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Consumer responses towards essential purchases during COVID-19 pan-India lockdown

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A R T I C L E I N F O

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A B S T R A C T

Humanity experienced one of the worst crises in recent history due to the COVID-19 pandemic. The spread of the disease and the lockdown announced by the government of India created an emergency, disrupting the supply of essential commodities and creating panic and anxiety among the people. This paper aims at capturing the behavior of consumers purchasing essential commodities before and during the lockdown using an online questionnaire. Responses from 730 households covering 20 states in India were used. The data analysis revealed that consumers made a lesser number of trips during lockdown but purchased excess commodities considering the future uncertainties. The local family grocery stores, called *kirana* shops served well during the pandemic. During the lockdown, consumers made shorter trips by vehicles and walked extensively. Income was found to influence purchase behavior. The disruptions at the organized retail stores for in-store as well as online purchases were identified using factor analysis. Out of the three factors identified each for in-store and online purchases, perceived risk and vendor distrust had major influence respectively. The findings of this study give pointers to many infrastructure and policy initiatives that target tackling such emergencies in the future.

1. Introduction

The consumer products supply-chain, especially related to the fast-moving consumer goods, operates through dynamic global networks. Improved access to information and the expansion of choice sets have made consumers respond to even minor perturbations in this network. The most unpredictable context which influences consumer habits is the occurrence of ad-hoc natural disasters such as hurricanes, tsunamis, and global pandemics. As a result, there has been an ever-increasing interest in understanding consumers' behavioral responses to disruptions. Such understanding is vital in handling uncertainties, informing decisions, and improving resilience. This paper focuses on studying the response of consumers in India towards purchasing essential commodities because of the uncertainties created by COVID-19 pandemic and the pan-India lockdown announced by the Government of India.

The severity of the unprecedented health crisis with the outbreak of COVID-19 was felt when the World Health Organization declared it as a global pandemic on 11 March 2020. By this time COVID-19 had spread in more than 114 countries with 118,326 active cases and 4292 deaths (WHO, Situation Report-51, 2020). The timeline of the virus-spread in India started with the first case being recorded in Kerala on 30 January 2020 and continued with transmission rate increasing rapidly to date. Apart from the dense population, several factors such as lack of awareness, ignorance of people towards precautionary measures like social distancing, usage of masks, and a considerable proportion of people living below the poverty line intensifies the threat in India (Buckshee, 2020; Kamath, Kamath, & Salins, 2020). Fig. 1 shows the timeline of COVID-19 cases in India from 30 January 2020 (detection of the first case) to 25 March 2020 (imposition of lockdown). As the total number of cases crossed a 400 mark, a 14-h curfew called 'Junta curfew' (people's curfew) was announced in India by the Prime Minister on 22 March 2020. Immediately after 3 days, a 21-day lockdown was imposed from 25 March 2020, which primarily resulted in the closure of all transportation services, public and private offices, businesses, factories,

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etc., throughout the country.

The logistics and supply chain sector form an essential part of a country's economy. This sector was adversely affected during the lockdown because freight movement almost stood still. Economic slowdown intensified when more than eight million people working in the logistics industry suddenly became jobless as an immediate impact of the imposed lockdown. Although the transportation of essential goods was still functional, about 90–95% reduction in the movement of freight was observed in the initial 2–3 days of the lockdown (Yabaji, 2020). According to the Indian Foundation of Transport Research and Training (IFTRT), Indian trucking faced a shortage of drivers, and 62.5% fleet owners stopped the work owing to less demand or safety of the drivers (Khan, 2020). The hindered movement of goods in the domestic supply chain resulted in increased operational cost, which in turn resulted in inflation (Kumar, 2020). While the demand for essential goods kept on increasing, numerous problems effected in supply chain disruptions.

Factors like travel restrictions, closure of shopping malls and supermarkets (Agrawal, Jamwal, & Gupta, 2020) reduced product availability at stores (Mahajan & Tomar, 2021) impacted consumer behavior with respect to shopping of essential commodities. Thus, their priorities quickly shifted towards essential commodities in food, healthcare, and personal hygiene categories (Biswas, 2020). On the other hand, sales of luxury products and services witnessed a slump. Because of several issues at retail stores such as long queues, uncertainty in opening and closing times, unavailability of items, and restrictions on purchase quantity, (Balachander, 2020; Mishra, 2020) consumers preferred approaching the local vendors and the family-owned local departmental stores in Indian localities called as '*Kirana*' shops. These stores are not a part of retail chain business and serve as a center for groceries and items of daily use for local community. Also, consumers became more price-sensitive due to a fall in their incomes (Hobbs, 2020) or loss of employment, which also explains their inclining interest towards local vendors and brands. Another shift observed was in the increased demand for online shopping for groceries and other essential items because of the movement restriction, social distancing norms, and the fear of getting infected.

In this study, we have analyzed the response of educated respondents towards the purchase of perishable and non-perishable essential commodities. The responses were collected from residents all over India. Our primary concern is to investigate the shift in frequency, transport mode, distance travelled, type of stores, etc. associated with shopping trips before and during the lockdown. Combined effects of behavioral variables including mode of travel, frequency of shopping, and average distance travelled have also been studied. Locality wise (city type wise) behavior of respondents across India with respect to shopping of essential commodities during lockdown has been analyzed. We also attempt to understand if this shift was consistent across the different income groups of Indian society. Factor analysis is performed to identify the type and frequency of disruptions experienced at the final vendor node that contributed to the shift in the response of the consumers.

2. Literature review

Consumption is habitual as well as contextual. The primary contexts that can influence consumers' habits are social events (migration, marriage, etc.), the advent of technology (internet, online shopping), government-imposed rules and regulations (promoting solar cars, etc.), and natural disasters (Sheth, 2020). The consumer goods ecosystem includes consumers on the demand-side and firms on the supply side. This ecosystem works well with the iterative process of consumers feeding into the supply side to improve the quality of products and delivery of such improved products feeding into the understanding of consumers (Fortin & Uncles, 2011). The occurrence of the above-mentioned events causes an imbalance in supply and demand, resulting in the disruption of this system.

COVID-19 pandemic has substantially tested the consumer goods industry. As people are trying to adapt to the 'new normal,' prominent changes in their attitude, priorities, and habits of purchasing are being observed. Supply chains have been severely hampered due to lockdown conditions resulting in the supply-side and the demand-side shocks. Demand-side shocks mainly include panic buying, changes in food purchasing patterns, and changed product priorities; supply-side shocks include a shortage of labor, closure of manufacturing factories, unstable fuel prices, and disruption to transportation and supply networks (Hobbs, 2020).

