelligently, accounting for inverted U-shaped effects and product-specific factors. This allows retailers to enhance advertising efficiency, reduce costs, and boost profitability through smarter AI-driven practices.

Therefore, the findings of this research provide practical guidance for online retailers on e-commerce platforms to engage in more effective advertising practices in search advertising. By optimizing their bidding strategies and considering the competitiveness of their advertised products, retailers can improve the efficiency of their advertising campaigns and reduce their advertising costs, ultimately leading to higher profitability.

6.3. Limitations and future research

This study provides novel insights into the impact of bidding price on advertising performance and the moderating role of product competitiveness on the effectuation of bidding price. Inevitably, it has some limitations that shed light on future research that delved into this topic. Firstly, our data comes from a retail company which sells fashion clothes on e-commerce platforms. The generalizability of our findings could be further validated using datasets from other product categories because different product categories may have their own features that may influence advertising performance [98]. Moreover, future studies are encouraged to collect data from multiple retail companies to validate whether findings are generalizable across retailers. With an expanded dataset with multiple retailers and different product categories, retailer attributes and product category attributes could be considered in the research model.

Second, this study only considers product competitiveness in terms of word-of-mouth and sale price, which fluctuate over time. Although word-of-mouth and sale price are prominent dynamic factors determining product competitiveness, future studies can explore other static factors in measuring product competitiveness, such as product design. Considering product competitiveness based on unchanged factors could yield insights on how to develop bidding strategies based on inherent attributes of advertised product.

Third, regarding advertising performance, this study solely concentrated on two metrics: CTR and CR. The rationale behind this decision is that these two metrics hold significant implications for retailers, as the advertisement's CTR directly reflects its attractiveness and CR impacts the retailers' return on investment [99]. Nevertheless, it is imperative to acknowledge that the effectiveness of an advertisement can be evaluated through other indicators, such as the sales generated by the advertisement, the revenue accrued from the advertisement, and so forth. Future research endeavors could potentially explore the impact of bidding strategies and product competitiveness on other dimensions of advertising performance.

Last, this study develops a research model at keyword level to investigate the relationship between bidding price and advertising performance from advertiser's perspective. Future studies are encouraged to build on the current study to delve into nuanced behavioral mechanisms at individual level from consumer's perspective. Specifically, the ranking effect and comparison effect inferred from attention theory could be empirically examined by conducting lab experiments to collect behavioral data of consumers. In addition, positions of advertised products could be manipulated in experiments, which renders insights into how consumers react to advertised products in various positions, which are embedded in different surrounding products.

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CRediT authorship contribution statement

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