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Protocol

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A protocol for the comprehensive evaluation of greenhouse gas and air pollutant emissions from shopping

Ruibin Xu[1,2,3*], Huizhong Shen[1,2], Peng Wang[3,4], Tao Wang[3], Jing Meng[5] and Shu Tao[1,2,6]

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Abstract

The global retail sector considerably contributes to climate change and air pollution through greenhouse gas (GHG) and air pollutant emissions associated with shopping activities—including freight transport, consumer travel, and packaging use. While prior studies have estimated these emissions, they hinder cross-study comparisons, limiting both scientific understanding and the development of effective mitigation strategies. To address this gap, we present a standardized protocol for comprehensive and consistent assessment of GHG and air pollutant emissions from shopping. Demonstrated through case studies on three major merchandise categories in China, our approach improves upon existing work by offering greater comprehensiveness, national representativeness, and temporal coverage. An agent model for emission calculation was built based on this protocol to provide ground-truth logic of retail activities for artificial intelligence agents, enabling emission calculations under varying consumer and supply-chain scenarios. We propose this protocol as a robust framework to enable comparable, transparent evaluations across shopping methods, product categories, regions, and time periods—thereby advancing evidence-based strategies for sustainable retail transformation.

Keywords: Shopping, Carbon dioxide, Air pollutant emissions, Supply chain phase, Transport, Packaging waste

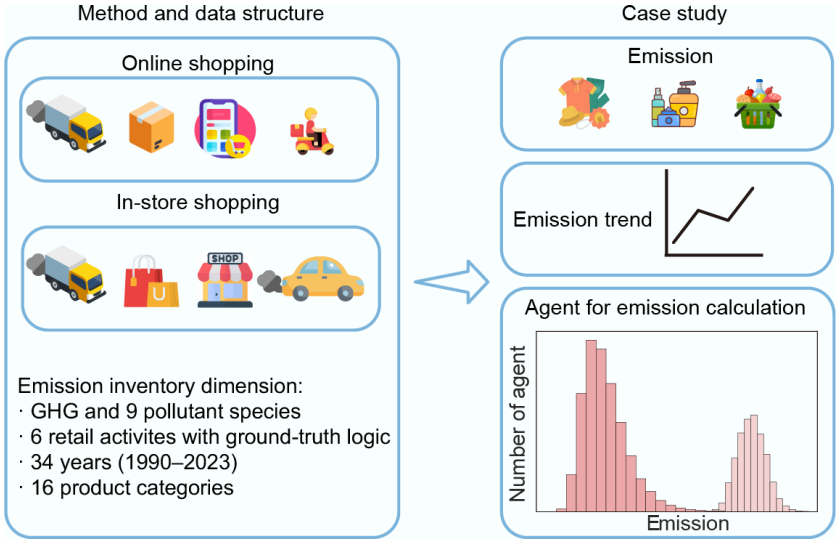
Highlights

- A comprehensive methodology for assessing emissions from traditional and online shopping has been developed.
- Nationwide parameters for China, covering 1990–2023 and 16 key merchandise categories, were recommended.
- Cases for evaluating emissions from shopping for necessities, textiles, and foodstuffs in China were presented.
- Cases showed the protocol enables comprehensive and temporal trend analysis of shopping emissions vs. prior methods.
- An agent-based emission calculation model was developed to provide a ground-truth reference framework for AI agents.

* Correspondence: Ruibin Xu (ruibin.xu@connect.polyu.hk)

Full list of author information is available at the end of the article.

Graphical abstract



Introduction

The retail sector considerably contributes to climate change and air pollution through greenhouse gas (GHG) and air pollutant emissions generated along retail supply chains[1–4]. Global retail sales have surged from 15 trillion USD in 2011 to 31 trillion USD in 2024, reflecting rising shopping demands[5]. Online and traditional in-store sales reached approximately 6.3 trillion USD and 25 trillion USD, respectively, in 2024[5]. These two sales methods exhibit distinct supply chain patterns—such as courier delivery versus consumer travel, extensive packaging use versus lightweight plastic bags, and reliance on electronic devices versus store operations—leading to differences in GHG and air pollutant emissions. Understanding these environmental impacts from both online and traditional retail supply chains is critical for advancing sustainable development.

Previous studies have assessed GHG and air pollutant emissions from traditional and online shopping[1,3,4,6–9]. For instance, Shahmohammadi et al.[6] evaluated GHG emissions from fast-moving consumer goods shopping, while Jaller and Pahwa[1] analyzed carbon monoxide (CO), fine particulate matter less than 10 micrometers (PM_{10}), fine particulate matter less than 2.5 micrometers ($PM_{2.5}$), sulfur oxides, and nitrous oxide (N_2O) emissions in Dallas and San Francisco, USA. Despite these efforts, cross-study comparisons remain challenging due to inconsistent methodologies that often omit key factors such as air freight use and packaging materials[2–4,7,9]. For example, Xu et al.[3] demonstrated that online shopping exhibits higher carbon dioxide (CO_2) emission intensities than traditional shopping, primarily due to air freight and packaging consumption. However, inconsistencies in data collection and regional assessments complicate comparisons, increasing uncertainty about whether online or traditional shopping is more emission-intensive. This data gap hinders mitigation efforts by policymakers, industries, and consumers, slowing progress toward sustainable retail development.

Xu et al.[3,4] conducted comprehensive assessments of CO_2 and air pollutant emissions from shopping in China, establishing a foundational framework for consistent evaluations and cross-study comparisons. However, a unified protocol compiling these methods and datasets for assessing GHG and air pollutant emissions has been lacking. This study addresses this gap by developing a robust methodology for assessing GHG and air pollutant emissions from shopping. It introduces standardized calculation methods and nationwide datasets, supported by case studies demonstrating the protocol's application and advantages over previous approaches.

Moreover, the absence of a standardized assessment framework for retail emissions—compounded by fragmented data, inconsistent baselines, and opaque supply chain dynamics—has impeded the development of next-generation artificial intelligence (AI) models aimed at modeling shopping-related environmental impacts. To bridge this gap, this protocol establishes an agent-based emission calculation model with essential ground-truth logic to enable emission calculations under varying consumer and supply-chain scenarios.

This protocol makes several key contributions to the field of AI and environmental science. First, it develops a standardized protocol for comprehensively assessing GHG and air pollutant emissions from both traditional and online shopping, addressing methodological inconsistencies in prior studies. Second, it provides nationwide parameters for China spanning 1990–2023 and covering 16 key merchandise categories, enabling robust evaluations across shopping methods, product types, and time periods. Third, through case studies on necessities, textiles, and foodstuffs, we demonstrate the protocol's ability to perform detailed temporal trend analyses, uncovering critical emission patterns. Finally, the protocol provides ground-truth logic of retail activities for AI agents. By enabling comparable, transparent, and comprehensive analyses of the retail sector's environmental impacts, this protocol supports evidence-based decision-making and accelerates sustainable retail transformation.

Materials and methods

Scope

This paper aims to evaluate emissions of GHG (CO_2, methane (CH_4), N_2O) and air pollutants, including primary $PM_{2.5}$, primary PM_{10}, black carbon (BC), organic carbon (OC), CO, ammonia (NH_3), sulfur dioxide (SO_2), NO_x, and non-methane volatile organic compounds (NMVOCs), from shopping activities, covering both traditional "in-store" shopping and online "pure player" shopping. Traditional shopping is defined as

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the method reliant on physical stores ("Brick and Mortar") rather than the internet, while online shopping relies on internet-based platforms rather than physical stores. The evaluation scope spans the supply chain from factory warehouses to consumers' homes, encompassing the following phases:

1. **Wholesaler transport**: Movement of goods from factory warehouses to e-commerce distribution centers (online shopping) or traditional distribution centers (in-store shopping)
2. **Long-distance transport**: Transfer of goods from distribution centers to parcel distribution centers (online shopping) or nearby physical stores (in-store shopping)
3. **Last-mile delivery**: Courier round-trip deliveries between parcel distribution centers and consumers' homes (online shopping), or consumers' round-trip travel between their homes and stores (in-store shopping)
4. **Packaging use**: Life-cycle assessment of packaging materials for both shopping methods
5. **Device and store operations**: Energy use associated with electronic devices (online shopping) or store operations (in-store shopping)
6. **Storage**: Warehousing at factories, distribution centers, and retail facilities for both shopping methods

Further details on these supply chain phases are provided later in the paper. The methodology employed here is based on the emission inventory approach recommended by the Intergovernmental Panel on Climate Change (IPCC) for most supply chain phases, except for the packaging phase, which adopts life-cycle assessment methods[10]. The emission inventory approach estimates emissions based on fuel combustion during each supply chain phase, while life-cycle assessment accounts for product-based emissions across all life cycle stages—raw material acquisition, manufacturing, transportation, use, and disposal—covering both fuel consumption and industrial processes[4].

