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Urban food delivery services as extreme heat adaptation

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More frequent global extreme heat events prompt behavioral adaptations, such as reducing outdoor activities to relieve potential distress. The emergence of innovative daily life services in cities offers new avenues for implementing such adaptive strategies. Here we investigate whether urban residents augment food delivery consumption as an immediate response to hot weather in China. Analyzing extensive food delivery service data across 100 Chinese cities from 2017 to 2023, we observe a significant surge in lunchtime orders, exceeding 12.6%, as temperatures escalate from 20 °C to 35 °C, and reaching 21.4% at 40 °C. These increments, coupled with reduced heat exposure via food delivery services, are more pronounced among female, high-income and older individuals, signifying varying degrees of benefit among consumers. We further reveal the transfer of heat exposure from consumers to delivery riders, highlighting the gains and pains introduced by food delivery services and the need for policy intervention. The quantification and findings in this study provide unique insights for the design of efficient policies promoting extreme heat adaptation and ensuring social equity while fighting climate change.

Extreme heat, fueled by global climate change, is becoming increasingly frequent and severe around the world, presenting profound threats to citizens' well-being and urban sustainability[1,2]. Heat exposure is associated with a range of adverse societal consequences, including exacerbated food insecurity[3], impaired cognitive performance[4] and intensified human conflict[5]. Moreover, it substantially jeopardizes human survival, elevating the risks of cardiac arrests[6], mental health issues[7], suicide[8,9] and mortality[10,11], particularly affecting older individuals[10,12,13]. In China, heat-related mortality among individuals aged 65 years and older has surged by 30% over the past decade[13,14]. As extreme heat events continue to escalate, with July 2023 marking the hottest month on record[15], exploring diverse strategies for adapting to such heat stress and harnessing their potential to mitigate heat-related threats across the entire population has become an imperative shared by both individuals and governments[16–18].

Previous research highlights that reducing outdoor activities is a widely adopted adaptive strategy to extreme heat[19,20]. The emergence of new daily life services in urban areas presents an opportunity to avoid outdoor activities during heat events. One such service is food delivery, which enables the direct delivery of restaurant meals to consumers' locations, eliminating the need for outdoor exposure. In recent years, this service has experienced substantial growth, driven by the rapid development of the mobile internet and smartphones[21–24]. In China, the food delivery market has seen remarkable expansion, reaching 483 billion Chinese Yuan (CNY), equivalent to US$66 billion, in 2022 and penetrating over 50% of the country's netizens[25]. These expenditures indicate that consumers could fulfill their daily food needs without exposing themselves to hazardous environmental conditions during extreme heat. However, despite the widespread use of food delivery services, scientific evidence regarding how these services are affected

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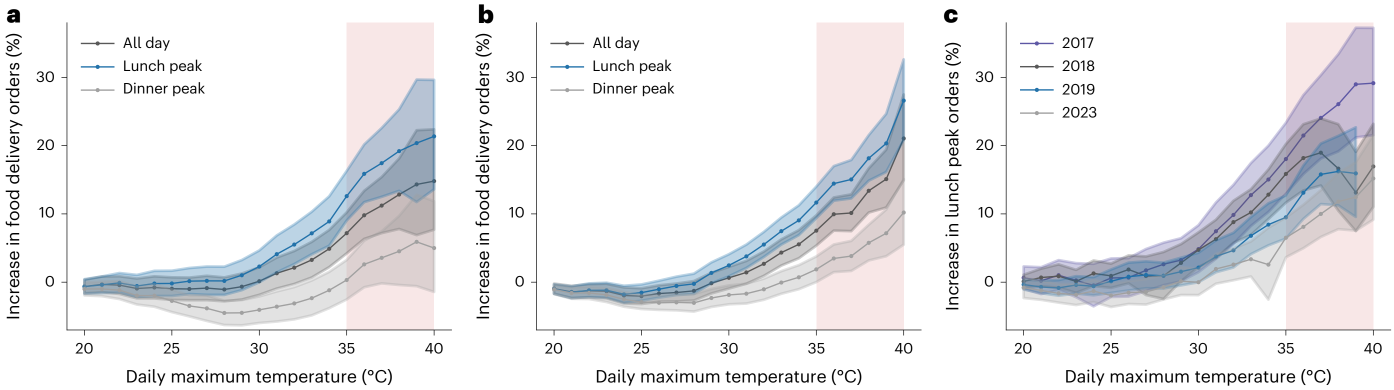

Fig. 1 | Increase in number of food delivery orders as heat stress rises. **a**,**b**, The estimated effects of daily maximum temperature on the number of all-day, lunch peak (10:30–13:30) and dinner peak (17:00–20:00) food delivery orders over 100 Chinese cities (**a**) and 9,638 urban neighborhoods (**b**). Food delivery order volume continues to rise as temperatures exceed the heat threshold in both geographic units. **c**, The estimated effect of daily maximum temperature on lunch peak food delivery orders over 100 Chinese cities in four separate years. Consistent annual trends validate food delivery services as an adaptive response to heat. Maximum temperatures are segmented into 1 °C bins, with 19–20 °C as the baseline temperature. The data points represent mean values and shaded areas show 95% CIs.

by heat events is still lacking. It is crucial to accurately quantify shifts in food delivery consumption in response to heat, measure the associated heat exposure and compare these effects across populations of different demographic backgrounds and roles within food delivery services (that is, consumers and delivery workers). Existing efforts rely on imprecise proxies of food delivery consumption with limited data granularity and representativeness[26–28], failing to explain the exact relation between food delivery and heat. Therefore, addressing the above challenges requires more refined empirical data with fine-grained spatial coverage.

In this study, we provide a large-scale examination of the role of food delivery services in urban residents' adaptation to extreme heat, specifically focusing on China, a representative case with the world's largest food delivery market[22]. We record daily food delivery order volumes (that is, the number of orders) across 100 Chinese cities and 9,638 urban neighborhoods over 4 years, constituting nearly 80% of nationwide orders (Supplementary Fig. 1). We conduct regression analyses at both the city and neighborhood levels to examine how order volumes vary with daily maximum temperature. Regression coefficients confirm the increase in food delivery consumption during extreme heat. Compared with the baseline of 20 °C, consumers purchase 21.4% more food delivery orders when the maximum temperature exceeds 40 °C. By sampling one million users and collecting their order records, we assess how this response varies across demographic groups. We find that women, high-income people and individuals of the highest age group exhibit greater food delivery increase and attribute these differences to the ability to afford food delivery service. We further provide an individual-level analysis of the reduction in consumers' heat exposure resulting from opting for food delivery, revealing an annual per-user decrease equivalent to avoiding 3.6 h of walking in extreme heat. In contrast, each delivery worker, who transports meals from restaurants to consumers' locations, endures heat exposure comparable to 6.7 days of consecutive riding in extreme heat annually. On average, each food delivery order transfers 45.8% of the consumer's mitigated heat exposure to the delivery worker.