There are studies in the literature that analyze the changes in consumer behavior in the context of the occurrence of natural disasters, economic recession, epidemics, wars, etc. Most of them discussed event-induced human emotions such as fear, depression, and stress, which influences the purchasing patterns of consumers. Many studies have researched how consumers' behavior changes the aftermath of natural disasters (Kennett-Hensel, Sneath, & Lacey, 2012; Larson & Shin, 2018; Sneath, Lacey, & Kennett-Hensel, 2009). Several studies talk about environmental (Singh & Chauhan, 2020) and mobility (de Vos, 2020;

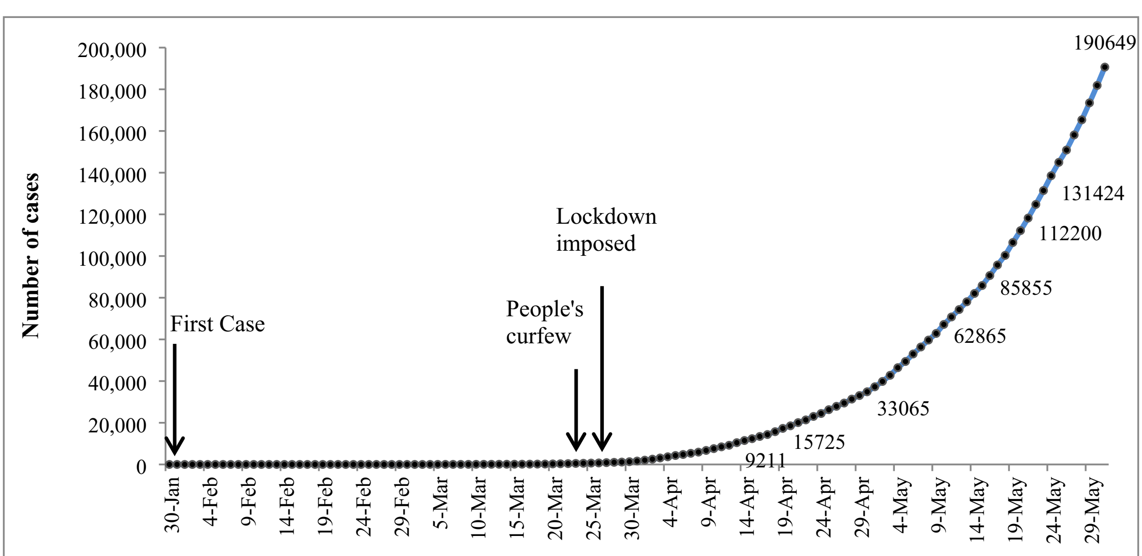

Fig. 1. Timeline of the total number of cases in India.

Park, 2020; Pawar, Yadav, Akolekar, & Velaga, 2020; Pawar, Yadav, Choudhary, & Velaga, 2021; Saha, Barman, & Chouhan, 2020) changes occurring during COVID-19 pandemic, but the impact of a pandemic on consumer behavior has not been explored much.

Li, Hallsworth, and Coca-Stefaniak (2020), through a survey in China, found a switching behavior with local retailers bouncing back into the market and, on the other hand, farmers losing their customers. According to the study conducted in Canada by Richards and Rickard (2020), a notable shift from foodservice channel to retail channel has been observed owing to the closure of restaurants and other food outlets during the lockdown. Harris, Depenbusch, Pal, Nair, and Ramasamy (2020), through a survey, found out that the disruptions in food systems due to pandemic had severely affected the farmers of India in terms of productions, sales, prices, and income. Laato, Islam, Farooq, and Dhir (2020) proposed a structural model that suggested that increased exposure to the internet during lockdown led to the anxiety-driven unusual purchasing behavior of consumers. Technology has always played a crucial role in transforming consumer behavior. Basic needs (food, clothing, shelter), too, have shifted to new necessities like mobile phones, internet, and apps (Sheth, 2020). The shift of consumers from in-store to online shopping during lockdown would be of no surprise.

The advent of any natural disaster or health crisis arouses a feeling of fear in the community, which profoundly influences their shopping behavior. According to Larson and Shin (2018), perceived convenience gets negatively impacted as panic and fear among consumers intensify. Sneath et al. (2009) stated that disaster-induced stress due to losses and perceived lack of control leads to impulsive and compulsive buying. Kennett-Hensel et al. (2012) found that consumers practice hoarding and stockpiling for alleviating their anxiety. Long and Khoi's (2020) study demonstrated that high-risk perception led consumers to purchase and hoard goods during the lockdown.

The literature review revealed that although numerous studies on linking consumer personality traits and their perception have been done in the past, very few describe their behavior in events of the crisis. Most of these studies highlight the stress and anxiety-driven behavioral changes prevailing during emergencies. The width of such research is limited in the context of developing countries like India. To the best of our knowledge, there are no studies in the literature that specifically describe consumer behavior changes during emergencies in the shopping option, shopping frequency, travel mode, trip length distribution, etc. to perishable and non-perishable essential commodities.

3. Data collection

Data was collected through an online questionnaire survey that targeted responses from consumers all over India. As discussed above, the focus of this study is on consumer behavior towards essential goods. During the pan-India lockdown, transporting or selling non-essentials goods was banned. The perishable essential commodities were restricted to fruits and vegetables only. Other perishable items, such as meat and dairy products, are not considered. In India, we have dedicated vendors for non-vegetarian items, and most families buy milk daily. The non-perishable commodities broadly include grains, flour, spices, packet food items, laundry items, and other household essentials. Medicines and personal protective products (such as masks) purchased from pharmacies are not considered.

The questionnaire is divided into three broad sections. The first section sought information about socio-demographic characteristics of respondents like the number of earning members, educational qualification, monthly family income, household type, and vehicle ownership. The detailed list of socio-demographic variables included in the survey is shown in Table 1. The second and third sections requested details about the behavior of respondents while buying essential commodities during and before lockdown, respectively. These sections asked information about the frequency of in-store shopping, frequency of online shopping, mode of travel, the average distance travelled, mode of payment, type of stores visited, type of shopping preferred (online or in-store). Besides, the future period considered while buying essential commodities was also recorded. Shopping related issues (both in-store and online) during lockdown were analyzed using a Likert scale in the consumer behavior

Table 1
Summary of socio-demographic characteristics of respondents.

Socio-demo. variables	Data range	Frequency	Socio-demo. variables	Data range	Frequency
Family members: <5 years age	0	576 (78.90%)	Family members: Age 5–18 years	0	502 (68.77%)
	1	125 (17.12%)		1	146 (20%)
	2	23 (3.15%)		2	70 (9.59%)
	3	3 (0.41%)		3	9 (1.23%)
	> 3	3 (0.41%)		> 3	3 (0.14%)
Family members: Age 18–35 years	0	172 (23.56%)	Family members: Age 35–60 years	0	139 (19.04%)
	1	208 (28.49%)		1	158 (21.64)
	2	253 (34.66%)		2	386 (52.88%)
	3	71 (9.73%)		3	27 (3.70%)
	> 3	26 (3.56%)		> 3	20 (2.74%)
Family members: More than 60 years	0	442 (60.55%)	Number of earning members	0	6 (0.82%)
	1	156 (21.37%)		1	308 (42.19%)
	2	110 (15.07%)		2	317 (43.42%)
	3	18 (2.47%)		3 or more	99 (13.56%)
	> 3	4 (0.55%)			
Highest qualification	10th class/less	3 (0.46%)	Monthly family income (INR '000')	<20	32 (4.38%)
	12th/Diploma	6 (0.92%)		20–50	168 (23.01%)
	Bachelor degree	141 (21.69%)		50–100	**226** (30.96%)
	Master's degree	380 (58.46%)		100–200	168 (23.01%)
	PhD	120 (18.46%)		>200	136 (18.63%)
Two-wheeler ownership	0	187 (25.92%)	Car ownership	0	285 (39.04%)
	1	324 (44.38%)		1	329 (45.07%)
	2	178 (24.38%)		2	93 (12.74%)
	3 or more	41 (5.62%)		3 or more	23 (3.15%)
Household type	Apartment	371 (50.80%)			
	Row house	193 (26.44%)			
	Indep. bungalow	157 (21.51%)			
	Slum	9 (1.23%)			

It is seen that majority of the respondent families mostly consist of young (76.44%) and middle-aged people (80.96%). More than 50% of respondent families had 2 or more earning members. Almost 98.61% of families had at least graduation as the highest qualification. 74.38% and 60.96% of families possess at least one two-wheeler and car, respectively.

section.