Emission calculation

Emissions from shopping were calculated using the emission inventory method, as shown in Eq. (1)[3,4]:

$$E_{os/ts} = E_{wt,os/ts} + E_{ldt,os/ts} + E_{lmd/cst} + E_{s,os/ts} + E_{w,os/ts} + E_{p,os/ts} \quad (1)$$

The emissions $E_{os/ts}$ represent the total emissions (in g) from six supply chain phases for online shopping (os) or traditional shopping (ts). These include:

- $E_{wt,os/ts}$: Emissions from wholesale transportation
- $E_{ldt,os/ts}$: Emissions from long-distance or long-haul transport
- $E_{lmd/cst}$: Emissions from last-mile delivery (lmd) or consumer shopping trips (cst)
- $E_{w,os/ts}$: Emissions from storage in warehouses and distribution centers
- $E_{s,os/ts}$: Emissions from device use (os) or store operations (ts)
- $E_{p,os/ts}$: Emissions from the lifecycle of packaging materials

The following sections outline the evaluation methods for each supply chain phase. Detailed descriptions of data sources and methodology are provided in Method S1.

Wholesaler transport

This phase evaluates emissions from wholesaler transport, which involves the movement of goods from factory warehouses to distribution centers. This transport phase typically relies on heavy-duty trucks (primarily diesel-powered) for bulk transportation[4]. The evaluation method for both online and traditional shopping is illustrated in Eq. (2)[11]:

$$E_{wt,os/ts} = D_t \cdot EF_t \cdot W \quad (2)$$

where $E_{wt,os/ts}$ denotes emissions (g) from wholesaler transport (wt) for online (os) or traditional shopping (ts); D_t represents the travel distance (km) from factory warehouses to distribution centers; EF_t denotes the emission factor for heavy-duty trucks (g·metric ton^{-1}·km^{-1}); and W represents the gross weight of merchandise (excluding the weight of transport-related packaging materials). Table 1 presents the recommended D_t values for China[3,12], while Supplementary Table S1 lists the corresponding EF_t values for each pollutant species[3].

The recommended EF_t values for each pollutant species are listed in Supplementary Table S1[3]. Emissions for GHGs were unified as CO_2-equivalent (CO_2eq) emissions using global warming potentials on a 100-year basis (i.e., 1 for CO_2, 27.9 for CH_4, and 273 for N_2O), according to the GHG Protocol[10,13–15].

The W value for a specific merchandise type j can be calculated using the following Eq. (3)[3]:

$$W_{j,y} = \frac{Sale_{j,y}}{P_j \cdot PAF_y} \cdot W_j \quad (3)$$

where $W_{j,y}$ denotes the total weight of merchandise j in year y; $Sale_{j,y}$ represents the total sales (USD) of merchandise j; P_j denotes the unit price (USD·item^{-1}) of merchandise j in 2022; PAF_y represents the adjustment factor for converting the unit price in 2022 to that of year y; and W_j denotes the unit gross weight of merchandise j (g·item^{-1}). The default data for W_j and P_j of 16 main merchandise categories in China are listed in Table 2[3]. While this method assumes a stable price-weight

Table 1 The average transport distances (D_t or $D_{ldt,k}$; km) by different freight modes for China

Year	Train	Ship	Truck	Airplane	Van, to store	R_{inter}
1990	1,880	1,447	121	1,447	24	–
1991	1,880	1,554	124	1,447	24	–
1992	1,880	1,433	127	1,447	24	–
1993	1,880	1,415	130	1,447	24	–
1994	1,880	1,465	132	1,447	24	–
1995	1,880	1,551	135	1,447	24	–
1996	1,880	1,402	138	1,447	24	–
1997	1,880	1,696	141	1,447	24	–
1998	1,880	1,771	143	1,452	24	–
1999	1,880	1,855	146	1,455	24	–
2000	1,880	1,939	149	1,459	24	75%
2001	1,723	1,959	152	1,450	24	75%
2002	1,632	1,940	154	1,461	24	75%
2003	1,560	1,817	157	1,460	24	75%
2004	1,575	2,211	160	1,460	24	75%
2005	1,689	2,261	163	1,479	24	75%
2006	1,639	2,231	165	1,490	24	75%
2007	1,624	2,286	168	1,481	24	75%
2008	1,734	1,707	171	1,483	24	75%
2009	1,686	1,804	175	1,482	24	75%
2010	1,661	1,806	177	1,463	24	76%
2011	1,636	1,771	182	1,468	24	77%
2012	1,736	1,781	187	1,497	24	76%
2013	1,849	1,419	181	1,518	24	74%
2014	1,851	1,551	183	1,525	24	74%
2015	1,788	1,496	184	1,533	24	73%
2016	1,577	1,525	183	1,530	24	75%
2017	1,487	1,477	181	1,525	24	76%
2018	1,349	1,410	180	1,534	24	77%
2019	1,174	1,391	174	1,550	24	82%
2020	998	1,390	176	1,509	24	84%
2021	1,017	1,403	177	1,527	24	87%
2022	971	1,415	186	1,534	24	87%
2023	961	1,387	183	1,558	24	87%

Note: Data are compiled from previous studies[3,4]. Distances follow a log-normal distribution (standard deviation in $\log_{10}$ = 0.05 and the number of samples = 2).

Table 2 Default gross weights (W_j; g·item^{-1}) and unit price (P_j; USD·item^{-1}) by merchandise category

Merchandise type	W_j, g·item^{-1}			P_j, USD·item^{-1}		
	GM	Log_{10} SD	N	GM	Log_{10} SD	N
Medicines	169	0.69	2251	10.8	0.6	2254
Press	1548	0.48	27	17.1	0.4	1898
Hardware	319	0.57	2036	8.4	0.6	2034
Recreation & sports	568	0.62	6702	28.8	0.7	6690
Cosmetics	356	0.59	3422	51.2	0.5	3411
Furniture	27692	0.81	814	582.2	0.5	807
Appliances	3616	0.64	6781	116.5	0.6	6828
Building & decoration	774	0.67	2126	16.9	0.6	2411
Culture & office supplies	1020	0.81	7303	6.1	0.5	3942
Necessities	389	0.58	5158	10.5	0.5	5164
Textile	547	0.36	16485	48.9	0.4	16506
Tobacco & liquor	1418	0.83	1275	148.4	0.5	1275
Foodstuffs	865	0.51	10016	7.8	0.4	12056
Communication devices	399	0.60	3280	75.2	0.7	3335
Jewelry	141	0.72	279	63.8	0.9	280
Beverage	3405	0.51	2558	13.7	0.3	2554

Note: Data are derived from reference[3]. The P_j for online shopping is assumed to be 8% lower than that for traditional shopping. GM, geometric mean. Log_{10} SD: the standard deviation of sample values in log_{10}. *N*, the number of samples.

relationship adjusted for inflation, we acknowledge that factors such as shrinkflation or material quality shifts may introduce nonlinearities over time[16]. For instance, product weights may decrease while prices remain stable (e.g., foodstuffs), or items may become both lighter and more expensive due to technological advancements (e.g., electronics). Future assessments would benefit from incorporating explicit logistics weight data to enhance precision.

Long-distance transport

Long-distance transport in traditional shopping involves long-haul transport using various freight modes, followed by intracity transport to deliver goods in relatively smaller quantities to local stores near consumers. Emissions from this phase are calculated using the following equation[3,6,11]:

$$E_{\mathrm{ldt,ts}} = \left[\sum\nolimits_k (M_{\mathrm{ldt,ts},k} \cdot D_{\mathrm{ldt,ts},k} \cdot \mathrm{EF}_{\mathrm{ldt},k}) + \sum\nolimits_{\mathrm{v,ev}} (M_{\mathrm{v/ev}} \cdot \mathrm{EF}_{\mathrm{v/ev}}) \cdot D_{\mathrm{s}}\right] \cdot W \cdot (1 + \mathrm{RR}_{\mathrm{ts}}) \quad (4)$$

where $E_{\mathrm{ldt,ts}}$ denotes emissions (g) from long-distance transport (ldt) for traditional shopping; $M_{\mathrm{ldt,ts},k}$ represents the share of freight mode k (including trains, ships, trucks, and airplanes); $D_{\mathrm{ldt,ts},k}$ denotes the travel distance (km) for freight mode k; $\mathrm{EF}_{\mathrm{ldt,ts},k}$ represents the per tonne-km emission factor (g·metric ton^{-1}·km^{-1}) for freight mode k; D_s denotes the distance from transit points to local stores via vans; $M_{\mathrm{v/ev}}$ represents the share of gasoline/diesel and electric vans (v/ev); $\mathrm{EF}_{\mathrm{v/ev}}$ denotes the emission factor (g·metric ton^{-1}·km^{-1}) for v/ev; and $\mathrm{RR}_{\mathrm{ts}}$ is the product return rate in traditional shopping.

