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Slower searching yields higher efficiency: A case study of taxi drivers

Qiuyue Li[a], Daqing Li[b,c,1], Orr Levy[d,1], and Shlomo Havlin[a,1]

Affiliations are included on p. 7.

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The movement patterns of animals while searching for food have been studied extensively in recent decades. However, although human search behavior has existed since the beginning of civilization, not much is known about human search patterns, particularly regarding strategies that yield higher efficiency. Although most humans no longer need to gather and hunt in the wild, human searching remains prevalent in modern times. A common example of human searching is performed by taxi drivers looking for passengers in a city. Here, we analyze GPS data of taxi drivers in three major cities over different time periods and find that when drivers search for passengers, the higher is their efficiency, the slower is their searching, and they tend to make more short-distance turns during the search. Our study further indicates that individuals are characterized by a specific level of efficiency, and thus, efficient drivers are consistently efficient across different days as they follow their own search strategies. Interestingly, only about 10% of drivers adopt the most efficient strategy, earning nearly 20% more than the average driver. Our findings shed light on human search behavior, a fundamental aspect of human decision-making in competitive and fast-paced environments.

human search | human mobility | efficient search

Significance

How do humans optimize search strategies in complex, real-world environments? By analyzing Global Positioning System (GPS) data from taxi drivers in three large cities, this study uncovers a counterintuitive finding: More efficient drivers search at slower speed and make more short-distance turns, improving their success. Notably, search efficiency appears to be an individual trait, with efficient drivers consistently outperforming others over time. However, only about 10% of drivers adopt this optimal strategy, earning nearly 20% more than the average driver. These findings provide insights into human decision-making, demonstrating that deliberate, slower search strategies can outperform faster ones—even in fast-paced, competitive settings. This research advances our understanding of cognitive and behavioral strategies, with implications for psychology, behavioral economics, and operations research.

For decades, patterns of food search behavior in animals under different conditions have been of interest to researchers (1–9). Although the search environment can be different such as in ocean or land, many animals exhibit similar movement patterns while foraging for food or other essential resources. In these systems, the step length (defined as the straight-line distance traveled between direction turning during foraging) is found to follow a power-law distribution,

$$p(l) \propto l^{-\mu}, \quad 1 < \mu < 3, \qquad [1]$$

where l is the straight-line step length and μ is the power-law exponent. Such a distribution, known as Lévy flight or Lévy walk (1), is characterized by frequent small steps interrupted by infrequent long-distance steps of all scales. Theoretical studies show that Lévy flight search strategy has advantages over pure random walks (i.e. Brownian motion), as the rare long steps make the search significantly more efficient (2, 3). Such Lévy search behaviors have been observed in a wide range of animals, from marine predators (4) to terrestrial mammals like monkeys (5) and deer (2), as well as birds and insects included but not limited to albatrosses (6), honeybees (7), and *Drosophila* (8, 9). Classical Lévy flight theory finds $\mu = 2$ to be optimal under the assumption that any target within visual range is always detected (2, 3). However, this assumption does not necessarily hold for human search in real urban environments, where targets may be overlooked at higher speeds. In our study, we find that the most efficient drivers exhibit μ larger than 2, reflecting more frequent short steps and slower search speeds (see *Discussion* for details).

Although further investigation is needed to fully understand the Lévy statistics search of certain species of animals (10), the discovery has been extended to the study of human hunting and searching behavior. Research shows that human hunter-gatherers in Hadza of northern Tanzania, perform Lévy walks in almost half of their foraging routes when searching for a variety of foods (11). Even when not in the wild, search behavior remains pervasive in contemporary human society, including seeking information on the World Wide Web (12, 13), locating target individuals in the social network (14, 15), etc. Various models have been developed to characterize the small-world properties of these types of networks (16, 17). Building on this foundation, algorithms and strategies (18–21) have been explored to enhance search efficiency.

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[1]To whom correspondence may be addressed. Email: daqingl@buaa.edu.cn, orr.levy@gmail.com, or havlins@gmail.com.

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In addition to search studies on virtual networks, the development of portable smartphones has enabled the recording and studying of human behaviors, including communications (22), movements and migrations (23). Based on the vast amount of GPS data provided by personal smart devices, researchers conducted several studies on general human mobility in modern cities (24–28), revealing the patterns of human movement at different time and spatial scales. The statistical features of human walks follow a truncated power-law, similar to Lévy-walk (29, 30). These studies on human mobility have focused on individuals with clearly defined destinations. Other studies are based on taxi GPS data which give a clear picture of passengers' movement, from origin to destination on an urban scale (31–37). There are also studies classifying taxi search patterns in the urban environment (38). However, the general relationship between taxi drivers' search strategies and their efficiency has not been systematically studied. Taxi drivers share analogous objectives with hunter-gatherers in the wilderness, both seeking their respective targets—whether they are passengers or prey and fruits, yet, the former is constrained by the predetermined road network of the city, limiting their ability to change directions at will. Nevertheless, studying taxi drivers' searching patterns may offer valuable insights into various aspects of human behavior. It provides a window into how individuals perceive, think, and decide in dynamic and complex environments and in particular, which strategy is more efficient for searching.