The survey was floated across different digital platforms from 29 April 2020 to 25 May 2020. At the end of the survey, a total of 733 samples were collected. Out of the 733 samples, three samples were discarded on account of redundancy. Therefore, 730 sample size has been considered in analysis throughout this paper. The state-wise distribution of respondents is depicted in Fig. 2. About 39% of respondents were from the state of Maharashtra, which is the worst affected state with the highest number of COVID-19 cases. Cities in India are in general classified as Tier I, Tier II, and Tier III. The share of respondents belonging to different classes of cities is represented in Fig. 3. About 63% of the respondents belonged to either tier 1 or tier 2 cities. With the participation of respondents from more than 20 states, generalized data depicting the pandemic situation in the country is obtained. Considering the English proficiency and internet penetration, the responses from the people located in remote areas and poor and inadequately educated could not be collected.

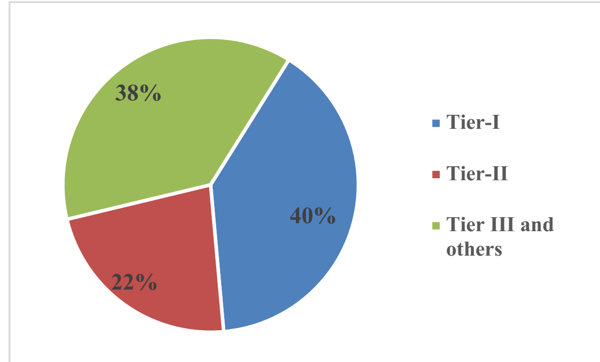

Fig. 3. Share of respondents belonging to different city types.

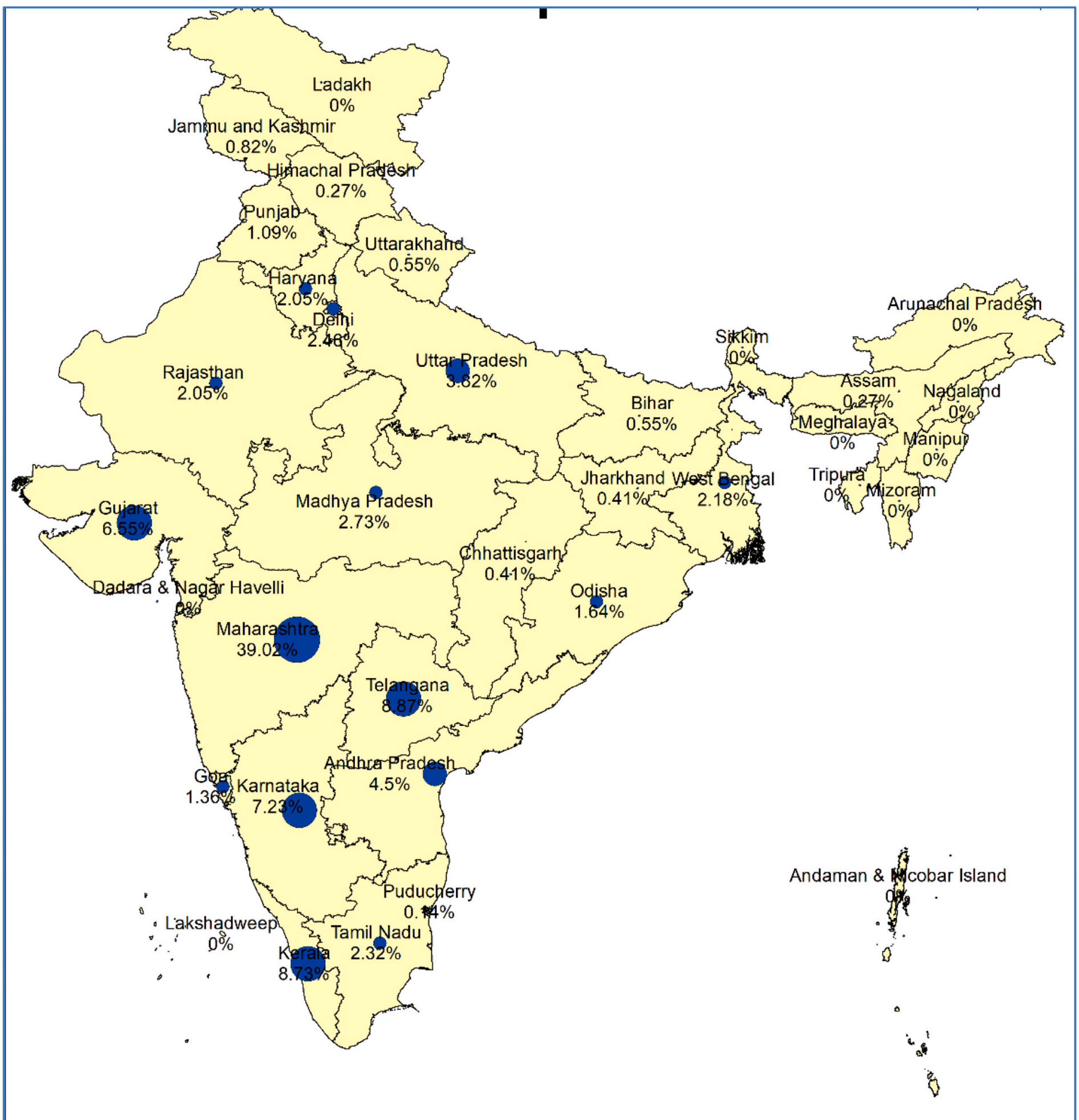

Fig. 2. State-wise distribution of respondents.

4. Socio-demographic characteristics

Socio-demographical characteristics play an important part in understanding the behavior of consumers in the time of crisis as these characteristics drive changes in demand, purchasing patterns, etc. (Cranfield, 2020). Moreover, these characteristics highly impact freight distribution and shopping mobility changes (Nuzzolo & Comi, 2014). Table 1 represents cross-tabulated and summarized socio-demographic variables with frequencies. All socio-demographic variables in the survey were either categorical or ordinal. The recorded variables include number of members on the basis of age groups (0, 1, 2, 3, more than 3), number of earning members in family (0, 1, 2, 3 and more), monthly family income (categories: <20,000; 20,000–50,000; 50,000–100,000; 100,000–200,000; >200,000 (in INR)), highest education qualification in family (categories: 10th class or less, 12th class, Bachelor's degree, Master's degree, PhD), household type (Categories: apartment, independent bungalow, row house, slum), two-wheeler and car ownership (0, 1, 2, 3 or more). Five age groups were identified: <5 years (infants), between 5 and 18 years (kids), between 1835 years (youth), between 35 and 60 years (middle-aged), more than 60 years (senior citizens).

5. Comparison of behavior before and during the lockdown

5.1. Frequency of in-store shopping

During the lockdown, when the stores providing essential commodities only were open, consumers were less likely to visit the stores frequently for buying essential commodities. Access convenience and transaction convenience (Larson & Shin, 2018) factors are likely to cause this shift in behavior. It is seen that about 56% and 36% of respondents frequently (daily and 2–3 times a week) visited markets before lockdown for buying perishable and non-perishable items, respectively, which drastically reduced to 34% and 23% respectively during the lockdown. Usage of the internet and subsequent information overload can lead to anxiety, stress, and distress during pandemics (Laato et al., 2020). Because of this perceived fear, consumers were reluctant to visit stores for shopping. Some of them had stocked up essential commodities sensing the uncertainty of the situation in the future. As a result, the percentage of people visiting markets less frequently for perishable goods (once in 2 weeks and once in a month) increased from 7.3% to 14.1% (Fig. 4).