The recommended data for $M_{\mathrm{ldt,ts},k}$ in China are listed in Table 3 and the recommended values for $D_{\mathrm{ldt},k}$ and D_s in China are provided in Table 1[10,13,15,17–26]. The default $\mathrm{RR}_{\mathrm{ts}}$ value was estimated at 8% for all merchandise categories in China[27]. The default $\mathrm{EF}_{\mathrm{ldt},k}$ values for railway, air, and waterway, as well as $\mathrm{EF}_{\mathrm{v/ev}}$ values for vans, are listed in Supplementary Tables S2–S6. Due to the lack of data for quantifying the share of v/ev ($M_{\mathrm{v/ev}}$) across time, we assigned 100% prior to 2019, with solid 85% gasoline vans and 15% electric vans starting in 2020, following a previous study[28]. These data gaps are worthwhile for further research. Moreover, the $M_{\mathrm{v/ev}}$ varies across cities and transport distances, which introduces uncertainty to the estimations, warranting further research.

In online shopping, long-distance transport or parcel delivery transport consists of intercity and intracity parcel transport[11,29]. An intercity transport is formed by three sub-phases of transport: (1) a transit from a parcel distribution center to an origin city's distribution center; (2) a mainstream (intercity) transport to the destination city's distribution center; and (3) a final transit to a terminal parcel

Table 3 Shares of freight mode ($M_{\mathrm{ldt},k}$) in China

Year	Rail	Ship	Road	Air
1990	16%	7.5%	77%	0.004%
1991	16%	7.6%	76%	0.005%
1992	15%	8.0%	77%	0.006%
1993	15%	7.8%	77%	0.006%
1994	14%	8.1%	78%	0.007%
1995	14%	8.1%	78%	0.008%
1996	13%	8.9%	78%	0.009%
1997	14%	7.5%	79%	0.010%
1998	13%	7.4%	79%	0.011%
1999	13%	7.4%	79%	0.014%
2000	14%	7.6%	79%	0.015%
2001	14%	7.8%	78%	0.013%
2002	14%	7.8%	78%	0.014%
2003	15%	8.2%	77%	0.015%
2004	15%	9.0%	76%	0.017%
2005	15%	9.6%	75%	0.017%
2006	15%	10%	75%	0.018%
2007	14%	10%	75%	0.018%
2008	13%	10%	77%	0.016%
2009	12%	9.8%	78%	0.016%
2010	12%	10%	78%	0.018%
2011	11%	10%	79%	0.016%
2012	10%	9.9%	80%	0.014%
2013	10%	12%	78%	0.014%
2014	9.5%	13%	77%	0.015%
2015	8.3%	13%	78%	0.016%
2016	7.9%	13%	79%	0.016%
2017	7.9%	13%	79%	0.015%
2018	8.1%	13%	79%	0.015%
2019	10%	15%	76%	0.017%
2020	11%	8.9%	80%	0.016%
2021	10%	8.7%	81%	0.015%
2022	11%	9.5%	80%	0.013%
2023	10%	9.6%	80%	0.010%

Note: Data are derived from references[3,12]. $M_{\mathrm{ldt},k}$ follows custom distribution.

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distribution center near consumer residences. In contrast, intracity transport moves parcels from one parcel distribution center to another through the city's distribution centers. The freight mode used in mainstream transport involves road, air, and railway freight, corresponding to heavy-duty trucks, airplanes, and trains, respectively. An intracity transit typically uses light-duty vehicles like vans. The emission in this phase for online shopping ($E_{ldt,os}$) is calculated using the following equation:

$$E_{ldt,os} = E_{inter,os} + E_{intra,os}$$
$$E_{inter} = R_{inter} \cdot \sum_k (M_{inter,os,k} \cdot (D_{inter,k} \cdot EF_k + 2D_{intra} \cdot \sum_{v,ev} (M_{v/ev} \cdot EF_{v/ev}))) \cdot W \cdot (1 + RR_{os})$$
$$E_{intra} = (1 - R_{inter}) \cdot 2D_{intra} \cdot \sum_{v,ev} (M_{v/ev} \cdot EF_{v/ev}) \cdot W \cdot (1 + RR_{os}) \quad (5)$$

where $E_{ldt,os}$ denotes emissions (g) from long-distance transport in online shopping; E_{inter} and E_{intra} represent emissions (g) from intercity and intracity freight transport, respectively; R_{inter} denotes the contribution (dimensionless) of intercity parcels; $M_{inter,os,k}$ represents the share (dimensionless) of freight mode k, including diesel trucks, airplanes, normal-speed rail, and high-speed railway (HSR); $D_{inter,k}$ denotes the transport distance (km) for freight mode k; EF_k represents the emission factor (g·t^{-1}·km^{-1}) of freight mode k; D_{intra} denotes the intracity transport distance (km); $M_{v/ev}$ represents the share of gasoline/diesel vans (v) and electric vans (ev); $EF_{v/ev}$ denotes the emission factor (g·t^{-1}·km^{-1}) of v and ev; and RR_{os} denotes the return rate for online shopping.

The values of R_{inter} are listed in Table 1. $D_{inter,k}$ were calculated as the straight-line distance between city administrative centers (271 ± 8 km), while D_{intra} represented the mean distance between parcel and city-level distribution centers (17.5 ± 1.6 km). EF_k align with those used for long-distance transport in traditional shopping, except for high-speed rail (HSR, 2014–2023), which are specified in Supplementary Table S7. Online product returns were assumed to reverse the long-distance and last-mile logistics chains, with suggested return rate (RR_{os}) values for China provided in Supplementary Table S8.

Products may be returned to e-commerce distribution centers, consolidated at local hubs, or liquidated without shipping. Due to limited data on these processes, we assume return logistics reverse the long-distance transport and last-mile delivery processes to maintain consistency with traditional shopping, which may overestimate return-related emissions. We recommend future studies incorporate a coefficient defining the proportion of products returned to distribution centers versus factories to refine RR_{os} estimates.

Shopping trips

Emissions from shopping trips are calculated via the following equation[3,6]

$$E_{cst} = 2D_{cst} \cdot \sum_k (M_{cst,k} \cdot EF_{cst,k}) \cdot N_{trip} \cdot (1 + RR_{ts}), N_{trip} = \frac{Sale_{ts}}{PV \cdot BS_{ts} \cdot P_{ts}} \quad (6)$$

where $E_{cst,y}$ denotes emissions (g) from consumer shopping trips (cst) between physical stores and consumers' residences; D_{cst} represents the one-way distance of the shopping trip; $M_{cst,k}$ denotes the share of travel method k; and $EF_{cst,k}$ represents the emission factor for travel method k (g·trip^{-1}·km^{-1}); N_{trip} denotes the total number of trips (trip·year^{-1}); $Sale_{ts}$ represents traditional sales (USD); PV denotes the average parcel volume during a delivery trip (order·trip^{-1}); BS_{ts} represents the basket size (item·order^{-1}) in traditional shopping; and P_{ts} denotes the retail price (USD·item^{-1}) of merchandise in traditional shopping.

The recommended shopping trip distance (D_{cst}) for China is 2.7 km (log10 standard deviation (log_{10} SD): 0.2; N = 8), representing the average one-way travel distance exclusively for shopping purposes[30–36]. The recommended value for shopping trip distance reflects an average shopping-specific travel distance rather than general mobility data[30–36], to minimize emission misallocation across different trip purposes (e.g., commutes and recreation). However, explicit modeling of trip-chaining behaviors—where shopping is combined with other errands—is excluded due to the complexity of allocation. Future research incorporating detailed trip-diary data is warranted to quantify the impact of multi-purpose trips on emission estimates.

The default shares of travel modes ($M_{cst,k}$) are listed in Table 4, covering gasoline and electric cars, multifuel buses, trains, taxis, motorcycles, electric bicycles, bicycles, and walking. Default emission factors ($EF_{cst,k}$) for each mode are provided in Supplementary Tables S9–S15. The basket size ($BS_{ts/os}$) varies by merchandise category, representing the number of products per purchasing order. Recommended values for 16 merchandise categories in China are listed in Supplementary Table S8.

Last-mile delivery

Emissions from last-mile delivery are calculated by the following equation[3,7]:

$$E_{lmd} = 2D_{lmd} \cdot \sum_k (M_{lmd,k} \cdot EF_{lmd,k}) \cdot N_{trip} \cdot (1 + RR_{os}) \cdot 10^{-3}$$
$$N_{trip} = \frac{Sale_{os}}{PV \cdot BS_{os} \cdot P_{os}} = \frac{Sale_{os}}{PV \cdot EO_{os}} = \frac{TO}{PV} \quad (7)$$

where E_{lmd} denotes emissions (g) from last-mile delivery; D_{lmd} represents the one-way distance (km·trip^{-1}) of a delivery trip; $M_{lmd,k}$ denotes the share of delivery vehicle mode k; $EF_{lmd,k}$ is the emission factor (g·km^{-1}) for delivery mode k; N_{trip} denotes the total number of trips (trips); $Sale_{os}$ represents online sales (USD); PV denotes the average parcel volume per delivery trip (orders·trip^{-1}); BS_{os} represents the basket size (items·order^{-1}) in online shopping; P_{os} denotes the retail price (USD·item^{-1}) of merchandise; EO_{os} represents the expenditure per order (USD·order^{-1}) in online shopping; and TO denotes the total number of orders (orders).

