Item-Ranking Position Effect, Price Effect and Refinement Tools

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Research on search engine marketing (SEM) has garnered attention across various fields, as it provides filtering and ranking recommendations to combat information overload. In the field of Information Systems (IS), researchers have studied consumer search behavior in order to design more effective search engines.

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click-through decision

1. Introduction

Search engines and social media platforms have been significant channels for recommending and selling products or services for tourism planning. The business model reshaped the way that travelers search for and filter tourism information over the last few decades [1][2][3][4]. Increasing the click-through rate on travel search platforms is essential for OTAs to earn agency commissions from hotel advertisers such as hotel booking sites and hotel chains. However, mobile commerce has drastically changed the way individuals plan and book their preferred hotels and handle other travel-related matters in the tourism industry [5][6][7]. A recent global report indicates that a majority of consumers, 70%, conduct research on mobile services [8]. It is particularly evident in the case of tourists making last-minute and quick booking decisions, as mobile hotel search engines dominate and account for 89% of web traffic [9]. This poses a challenge for OTAs in understanding the intentions of individual users during mobile hotel reservation search sessions and employing personalized search engine marketing and optimization tactics to recommend accurate items in real time to meet their demands.

Owing to the information overload problem, users often struggle to find relevant content even with the help of search engines [10]. The position of items ranking on search engine result pages (SERPs) seems to alleviate such issues in the context of both information search engines [11][12][13][14] and travel product search platforms on personal computers (PC) [3][15][16][17][18]. The empirical evidence shows that the effect of item-ranking positions on SERPs negatively affects users' decisions. Prior studies have shown that the process of making a hotel reservation is considered a high-involvement product decision [15][17]. However, these findings from studies on information search engines on PCs cannot be easily generalized to the field of mobile commerce and Information Systems (IS) due to the smaller screen size of mobile devices. The limited interface of mobile devices has been found to complicate users' navigation tasks and decrease the effectiveness of learning [19][20]. Additionally, the layout of

SERPs on mobile devices may be hindered by information chunking [21][22], potentially leading to different mobile-end position effects.

Previous research has shown that there is a negative association between price and CTDs on PC-based internet [15][23]. Users who are more responsive to screen position are also more price-sensitive [12]. The high web traffic of last-minute and quick booking in mobile search suggests that the closer to the check-in date, the more urgent the search for items in mobile services [9]. Due to time constraints in mobile hotel booking, mobile users may use hotel price as a positive quality signal when making high-involvement product purchase decisions. Mobile CTDs may be affected by fluctuation of item prices listed on the SERPs during a session. Bronnenberg et al. found that users tend to make purchases based on the characteristics of products they searched for early on [24]. It is plausible to speculate that an individual mobile user's CTDs depends on the price perception comparison among items on the current SERP locally or the price fluctuation globally during a session.

Early search costs can have a significant impact on the decisions made by users in product search engines [1][24][25][26]. This suggests a sequence of interdependent decisions, in which earlier outcomes can affect subsequent decisions [5][27]. Quantifying the specific search cost for a user can involve measuring the cumulative time duration toward an item up to the current moment within a consumer search session [25][28]. Researchers argument is that the previous search cost invested by a user in obtaining information about a specific hotel, which forms the current individual-level hotel perception, can influence their later CTDs toward that hotel. In order to effectively select a hotel, it is indispensable to understand the relevance of hotel attributes to the needs of the user. Search engines often provide refinement tools such as filtering and sorting, which are personalized functions [15][23]. The use of these tools can help involve users more actively in the search process and reveal their specific demands [16][29]. Once users employ these refinement tools, the ranking of hotels on SERPs can be re-ordered based on criteria such as price and distance to a point of interest. However, due to the multiple and conflicting criteria used, users may be presented with options that are the cheapest but furthest away or vice versa [10][29]. The use of refinement tools might complicate the process of mobile CTDs.

2. Item-Ranking Position Effect

Prior research has shown that a primacy effect exists in information search engines such as Google and Bing. An eye-tracking experiment revealed that when users click on a hyperlink from Google's search results, their clicks are strongly biased toward higher-ranking hyperlinks [11]. For example, researchers have proposed a two-stage Bayesian model to examine the effects of the properties of paid search ads on ad performance, and they found that lower-ranking positions on SERP lead to lower click-through rates [12]. Similarly, items ranked earlier on SERP tend to attract more clicks and result in improved SME profits in desktop search [13]. In recent years, researchers in the tourism and hospitality field have also begun to investigate the primacy effect on the performance of small and medium-sized enterprises (SMEs). Pan developed a click-through rate model for public websites and examined the click-through rates of destination marketing organizations at different ranking positions [3]. He found that the power-law distribution of click-through rates varies depending on the rank on a web search: the top results receive high click-through rates, but the rates decrease significantly as the ranks go down. Law and Huang conducted an empirical study which found that about 50% of users viewed three screens of items at most on SERPs [14].