This study provides empirical evidence of a growing dependence on food delivery services as urban residents' adaptive behavior to cope with extreme heat, highlighting a critical inequality between the associated benefits and losses: consumers' ability to alleviate heat exposure and the resulting heat-related health risks of delivery workers. Our findings hold implications for climate adaptation and policy intervention within the food delivery sector. We underscore the need for equal access to urban life services, subsidies to compensate delivery workers, the development of effective urban shading infrastructure and the promotion of sustainable practices within the industry, which are responsibilities shared by both food delivery companies and policymakers.

Results

Food delivery services as an adaptation means to heat

Urban residents significantly increase food delivery order volume on hot days (Fig. 1a,b and Supplementary Tables 2 and 3), which are days with a maximum temperature exceeding 35 °C (in accordance with the threshold of heat warning established by China Meteorological Administration[29,30]). The rise of maximum temperature to 35 °C produces a 7.2% increase ($P < 0.001$, 95% confidence interval (CI) 4.2% to 10.2%) in city-level order volume and a 7.5% increase ($P < 0.001$, 95% CI 5.3% to 9.8%) in neighborhood-level order volume compared with the baseline of 20 °C. Moreover, as heat becomes more intense, the relative growth in order volume continues to escalate. When the maximum temperature exceeds 40 °C, the daily order volume increase reaches 14.8% (city level, $P < 0.001$, 95% CI 7.7% to 22.4%) and 21.1% (neighborhood level, $P < 0.001$, 95% CI 15.0% to 27.5%). These results confirm the immediate increase in food delivery orders as a response to heat, demonstrating that urban residents utilize food delivery services as an adaptation behavior to mitigate heat exposure associated with dining out.

The magnitude of the increase in food delivery order volume differs in different periods of the day (Fig. 1a,b and Supplementary Tables 2 and 3). On the city level, the relative increase in lunch peak order volume surges to 21.4% ($P < 0.001$, 95% CI 13.6% to 29.6%) in an extreme temperature over 40 °C. In contrast, dinner order volume only increases insignificantly by 5.0% ($P = 0.13$, 95% CI −1.4% to 11.8%) when temperatures exceed 40 °C (Fig. 1a). Neighborhood-level analysis shows the same pattern (Fig. 1b). This distinction underscores the temporal sensitivity of residents' consumption patterns in response to extreme heat. People exhibit greater flexibility in their dinner choices, such as cooking at home. Office workers, on the other hand, mainly decide between dining out or waiting for food delivery at lunch. Consequently, urban residents raise their food delivery consumption most during the hottest periods of the day. In subsequent analysis, we use lunchtime orders as representatives.

Prolonged heatwave events may further intensify adaptive behaviors among urban residents. Regression results indicate that heatwave events, defined as three or more consecutive hot days, significantly increase order volumes across all time periods (Supplementary

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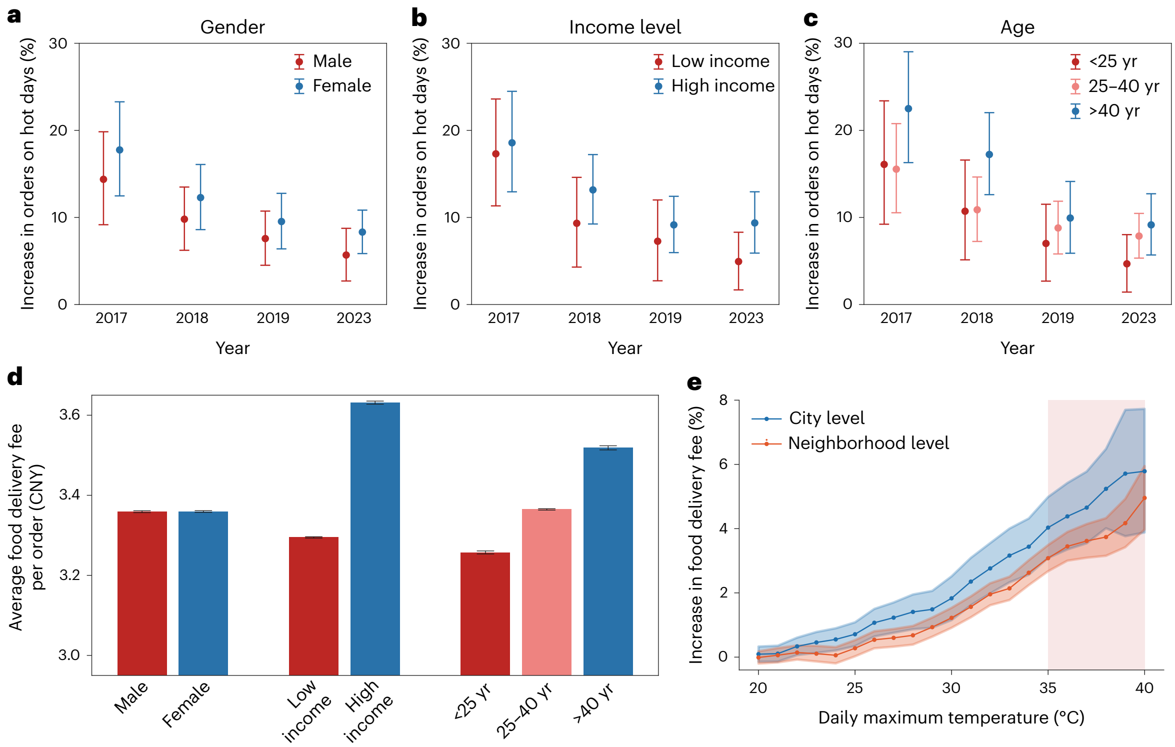

Fig. 2 | Heterogeneous response to heat stress of users over different demographic groups. a–**c**, The relative increase in food delivery orders on hot days over 35 °C across gender (**a**), income (**b**) and age (**c**) groups over 100 Chinese cities in four separate years. The data points represent mean values and the bars represent 95% CIs. Female, high-income and older users exhibit higher increased order volumes in response to extreme heat, with relative advantages of 30.3%, 41.0% and 59.5%, respectively. **d**, The average delivery fees per order of users in different demographic groups. The error bars represent 95% CIs. Number of observations for each group: male, 388,680; female, 480,651; low income, 702,271; high income, 175,634; below 25 years, 174,997; 25–40 years, 625,743; over 40 years, 99,233. High-income users pay 10.2% more delivery fees than low-income users. Users over 40 years old pay 8.0% more delivery fees than users below 25 years old. **e**, City- and neighborhood-level estimated effects of daily maximum temperature on the average delivery fee per order. Delivery fees increase during hot days. The data points represent mean values and shaded areas represent 95% CIs.