Here, we analyze the taxi drivers' search patterns and explore how humans interact with their surroundings and with one another, adapting their strategies for being efficient while coping with the challenges of uncertainty and competition. Surprisingly, we find that higher efficiency is attained through slower searches. Our study of taxi drivers' search patterns sheds light on human reasoning and the behavioral patterns that drive decision-making in complex search processes. Overall, our findings indicate that a slower search process—probably due to increased attention—yields higher efficiency and thus saves search time.

Methods

Here, based on a total of 2.3 billion GPS data points with 60-s time intervals collected from nearly 40,000 taxi drivers in three major Chinese cities–Beijing, Shanghai, and Chengdu (*SI Appendix*, Tables S1 and S2), we investigate taxi drivers' search behavior. We focus on their search processes to identify search strategies that distinguish efficient drivers from less efficient ones. The daily routine of a taxi driver can be divided into two distinct tasks: the search process and the trip process. In the search process, the driver travels along the roads without passengers, whereas in the trip process, passengers are transported to their destinations. Our analysis covers the years when taxi-hailing applications were largely absent, and trips with passengers serve as a control for interpreting our findings. As demonstrated in Fig. 1 *A*and *B*, these two processes alternate during the working hours of a taxi driver. In this figure, drivers start their daily routine at the open black circle and end their day at the full black circle. The blue dashed paths represent trips, i.e., the periods when passengers are being carried. The red paths represent periods with no passengers, that is the process of searching for the next passenger, referred to as "search" in the figures. During each search or trip process, the path is divided into multiple steps based on the driver's turning points. Each step begins and ends at two consecutive turns. In our method, the length of each step should exceed 25 m, and the turning angle must be greater than 45 degrees (see Step Calculation in *SI Appendix*). The *Inset* plot in the *Upper Right* corner of Fig. 1*B* depicts the 14 steps taken by a driver during the sixth search process, separated by 13 turns. Analyzing road networks of different cities in different time periods in our datasets can yield insight into the generality and robustness of the results.

In order to evaluate and quantify the efficiency of taxi drivers, we consider two main quantities E_t and E_d to describe the efficient performance of a given taxi driver in time and space separately:

$$E_{\mathrm{t}} = \frac{T_{\mathrm{trip}}}{T}, E_{\mathrm{d}} = \frac{D_{\mathrm{trip}}}{D}, \qquad [2]$$

Here, T and D represent a single driver's total driving time and driving distance respectively, while T_{trip} and D_{trip} are the sum of a driver's trip times and trip distances respectively, with passengers during 06:00 to 22:00. Daily distributions of drivers' efficiency in time and space for different cities are shown in Fig. 1 *C* and *D* respectively. We additionally fit E_d distributions to Beta distributions (*SI Appendix*, Fig. S35), finding that the fit is reasonable for most cities but less accurate for Chengdu (2014). We also find that the daily values of E_t and E_d for the same driver are highly correlated (*SI Appendix*, Fig. S6) and the daily income of a taxi driver is positively correlated with both E_t and E_d (*SI Appendix*, Figs. S2 and S3), which strongly supports the validity of the efficiency definition. Fig. 1 compares the efficiency distributions in three cities, where Chengdu in 2014 has the highest relative search efficiency in both time and space. To investigate possible reasons for this intercity difference, we surveyed the official Statistical Yearbooks and National Economic and Social Development Reports for the corresponding cities and years to obtain the number of taxis and the resident population, and then obtained the number of taxis per 10,000 residents (*SI Appendix*, Table S3). Chengdu has significantly fewer taxis per capita (12.8 per 10,000 residents) compared to Beijing and Shanghai (over 26 per 10,000). This lower taxi supply relative to population suggests that the effective demand per taxi in Chengdu was higher, leading to a higher match rate and shorter search time per driver. These results provide a plausible explanation for the higher observed search efficiency in Chengdu despite its smaller population size, as the effect of reduced overall demand is likely offset by the much lower supply of taxis.

In contrast to other cities, the patterns of search efficiency in Beijing (2012) and Beijing (2017) exhibit some similarities, but are not identical to each other. These differences could be attributed to changes in traffic conditions, road network configuration, or the early adoption of taxi-hailing software. Fig. 1 also shows that the overall distribution of efficiency varies substantially between cities and time periods. In this study, we therefore focus on understanding the strategies that distinguish efficient from less efficient drivers within the same city.

Ethics Statement. All GPS data analyzed in this study were deidentified prior to our access and use. Vehicles were associated with nonpersonally identifiable IDs that cannot be traced to individual drivers or license plates. In accordance with institutional guidelines, the use of such deidentified data is considered exempt from IRB review and informed consent requirements.

Results

Since the daily efficiency of taxi drivers is measurable, it is natural to ask whether a driver's efficiency remains consistent across different days. In the datasets used in our study, many taxis are frequently observed across multiple days, allowing us to assess their efficiencies and their consistency across days. Consistency of a driver's efficiency could be important, suggesting that efficiency is a characteristic behavior of a taxi driver, and relates to their personal strategy.