The last-mile delivery distance (D_{lmd}) and average parcel volume per trip (PV_y) are listed in Supplementary Table S16. Delivery mode shares ($M_{lmd,k}$)—including electric tricycles/bicycles, gasoline/diesel vans, and electric vans—are also provided in Supplementary Table S16[3,37]. Default emission factor ($EF_{lmd,k}$) values for each mode are available in Supplementary Tables S17–S20[3].

Packaging

Emissions from life cycle packaging use are calculated using the following equation[3,38]:

$$E_{p,os/ts} = \sum_k (R_{pm,k} \cdot W_{pm,k} \cdot EF_{pm,k}) + \sum_k E_{pmt,k} \quad (8)$$

where $E_{p,os/ts}$ denotes the emissions from the packaging use phase for online shopping (os) or traditional shopping (ts); $R_{pm,k}$ represents the share of packaging genre k; $W_{pm,k}$ denotes the weight (g) of the consumption of packaging genre k; $EF_{pm,k}$ represents the emission factor (g·kg^{-1}) of packaging materials for lifecycle phases, including raw material acquisition, manufacturing, and disposal for packaging genre k; and $E_{pmt,k}$ denotes the emissions from long-distance transport for packaging genre k.

Supplementary Table S21 provides the recommended parameters for the packaging use phase[3,38,39]. Eight packaging genres were considered for online shopping, while only plastic bags ($R_{pm,k}$ = 1) were included for traditional shopping[11,38,39]. The $E_{pmt,k}$ for online shopping was calculated using the methods outlined for long-distance transport, while $E_{pmt,k}$ = 0 for traditional shopping. For air pollutants, the life-cycle emission factors for each packaging genre are provided in Supplementary Data S1[4].

Table 4 The share of travel methods ($M_{cst,k}$) between 1990 and 2023 in China

Year	Private car	Bus	Railway	Taxi	Motorcycle	Electric bike	Electric car	Walk or bicycle
1990	0.0%	3.3%	0.1%	0.3%	0.5%	0.0%	0.0%	96%
1991	0.1%	3.4%	0.1%	0.4%	0.6%	0.0%	0.0%	95%
1992	0.1%	3.2%	0.1%	0.6%	0.6%	0.0%	0.0%	95%
1993	0.1%	3.1%	0.1%	0.8%	1.1%	0.0%	0.0%	95%
1994	0.1%	2.9%	0.1%	0.9%	1.3%	0.0%	0.0%	95%
1995	0.2%	3.4%	0.1%	1.1%	1.7%	0.0%	0.0%	94%
1996	0.2%	2.8%	0.1%	1.2%	1.9%	0.0%	0.0%	94%
1997	0.3%	3.0%	0.1%	1.4%	2.4%	0.0%	0.0%	93%
1998	0.3%	3.1%	0.1%	1.6%	3.0%	0.0%	0.0%	92%
1999	0.5%	3.5%	0.1%	1.7%	3.9%	0.0%	0.0%	90%
2000	0.5%	3.7%	0.1%	1.7%	4.6%	0.1%	0.0%	89%
2001	0.7%	3.8%	0.1%	1.9%	5.3%	0.1%	0.0%	88%
2002	0.9%	4.1%	0.1%	1.8%	6.1%	0.3%	0.0%	87%
2003	1.3%	4.0%	0.1%	1.9%	7.1%	0.8%	0.0%	85%
2004	1.6%	4.5%	0.1%	1.9%	7.6%	1.6%	0.0%	83%
2005	2.1%	5.0%	0.2%	1.9%	8.4%	3.0%	0.0%	79%
2006	2.7%	4.6%	0.2%	1.8%	9.2%	5.1%	0.0%	76%
2007	3.4%	5.5%	0.2%	2.2%	10%	7.5%	0.0%	71%
2008	4.3%	7.0%	0.4%	2.3%	10%	10%	0.0%	66%
2009	5.8%	6.8%	0.4%	3.8%	11%	11%	0.0%	61%
2010	7.4%	6.5%	0.6%	3.6%	11%	12%	0.0%	58%
2011	10%	7.2%	0.8%	4.1%	12%	16%	0.0%	50%
2012	11%	6.8%	0.9%	3.8%	11%	17%	0.0%	50%
2013	13%	7.0%	1.1%	3.9%	10%	19%	0.0%	45%
2014	16%	7.0%	1.2%	4.0%	10%	21%	0.0%	42%
2015	18%	7.0%	1.4%	4.0%	10%	25%	0.1%	35%
2016	20%	6.5%	1.5%	3.6%	8.5%	26%	0.15%	33%
2017	24%	6.3%	1.8%	3.5%	8.6%	26%	0.21%	30%
2018	26%	6.1%	2.0%	3.4%	7.2%	28%	0.36%	27%
2019	30%	6.3%	2.4%	3.5%	7.8%	32%	0.55%	18%
2020	31%	3.8%	1.7%	2.5%	7.8%	32%	0.68%	21%
2021	34%	4.9%	2.4%	2.7%	8.3%	38%	1.1%	8.7%
2022	35%	3.4%	1.9%	2.0%	8.6%	37%	1.8%	10%
2023	36%	3.7%	2.9%	3.3%	9.1%	37%	2.7%	5.3%

Note: $M_{ldt,k}$ follows custom distribution.

Store operations

Emissions from store operations in traditional shopping account for electricity-use-related emissions. Emissions from this phase are calculated using the following equation:

$$E_{s,ts} = \frac{EleI_s}{H_s} \cdot SAF_{sr} \cdot \frac{SH_s}{H_s} \cdot V_{tot,ts} \cdot ST_s \cdot EF_{grid}$$
$$V_{tot,ts} = V \cdot \frac{Sale_{ts}}{P_{ts}} \cdot 10^{-6} \quad (9)$$

where $E_{s,ts}$ denotes the emissions (g) from store operations; $Elel_s$ represents the intensity of grid electricity use (kWh·m^{-2}·day^{-1}) in stores; H_s is the height of the stores; SAF_{sr} denotes the share of areas for product display and storage relative to the total store area; SH_s represents the height (m) of goods shelves in stores; $V_{tot,ts}$ denotes the total volume (m^3) of products; ST_s is the storage time (days) in stores; EF_{grid} represents the emission factor (g·kWh^{-1}) for electricity use; V denotes the volume (cm^3·item^{-1}) per item of product; $Sale_{ts}$ represents traditional sales (USD); and P_{ts} denotes the retail price (USD·item^{-1}) for traditional shopping. The suggested $Elel_s$ values are 0.57 kWh·m^{-2}·day^{-1} and recommended values for other parameters in this phase are listed in Supplementary Tables S8 and S22–S24[40].

Device use

Emissions from device use account for electricity consumption by devices during online shopping. The emissions from this phase are calculated using the following equation:

$$E_{s,os} = \frac{(\sum_k (R_{dev,k} \cdot P_{dev,k}) \cdot BT + (EleI_{dc} + EleI_{net}) \cdot DS \cdot N_{web}) \cdot EF_{grid} \cdot Sale_{os}}{BS_{os} \cdot P_{os}} \quad (10)$$

where $E_{s,os}$ denotes emissions from device use for internet access in online shopping; $R_{dev,k,y}$ represents the share of device k; $P_{dev,k}$ denotes the power or electricity intensity (kW) attributable to website browsing, defined as the difference in power (kW) between website browsing and standby modes for consumers' terminal device k; BT represents the browsing time (hours·order^{-1}) on online platforms; $Elel_{dc}$ and $Elel_{net}$ denote the electricity intensity (kWh·megabyte^{-1}) for data centers and networks, respectively; DS represents the data size per website page (megabytes·page^{-1}); N_{web} denotes the number of website pages per purchasing order (pages·order^{-1}); EF_{grid} represents the emission factor (g·kWh^{-1}) for electricity use; $Sale_{os}$ denotes the online sales volume (USD); BS_{os} represents the basket size (items·orde^{-1}); and P_{os} denotes the price (USD·item^{-1}) for online shopping.