Several studies have paid attention to the impact of online screen positions on travel product search engines. Ghose et al. used a hierarchical Bayesian model and data from a real-world travel search engine to examine the effect of ranking on consumer search and search engine marketing (SEM) revenue [15]. They found that top-ranking hotels received more clicks, but default hotel rankings resulted in more profits than those customized to users' attributes. Evidence from PCs also shows that the ranking position of a hotel on SERP greatly influences users' booking intentions [18], leading to differences in the market share of online hotel firms [16].

Mobile commerce has changed the consumer decision-making environment [5][21][30]. Mobile device traffic is dominated by last-minute and quick booking tasks [9], indicating the more urgent time constraints of mobile travel search engines [3][5][6]. The small screen of a mobile OTA search may change the effects of item-ranking positions, as the narrow screen restricts users to local perception [21][22]. Those previous findings may not necessarily apply to high-involvement purchase decisions in a mobile OTA search. There is potential to research the effect of item-ranking positions in mobile travel search engines.

3. Price Effect in Consumer Search

Out of the screen position effect, the effect of price on consumer search has been discussed [12][15][23]. Baye et al. found that a lower price leads to more clicks received by an online retailer [23]. Similarly, Ghose et al. also displayed that price is negatively associated with consumer click-through rate on the PC-based internet [15]. Hotel booking is a specific type of high-involvement product purchase decision-making [17]. Price search activity is driven by a user's perceived search efficiency and motivation [31]. As the date of check-in approaches, mobile users have limited time to make a decision about their hotel choice. In this context, it is possible that a higher hotel price is perceived as an indication of higher quality for high-involvement products such as hotel bookings.

Previous research by Rutz and Trusov has shown that users who are sensitive to the ranking positions of products on a screen are also more sensitive to price [12]. Studies on digital cameras as another type of high-involvement product have found that users tend to purchase cameras that closely match the characteristics of the cameras they initially searched for [24]. In mobile searches, users may base their decisions on the price rankings of products displayed on the current SERPs or by comparing them to the average price of items they have recently interacted with during their online session. Research assert that the price of click-through items is associated with the user's perception of price.

4. Refinement Tools and Search Cost in Consumer Search

In context of a product search engine, search cost is associated with acquiring information about a product [1][24][28]. Achieving a trade-off SEM between users' search cost and efficiency is a challenging task, particularly when dealing with the limitations of small screens and time constraints on mobile devices [3][9][21]. The vast amount of information available online can overwhelm users' ability to process it due to the limitations of human attention [10]. Refinement tools are designed to help mitigate this problem by narrowing down the amount of information presented to users. However, previous research on e-commerce search engines, where the number of products is much larger than in tourism, has found that the re-ranking effect of refinement tools is not always beneficial to consumers' search [29]. In other words, the use of refinement tools can increase users' involvement in the search process, but this increased involvement may not always lead to better results [16][29]. Additionally, time constraints can increase the cost of searching for information both online and offline [16][32]. It raises the question of whether using refinement tools in mobile search environments maximizes the match between users' demands and the most relevant products.

Behavioral engagement influences the user's dynamic perceived intent, which can affect their subsequent decisions [24][33][34]. Before a user decides to click through and make a purchase decision, the cumulative search duration, which includes processing information about specific items (such as ratings, images, deals, etc.), affects their perception toward distinct items [25][28]. Both current users' psychological and behavioral engagement have a positive influence on subsequent decisions, such as digital item sales [35]. There are sequences of interdependent tourism decisions, where later decisions depend on the outcomes of earlier ones [5][27]. Mobile CTDs can be defined as dynamic decision making in an ongoing or en route paradigm due to their sequential characteristics during a session [12][21].

References

1. Ghose, A.; Ipeirotis, P.G.; Li, B. Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. Mark. Sci. 2012, 31, 493–520.
2. Pop, R.-A.; Săplăcan, Z.; Dabija, D.-C.; Alt, M.-A. The impact of social media influencers on travel decisions: The role of trust in consumer decision journey. Curr. Issues Tour. 2022, 25, 823–843.
3. Pan, B. The power of search engine ranking for tourist destinations. Tour. Manag. 2015, 47, 79–87.
4. Xiang, Z.; Wöber, K.; Fesenmaier, D.R. Representation of the online tourism domain in search engines. J. Travel Res. 2008, 47, 137–150.
5. Lamsfus, C.; Wang, D.; Alzua-Sorzabal, A.; Xiang, Z. Going mobile: Defining context for on-the-go travelers. J. Travel Res. 2015, 54, 691–701.
6. Liang, S.; Schuckert, M.; Law, R.; Masiero, L. The relevance of mobile tourism and information technology: An analysis of recent trends and future research directions. J. Travel Tour. Mark. 2017, 34, 732–748.
7. Rondović, B.; Djuričković, T.; Kašćelan, L. Drivers of E-Business Diffusion in Tourism: A Decision Tree Approach. J. Theor. Appl. Electron. Commer. Res. 2019, 14, 30–50.