By collecting the search efficiency of taxi drivers who appear on more than 10 different days, we find that efficient drivers tend to remain systematically efficient on different days, while less efficient drivers remain largely inefficient. For example, for the two typical drivers whose one-day-trajectory are shown in Fig. 1 *A* and *B*, the driver with high daily efficiency performs well also on other days (Fig. 2 *A* and *B*, red open circles). His efficiency score is mostly above the 25th percentile of the day's efficiency (red dashed line). In contrast, the driver with low daily efficiency mostly underperforms (Fig. 2 *A* and *B*, blue crosses), falling below the 75th percentile of the day's efficiency (blue

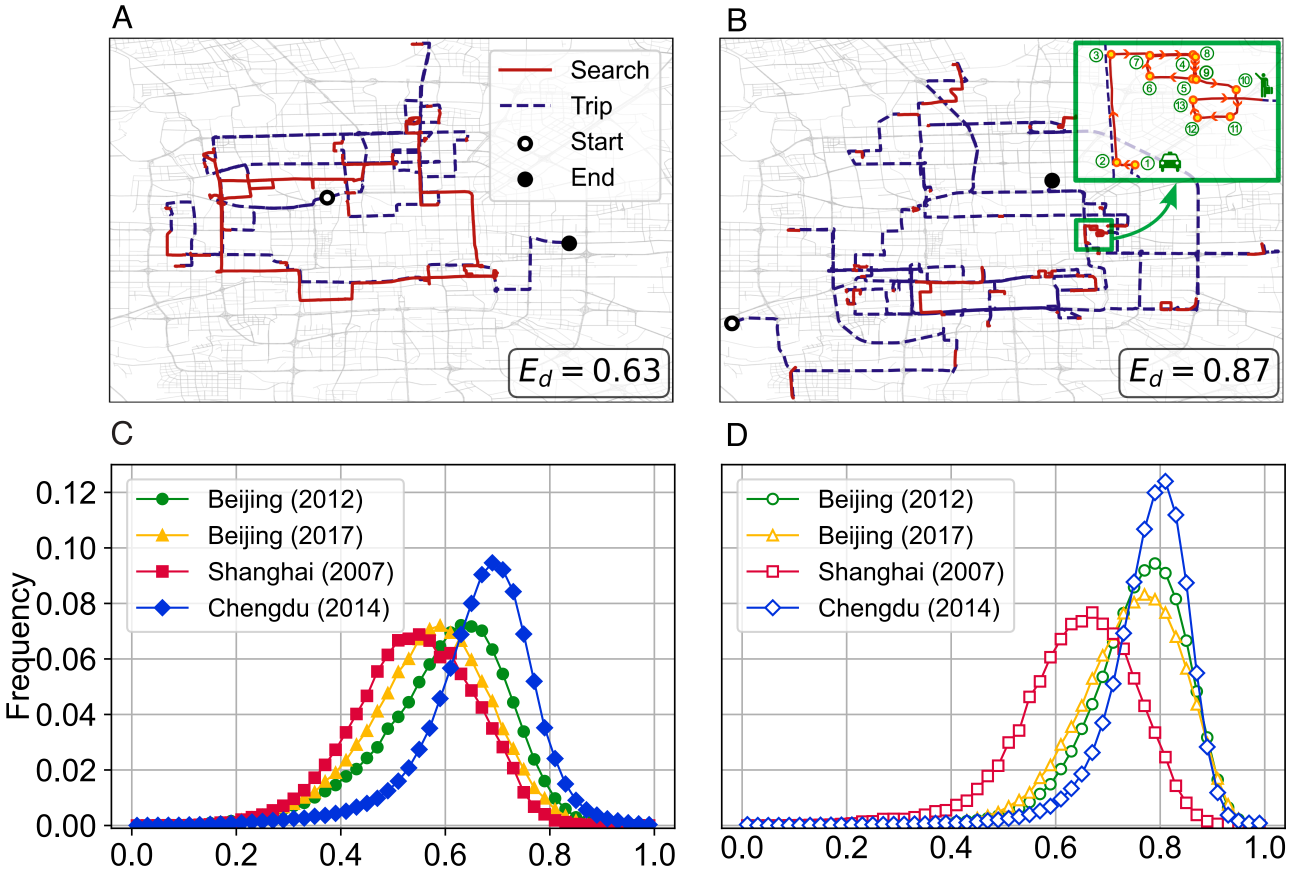

Fig. 1. Demonstration and measurement of taxi drivers' efficiency. (*A* and *B*) Daily trajectory of (*A*) a less efficient and (*B*) an efficient driver. The driver took his first passenger during the day at the open circle and brought the last passenger to his destination at the full circle. The solid red lines and dashed blue lines represent the driver's trajectories during the search and trip processes respectively. The driver in (*A*), who took 23 passengers on 17 November 2012, was among the least efficient 25% of drivers that day ($E_t = 0.48$, $E_d = 0.63$). The driver in (*B*), who took 39 passengers on 10 November 2012, was among the most efficient 25% of drivers that day ($E_t = 0.71$, $E_d = 0.87$). (*C* and *D*) The distributions of E_t and E_d for the four city datasets. We consider only drivers who took at least five passengers and drove more than six hours and more than 100 km between 06:00 and 22:00 on a given working day.