5.2. Frequency of online shopping

Food supply chains are believed to be impacted by the developments in digitalization and innovation (Gharehgozli, Iakovou, Chang, & Swaney, 2017). As the e-commerce industry continues to grow, researchers are keen on studying the behavior of consumers in the context of online shopping (Elms, de Kervenoael, & Hallsworth, 2016; Hand, Riley, Harris, Singh, & Rettie, 2009; Mortimer, Fazal e Hasan, Andrews, & Martin, 2016; Picot-Coupey, Huré, Cliquet, & Petr, 2009). Usage of the internet by consumers for shopping is greatly affected by the prevailing situations (Hand et al., 2009). The lockdown induced anxiety has compelled them to use the internet for shopping purposes. Our survey findings support this theory as there has been a rise of 8% and 4% in the number of respondents who performed online shopping for perishable and non-perishable goods, respectively, during lockdown (Fig. 5). Moreover, we believe, this share will further increase if the online retailers introduce safe and no-contact delivery systems.

5.3. Stores visited

India has around 12 million family-owned grocery stores—called *kirana* shops; they are primary final node vendors for groceries. Their share is reducing in recent years because of the comfort and convenience of organized physical and online stores. However, this trend is found to be reversed during the lockdown. About 88% (increased from 77%) respondents preferred visiting local markets, and vendors for purchasing perishable items and 72% (increased from 44%) preferred visiting the local vendors during lockdown for purchasing non-perishable items (Fig. 6). According to a report by Yadav (2020), there was a rise of 40% more than ever at kirana stores since the announcement of lockdown. This rise of dominance of local family grocery stores during lockdown was supported by several other media reports like Balachander (2020), Mishra (2020) which reported that long queues, frequent stockouts, fluctuations in opening and closing timings of supermarkets have results in this shift. Similar findings are reported by Li et al. (2020) in China.

5.4. Mode of payment

Before lockdown, about 55% of respondents were performing cashless transactions for purchasing groceries, out of which about 24% were performing mostly cashless payment, indicating they were either buying online or from retail chain stores. During the lockdown, the percentage of 'mostly cashless' payments reduced to about 15%. This is the result of

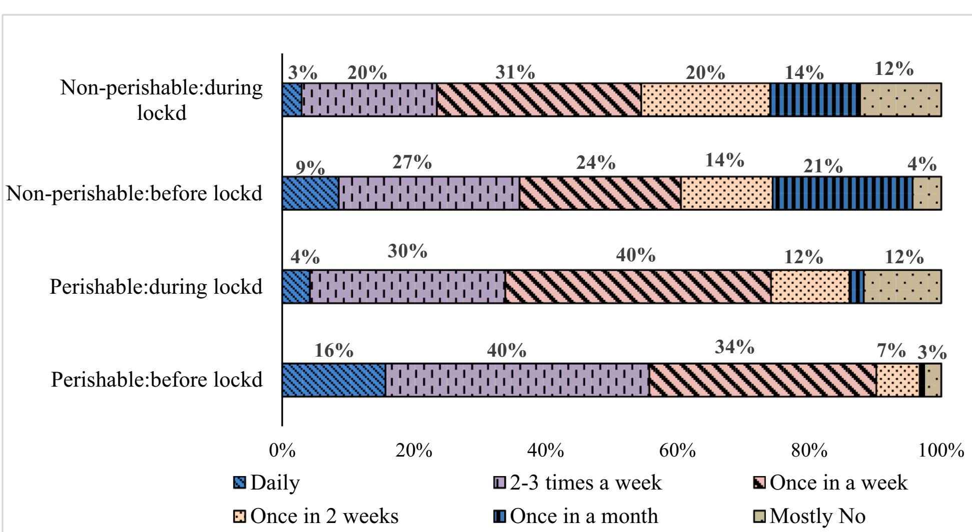

Fig. 4. Frequency of in-store shopping (comparison).

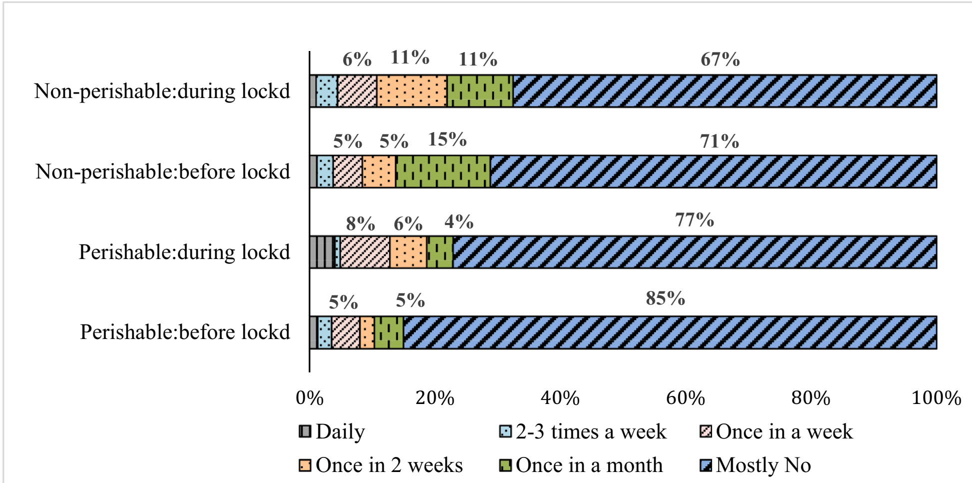

Fig. 5. Frequency of online shopping (comparison).

Fig. 6. Type of stores visited (comparison).

consumers shifting from retail stores to the local store (Fig. 7). The shift is primarily due to the disruptions at the retail chain stores and they being farther from residences. Most of the local stores do not accept card payments, although a few of them accept payment through e-wallets such as Google pay and Paytm.

5.5. Mode of travel

The imposition of lockdown resulted in movement restriction of citizens. Most of the respondents visited stores/markets for buying essentials by walking since they might be visiting places that are located nearby their areas of residence. The use of two-wheelers and cars significantly reduced during the lockdown as compared to their use before lockdown (Fig. 8). The bicycle as a mode of travel while visiting

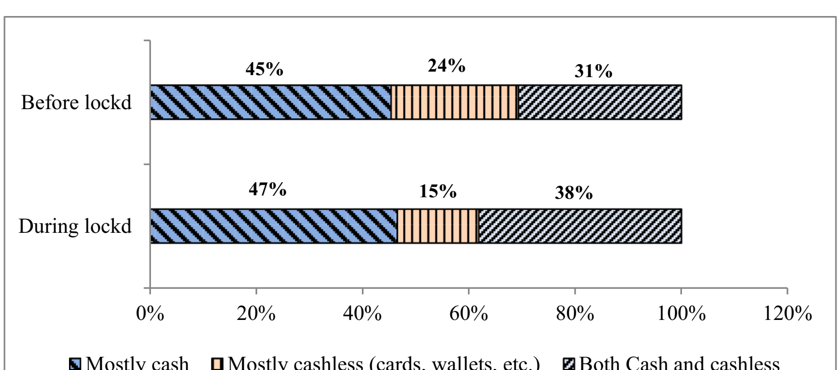

Fig. 7. Mode of payment (comparison).