Tables 23 and 24), with a 4.1% (city level, $P < 0.001$, 95% CI 2.0% to 6.2%) and 3.6% (neighborhood level, $P < 0.001$, 95% CI 2.6% to 4.5%) rise observed during the lunch peak.

The trend of increased food delivery orders in response to heat has been consistent over 4 years. Regression analyses on four 1-year city-level panels show significant increases in both lunch peak order volume ($P < 0.001$; Fig. 1c and Supplementary Table 4) and all-day order volume ($P < 0.05$; Supplementary Fig. 3 and Supplementary Table 5) when the maximum temperature exceeds 35 °C. When temperatures exceed 40 °C, the lunch peak order volume consistently increases by over 15%. This consistent trend substantiates the robustness of food delivery services as an adaptation means to heat stress.

Heterogeneous responses over different demographic groups

Unequal exposure to extreme heat is widely observed among urban residents[17,31–33], leading to the concern of limited adaptation capability for vulnerable groups. We compare heterogeneous responses in food delivery consumption of users across different gender, income and age groups. Specifically, we estimate fixed-effect regression analysis on annual city-wise order panels for each demographic group and report the increase when the maximum temperature exceeds 35 °C relative to days with temperatures between 15 °C and 20 °C (see Methods for details). During hot days, female users exhibit slightly higher order volume increases compared with male users, with relative differences ranging from 23.5% to 46.4% (Fig. 2a and Supplementary Tables 6 and 7). High-income users, on the other hand, experience a relative increase of 7.3–89.9% greater than their low-income counterparts (Fig. 2b and Supplementary Tables 8 and 9). Moreover, older age is associated with a significantly larger surge in order volume. On hot days, the relative increase of users over 40 years is 39.8–95.7% higher than users under 25 years and 13.0–58.4% higher than users aged from 25 to 40 years (Fig. 2c and Supplementary Tables 10 and 12). These trends are consistently observed in the context of all-day order volume as well (Supplementary Fig. 4 and Supplementary Tables 13 and 19). These variations could be attributed to specific groups' vulnerability to heat exposure. Women are more sensitive to heat[34–36], which could explain their higher reliance on food delivery during hot days. People with higher income may be less inclined to prepare food by themselves[37] and more willing to pay for urban life services that enhance convenience as substitution[38,39]. Low-income groups, on the other hand, may have less affordability in terms of the cost of food delivery services.

We examine the relationship between food delivery service costs and users' heterogeneous responses to heat. As a proxy for price sensitivity, we compare the average delivery fee paid per order across different demographic groups. On average, high-income users pay 0.34 CNY more than low-income users for each order. Users over 40 years old pay 0.15 CNY more than users between 25 and 40 years old and 0.26 CNY more than users under 25 years old (Fig. 2d). This disparity in the affordability of food delivery services may prevent low-income and younger groups from increasing their orders as much as their high-income and elder counterparts.

Increased delivery service fees may further intensify this disadvantage during extreme weather days. Food delivery companies often adjust their fees based on weather conditions, such as raising charges during heavy rain and typhoons[21]. Similar adjustments occur during hot weather when demand for food delivery rises. On hot days, users

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are required to pay at least 3.1% more in delivery fees (Fig. 2e and Supplementary Tables 20 and 21). When temperatures exceed 40 °C, this increase reaches 5.8% (city level, $P < 0.001$, 95% CI 3.9% to 7.7%) and 5.0% (neighborhood level, $P < 0.001$, 95% CI 4.0% to 5.9%), equivalent to an average increase of 0.19 CNY. This price fluctuation further exacerbates the disadvantage faced by low-income and younger users, who tend to be more sensitive to such price changes, leading to unequal access to the benefits of food delivery services.

Heat exposure mitigated by food delivery service

To quantify the health benefit of consumers' adaptive behavior, we estimated the amount of heat exposure mitigated by food delivery services. We assume this mitigation is the reduction in heat exposure equivalent to what users would have experienced during a round trip to the restaurant. Heat exposure is calculated as the product of exposure time, the metabolic equivalent of task (MET) associated with travel activities and the heat index (determined by both temperature and humidity) exceeding 27 °C, with a unit of MET min °C (ref. 32). The expected values and uncertainties of mitigated heat exposure are modeled as a function of the distance between the restaurant and the user (see Methods for details).

We analyzed 36,086,316 lunch peak food delivery orders from 903,961 users between 2017 and 2019. As expected, we found a positive correlation between each individual order's mitigated heat exposure and the maximum temperature (Fig. 3a). On average, each user pays delivery fees of 133.9 CNY to reduce heat exposure by 15,306.2 (95% CI 15,303.8 to 15,308.6) MET min °C. This is akin to walking for 3.6 h or cycling for 1.9 h outdoors at 35 °C. Additionally, the average mitigated heat exposure per order is 383.42 (95% CI 383.36 to 383.48) MET min °C, equivalent to 5.4 min of walking or 2.8 min of cycling at 35 °C. In three southeastern coastal provinces (Hainan, Guangdong and Guangxi), users can reduce over 500 MET min °C of heat exposure with one food delivery order on average, reaching 824.7 in Hainan (Supplementary Fig. 6). This substantially reduces heat exposure risks in hot and humid regions. To put these results into perspective, based on a 2022 baseline of 105 million daily food delivery orders nationwide, our previous estimation implies an additional 3.7 million lunchtime orders when the maximum temperature shifts from 30 °C to 35 °C (assuming 35% of orders occurs at lunchtime). This collectively reduces heat exposure by 1.42 billion MET min °C daily, equivalent to 38.2 years of outdoor walking.

We evaluated the disparities in heat exposure reduction across demographic groups. On average, female users manage to mitigate 15.0% more heat exposure than male users, and high-income users reduce 34.4% more heat exposure than low-income users. Among different age groups, users aged 25–40 years experience the most heat exposure mitigation, which is 79.1% more than users under 25 years and 6.5% more than users over 40 years (all differences $P < 0.001$; Fig. 3b). These significant differences are linked to discrepancies in total delivery distance (Fig. 3c), where female users, high-income users and users aged 25–40 years have significantly longer total delivery distances over 3 years. When examining daily trends (Fig. 3d), these discrepancies persist, although disadvantaged users are gradually closing the gaps. By 2019, the gender and income difference decreased to 10.5% and 24.7%, respectively. Users aged 25–40 years have 35.9% more mitigated heat exposure than users below 25 years. Although these differences remain statistically significant ($P < 0.001$), the expanding availability of affordable food delivery services holds the potential for equalizing benefits among user groups.