dashed line). To statistically ensure that neither the performance of efficient drivers nor the performance of less efficient drivers is coincidental, we calculate the average and SD of efficiency, both E_t and E_d, for each driver across days. A random sample of 10 drivers, presented as black circles, is shown in Fig. 2 *C* and *D*. We find a significant difference (*P*-value < 0.05) between the distributions of the SD of efficiency, $\sigma(E_t)$ and $\sigma(E_d)$, in the original data and the shuffled data, as shown in *SI Appendix*, Figs. S4 and S5 (more details about the calculations are provided in *SI Appendix*). Also, $\overline{E_t}$ and $\overline{E_d}$ of the same driver are strongly correlated with Pearson correlation coefficient ranging from 0.68 to 0.81 in the four cities (*SI Appendix*, Fig. S6). Thus, we conclude that efficiency is a characteristic of a driver rather than a random outcome. Therefore, taxi drivers may have their own strategies to maintain their efficiency, a question that we explore next.

Our focus is now to explore whether distinct strategies exist between efficient and less efficient drivers and, if so, to identify and analyze them. By performing statistical analyses on drivers from different efficiency groups, we find that the distributions of their daily average trip distances are remarkably similar, whereas their average search distances become significantly shorter as efficiency increases (*SI Appendix*, Figs. S7 and S8). Moreover, the total daily driving time shows only minor variation across efficiency groups, with some cities (e.g., Beijing) even exhibiting slightly shorter driving time for more efficient drivers (*SI Appendix*, Figs. S11 and S12). This indicates that, given the roughly fixed number of passengers carried per day (*SI Appendix*, Figs. S9 and S10), the key factor distinguishing drivers' efficiency is dominated by the searching process itself, rather than the passengers they picked up. Therefore, the first possibility that we explored is whether the search environment or the locations from which passengers are picked up differ between the two groups of drivers, thereby impacting the search efficiency of the taxi drivers. To test this assumption, we compared the heatmaps of pick-up points for the top 25% most efficient (E_t) and bottom 25% least efficient (E_t) drivers (Fig. 2 *E* and *F*). Our results show that the pick-up hot spots in both groups are mostly concentrated in the city center. Other cities showing similar results can be found in *SI Appendix*, Figs. S13–S18. Quantitative analysis using the Jaccard tests shows the large overlap of pick-up locations in all types of drivers (*SI Appendix*, Table S5). Thus, the spatial differences between efficient, moderately efficient and less efficient drivers are minor. The second possibility that we considered is the temporal difference: Are efficient drivers more likely to search for passengers at different times of the day? By examining the time-of-day distributions of search time, trip time, and number of trips (*SI Appendix*, Figs. S19–S21), we find that temporal fluctuations dominate the overall pattern, yet efficiency groups remain clearly separated for search time across almost the entire day, whereas their trip times show much smaller separation. This indicates that efficient drivers consistently maintain higher efficiency in all time periods and that the efficiency gap is primarily