The recommended values for $R_{dev,k,y}$ and $P_{dev,k}$ for each terminal device (smartphones/mobile phones, desktops, and laptops), as well as $Elel_{dc}$, $Elel_{net}$, and DS, are listed in Supplementary Table S25[3]. $Elel_{dc}$ and $Elel_{net}$ varied over time with a decreasing trend due to improved infrastructure efficiency (Supplementary Table S25). However, emerging shopping methods (e.g., 5G and video-based platforms) increase data intensity due to higher bandwidth demands and energy-intensive network infrastructure. This trade-off warrants further research to quantify the emission impacts of evolv-

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ing digital shopping behaviors. The recommended values of BT for the 16 merchandise categories are provided in Supplementary Table S8. The N_{web} value is set at 14.5 pages·order^{-1} ($\log_{10}$ SD = 0.60, N = 42,960), derived from data collected from online platforms.

Storage

Emissions from storage for both shopping methods are calculated using the following equations:

$$E_{w,os} = (Ele_w + Ele_{edc} + Ele_{pdc}) \cdot EF_{grid}$$

$$Ele_{w/edc/pdc} = \frac{EleI_{w/edc/pdc}}{H_{w/edc/pdc}} \cdot \frac{SH}{H_{w/edc/pdc}} \cdot SAF_{w/edc/pdc} \cdot V_{tot,os} \cdot ST_{w/edc/p/dc}$$

$$V_{\text{tot,os}} = V \cdot \frac{\text{Sale}_{\text{os}}}{P_{\text{os}}} \cdot 10^{-6} \quad (11)$$

$$E_{w,ts} = (Ele_w + Ele_{tdc}) \cdot EF_{grid,y}$$

$$Ele_{w/tdc} = \frac{EleI_{w/tdc}}{H_{w/tdc}} \cdot (SAF_{w/tdc} \cdot \frac{SH}{H_{w/tdc}}) \cdot V_{tot,ts} \cdot ST_{w/tdc}$$

$$V_{\text{tot,ts}} = V \cdot \frac{\text{Sale}_{\text{ts}}}{P_{\text{ts}}} \cdot 10^{-6} \quad (12)$$

where $E_{w,os/ts}$ denotes emissions (g) from the storage phase for online or traditional shopping; $Ele_{w/pdc/edc/tdc}$ represents the total electricity use (kWh) in factory warehouses (w), parcel distribution centers (pdc), e-commerce distribution centers (edc), or traditional distribution centers (tdc), respectively; EF_{grid} denotes the emission factor (g·kWh^{-1}) of electricity use; $Elel_{w/edc/pdc/tdc}$ represents the electricity intensity (kWh m^{-2}·day^{-1}) of storage facilities; $H_{w/edc/pdc/tdc}$ is the height (m) of w, edc, pdc, or tdc, respectively; $SAF_{w/edc/tdc/pdc}$ denotes the share of storage area (m^2) in w, edc, pdc, or tdc; SH represents the shelf height (m); $V_{tot,ts}$ denotes the total volume for traditional shopping; $ST_{w/tdc/pdc/edc}$ represents the storage time for w, tdc, pdc, or edc; V denotes the volume per item of merchandise (cm^3·item^{-1}); and P_{ts} represents the price in traditional shopping. Parameters for this phase are listed in Supplementary Table S22, and values for $ST_{w/tdc}$, SH, and V are provided in Supplementary Table S8.

Uncertainty of emissions

The Monte Carlo simulation method was applied in this study to quantify the uncertainty of emissions. This approach has been widely adopted in previous research[3,4,41–43]. The method assesses the uncertainty of each parameter by simulating its probability distribution using assumed theoretical distributions, such as normal or log-normal distributions. Through this process, uncertainties in the parameters are propagated through the calculations to generate the overall uncertainty in the emission results.

The assumed distributions and associated statistical values used for the simulations, including the coefficient of variation for normal or uniform distributions, $\log_{10}$ SD, and N for log-normal distributions, are provided in the tables. Emissions are reported as the median of their simulated distributions, with the uncertainty range defined by the 5th and 95th percentiles of the distribution, representing a 90% confidence interval.

Results and discussion

Case study: GHG emissions from shopping for necessities, textiles, and foodstuffs in China

Previous studies have primarily focused on the emission intensity of shopping, while comprehensive assessments of total emissions from shopping in broader contexts remain insufficient[3]. This gap has led to uncertainties regarding retail-related emissions and mitigation potentials for specific cities, regions, or countries. To address this, the protocol presented here utilizes sales data and related product features (e.g., price, basket sizes, and weights) to calculate emissions from total shopping activities. We applied this protocol to evaluate GHG emissions from shopping for necessities, textiles, and foodstuffs—three classical merchandise categories—in China. Online and traditional sales for necessities, textiles, and foodstuffs were estimated at 0.49, 0.75, and 0.24 trillion USD, and 0.34, 0.65, and 0.86 trillion USD, respectively, in 2023[3].

The results indicate that total GHG emissions from shopping in 2023 were estimated at 11 Tg (90% CI: 8.2–23 Tg) for necessities, 8.2 Tg (6.5–17 Tg) for textiles, and 23 Tg (11–32 Tg) for foodstuffs (Fig. 1). Online shopping contributed 6.2 Tg (60%), 6.4 Tg (77%), and 5.8 Tg (26%) of emissions, while traditional shopping contributed 4.5 Tg (40%), 1.9 Tg (23%), and 17 Tg (74%) for these categories, respectively. Among the six supply chain phases in online shopping, long-distance transport and life-cycle packaging use were identified as the dominant sources of GHG emissions. For necessities, textiles, and foodstuffs, long-distance transport contributed 34%, 18%, and 56%, while life-cycle packaging use contributed 54%, 70%, and 31%, respectively.

Most existing studies fail to account for multimodal freight, packaging diversity, and vehicle use, resulting in incomplete assessments[2,3,6,9]. This protocol incorporates air freight in online shopping, revealing that emissions are higher when air freight is considered compared with truck-only scenarios due to the higher emission intensities of air freight (Supplementary Tables S1–S2)[3,9,44,45]. Approximately 6% of freight in China is transported via air, which increases emissions from long-distance transport compared to truck-only estimates (Fig. 1).

Furthermore, this protocol considers eight packaging genres in the packaging use phase, a critical emission source in online

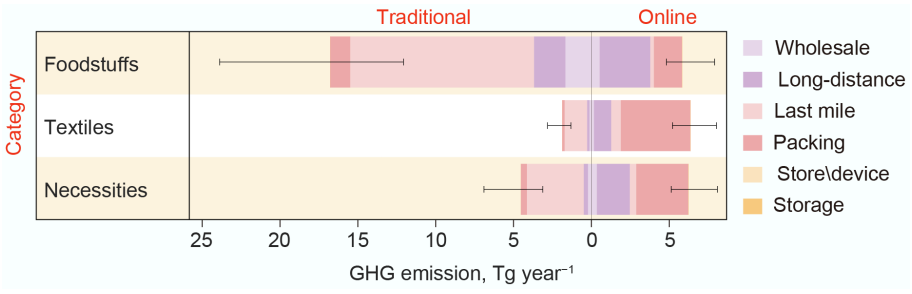

Fig. 1 GHG emissions from traditional (left bars) and online (right bars) shopping for necessities, textiles, and foodstuffs in China. Error bars represent the 90% confidence intervals of emissions, corresponding to the 5th and 95th percentiles of the simulated distribution obtained through Monte Carlo simulation.

shopping, compared to the typical inclusion of only one genre, such as corrugated boxes (Supplementary Table S21). In China, corrugated boxes account for 83% of the total weight of packaging materials, while other genres, such as plastic cartons and plastic bags, make up the remainder[3]. Corrugated boxes contribute 69% of total CO_2 emissions from the packaging use phase, while plastic cartons and plastic bags also contribute 13% and 8% of total packaging-related emissions, respectively[3].

Consumer vehicles represent a critical source of emissions in traditional shopping, with previous studies often focusing on single-vehicle scenarios, typically private car use, to assess their impact[2]. This protocol incorporates multimodal travel modes, including private cars, public transit, taxis, motorcycles, electric bikes, and walking or cycling, providing a more comprehensive evaluation of shopping trips[2,6,46,47]. The case study shows that consumer shopping trips dominate GHG emissions in traditional shopping, contributing 80%, 77%, and 70% of emissions for necessities, textiles, and foodstuffs, respectively, primarily due to private car use[3]. However, assessments based solely on car emissions would overestimate total emissions, as cars have higher emission intensities than other modes of transport (e.g., public transit, electric bikes, or motorcycles), and walking or cycling produces zero GHG emissions (Supplementary Table S9).

Compared to the methodology of Shahmohammadi et al[6], our protocol yields substantially higher GHG emissions for total shopping across all categories. For example, estimates for necessities (11.0 vs. 7.2 Tg·year^{-1}), textiles (8.2 vs. 3.4 Tg·year^{-1}), and foodstuffs (23.0 vs. 4.2 Tg·year^{-1}) exceed the prior estimates by approximately 50% to 400%. These disparities underscore the necessity of incorporating comprehensive retail activities, including multimodal freight modes (particularly air freight) and diverse packaging materials (e.g., plastic cartons and bags).