Heat exposure transferred to food delivery workers

Evidently, the increase in food delivery consumption during hot days implies a reduction in heat exposure for users, while simultaneously indicating increased heat exposure experienced by delivery workers transporting prepared meals from the restaurants to consumer locations. Accurate quantification of this shift is essential for comprehensively understanding the role of food delivery services in redistributing heat exposure and for designing effective policies. Here, we quantify this process from a daily panel that records the total working hours and completed orders of delivery workers in each city. Similar to the trend illustrated in Fig. 1, the average completed order of each worker increases as temperature rises. When the maximum temperature exceeds 35 °C, each worker is required to transport, on average, 7.3% ($P < 0.001$, 95% CI 4.8% to 9.7%) more orders compared with the baseline at 20 °C (Fig. 4a and Supplementary Table 22). At a temperature of 40 °C, the relative increase reaches 18.0% ($P < 0.001$, 95% CI 12.6% to 23.6%).

Given the significantly increased workload of delivery workers on hot days, we further quantify their daily experienced heat exposure by integrating the weather conditions and the per-worker outdoor working duration during the lunch peak (see Methods for details). The daily per-worker heat exposure in each city demonstrates a positive correlation (Pearson $r = 0.84$, $P < 0.001$) with the corresponding maximum temperature (Fig. 4b). On average, each worker accumulates 5.46×10^5 (95% CI 5.43×10^5 to 5.49×10^5) MET min °C of heat exposure annually, which is equivalent to 6.7 days of riding an electric motorcycle (the most popular transportation mode among delivery workers) at a temperature of 35 °C. Specifically, the accumulated heat exposure during July and August accounts for 52.8% of the annual total, comparable to riding 1.4 h at 35 °C each day. This quantitative result highlights the urgent need to address the health risks faced by delivery workers.

By integrating delivery workers' workload data with individual transaction data, we calculate the proportion of heat exposure mitigated by users transferred to delivery workers. The expected per-order heat exposure mitigated by users exceeds the expected per-order heat exposure experienced by workers at the same temperature level (Fig. 4c). Additionally, the daily trend of per-order user-mitigated heat exposure is above the curve of worker-experienced heat exposure (Fig. 4d). On average, each delivery order imposes 180.1 (95% CI 179.1 to 181.2) MET min °C on a delivery worker, which is 45.8% of the per-order heat exposure mitigated for consumers. Consequently, food delivery services reduce overall heat exposure across the population, but they also exacerbate the inequality of heat exposure between consumers and delivery workers. One reason for a transfer rate of less than one is that workers are exposed to heat only during the one-way trip from the restaurant to the user's location, in contrast to consumers who would be exposed during a round trip. Another factor is the impact of the order bundling strategy, where multiple orders with proximate delivery locations are simultaneously delivered by the same worker to enhance efficiency. Notably, during summer months (June, July and August), the heat exposure transfer rate falls below the annual average (Fig. 4d and Supplementary Fig. 7). This trend may be linked to improved delivery efficiency in these months, which exhibits a negative correlation with the transfer rate (Supplementary Fig. 7).

This analysis underscores a crucial inequality in urban residents' adaptive behavior to extreme heat. By paying for food delivery services, users transfer a consideration portion of heat exposure risk to delivery workers, who are often rural migrants[40] and freelance workers[41] with low socioeconomic status[24]. This transfer represents a negative externality and poses potential long-term health risks. It necessitates the formulation of policies and mechanisms aimed at compensating this vulnerable population, ensuring that health disparities engendered by this new economic activity are adequately addressed.

Discussion

While a growing literature supports the idea that urban residents adapt their behavior to extreme heat by limiting outdoor activities[19,20], research on the human behavior of utilizing urban daily life services as part of this adaptation is scarce. This study contributes to existing

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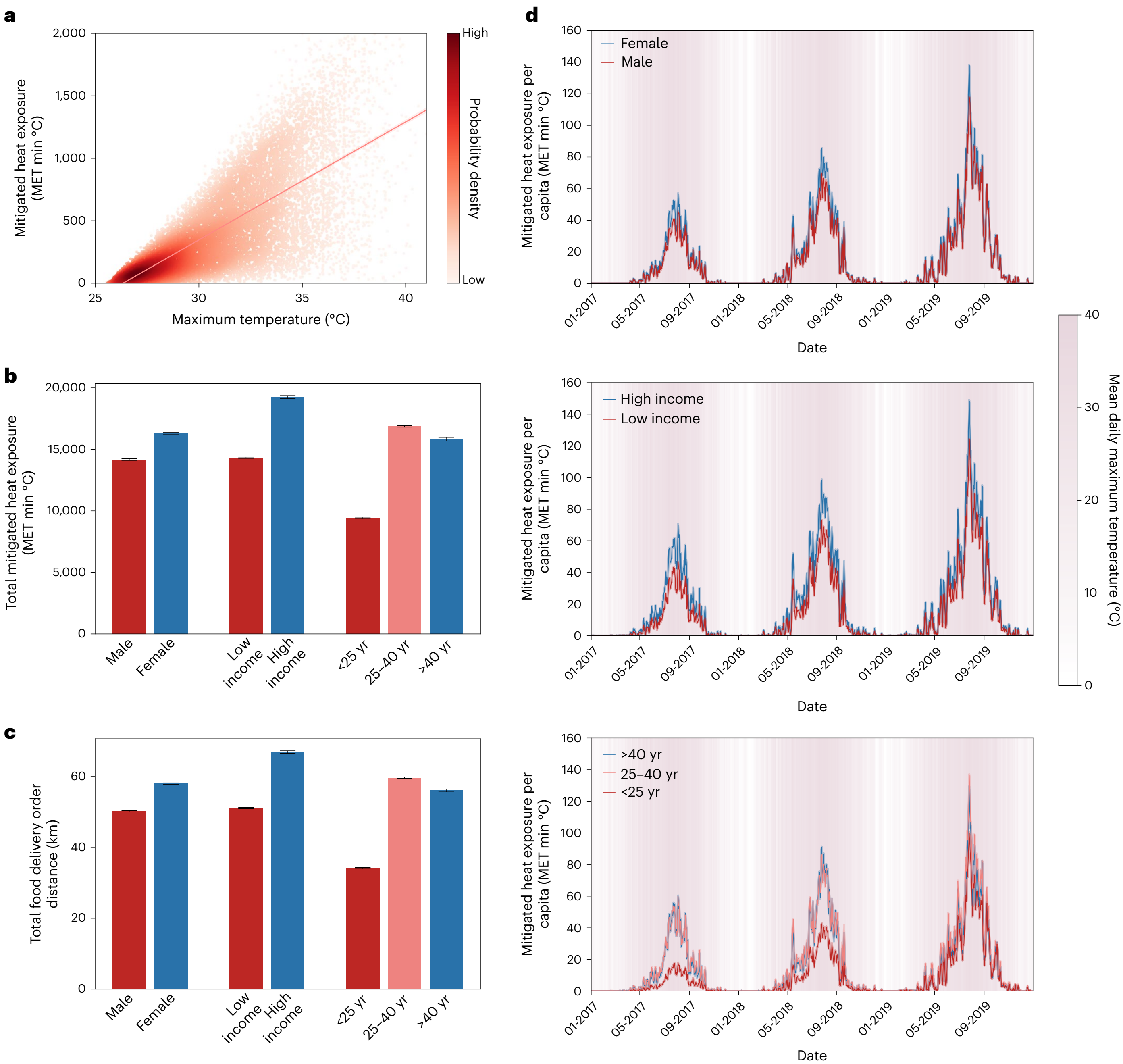