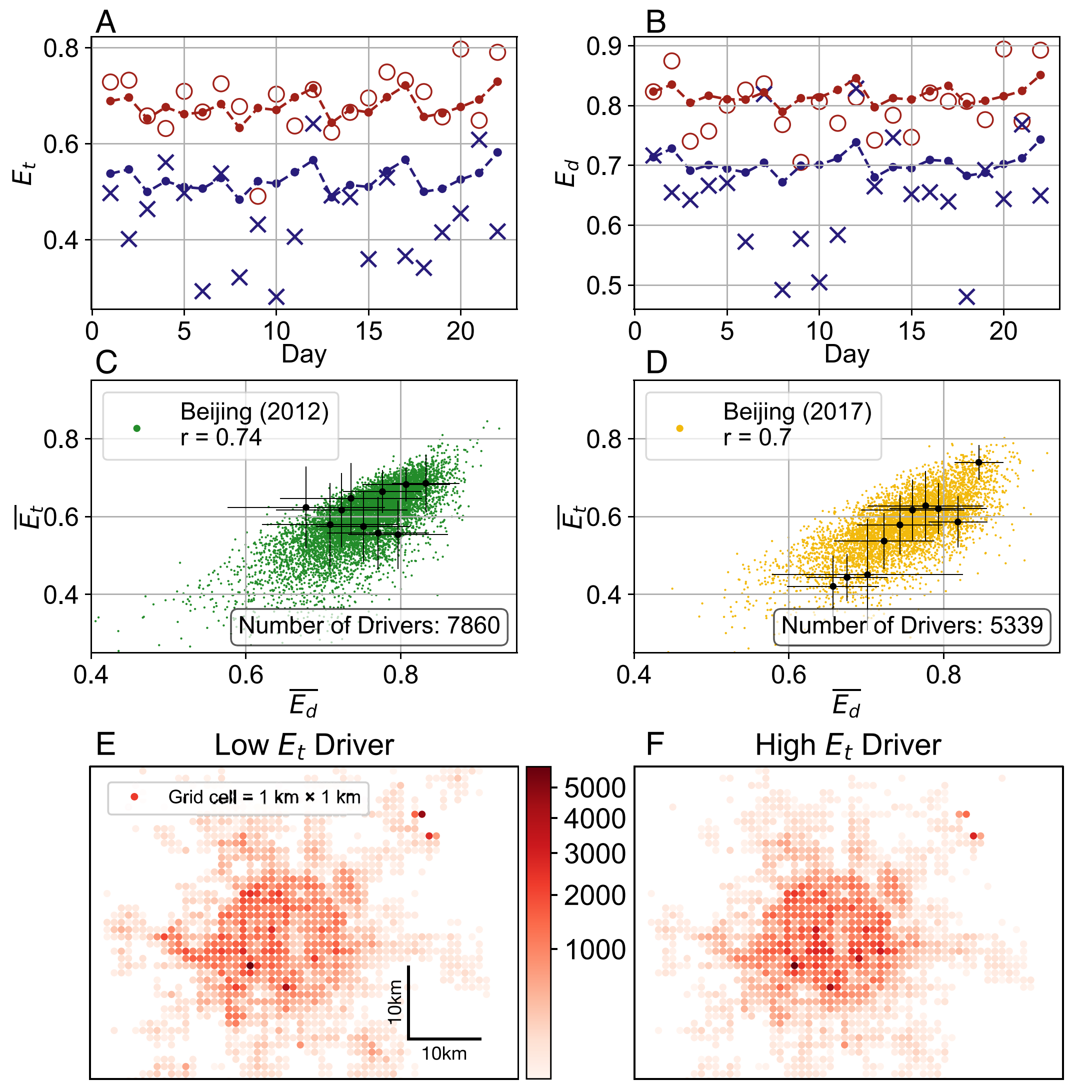

Fig. 2. Consistency of driver efficiency and spatial distribution of passengers for drivers with varying efficiency. (*A* and *B*) Two taxi drivers' efficiency (E_t and E_d) across different working days. The blue crosses represent the performance of a typical less efficient driver over 23 working days within one month. The red circles show the same for a typical efficient driver. The blue dashed line and red dashed line respectively show the 25th percentile and 75th percentile of daily taxi efficiency for 23 working days within one month. (*C* and *D*) Scatter plots of the average E_t and E_d for the same drivers in Beijing (2012) dataset and Beijing (2017) datasets. Each point represents a single driver that appears more than 10 d in the dataset. The Pearson correlation coefficient r between $\overline{E_t}$ and $\overline{E_d}$ in the four datasets are reported as 0.74 (Beijing 2012), 0.7 (Beijing 2017), 0.68 (Shanghai 2007) and 0.79 (Chengdu 2014). Figures for the last two cities are shown as *SI Appendix*, Fig. S6. A random sample of 10 drivers illustrates the SD of their search efficiency across days, indicating that each driver has a characteristic efficiency. (*E* and *F*) Heatmap of pickup locations in Beijing (2017). The city is divided into 1-km grids. The pick-up locations of the least efficient and most efficient 25% of drivers are shown in (*E* and *F*), respectively. The color represents the number of pick-up points in certain grids during 22 work days. The intensity of the red color in each grid cell corresponds to the frequency of passenger trip origins, with darker shades indicating a higher concentration. The Jaccard index of the grids in the two figures is 0.82, suggesting that the difference between efficient and less efficient drivers cannot be attributed to different pick-up points.

attributable to differences in searching behavior rather than trip durations.

Motivated by these findings, we next analyze the search trajectories themselves to identify the underlying strategies associated with different efficiency levels. Numerous studies have investigated animal behavior during the search process by analyzing the distributions of step lengths. Similarly, in this study, we use an analogous approach to examine the distribution of step lengths (between two turns) during taxi drivers' search process (*SI Appendix*, Fig. S23). We divide the taxi drivers into five groups based on their level of efficiency. For each group, the distributions of step time and step length during search and trip are shown in Fig. 3. Comparing with the results of trip process, where all groups behave similarly (Fig. 3*A*), the distribution of search step time and step length for different efficiency drivers shows systematic changes (Fig. 3*B*). Our analysis reveals that more efficient taxi drivers consistently employ fewer long steps and more short steps (i.e., make more turns) during their search process (Fig. 3 *A*–*D*). The theoretical reason for obtaining μ greater than 2 for more efficient drivers is due to higher searching success at low speeds, as explained in *Discussion* and in *SI Appendix*. To further test whether this is related to the taxi search locations, we focus only on the top 5% of pick-up sites when analyzing the step distribution statistics, and the results remain consistent (Fig. 3 *E* and *F*). Similar results were obtained for other cities (*SI Appendix*, Figs. S24–S26). This suggests that