8. StratosJets. Over 60 Online Travel Booking Statistics. 2022. Available online: https://www.stratosjets.com/blog/online-travel-statistics/ (accessed on 16 August 2022).
9. Criteo. Summer Travel Report. 2018. Available online: https://www.criteo.com/wp-content/uploads/2018/06/Criteo-Summer-Travel-2018.pdf (accessed on 6 June 2019).
10. Jacoby, J. Perspectives on information overload. J. Consum. Res. 1984, 10, 432–435.
11. Pan, B.; Hembrooke, H.; Joachims, T.; Lorigo, L.; Gay, G.; Granka, L. In Google we trust: Users' decisions on rank, position, and relevance. J. Comput.-Mediat. Commun. 2007, 12, 801–823.
12. Rutz, O.J.; Trusov, M. Zooming In on Paid Search Ads—A Consumer-Level Model Calibrated on Aggregated Data. Mark. Sci. 2011, 30, 789–800.
13. Agarwal, A.; Hosanagar, K.; Smith, M.D. Location, location, location: An analysis of profitability of position in online advertising markets. J. Mark. Res. 2011, 48, 1057–1073.
14. Law, R.; Huang, T. How do travelers find their travel and hotel websites? Asia Pac. J. Tour. Res. 2006, 11, 239–246.
15. Ghose, A.; Ipeirotis, P.G.; Li, B. Examining the impact of ranking on consumer behavior and search engine revenue. Manag. Sci. 2014, 60, 1632–1654.
16. Chen, Y.; Yao, S. Sequential search with refinement: Model and application with click-stream data. Manag. Sci. 2017, 63, 4345–4365.
17. Ert, E.; Fleischer, A. Mere position effect in booking hotels online. J. Travel Res. 2016, 55, 311–321.
18. Van der Rest, J.-P.I.; Cordella, P.; Loosschilder, G.; Schwartz, Z. Connecting search marketing to hotel revenue management: Conjoint analysis as a methodology to evaluate the optimal online travel agency commission fee. Serv. Sci. 2016, 8, 169–183.
19. Maniar, N.; Bennett, E.; Hand, S.; Allan, G. The effect of mobile screen size on video-based learning. J. Softw. 2008, 3, 51–61.
20. Chae, M.; Kim, J. Do size and structure matter to mobile users? An empirical study of the effects of screen size, information structure, and task complexity on user activities with standard web phones. Behav. Inf. Technol. 2004, 23, 165–181.
21. Ghose, A.; Goldfarb, A.; Han, S.P. How is the mobile Internet different? Search costs and local activities. Inf. Syst. Res. 2013, 24, 613–631.
22. Sim, J.J.; Loh, S.H.; Wong, K.L.; Choong, C.K. Do we need trust transfer mechanisms? An M-commerce adoption perspective. J. Theor. Appl. Electron. Commer. Res. 2021, 16, 2241–2262.
23. Baye, M.R.; Gatti, J.R.J.; Kattuman, P.; Morgan, J. Clicks, discontinuities, and firm demand online. J. Econ. Manag. Strategy 2009, 18, 935–975.

24. Bronnenberg, B.J.; Kim, J.B.; Mela, C.F. Zooming In on Choice: How Do Consumers Search for Cameras Online? Mark. Sci. 2016, 35, 693–712.
25. Gao, H.; Ou, C.; Liu, H. Modeling shopping cart decisions with heterogeneous product involvement and reviews. In Proceedings of the 23rd Pacific Asia Conference on Information Systems, Xi'an, China, 8–12 July 2019.
26. Zhan, M.; Gao, H.; Liu, H.; Peng, Y.; Lu, D.; Zhu, H. Identifying market structure to monitor product competition using a consumer-behavior-based intelligence model. Asia Pac. J. Mark. Logist. 2020, 33, 99–123.
27. Hwang, Y.-H. A theory of unplanned travel decisions: Implications for modeling on-the-go travelers. Inf. Technol. Tour. 2010, 12, 283–296.
28. Ursu, R.M.; Wang, Q.; Chintagunta, P.K. Search duration. Mark. Sci. 2020, 39, 849–871.
29. Liu, H.; Zhan, M.; Gao, H.; Zhu, H.; He, R. Research on assistant decision-makings of E-commerce platform with refinement tools. J. Control Decis. 2020, 8, 303–313.
30. Pop, R.-A.; Hlédik, E.; Dabija, D.-C. Predicting consumers' purchase intention through fast fashion mobile apps: The mediating role of attitude and the moderating role of COVID-19. Technol. Forecast. Soc. Chang. 2023, 186, 122111.
31. Jiang, P. A model of price search behavior in electronic marketplace. Internet Res. 2002, 12, 181–190.
32. Seiler, S.; Pinna, F. Estimating search benefits from path-tracking data: Measurement and determinants. Mark. Sci. 2017, 36, 565–589.
33. Bronnenberg, B.J.; Dubé, J.-P.H.; Gentzkow, M. The evolution of brand preferences: Evidence from consumer migration. Am. Econ. Rev. 2012, 102, 2472–2508.
34. Gao, H.; Liu, H.; Lin, W.; Chen, C. Graph-theoretic approach to detecting real-time intents within purchase conversion funnel using clickstream data. Kybernetes, 2022; ahead-of-print.
35. Bonilla-Quijada, M.; Tugores-Ques, J.; Olmo Arriaga, J.L. Promotion of urban tourism: Insights into user engagement on social media. Inf. Technol. Tour. 2021, 23, 611–632.