Fig. 3 | Food delivery service mitigates consumers' exposure to heat environment. a, The joint distribution of temperature and mitigated heat exposure for each food delivery order. The red line characterizes a linear fit of mitigated heat exposure over daily maximum temperature. **b**,**c**, The mean values of total mitigated heat exposure per capita (**b**) and total food delivery order distance per capita (**c**) across different demographic groups. The error bars represent 95% CIs. Number of observations for each group: male, 388,680; female, 480,651; low income, 702,271; high income, 175,634; below 25 years, 174,997; 25–40 years, 625,743; over 40 years, 99,233. **d**, Daily mitigated heat exposure per capita across users with different gender (upper), income (middle) and age (lower) groups in 3 years. The shaded areas represent 95% CIs and background colors represent the mean daily maximum temperature.

knowledge by leveraging a vast amount of observations of food delivery services to investigate shifts in urban residents' food delivery consumption patterns during extreme heat. Our findings reveal a robust and substantial increase in food delivery orders during hot days with maximum temperature exceeding 35 °C. This increase is most pronounced during the hottest lunch peak hours. We provide the first quantification of consumers' resultant heat exposure mitigation benefits from this adaptation behavior. This finding provides unprecedented nationwide empirical evidence that food delivery services offer urban residents an adaptive means of avoiding severe heat exposure while satisfying their essential dining needs.

While consumers benefit from food delivery services by avoiding heat exposure, 45.8% of this mitigated exposure is transferred to delivery workers, highlighting that this heat adaptation behavior involves both gains and pains. The shift is partial, which means a reduction of society's overall heat exposure. But this does not necessarily mean that the overall health cost of heat exposure is reduced. The transfer-induced high accumulated exposure of delivery workers raises serious concerns about workers' heat-related health risks, such as cardiovascular failure[12] and kidney disease[42,43]. To compensate for health losses in the food delivery industry, it is imperative that mechanisms are established to provide delivery workers with heat allowances or subsidies,

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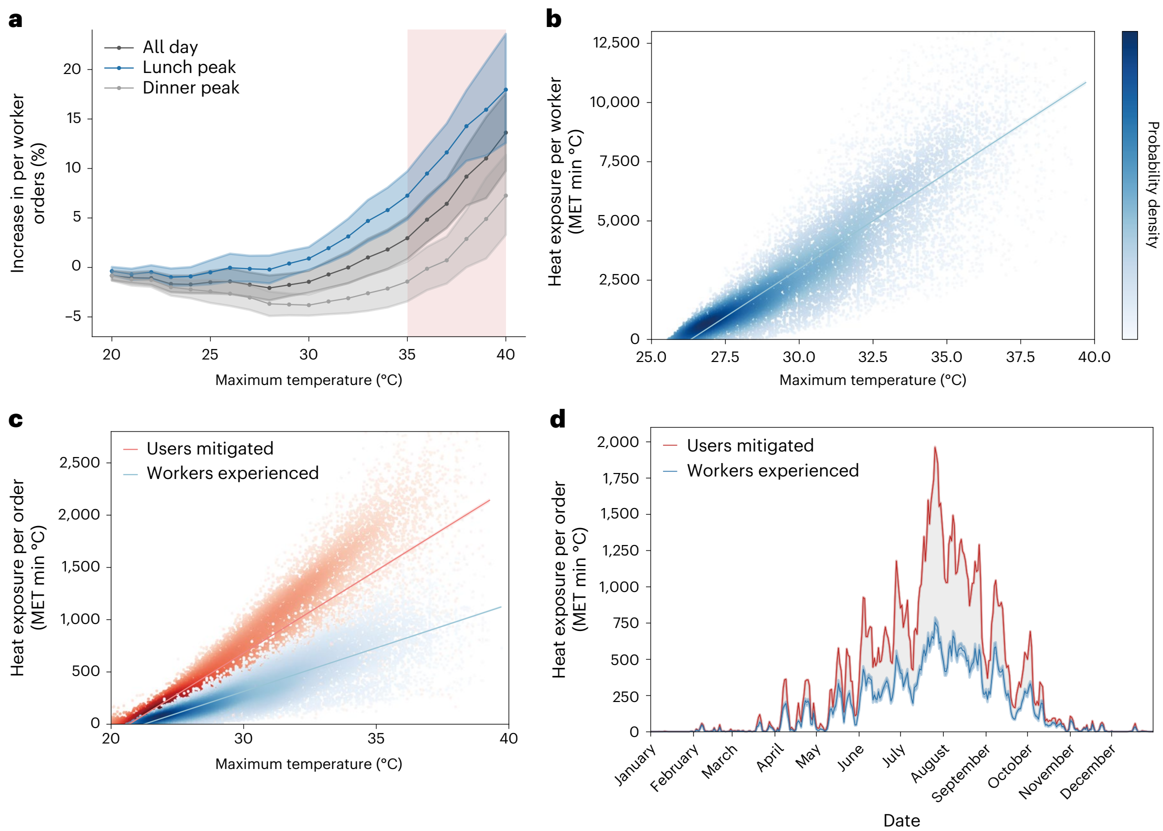

Fig. 4 | Food delivery workers' workload and experienced heat exposure. **a**, The estimated effects of daily maximum temperature on the average number of orders completed by each delivery worker over 100 Chinese cities. The workload continues to rise as temperature exceeds the heat threshold. The data points represent mean values and shaded areas represent 95% CIs. **b**, The joint distribution and linear fit of daily maximum temperature and per-worker experienced heat exposure over 100 Chinese cities in 1 year. Each dot represents a daily observation in one city. **c**,**d**, A comparison of per-order heat exposure mitigated by users (red) versus per-order heat exposure experienced by delivery workers (blue) under varying temperature conditions (**c**) and across different dates (**d**) over 100 Chinese cities in 1 year. The shaded areas in **d** represent 95% CIs. Owing to shorter delivery trips and order bundling strategies, only 45.8% of the user-mitigated heat exposure is transferred to delivery workers on average.

essential health insurance and training programs to recognize and mitigate heat-related risks[43,44]. Also, authorities can contribute directly by creating cooler urban environments for delivery workers, such as implementing shaded pathways and rest areas with cooling facilities, and integrating more green spaces and water bodies to help lower ambient temperatures[45]. Additionally, a promising solution to reduce the burden on disadvantaged groups during hot days is the adoption of autonomous delivery technologies, such as driverless vehicles and drones, which have already been implemented in some Chinese cities[46].