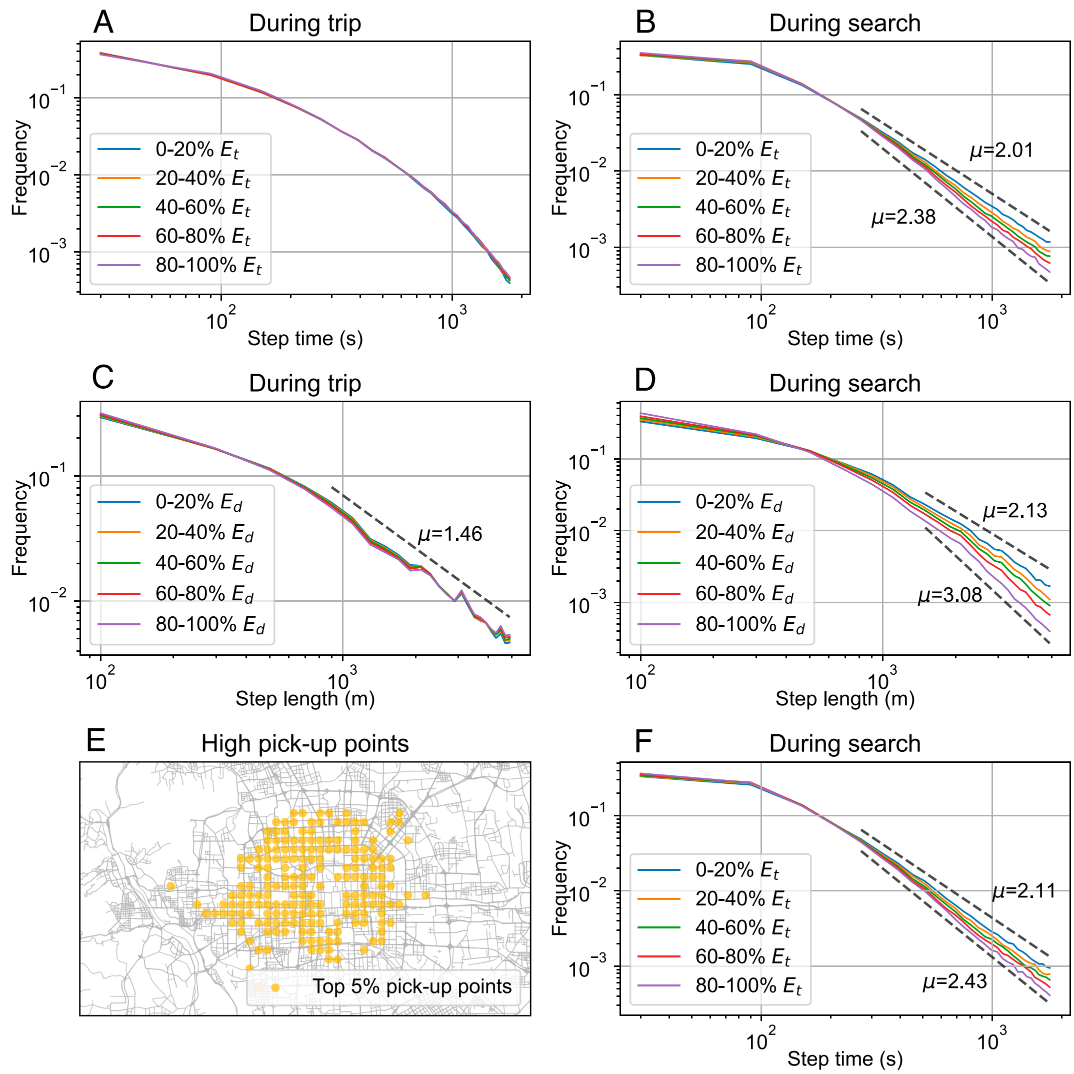

Fig. 3. Step length and step time distributions reveal systematic differences in search behavior across efficiency groups in Beijing (2017). Drivers are divided into five groups based on their efficiency: The 0 to 20% E_t (E_d) group represents the least efficient drivers, whereas the 80 to 100% E_t (E_d) group represents the most efficient. The step distributions of the five groups are shown separately. (*A* and *B*) show the step time distributions during the trip and search processes, respectively. (*C* and *D*) show the step length distributions during trip and search processes, respectively. (*E*) shows the top 5% pick-up points, labeled as yellow squares. (*F*) shows the step time distribution for the top pick-up locations shown in (*E*).

efficient taxi drivers obtain higher search efficiency by making turns more frequently compared to less efficient drivers in the urban road network. Importantly, the obtained results remain consistent regardless of the presence at low fraction or absence of taxi-hailing software, as demonstrated by the replication of findings in both the Beijing (2012) and Beijing (2017) datasets.