Case study: Air pollutant emissions from shopping for necessities, textiles, and foodstuffs in China

This protocol integrates emission factor data derived from the GEMS, EEA, national standards, technical guidelines, and previous studies to evaluate air pollutant emissions from shopping activities[4,10,19,23–25,48–50]. In this case study, we assessed air pollutant emissions from shopping for necessities, textiles, and foodstuffs in China. Results in Fig. 2 indicate that NO_x, SO_2, $PM_{2.5}$, and NMVOCs emissions from total shopping in 2023 were estimated at 28 Gg (20–40 Gg), 9.2 Gg (4.9–18 Gg), 1.9 Gg (1.1–3.5 Gg), and 21 Gg (9.1–71 Gg) for necessities; 17 Gg (12–24 Gg), 10 Gg (5.4–20 Gg), 1.2 Gg (0.8–1.9 Gg), and 12 Gg (5.1–43 Gg) for textiles; and 80 Gg (56–114 Gg), 9.1 Gg (5.3–16 Gg), 5.4 Gg (3.1–10 Gg), and 46 Gg (24–125 Gg) for foodstuffs.

From the perspective of shopping methods, SO_2 emissions were higher in online shopping, contributing 89%, 96%, and 62% of total SO_2 emissions for necessities, textiles, and foodstuffs, respectively, compared with traditional shopping (Fig. 2). NO_x and NMVOC emissions were also higher in online shopping than in traditional shopping for necessities (69% and 60%, respectively) and textiles (74% and 72%, respectively). However, for foodstuffs, NO_x emissions were higher in traditional shopping than in online shopping (68% vs. 32%), as were NMVOCs emissions (64% vs. 36%). $PM_{2.5}$ emissions showed similar contributions from both shopping methods for textiles (50% each), but were lower in online shopping than in traditional shopping for necessities (26% vs. 74%) and foodstuffs (7% vs. 93%).

By supply chain phases, consumer shopping trips dominate all air pollutant emissions from traditional shopping across the three categories, except for NO_x emissions, which are primarily driven by wholesaler transport and long-distance transport (Fig. 2). For instance, for necessities, wholesaler transport and long-distance transport contributed 35% and 38% of NO_x emissions, respectively.

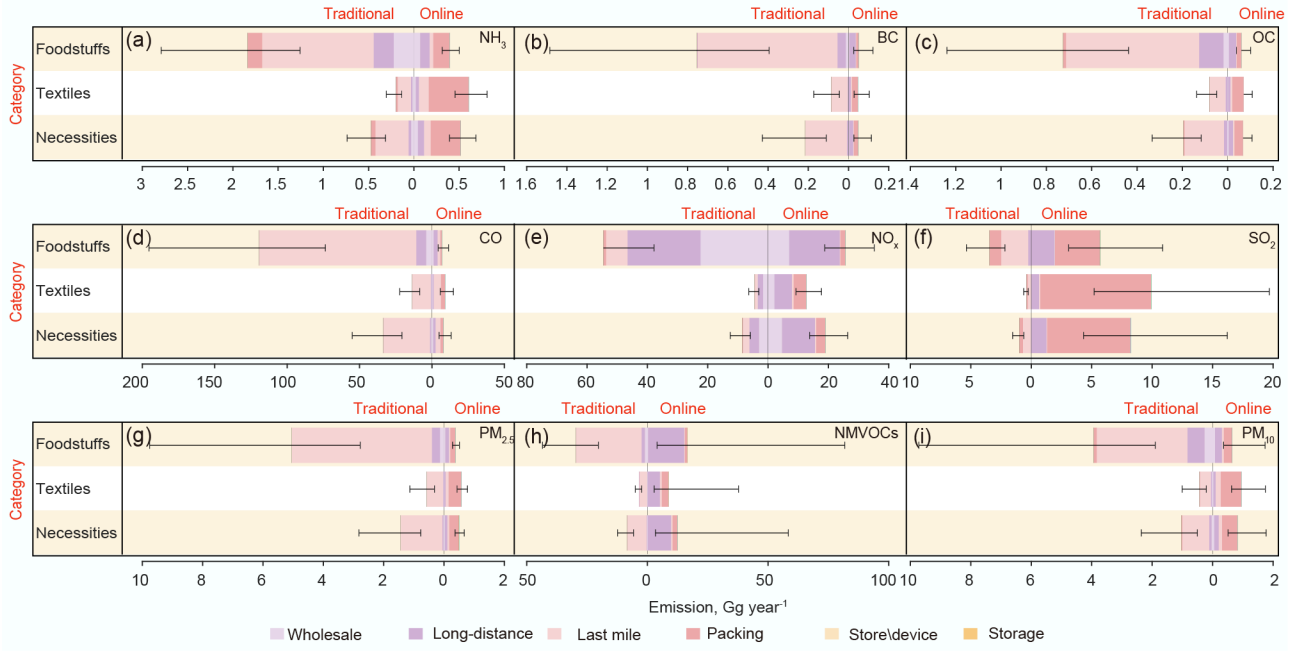

Fig. 2 Air pollutant emissions from traditional and online shopping for necessities, textiles, and foodstuffs in China. (**a**–**i**) Air pollutant emissions of NH_3 (**a**), BC (**b**), OC (**c**), CO (**d**), NO_x (**e**), SO_2 (**f**), $PM_{2.5}$ (**g**), NMVOCs (**h**), and PM_{10} (**i**) from traditional (left bars) and online (right bars) shopping for textiles, necessities, and foodstuffs. Error bars represent the 90% confidence intervals of emissions, corresponding to the 5th and 95th percentiles of the simulated distribution obtained through Monte Carlo simulation.

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For online shopping, packaging use or long-distance transport dominates air pollutant emissions. For example, long-distance transport accounted for 57% of NO_x emissions for necessities and 58% of NMVOC emissions for textiles, while packaging use contributed 84% of SO_2 emissions for necessities and 92% for textiles.

In comparison to Shahmohammadi et al.[6], the air pollutant emissions derived from our protocol were similarly elevated. For instance, NO_x emissions for textiles were approximately 33-fold higher (17 vs. 0.5 Gg·year^{-1}). These differences further highlight the critical role of accounting for comprehensive supply chain activities.

Case study: Trend of emissions from shopping for necessities, textiles, and foodstuffs in China

Previous studies often overlook the evolution of retail supply chains and their impact on shopping-related emissions[2,6,7,44,51–53]. Over the past three decades, various socio-economic and political factors have influenced shopping emissions, including changes in car use, emission standards, freight modal structures (e.g., road, water, railway, and air), and delivery efficiency (e.g., the number of parcels delivered per courier trip) (Supplementary Tables S1–S7, S9–S20, and S23–S25)[3]. This protocol provides datasets and methodologies for analyzing trends in shopping-related emissions and identifying underlying driving forces, thereby helping to uncover mitigation opportunities.

Figure 3 illustrates the trends in GHG and air pollutant emissions from shopping for necessities, textiles, and foodstuffs between 1990 and 2023. During this period, GHG emissions from shopping increased substantially: from 0.06 (0.04–0.07) to 10 (8.1–14) Tg·year^{-1} for necessities, from 0.04 (0.03–0.06) to 8.1 (6.5–10) Tg·year^{-1} for textiles, and from 0.28 (0.21–0.37) to 22 (17–30) Tg·year^{-1} for foodstuffs. By shopping method, necessities and textiles exhibited lower emissions in traditional shopping (4.3 Tg and 1.8 Tg, respectively) compared to online shopping (6.2 Tg and 6.3 Tg, respectively) in 2023. Conversely, foodstuffs showed higher emissions in traditional shopping (17 Tg) than in online shopping (5.7 Tg; Fig. 4).

The trends in air pollutant emissions varied across species over the three decades (Fig. 3). Overall, emissions increased due to rising shopping demands for the three categories, although fluctuations occurred during specific periods. For example, NO_x emissions from shopping for textiles rose from 0.72 Gg·year^{-1} in 1990 to 17 Gg·year^{-1} in 2023. Despite this general upward trend, there were notable declines in emissions during 2001, 2011–2012, 2018, and 2020, primarily due to the implementation of stricter emission standards for diesel trucks (China I to China VI)[4,48]. The implementation of stricter emission standards has driven the primary reductions in emissions for traditional shopping, leading to the observed drops in total shopping emissions (Figs. 3–4). In contrast, increased demands for both online and traditional shopping and car use contributed to emission increases during other periods (Table 4)[4]. These observations highlight that while stringent emission standards have helped reduce air pollutant emissions, it remains crucial to decrease car use during shopping trips in China.