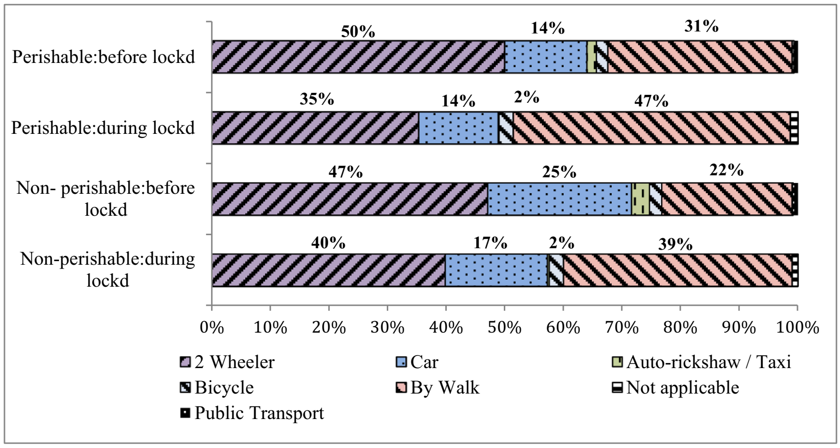

Fig. 8. Mode of travel (comparison).

stores gained significance during the lockdown.

5.6. Trip length distribution

The trip length distribution combined with the mode choice behavior is an important input for the policymakers to adapt to cater to the transport needs during emergencies such as the present pandemic. The trip length distributions for non-perishable and perishable commodities before and during lockdown are presented in Fig. 9. Respondents did not prefer stores that are located beyond 2 km of the residence during the lockdown. Consumers visiting stores within 1 km distance increased during the lockdown. Overall, respondents did not prefer travelling large distances for buying essentials. Some of them also started performing online shopping to reduce the risk of getting infected.

We tested the fitting of normal, lognormal, gamma, and exponential distributions to the average distance travelled by the respondents before and during the lockdown. Kolmogorov-Smirnov (K—S) test was used to measure the goodness of fit for these distributions. K—S test value is the maximum distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution. The null hypothesis for the K—S test is that the sample follows a specific distribution. We reject the null hypothesis when the test

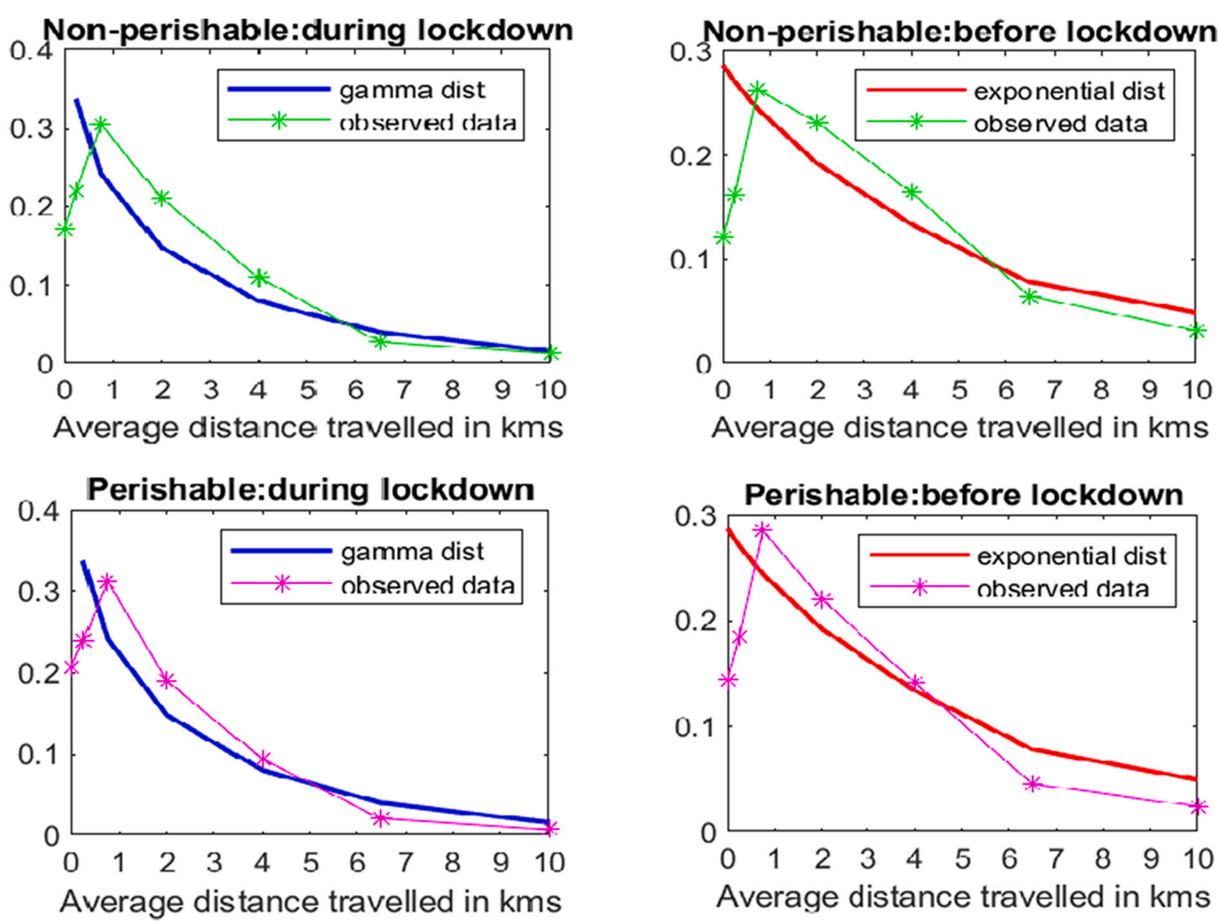

Fig. 9. Average distance travelled for essential commodities (comparison).

statistic is greater than the critical value. The statistical parameters for fitting these distributions are presented in Table 2. It was seen that average distance travelled by the respondents for buying essential commodities (both perishable and non-perishable) before lockdown followed exponential distribution and during the lockdown followed gamma distribution (Fig. 9).

5.7. Panic and excessive buying

The sudden announcement of the 21-day lockdown aroused a feeling of fear, which eventually led to panic buying by the consumers. From the survey findings, about 48.63% respondents purchased essentials before the announcement of national lockdown, out of which 24.04% bought goods before the announcement of Junta curfew (22nd March), and 24.59% shopped essentials in the period between Junta curfew (22nd March) and the announcement of National lockdown (25th March). Despite the assurance given by the government authorities that essentials would be made available during the lockdown, consumers preferred to hoard essential goods for a longer period as a precautionary measure. About 37.54%, 8.87%, 2.73% (total 49.14%) respondents purchased items considering the future period as 1 month, 2 months, and 3 months respectively.

6. Combined effect of frequency of shopping with mode of payment and average distance travelled

6.1. Respondents visiting stores more frequently

The combined effect of mode of payment preferred and average distance travelled for shopping during lockdown for respondents who more frequently visited stores for buying essential commodities is represented in Fig. 10. Respondents visiting stores daily, 2–3 times a week and once in a week are considered as more frequently visiting consumers. It is evident from the chart that 42% of more frequently visiting respondents preferred travelling <0.5 km distance and 53% of them preferred cash payments while buying from nearby stores. Respondents frequently visiting stores far away from their homes preferred mixed cash and cashless payments.

Fig. 11 represents combined effect of mode of travel and average distance travelled for shopping during lockdown for respondents who more frequently visited markets for buying essential commodities. About 42% of more frequently visiting respondents preferred travelling <0.5 km distance and majority of them (72%) preferred walking for visiting stores. Whereas 90% of frequently store visiting consumers travelling beyond 5–8 kms (2%) travelled by cars.

6.2. Respondents visiting stores less frequently

Fig. 12 represents combined effect of mode of payment preferred and average distance travelled for shopping during lockdown for respondents who less frequently visited markets for buying essential commodities. Respondents visiting stores- once in 2 weeks and once in a month are considered as less frequently visiting consumers. It is evident from the chart that 27% of less frequently visiting respondents preferred travelling up to 3 km distance and 51% of them preferred cash payments while buying. Respondents frequently visiting stores far away from their homes preferred mixed cash and cashless payments.