Additionally, we find that most drivers tend to drive more slowly during searches compared to trips, not only in general but also in every step (Fig. 4 *A*–*D*). Similar findings are obtained for the other cities (*SI Appendix*, Figs. S27–S29). Recognizing the importance of speed in searching, we delve into this factor and observe that drivers with higher efficiency drive more slowly during the search process compared to less efficient drivers, likely for focusing more on locating passengers. Since turning usually takes more time than traveling straight, we further test the speed distributions of efficient drivers with the same number of turns during search and find that the results remain consistent (*SI Appendix*, Figs. S30–S33). Thus, more efficient drivers typically have slower searching speed (see also *SI Appendix*, Fig. S22), showing a clear negative relationship between E_d and average searching speed). Conversely, when examining drivers with on-average shorter step lengths during search, they usually have a higher fraction of being efficient drivers (Fig. 4 *E* and *F*). Importantly, we note that this distinction between efficient and less efficient drivers still exists in 2017, when ride-sharing software had already become more widely used. However, according to Dida Inc.'s IPO prospectus submitted to the Hong Kong Stock Exchange in March 2024 (39), taxi roadside hailing accounted for 464.8 billion RMB out of a total market size of 495 billion RMB in 2017. Moreover, traditional roadside hailing in China continued to dominate the industry with a market share of 90.8% in terms of GTV (Gross Transaction Value) in 2022, according to the same source. This suggests that taxi-hailing apps did not have a major impact on our current taxi search study.

Discussion

Classical Lévy flight search theory predicts an optimal exponent $\mu = 2$ for random search (2, 3). However, our empirical analysis of taxi driver searches reveals a higher optimal value. This discrepancy motivated us to extend the classical Lévy model