Applying Shahmohammadi et al.'s static methodology[6]—which assumes invariant emission intensities across 1990–2023—we found GHG increases of 33-, 57-, and 22-fold for necessities, textiles, and foodstuffs (0.10 to 3.4, 0.13 to 7.2, and 0.79 to 18.2 Tg·year^{-1}, respectively). These growth factors are substantially lower than our estimates (167-, 202-, and 79-fold), highlighting the advantage of incorporating temporal parameter dynamics over static approaches.

An agent model for GHG emission calculations

Building on the protocol framework, we developed an agent-based model to calculate GHG emissions from shopping. The model integrates ground-truth methodology and structured data to quantify emission impacts from both online and traditional shopping pathways. It comprises three core modules: (1) a data repository containing

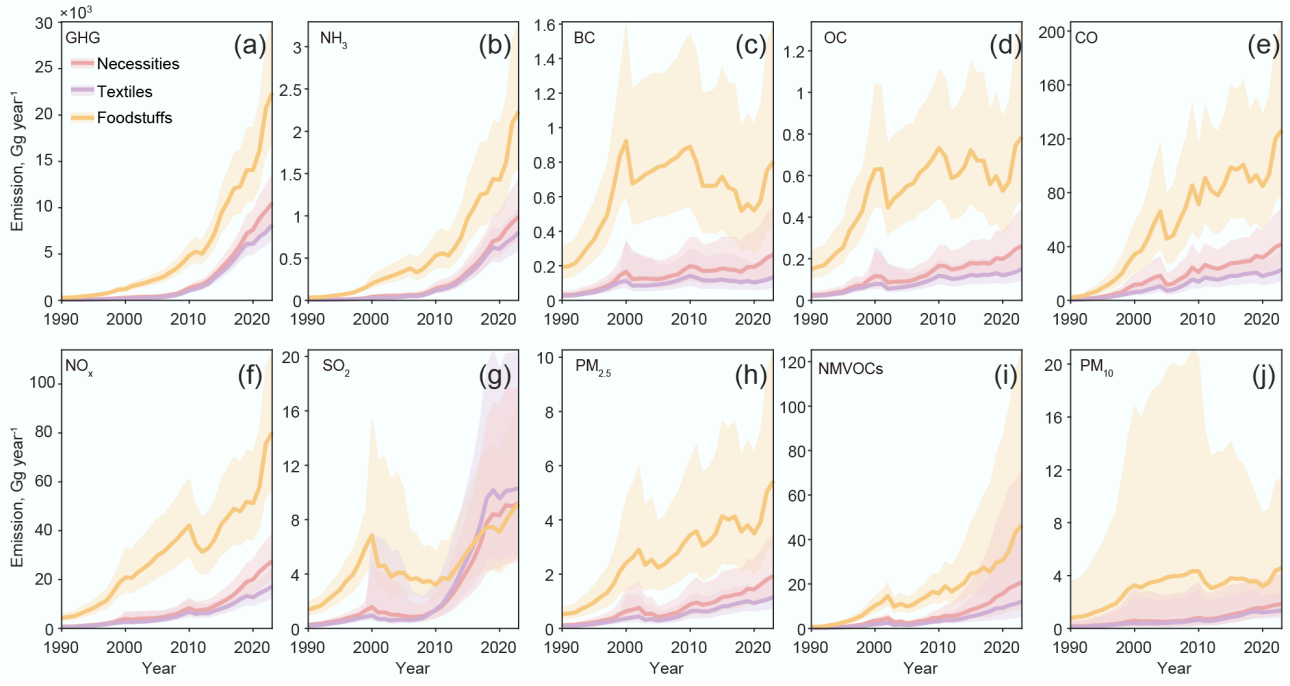

Fig. 3 Trends of GHG and air pollutant emissions from total shopping for necessities, textiles, and foodstuffs in China (1990–2023). (**a**–**j**) Trends of emissions from total shopping for GHGs (**a**), NH_3 (**b**), BC (**c**), OC (**d**), CO (**e**), NO_x (**f**), SO_2 (**g**), $PM_{2.5}$ (**h**), NMVOCs (**i**), and PM_{10} (**j**). Shaded areas represent the 90% confidence intervals of emissions, corresponding to the 5th and 95th percentiles of the simulated distributions derived from Monte Carlo simulation.

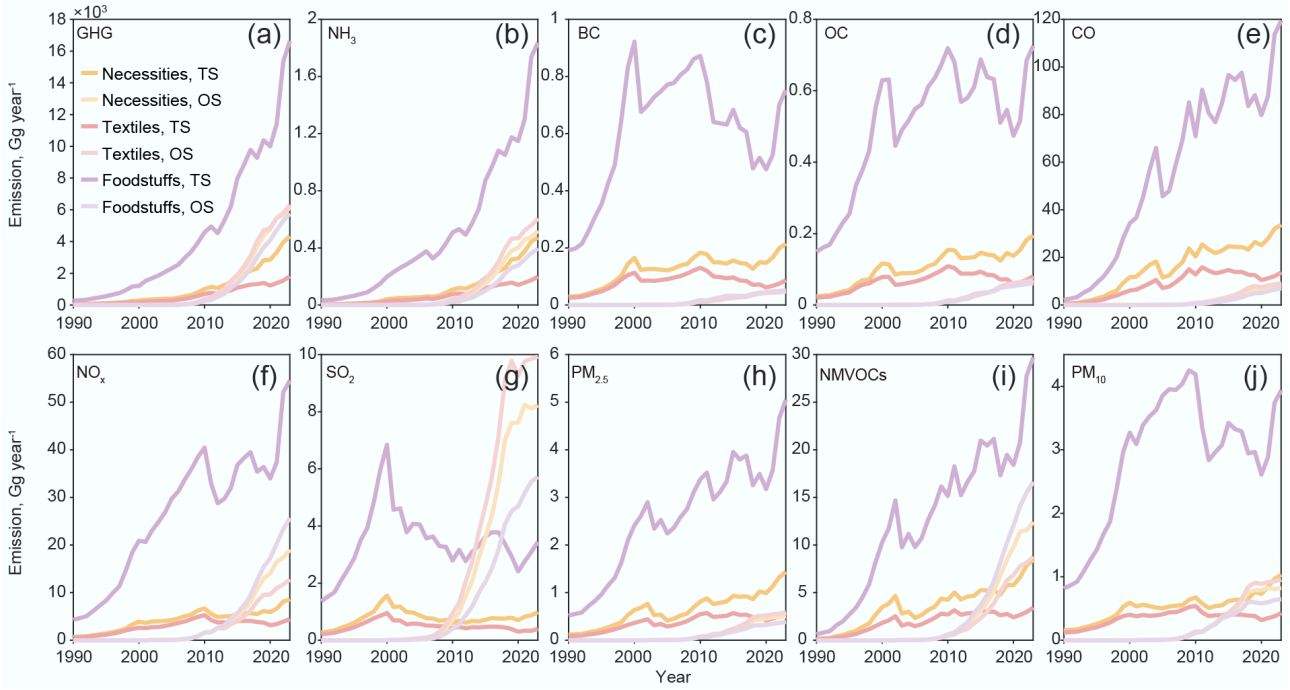

Fig. 4 Trends of GHG and air pollutant emissions from online shopping (OS) and traditional shopping (TS) for necessities, textiles, and foodstuffs in China (1990–2023). (**a**–**j**) Trends of emissions of GHGs (**a**), NH_3 (**b**), BC (**c**), OC (**d**), CO (**e**), NO_x (**f**), SO_2 (**g**), $PM_{2.5}$ (**h**), NMVOCs (**i**), and PM_{10} (**j**) from OS and TS for necessities, textiles, and foodstuffs in China (1990–2023).

activity parameters and emission factors for each supply chain phase; (2) a protocol engine that orchestrates the sequential emission calculation workflow; and (3) an emission simulator that executes calculations at the agent (i.e., purchase order) level. Within the simulator, consumer agents are instantiated to represent micro-level shopping behaviors of retail supply chain activities. Given input sales weights, the simulator generates corresponding shopping events (orders); for each event, the protocol engine guides the agent through emission calculations across six supply chain phases and two shopping methods. To account for stochastic supply chain dynamics and consumer variability, emissions for each agent are estimated via Monte Carlo simulation, sampling parameters from assumed distributions.

We demonstrated the model using a 2023 case study of necessities, with input weights of 10 tons for online shopping and 20 tons for traditional shopping (total: 30 tons). The simulation generated 32,132 shopping events, with online and traditional channels accounting for 20% and 80% of order volume, respectively. These channels exhibited distinct GHG emission distributions, reflecting divergent activity and emission patterns (Figs. 5a–b). The average GHG emissions per event were 0.30 kg CO_2eq for traditional shopping and 0.51 kg CO_2eq for online shopping. These correspond to 380 and 330 kg CO_2eq metric ton^{-1} necessities, respectively. Total emissions for the 30-ton basket amounted to 11 tons CO_2eq, with online and traditional shopping contributing 30% (3.3 tons) and 70% (7.7 tons), respectively. These contributions were driven by differences in shopping volumes (10 vs. 20 tons) and emission intensities (Figs. 5c–d). By enabling emission calculations under varying consumer and supply-chain scenarios, this model provides verifiable, protocol-aligned ground-truth logic for AI agent frameworks.