Food delivery services also potentially introduce other adverse effects, especially in light of the growing demand in response to future climate change. By projecting climate data for 2050 using the Coupled Model Intercomparison Project Phase 6 ensemble models[47] under the SSP 585 scenario (see Supplementary Note 4 for details), we anticipate a 1.0% relative increase in annual food delivery orders by 2050 (Supplementary Fig. 8), which equates to a notable increase of 444.8 million orders during the four summer months. This projection underscores the imminent challenges facing the food delivery industry, especially urban environment risks. One major concern is the potential surge in plastic pollution due to the rise in food packaging[48]. It is imperative for authorities to regulate the use of sustainable packaging materials among food vendors and discourage single-use plastics among customers to address these environmental sustainability challenges. Another concern is the high carbon and environmental footprint of food delivery services[49]. It is important to promote the use of electric bikes and optimize delivery routes to mitigate future increases in footprints. In the face of the above challenges, appropriate policy interventions are critical to promoting the sustainable development of the food delivery industry, especially regarding delivery workers' labor practices, environmental impact and safety standards[21,23,50].

Furthermore, we demonstrate heterogeneity in users' adaptive behaviors, which extends existing knowledge on the heterogeneity in heat exposure[31–33]. The average heat exposure avoided by different gender, income and age groups through food delivery services varies significantly. Males, low-income groups and users below 25 years of age experience insufficient benefits in terms of mitigated heat exposure. The inequality in adaptive behaviors may also imply that, as overall income levels rise in the future, the demand for food delivery services is likely to increase alongside its negative impacts such as heat exposure redistribution and the environmental footprint. It is essential to undertake strategic planning and policy design to mitigate these adverse effects. Additionally, we reveal a correlation between adaptive capacity and the service fees paid for food delivery orders, suggesting that increased delivery fees could potentially be a barrier for low-income and younger users. This phenomenon, along with the substantial transfer of heat exposure from consumers to workers, indicates that the emergence of new urban services introduces new forms of social inequalities. These may manifest through various channels, such as differing spending power across income groups or disparities between service consumers and providers. Recognizing these inequalities, it becomes crucial to implement policies that anticipate future developments in urban services, aiming to minimize consumer–worker disparities and enhance equitable access to these services for all residents.

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We acknowledge some limitations in our study. First, our research data are sourced from a single food delivery platform in China. It is important to note that this platform is one of the largest companies and is widely regarded as representative. Future work could benefit from conducting comparative analyses to validate the universality of our findings across global regions with diverse climatic and socioeconomic conditions and varying urban structures. Owing to data limitations, a detailed analysis of the adaptive behaviors of seniors, who are particularly vulnerable to heat, is identified as an important direction for future research. In calculating the mitigated or experienced heat exposure, we derive the heat index using the daily maximum temperature and relative humidity, though the outdoor temperature at the time of order placement may not be the highest of the day. We focus on orders during the lunchtime peak to minimize this bias. While we highlight the potential health benefits of food delivery for specific populations, the potential negative environmental impact, particularly concerning plastic packaging waste and carbon emissions, should be assessed against these benefits in future research efforts. This study contributes to the literature on urban resident behaviors by extending our understanding beyond prior studies that relied on inaccurate approximations and data with limited sample sizes[26–28].

Methods

Food delivery data

Food delivery order data are recorded by an online food delivery platform in China. We aggregated raw data into two distinct geographical levels, that is, city level and neighborhood level. Prefecture cities were divided into Geohash-5 neighborhoods, each covering an area of approximately 4.9 km × 4.9 km. For each of these geographic units, we obtained two metrics in the entire day, during the lunch peak (10:30–13:30) and during the dinner peak (17:00–20:00). These metrics include the volume of delivery orders and the total delivery fees paid for these orders. The data spans from 1 January 2017 to 31 December 2019, and further extends from 1 January 2023 to 20 August 2023. We excluded the period of the COVID-19 pandemic from our analysis as lockdown policies disrupted the regular operation of the food delivery industry in many cities, introducing uncertain and heterogeneous effects beyond the impact of temperature (Supplementary Fig. 10). We focused on geographic units within the 100 cities that exhibit the highest food delivery order volumes. Collectively, these units account for a substantial 78.5% of the platform's total orders within the Chinese mainland (Supplementary Table 1 and Supplementary Fig. 1). This dataset encompasses 100 cities and 9,638 neighborhoods.

In addition to the aggregated data, food delivery order records of one million users are provided. These records document the order placement time, the origin of delivery (restaurant location), the delivery destination (user's location), the delivery fee paid and the total order amount paid. User profiles, including gender, income level and age, are provided. To ensure user privacy, income levels are simplified into two categories: 'high income' and 'low income'. Similarly, age groups are categorized as 'below 25', '25 to 40' and 'over 40' (see the distribution of user demographics in Supplementary Table 25). Owing to data limitations, finer subdivisions within the 'over 40' age group are not accessible. By combining user profiles with their respective city locations, we construct city-level daily order panels for each demographic group.

Aside from food delivery order data, we also obtained the daily workload of food delivery workers in each city. These records include the number of active delivery workers, the total number of completed orders and the total working hours of workers throughout the entire day, as well as during the lunch and dinner peaks. See Supplementary Note 1 for details of data collection.

All data collected were processed under stringent user privacy protection protocols. Specifically, users grant permission to access their order behaviors and demographic information via a confidentiality agreement. They are informed about the purpose of the data collection and consent to the use of their data for research purposes. The datasets are thoroughly anonymized in the data processing, ensuring that no real user IDs are accessible during processing. Moreover, to prevent privacy breaches from online attacks, datasets are stored offline and access is restricted to authorized researchers only. These measures guarantee that our analysis is conducted with full protection of user privacy.

Weather data

We linked geographic units with ground-station level meteorological records sourced from Global Surface Summary of the Day (GSOD)[51]. Following the procedure in ref. 52, we matched each city and neighborhood with all available climate stations situated within a 100 km radius buffer of its administrative center (for cities) and geographic center (for neighborhoods). We calculated the average of recorded maximum temperature, precipitation, relative humidity index and wind speed of all the matched stations as the geographic unit's daily weather indicators. Subsequently, for each order record, we used the daily weather indicators corresponding to the neighborhood in which the user is located.

Impacts of temperature on order volumes

By combining the aforementioned datasets, we constructed daily panels that capture the trends in online food delivery orders and concurrent weather conditions across two geographical unit levels. We used a fixed-effects panel model to examine the influence of daily maximum temperature on food delivery ordering behavior.