Fig. 13 represents combined effect of mode of travel and average distance travelled for shopping during lockdown for respondents who more frequently visited markets for buying essential commodities. About 27% of less frequently visiting respondents preferred travelling up to 3 km distance and majority of them (60%) preferred two-wheeler as a mode for visiting stores. Whereas 57% of less frequently store visiting consumers travelling beyond 5–8 kms (15%) travelled by cars during lockdown.

7. Shopping behaviour comparison for different city types

This section discusses behavioral changes of respondents with respect to their area of residence. About 63% of the respondents belonged to either tier 1 or tier 2 cities (refer Fig. 3). Table 3 represents locality-wise comparison of behavior of respondents before and during lockdown. It was seen that several factors such as shift towards visiting local stores, increased online shopping, reduced frequency of visiting stores, increased expenditure for buying essential commodities were more or less the same across respondents residing in all the locations in India.

8. Influence of income on the purchase behavior

We included five ranges of household monthly income in the questionnaire. To analyze how the income influenced different aspects of purchasing; we merged them into three groups as below:

- Group I: <50,000 INR (Lower income group)
- Group II: between 50,000–200,000 INR (Middle income group)
- Group III: more than 200,000 INR (Higher income group)

The shares of respondents in group 1, group 2, and group 3 are 27.39%, 53.97%, and 18.63%. The behavior of these groups with reference to frequency of in-store shopping, frequency of online shopping, travel mode, the average distance travelled, and type of stores preferred is presented in Tables 4 and 5. Table 4 is for non-perishable commodities, and Table 5 is for perishable commodities. A Chi-square test is performed to test the association between the three income groups and their corresponding behavior during the lockdown. In other words, we are interested in finding whether the group-wise behavior is different. The null hypothesis assumed that the behavior of consumers during lockdown is independent of the group or income of the family in general. Results from Tables 4 and 5 suggest that the frequency of in-store shopping (non-perishable items), frequency of online shopping (both perishable and non-perishable items), mode choice used while visiting during lockdown varied within the income groups of respondents (at significant level $p = 0.05$).

From Tables 4 and 5, the daily visits to stores are higher in income groups I and II, probably because these consumers do purchase commodities that are currently needed. The shares of online purchases decrease with decreased income ranges. The online purchase of perishable commodities is lower for each income group. While considering the travel modes, the walk is widely used across all income groups

Table 2
Statistical parameters for average distance travelled by respondents.

Type of commodity	During lockdown (K—S test values)				Before lockdown (K—S test values)				Critical value**
	Nl.	Lognl.	Gam.	Exp.	Nl.	Lognl.	Gam.	Exp.	
Non-perishable	0.500	0.539	**0.361**	0.405	0.506	0.539	0.447	**0.405**	0.483
perishable	0.517	0.539	**0.319**	0.405	0.502	0.539	0.469	**0.405**	0.483

Nl: normal; Lognl: lognormal; Gam: gamma; Exp: exponential.
Bold data indicates significant are the lowest K—S test values among four distributions.
** 95% confidence interval.

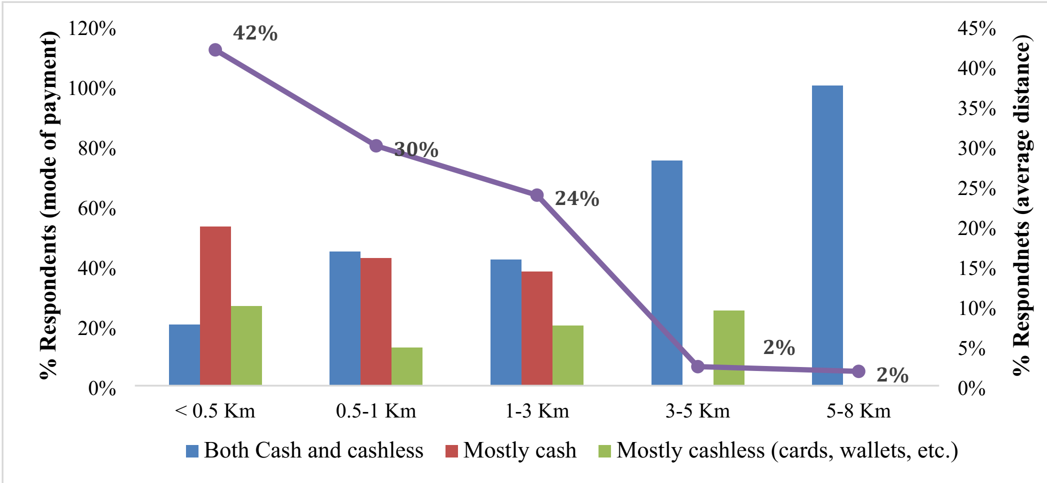

Fig. 10. Mode of payment and average distance travelled by frequent store visitors during lockdown.

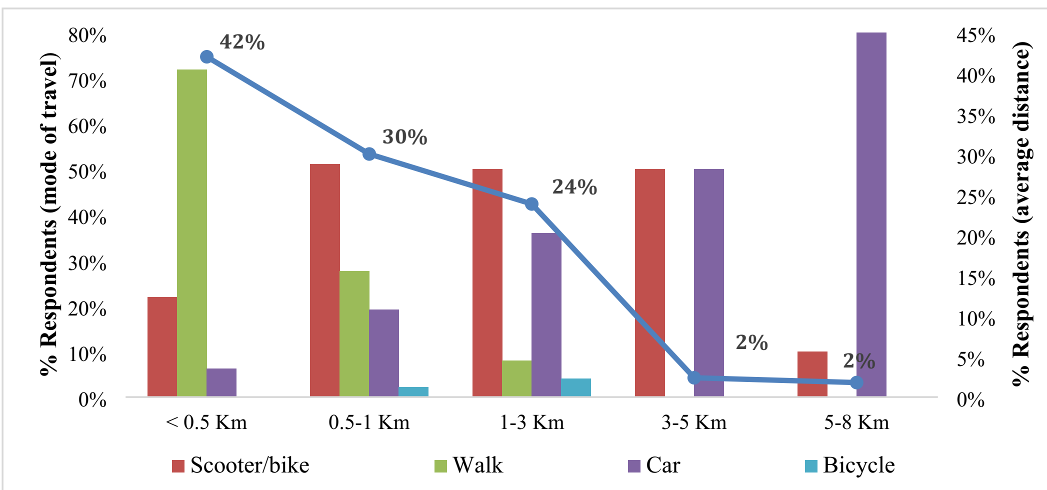

Fig. 11. Mode of payment and mode of travel by frequent store visitors during lockdown.