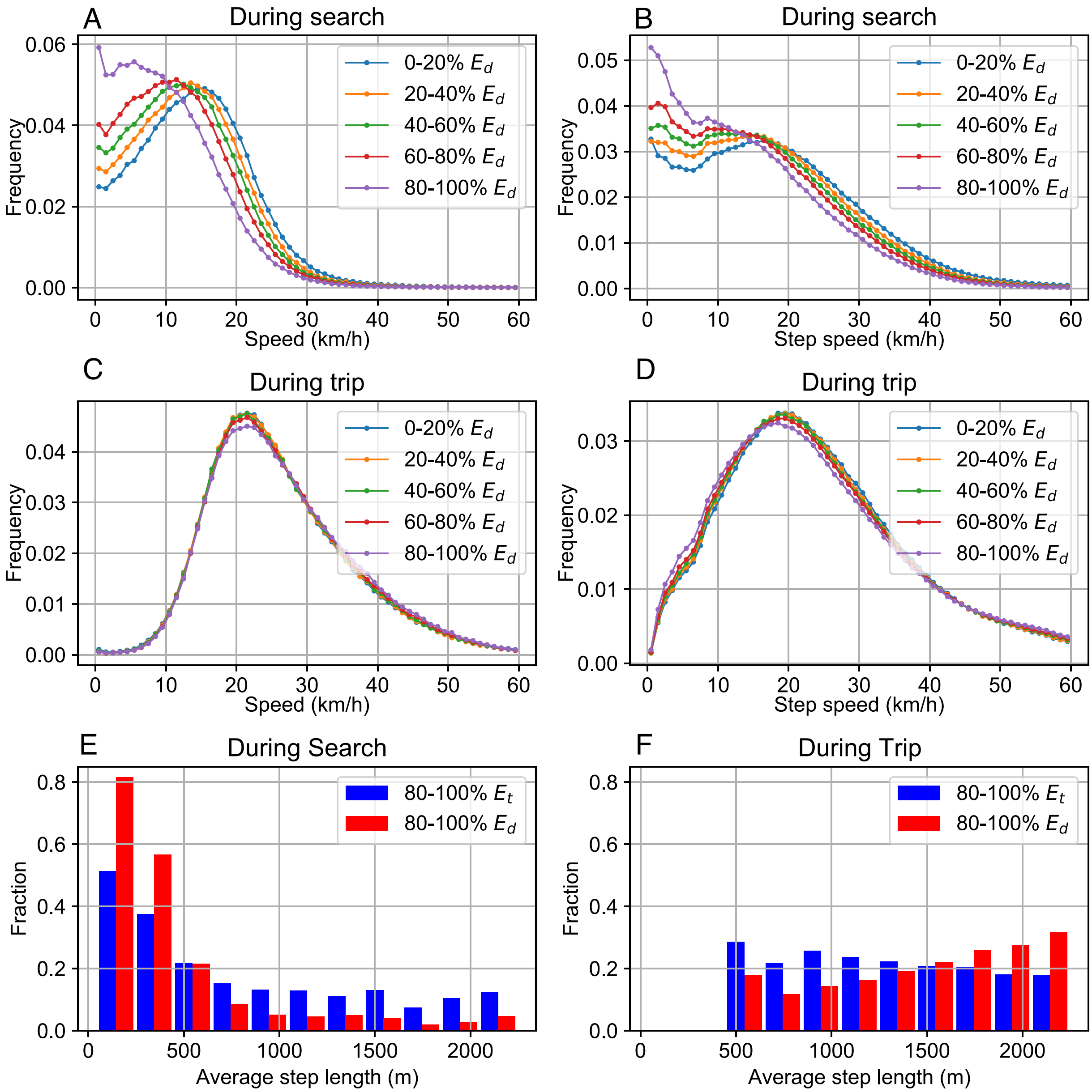

Fig. 4. Speed distributions and fractions of efficient drivers across average step length intervals in Beijing (2017). Drivers are divided into five groups based on their efficiency: The 0 to 20% group represents the least efficient drivers, whereas the 80 to 100% group represents the most efficient. (*A*) Speed distribution during the search. (*B*) Step speed distribution during the search. (*C*) Speed distribution during the trip. (*D*) Step speed distribution during the trip. (*E*) For taxi drivers with different average step length during search, the fraction of efficient drivers in each step interval. (*F*) For taxi drivers with different average step length during trip, the fraction of efficient drivers in each step interval.

and provide a theoretical perspective to help interpret these empirical findings. Specifically, we generalized the classical Lévy flight model (2, 3) by introducing a realistic missing probability $P_{\text{miss}} = 1 - \exp(-\ell/a)$, where ℓ is the step length. This parameter captures the increasing likelihood of missing passengers as speed, and consequently step length, increases. Simulation results of this generalized model (*SI Appendix*, Fig. S34) indeed show that when the probability of detection decreases with step length, the optimal exponent μ shifts to significantly higher values of μ, consistent with our empirical finding that more efficient drivers exhibit exponents higher than 2. Note that for the classical model, $P_{\text{miss}} = 0$, the known result $\mu = 2$ is recovered, in agreement with previous theoretical studies (2, 3).

These results highlight that incorporating speed-dependent detection probability is essential to model human search in realistic settings and could have implications for other systems where searchers risk overlooking targets at high speed. Our findings may also offer insights beyond the taxi context: Situations such as job seeking, information retrieval, or resource allocation in competitive environments might similarly benefit from slower, more focused search strategies. Framing our results in this broader behavioral context suggests that deliberately reducing search speed and concentrating efforts locally can, counterintuitively, improve success rates. This perspective highlights interesting directions for future interdisciplinary research.

In this paper, we aim to understand the behavioral patterns and search strategies of efficient taxi drivers, exploring what makes human search efficient. While the movement patterns of animals during foraging have received considerable attention, very little is known about the analogous behavior of human search strategies. In a general perspective, we explore the search strategies of taxi drivers for passengers as a typical model for human search behavior by analyzing large-scale GPS data of three major cities over different time periods. We find that more efficient drivers drive slower when searching for passengers compared to less efficient drivers. The more efficient they are, they drive slower. We also find that the more efficient drivers tend to make more turns compared to less efficient drivers. In contrast, and as a control, the trajectory characteristics observed during passenger searching are not observed during trips with passengers. We find that each driver generally maintains a relatively stable search performance across different days. This consistency indicates that their efficiencies are not achieved randomly but rather the result of a distinct, individual search strategy. While studying the distribution of passenger pick-up areas, we find there is no significant spatial difference between efficient and less efficient drivers. This suggests that the observed performance in efficiency is unlikely to stem from differences in targeted area selection.

In addition to the above analysis, the nature of taxi drivers' behavior raises some intriguing questions. What human qualities and characteristics enable efficient taxi drivers to navigate slowly with shorter turns in the busy, densely populated areas of the city? Understanding efficient search strategies is a significant challenge in human behavior research. In this context, studying the search patterns of taxi drivers actively seeking passengers in densely populated and congested urban areas can represent a prototype of this challenge. Our findings suggest that slower searching, in general, leads to higher efficiency. While many drivers rush through dense passenger areas to cover bigger regions, those who adopt a more patient approach-driving slowly and making more turns-often achieve better results. This strategy enables them to perform their job more effectively, possibly due to their enhanced attention to identify potential passengers earlier or to reduce the risk of making hasty decisions that could lead to detours or missed opportunities. Consequently, slower searching allows them to optimize their routes and maximize their earnings in complex urban environments. This prototype example of human search of taxi drivers illustrates that fast search is less efficient compared to slow search. Importantly, we also developed a generalized Lévy flight model incorporating a speed-dependent missing probability, which reproduces the observed shift of the optimal exponent μ toward higher values. This theoretical result strengthens our interpretation that slower and more focused searching is advantageous in realistic urban settings where passengers can be missed at high speeds of a taxi.

Data, Materials, and Software Availability. The datasets analyzed in the current study are not publicly available under the restrictions of the data provider, but they are available upon request from the corresponding author(s).

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Author affiliations: [a]Department of Physics, Bar-Ilan University, Ramat Gan 5290002, Israel; [b]School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China; [c]College of Safety Science and Engineering, Civil Aviation University of China, Tianjin 300300, China; and [d]Faculty of Engineering, Bar-Ilan University, Ramat Gan 5290002, Israel

Author contributions: Q.L., D.L., and S.H. designed research; Q.L. and O.L. performed research; and Q.L., D.L., O.L., and S.H. analyzed data; performed review and editing of the paper; and wrote the paper.

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