At the city level, we estimated the following regression using the ordinary least squares method:

$$\ln(Y_{ct}+1) = f(\mathrm{temp}_{ct},\beta) + \alpha Z_{ct} + \mu_c + \lambda_t + \epsilon_{ct}, \qquad (1)$$

where c indexes the city and t indexes calendar date. Y_{ct} is the dependent variable for c at date t, for example, food delivery order volume, food delivery fee per order, orders completed per worker and so on. Z_{ct} comprises the precipitation, relative humidity and wind speed of c at t. Precipitation bins are segmented at 0.1, 10, 25 and 50 mm, corresponding to the division of precipitation levels defined by the China Meteorological Administration. Relative humidity is cut into 10% bins from 0% to 100%. Respectively, μ_c and λ_t are city effects and date effects. The former accounts for spatial variations in the prevalence of the food delivery service, while the latter captures seasonal trends and the natural expansion of the food delivery services. The standard error term ϵ_{ct} is clustered on both city and date[53].

Similarly, at the neighborhood level, we estimated the following regression using the ordinary least squares method:

$$\ln(Y_{ict}+1) = f(\mathrm{temp}_{it},\beta) + \alpha Z_{it} + \mu_i + \theta_{\mathrm{dow}} + \gamma_{\mathrm{holiday}} + \lambda_{cm} + \epsilon_{ict}, \qquad (2)$$

where i indexes a neighborhood, c indexes the city in which it is located, m indexes the month and t indexes calendar date. Y_{ict} is the dependent variable for i at date t and αZ_{it} is the binned level of precipitation and relative humidity as well as the wind speed of i at t, while μ_i represents the neighborhood fixed effects. θ_{dow} and $\gamma_{\mathrm{holiday}}$ are day-of-week fixed effects and holiday fixed effects, respectively, controlling for the weekly seasonal variation factors and order fluctuation during holidays. λ_{cm} represents city-by-month fixed effects accounting for locally seasonally variation. The standard error term ϵ_{ict} is clustered on neighborhood, city and date levels.

Our main independent variables, temp_{ct} and temp_{it}, represent the daily maximum temperature for a geographic unit at date t. Our relationship of interest is represented by $f(\mathrm{temp}_t,\beta)$, which provides individual indicator variables for each 1 °C daily maximum temperature bin from 0 °C to 40 °C. This allows for a flexible estimation of

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the non-linear relationship between temperature and food delivery order volume. We take the 19–20 °C indicator as the relative baseline. Therefore, the regression coefficients β for a temperature bin can be translated to $e^{\beta}-1$ to get the percentage change in Y at that temperature relative to the baseline. We estimate regressions on different Ys, (for example, all-day food delivery order volume, lunch peak order volume and lunch peak per order delivery fee and so on), and different time spans (2017, 2018, 2019, 2023 and all 4 years combined).

To investigate the varying responses to heat stress among different demographic groups, we employed equation (1) on separate city-level panels generated from individual order records. In these regressions, we segmented the daily maximum temperature into indicator variables, each corresponding to a 5 °C bin within the range of 0–35 °C, with the 15–20 °C indicator serving as the relative baseline. The regression coefficient for temperatures above 35 °C is interpreted as the group's response to extreme heat.

Quantifying heat exposure

We assessed how food delivery services redistribute heat exposure by quantifying both the reduction in heat exposure achieved by consumers and the corresponding heat exposure experienced by food delivery workers. Here, we adopted the approach outlined in ref. 32, which defines heat exposure as the product of activity intensity, activity duration and the National Weather Service (NWS) heat index above 27 °C (ref. 54). The intensity of an activity was characterized by the ratio of the energy consumption rate during that activity to the resting metabolic rate, with a unit of MET. For instance, the intensity of walking is 3.5 MET according to the 2024 Adult Compendium of Physical Activities[55]. Considering the variability in resting metabolic rates across individuals[56] and the increased metabolic rate in heat environments[57], we calibrated the values of activity intensity using the population average resting metabolic rate and temperature (see Supplementary Note 3 for details). The NWS heat index quantifies the outdoor ambient temperature incorporating both temperature and humidity[58]. NWS recommends precautionary measures when the ambient temperature exceeds 27 °C. For each order placed during the lunch peak period (10:30–13:30), we computed its corresponding NWS heat index based on the daily maximum temperature and relative humidity of the city in which it is located. Heat exposure for a specific activity was then calculated by multiplying its intensity, duration and the NWS heat index exceeding 27 °C, indicating higher activity duration and ambient temperature increases heat stress. Heat exposure is expressed with a unit of MET min °C.

User-mitigated heat exposure. We first computed the reduction in heat exposure achieved for each user with each delivery order. When consumers opt for food delivery, it replaces the need for them to travel to the restaurant in person. Therefore, we approximated the value of mitigated exposure as the exposure users would encounter if they were to make a round trip to the restaurant themselves.

The above calculation requires knowledge of the specific transportation modes users employ for their trips to the restaurant. Prior studies in the transportation literature have developed effective models for characterizing transportation mode choices[59,60]. One pivotal determinant is the travel distance[61,62]. Therefore, for each delivery order, we assigned the probability distribution of transportation mode based on the order's distance d from the restaurant to the user. The distribution of travel distance $P(d|\text{mode})$ is often represented by a gamma distribution[63–65], with different shape and scale parameters associated with various transportation modes. We adopted the parameters for walking, cycling, driving and public transit as provided in ref. 66 (see Supplementary Table 26 for details), which are derived from extensive observations of travel behavior among Chinese citizens. Combining annual transportation reports in several major Chinese cities, we established the overall distribution of transportation modes $P(\text{mode})$ comprising 30% for walking, 12% for cycling, 28% for driving and 30% for public transit. Given these assumptions, the transportation mode distribution for an order with distance d is computed using the Bayes' theorem $P(\text{mode}=m|d)=\frac{P(d|\text{mode}=m)P(\text{mode}=m)}{\sum_{m'}P(d|\text{mode}=m')P(\text{mode}=m')}$. Supplementary Fig. 5 provides an illustration of $P(\text{mode}=m|d)$ for the four modes within a 10 km range.

The activity intensity I_m for walking, cycling, driving and public transit are 3.5, 6.8, 2.0 and 1.3 MET, respectively[55]. Drawing from transportation reports in Chinese cities, we set the average travel speeds υ_m for walking, cycling, driving and public transit as 4.8 ± 0.5, 9.7 ± 3.0, 30 ± 5.0 and 15 ± 5.0 km h^{-1}, respectively. Consequently, for an order with a distance d, we calculate its expected heat exposure as

$$\text{Heat exposure}\,(d)=\sum_m\left[P(\text{mode}=m|d)\times I_m(T)\times\frac{2d}{\upsilon_m}\right]\times(\text{NWS heat index}-27^{\circ}\text{C}),\qquad(3)$$

where m corresponds to each of the transportation modes. Activity intensity $I_m(T)$ is calibrated by the resting metabolic rate and temperature T. Supplementary Fig. 5 illustrates the expected heat exposure per °C and corresponding 95% CIs within a 10 km range.