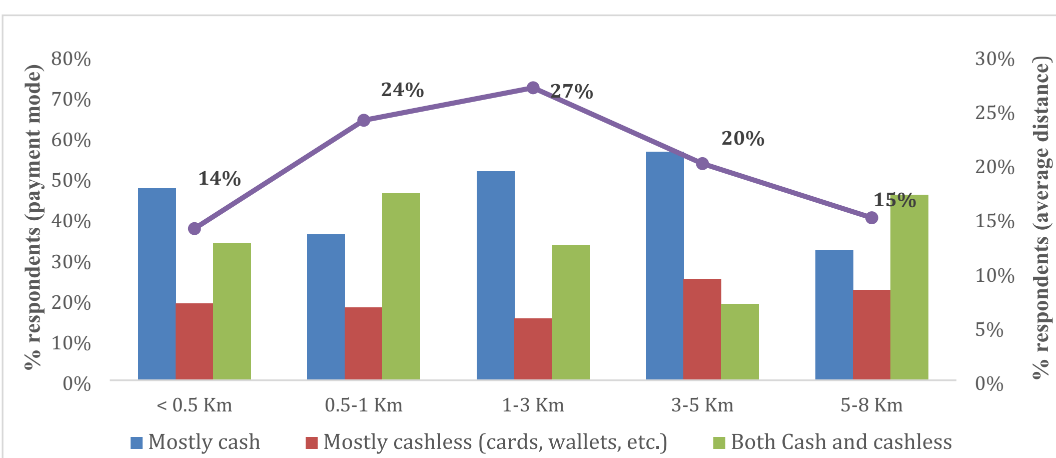

Fig. 12. Mode of payment and distance travelled by non-frequent visitors during lockdown.

for both perishable and non-perishable commodities; the share of the walk is higher for perishable goods. This is also reflected in the trip length distribution as the significant share of trips was <1 km. Two-wheeler is the most preferred mode by group I and group II respondents, where the walk is the most preferred by group III. It may be noted that the share of <1 km trips is approximately the same for all

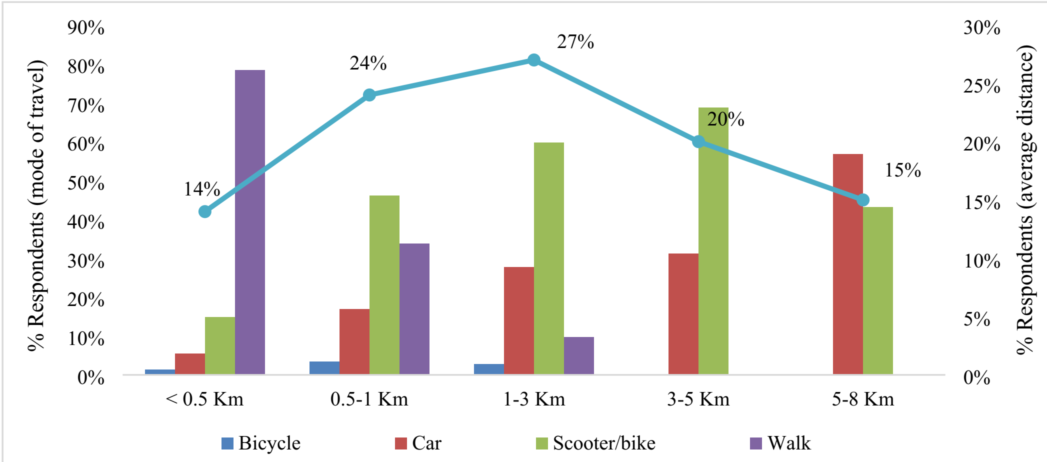

Fig. 13. Mode of travel and distance travelled by non-frequent visitors during lockdown.

Table 3
Behavioral changes during and before lockdown in different city types (comparison).

Behavioral variables	Data range	Tier I cities		Tier II cities		Tier III cities and other	
		During lockdn	Before lockdn	During lockdn	Before lockdn	During lockdn	Before lockdn
Frequency of shopping (physical)	Daily	3%	7%	2%	10%	4%	10%
	2–3 times a week	18%	27%	20%	31%	23%	28%
	Once in a week	30%	23%	24%	22%	32%	26%
	Once in 2 weeks	18%	24%	30%	17%	16%	21%
	Once in a month	18%	15%	12%	16%	12%	11%
	Not applicable	13%	5%	12%	5%	12%	4%
Frequency of shopping (online)	Daily	1%	1%	2%	1%	0%	2%
	2–3 times a week	4%	3%	4%	2%	1%	2%
	Once in a week	10%	5%	5%	2%	3%	5%
	Once in 2 weeks	16%	6%	9%	6%	7%	4%
	Once in a month	17%	17%	8%	16%	5%	11%
	Not applicable	51%	78%	74%	70%	81%	68%
Types of stores visited	Mostly local vendors/ stores	93%	42%	89%	45%	88%	47%
	Mostly retail store chains	2%	34%	1%	30%	3%	27%
	Both local and retail stores	5%	24%	10%	25%	9%	26%
Amount of money spent on buying essential commodities (monthly)	Average (in INR)	7254	6791	6789	6559	6544	63.06

groups. One of the possible reasons for this observation is the walkability in the neighborhood of the respondents.

9. Disruptions experienced at final vendor node

Likert scale responses were considered for accessing the consumer experience during the lockdown for both in-store shopping and online shopping. Exploratory factor analysis (EFA) is used to determine the number and nature of the factors that explain maximum covariance in the data. EFA is a statistical method that helps to identify the fewest possible constructs which can reproduce the original data (Gorsuch, 1997). Out of 733 respondents, 603 of them responded to the Likert scale questions corresponding to in-store shopping, and 366 respondents answered questions related to online shopping. The significant reduction in the later was because it was not asked those respondents who did only in-store purchasing.

The suitability of the respondent data for factor analysis can be assessed using two tests- Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) test. Bartlett's sphericity test checks whether the correlation matrix is an identity matrix, and KMO test tests the sample adequacy of data. If the P-value for Bartlett's test of sphericity is <0.05 and the KMO test value is more than 0.5, then data is said to be suitable for exploratory factor analysis (Williams, Onsman, Brown, Andrys Onsman, & Ted Brown, 2010). The purpose of factor extraction is to reduce a large number of items into a few factors. According to Thompson (2004), parallel analysis method is the best and commonly used method for deciding the number of factors to extract. This method compares the actual eigenvalues with the randomly ordered eigenvalues (from simulated and resampled data) and retains factors when the difference between the two is minimum (Williams et al., 2010). Rotation further helps in minimizing the complexity of factor loadings and thus producing the best fit solution. The rotation method used in this study is 'varimax' technique, which is commonly used in factor analysis (Thompson, 2004). This rotation method produces factor structures that are uncorrelated.

The results and interpretations of this analysis are presented in the subsequent sub-sections for both in-store and online shopping data samples. Nine research components were included for in-store shopping and online shopping, each as shown in Tables 5 and 8. The Likert scale ranged from 1 = 'strongly disagree' to 5 = 'strongly agree.' For each factor, the corresponding variance explained, and factor loadings were described. Hair, Anderson, Tatham, and Black (2000) categorized

Table 4
Descriptive statistics of behavioral variables and chi-square test results (non-perishable commodities).