Conclusion

This protocol provides a robust methodology and recommends datasets for comprehensively assessing GHG and air pollutant emissions from shopping. Additionally, it demonstrates the application of this methodology through case studies on necessities, textiles, and foodstuffs, highlighting its advantages over previous assessments in terms of comprehensiveness, national representativeness, and emission trend analysis. Finally, the agent-based emission calculation model enables GHG accounting under varying consumer behaviors and supply-chain configurations, delivering protocol-aligned, phase-traceable ground-truth logic for future AI agent models.

This protocol outweighs previous methods in the following ways. First, this methodology involves primary retail activities, involving air freight and packaging, which are typically omitted in previous studies but are important factors[2–4]. Second, multimodal travel and transport methods are considered rather than a single-mode approach, which aligns better with real-world conditions. Third, temporal trends of key parameters, such as freight distances and travel modes, have been involved to improve the precision of assessments in terms of different developing periods. Fourth, this protocol involves nationwide retail activities covering 16 merchandise categories, showing national representativeness of assessment. However, this methodology omitted emerging shopping methods (such as video-based shopping), omnichannel shopping methods (such as online ordering with store delivery and online ordering with shopping trips to store), browsing trips, remote or rural shopping, bulk-item trips, pick-up, and failed delivery. These topics are worthwhile for further research.

Looking forward, three key research gaps remain. First, uncertainty persists in how GHG and air pollutant emissions are distributed across consumer shopping trips, last-mile delivery, inter- and intra-city goods transport, life-cycle packaging use, and electricity consumption[54,55]. Addressing these gaps is critical for identifying emission patterns and hotspots, with disproportionate impacts on populations near transport hubs, packaging facilities, and power plants. Mapping air pollutant emissions is also essential for assessing public health risks from ambient $PM_{2.5}$, NO_2, and ozone

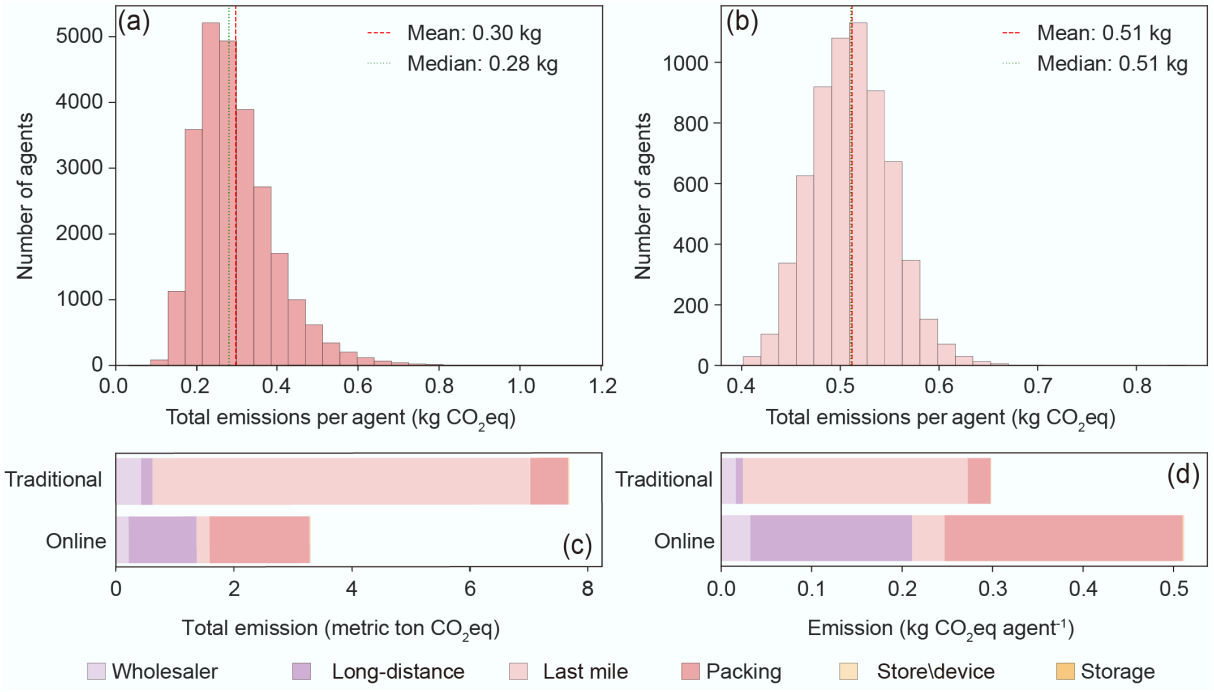

Fig. 5 Results of the agent-based emission calculation model. (**a**–**b**) Distribution of GHG emissions per agent for necessities purchased via traditional (**a**) and online (**b**) shopping. (**c**–**d**) Comparison of total emissions (**c**) and average emission intensities per agent (**d**) between traditional and online shopping.

exposure, the leading causes of premature deaths[54,56,57]. Second, more precise temporal analyses of shopping emissions are crucial to uncovering patterns linked to residents' routines and specific events, such as peak shopping periods (e.g., "Double Eleven" and Spring Festival in China) or the 2019 coronavirus pandemic[58,59]. Third, predicting consumer behaviors and supply chain dynamics is vital for understanding future emission trends and devising practical mitigation measures[60].

Moreover, big data and AI offer transformative tools to address these challenges. For instance, big data sources—such as remote sensing, smartphone sensors, and global positioning systems—combined with AI techniques like machine learning and agent-based modeling, can generate high-resolution spatio-temporal distributions of shopping emissions[55,60–69]. Notable examples include Reiffer et al.[55], who used agent-based models to simulate interactions between online shopping and last-mile deliveries, and Shahariar et al.[60], who employed support vector machines and regression models to predict CO_2 and NO_x emissions from vehicles. Deng et al.[66] leveraged billions of GPS trajectories to construct high-resolution emissions data (0.01° × 0.01°) for heavy-duty trucks, while Feng et al.[67] estimated CO_2 emissions using co-emitted NO_2 data from remote sensing. Zhang et al.[69] utilized mobile data to assess GHG emissions from personal travel in Greater London. These studies highlight the potential of big data and AI to advance spatio-temporal analyses of shopping emissions, enabling more effective emission reductions in the retail sector. By integrating these technologies, future research can provide actionable insights to mitigate shopping-related emissions and their associated environmental and public health impacts.

In conclusion, this protocol establishes a comprehensive assessment framework for evaluating GHG and air pollutant emissions from the retail sector, enhancing our understanding of the environmental impacts of shopping and consumer behaviors. We recommend this methodology as a standardized tool to enable meaningful comparisons across different shopping methods, merchandise categories, supply chain phases, locations, and time periods. By doing so, it supports evidence-based decision-making and advances the sustainable development of the global retail sector.

Supplementary information

It accompanies this paper at: https://doi.org/10.66178/aie-0026-0013.

Data description (Supplementary Method S1) and associated datasets (Supplementary Tables S1–S25 and Supplementary Data S1) used for the emission evaluation.

Ethical statements

Not applicable.

Author contributions

Ruibin Xu, Huizhong Shen, Shu Tao, Peng Wang, and Jing Meng conceived the initial framework. Ruibin Xu and Huizhong Shen were involved in data collection and cleaning. Ruibin Xu wrote the codes and carried out the analysis. Huizhong Shen, Shu Tao, Peng Wang, and Tao Wang supervised and coordinated the overall research. Ruibin Xu and Huizhong Shen contributed to the writing, revisions, and editing.

Data availability

The datasets used or analyzed during the current study are available within this study, and other related datasets are available from the corresponding author upon reasonable request.

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Competing interests

The authors declare no competing interests.

Author details

[1]State Key Laboratory of Soil Pollution Control and Safety, Shenzhen Key Laboratory of Precision Measurement and Early Warning Technology for Urban Environmental Health Risks, School of Environmental Science and Engineering, Southern University of Science and Technology, Shenzhen 518055, China; [2]Guangdong Provincial Field Observation and Research Station for Coastal Atmosphere and Climate of the Greater Bay Area, Southern University of Science and Technology, Shenzhen 518055, China; [3]Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China; [4]Institute of Carbon Neutrality and Green Development, School of Environmental Science and Engineering, Guangdong Provincial Key Laboratory of Environmental Pollution Control and Remediation Technology, Sun Yat-sen University, Guangzhou 510275, China; [5]The Bartlett School of Sustainable Construction, University College London, London WC1E 7HB, United Kingdom; [6]Institute of Carbon Neutrality, Laboratory for Earth Surface Processes, College of Urban and Environmental Sciences, Peking University, Beijing 100871, China

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