Worker-experienced heat exposure. We then computed the heat exposure experienced by delivery workers during the lunch peak following the same procedure. Given the total working hours of delivery workers in each city, we multiplied it by the average proportion of time spent on outdoor delivery activities by individual workers to estimate the duration of their exposure to outdoor environments (see Supplementary Note 3 for details). We then calculated their accumulated heat exposure by multiplying the outdoor working time t by the activity intensity I and the heat index exceeding 27 °C: heat exposure = $I\times t\times$ (NWS heat index − 27 °C). In Chinese cities, delivery workers typically use electric bikes or electric motorcycles to transport meals[49], with an intensity I of 2.8 MET[55]. By dividing the total accumulated heat exposure by the number of workers and the number of completed orders, we further derived the per-worker and per-order heat exposure every day in each city.

Uncertainties in heat exposure. The quantification of heat exposure may be influenced by two primary sources of uncertainty: variability in activity intensity and the duration of time spent in outdoor environments. Regarding the first source of uncertainty, the resting metabolic rate of a typical adult is measured at 0.863 (95% CI 0.852 to 0.874) MET[56]. We employed a normal distribution of resting metabolic rates to calibrate activity intensity levels. For the uncertainty associated with users' travel time, we assume that in equation (3), the travel speed υ_m for each mode of transportation follows a normal distribution[67] (Supplementary Table 26). To address the uncertainty in workers' exposure time to outdoor environments, we derived the distribution of outdoor activity proportions during working hours from fine-grained behavioral data collected from 10,000 sampled workers. Utilizing these distributions, we conducted a Monte Carlo analysis with 10,000 iterations by varying the input variables[68]. We report the 95% CIs for heat exposure in Results. The narrow CIs, less than 1%, support the robustness of our quantification.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Data of online food delivery orders are proprietary owing to the non-disclosure agreement with the platform. Daily meteorological records were collected through the 'get_GSOD' function of the R package 'GSODR'[69]. Temperature projections of Coupled Model Intercomparison Project Phase 6 models were collected from Earth System Grid Federation's Metagrid Support (https://aims2.llnl.gov/search). The data supporting the results of this study are available via Zenodo at https://doi.org/10.5281/zenodo.13373472 (ref. 70) and GitHub at https://github.com/tsinghua-fib-lab/Food-Delivery-as-Heat-Adaptation.

Code availability

The major data processing and figure production were conducted in Python 3.9 with packages pandas, geopandas, seaborn, scipy, matplotlib and numpy. The regression analyses were conducted in R studio 2024.04.2 based on R 4.1.1 with packages GSODR, fixest and sf. Reproduction codes for the figures are available via Zenodo at https://doi.org/10.5281/zenodo.13373472 (ref. 70) and GitHub at https://github.com/tsinghua-fib-lab/Food-Delivery-as-Heat-Adaptation.

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Author contributions

Y.Z., D.W., Y. Liu and Y. Li jointly launched this research. Y.Z., D.W., Y. Liu, K.D., P.L., P.H. and Y. Li contributed ideas. Y.Z. performed data analyses and prepared figures, with support from D.W. and P.H. on analytical approaches and from D.W., Y. Liu, P.L., P.H. and Y. Li on discussions. D.W., P.L. and Y. Li managed the project. All authors jointly participated in the writing of the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Software and code

Policy information about availability of computer code

Data collection	No software was used for data collection.
Data analysis	This study used R 4.1.1 (with R Studio 2024.04.2) and Python 3.9 to conduct data analysis. Required R packages are "GSODR", "fixest", "sf". Required Python packages are "pandas", "geopandas", "seaborn", "scipy", "matplotlib", "numpy". Reproduction codes for the figures are deposited in Zenodo (https://doi.org/10.5281/zenodo.13373472).

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Data of online food delivery orders are proprietary due to the non-disclosure agreement with the platform. Daily meteorological records are collected through the "get_GSOD" function of the R package "GSODR". Temperature projections of CMIP-6 models are collected from Earth System Grid Federation's Metagrid Support (https://aims2.llnl.gov/search). The data supporting the results of this study is available on Zenodo (https://doi.org/10.5281/zenodo.13373472) and Github (https://github.com/tsinghua-fib-lab/Food-Delivery-as-Heat-Adaptation).

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Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	No human participants were involved in this study.
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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study examined whether citizens increase their consumption of food delivery services immediately in response to extreme heat based on quantitative data. Quantitative approaches, including as fixed-effect regressions, numerical analysis, and multivariate regressions, were employed to validate this hypothesis. Our findings confirmed a substantial influence of heat on the volume of food delivery orders and revealed varying benefits of this increase for consumers among different demographic segments. Meanwhile, we revealed a substantial share of mitigated heat exposure is transferred to delivery workers. This study underscores significant policy implications for climate change adaptation and ensuring social equity.
Research sample	This study used data provided by an online food delivery platform. Each raw data point represented an order made by a platform user, recording the placement timestamp, payment, delivery fee, order category, user location (geohash7 grid). We aggregated the raw data into city- and neighbourhood-level daily order volume panel datasets. We also randomly sampled an individual-level user order dataset of one million platform users, covering a sufficient proportion of all active users. In addition, we use a daily workload panel dataset of delivery workers recording the number of completed orders and working times in each city.
Sampling strategy	We randomly sampled one million platform users who had placed at least one order before the year of 2020, covering a sufficient proportion of the active user population. We take their food delivery records as the individual-level food delivery order dataset.
Data collection	We did not collect data, but utilized existing datasets. The datasets are stored offline and are thoroughly anonymised by the food delivery platform. Data access is restricted to authorized researchers only.
Timing	2017-01-01~2019-12-31, 2023-01-01~2023-08-20
Data exclusions	No data were excluded from analysis.
Non-participation	Non participants were involved in the study.
Randomization	This study does not include randomized controlled trials, and data were not organized into experimental groups.

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Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Plants

Seed stocks	*Report on the source of all seed stocks or other plant material used. If applicable, state the seed stock centre and catalogue number. If plant specimens were collected from the field, describe the collection location, date and sampling procedures.*
Novel plant genotypes	*Describe the methods by which all novel plant genotypes were produced. This includes those generated by transgenic approaches, gene editing, chemical/radiation-based mutagenesis and hybridization. For transgenic lines, describe the transformation method, the number of independent lines analyzed and the generation upon which experiments were performed. For gene-edited lines, describe the editor used, the endogenous sequence targeted for editing, the targeting guide RNA sequence (if applicable) and how the editor was applied.*
Authentication	*Describe any authentication procedures for each seed stock used or novel genotype generated. Describe any experiments used to assess the effect of a mutation and, where applicable, how potential secondary effects (e.g. second site T-DNA insertions, mosiacism, off-target gene editing) were examined.*