Behavioral variables	Data range	Income group I	Income group II	Income group III	P value
Frequency of in-store shopping (non-perishable)	Daily	9 (6.42%)	4 (1.47%)	2 (2.44%)	0.015
	2–3 times a week	30 (21.42%)	52 (19.11%)	21 (25.6%)	
	Once in a week	35 **(25.0%)**	92 **(33.82%)**	30 **(31.78%)**	
	Once in 2 weeks	31 (22.14%)	68 (25.0%)	13 (22.6%)	
	Once in a month	18 (12.85%)	43 (15.8%)	10 (14.37%)	
	Not applicable	17 (12.14%)	13 (4.77%)	6 (7.28%)	
Frequency of online shopping (non-perishable)	Daily	1 (0.71%)	3 (1.11%)	1 (1.21%)	0.042
	2–3 times a week	7 (5.0%)	5 (1.83%)	3 (3.65%)	
	Once in a week	3 (2.14%)	10 (3.67%)	6 (7.31%)	
	Once in 2 weeks	5 (3.57%)	29 (10.66%)	7 (8.5%)	
	Once in a month	10 (7.14%)	27 (9.9%)	13 (15.85%)	
	Not applicable	**119 (81.42%)**	**198 (72.79%)**	**52 (63.14%)**	
Travel mode (non-perishable)	Walk	51 (36.4%)	105 (38.6%)	**37 (45.12%)**	0.0010
	Bicycle	8 (5.7%)	4 (1.47%)	1 (1.2%)	
	2-wheeler	**67 (47.85%)**	**107 (39.3%)**	19 (23.17%)	
	car	10 (7.1%)	52 (19.11%)	25 (30.48%)	
	Auto-rickshaw/ Taxi	1 (0.71%)	1 (0.36%)	0 (0.00%)	
	Not applicable	3 (2.1%)	3 (1.1%)	0 (0.00%)	
Average distance travelled (non-perishable)	<0.5 km	**47 (33.57%)**	**91 (33.45%)**	**27 (32.92%)**	0.746
	0.5–1 km	42 (30%)	86 (31.61%)	**27 (32.92%)**	
	1–3 km	32 (24.28%)	76 (27.94%)	20 (24.39%)	
	3–5 km	11 (7.85%)	11 (4.04%)	6 (7.31%)	
	5–8 km	3 (2.14%)	4 (1.47%)	2 (2.43%)	
	8–12 km	0 (0.00%)	2 (0.735%)	0 (0.00%)	
	Not applicable	3 (2.14%)	2 (0.735%)	0 (0.00%)	
Stores preferred (non-perishable)	Mostly local stores	**111 (79.28%)**	**138 (67.29%)**	**57 (69.51%)**	0.14
	Mostly retail stores	11 (7.85%)	38 (13.97%)	11 (13.41%)	
	Both local and retail stores	18 (12.85%)	51 (18.75%)	14 (17.07%)	

loadings ±0.3 as minimal, ±0.4 as necessary, and ±0.5 as practically significant. Here, loadings >0.4 were considered for identifying the factors. Factor analysis was performed using Rstudio software.

9.1. *In-store shopping*

Table 6 shows the list of research components used to understand the respondents' experience for in-store shopping. Bartlett's test results gave a P-value <0.05, and the KMO value obtained is **0.75** (>0.5). Thus, the success of both sphericity and KMO tests makes the data suitable for factor analysis. The parallel analysis test helps to determine the number of factors to be extracted by comparing the eigenvalues obtained from observed data and simulated (or random) data. The observed eigenvalues higher than their corresponding random eigenvalues are more

Table 5
Descriptive statistics of behavioral variables and chi-square test results (perishable commodities).

Behavioral variables	Data range	Income group I	Income group II	Income group III	P value
Frequency of in-store shopping (perishable)	Daily	10 (7.14%)	8 (2.94%)	3 (3.65%)	0.254
	2–3 times a week	46 (32.85%)	87 (31.98%)	26 (31.5%)	
	Once in a week	56 **(40.0%)**	119 **(43.75%)**	37 **(45.12%)**	
	Once in 2 weeks	13 (9.28%)	43 (15.8%)	11 (13.41%)	
	Once in a month	4 (2.85%)	4 (1.47%)	0 (0.00%)	
	Not applicable	11 (7.85%)	11 (4.04%)	5 (6.09%)	
Frequency of online shopping (perishable)	Daily	1 (0.71%)	1 (0.36%)	1 (1.21%)	0.0027
	2–3 times a week	2 (1.42%)	12 (4.41%)	2 (2.43%)	
	Once in a week	4 (2.85%)	7 (2.57%)	8 (9.75%)	
	Once in 2 weeks	2 (1.42%)	14 (5.14%)	5 (6.09%)	
	Once in a month	2 (1.42%)	13 (4.77%)	8 (9.75%)	
	Not applicable	**129 (92.1%)**	**225 (82.72%)**	**58 (70.73%)**	
Travel mode (perishable)	Walk	59 **(42.14%)**	127 **(46.69%)**	46 **(56.09%)**	0.0113
	Bicycle	7 (5.00%)	4 (1.47%)	2 (2.4%)	
	2-wheeler	59 **(42.14%)**	96 (35.29%)	20 (24.39%)	
	car	10 (7.14%)	42 (15.44%)	14 (17.07%)	
	Auto-rickshaw/ Taxi	1 (0.714%)	0 (0.00%)	0 (0.00%)	
	Not applicable	4 (2.8%)	3 (1.1%)	0 (0.00%)	
Average distance travelled (perishable)	<0.5 km	**55 (39.28%)**	**115 (42.27%)**	**33 (40.24%)**	0.079
	0.5–1 km	41 (29.28%)	78 (28.67%)	29 (35.36%)	
	1–3 km	27 (19.28%)	68 (25.0%)	16 (19.51%)	
	3–5 km	10 (7.14%)	7 (2.57%)	3 (3.6%)	
	5–8 km	3 (2.14%)	3 (1.1%)	1 (1.21%)	
	8–12 km	0 (0.00%)	1 (0.36%)	0 (0.00%)	
	>12 km	4 (2.85%)	0 (0.00%)	0 (0.00%)	
Stores preferred (perishable)	Mostly local stores	**127 (90.71%)**	**235 (86.39%)**	**73 (89.02%)**	0.533
	Mostly retail stores	1 (0.714%)	9 (3.3%)	2 (2.44%)	
	Both local and retail stores	12 (8.57%)	28 (10.29%)	7 (8.53%)	

Table 6
Components used in the questionnaire (offline shopping).

Component notation	Measurement
P1	Limitations on buying
P2	Some regular items not available
P3	Increased prices of some items
P4	Restrictions on payment mode
P5	No proper precautions taken at the stores
P6	Absence of crowd management forces at the stores
P7	Fluctuation in opening and closing timings of stores
P8	Issues not sorted within 2 weeks
P9	Risk of getting infected if visited the stores

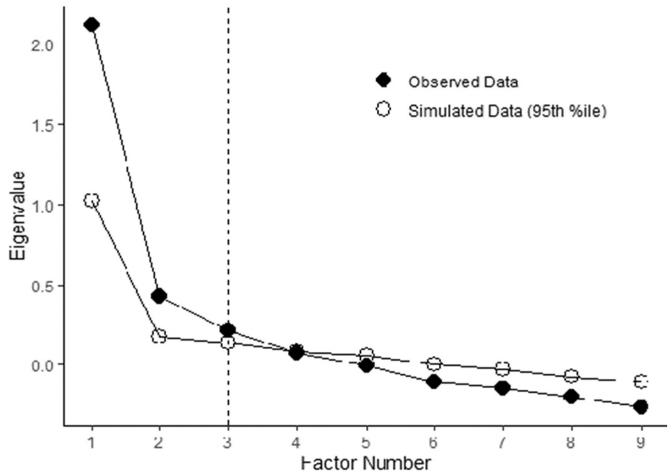

Fig. 14. Parallel analysis scree plot (in-store shopping).

likely to form significant factors, and accordingly, Fig. 14 suggests the retention of 3 factors.

After conducting factor analysis using 3 factors and rotating them by the 'varimax' method, Table 7 shows the loadings of items on different factors. The three factors resulted are labeled as *perceived threat* (PT), *supply-chain side disruption* (SSD), and *excessive pricing* (DP). The cumulative variance explained by these three factors is *41%*. Table 8 shows the residual test results. The root mean square of residuals is *0.02*, which is in the range of acceptance of closer to zero. The root mean square error of approximation (RMSEA) is *0.043* showing a good model fit as the value is well below 0.05. The Tucker–Lewis index (TLI) here is *0.953*, while the cut off for TLI is 0.9.

The factor MR1, named as *perceived fear/risk*, explained 16% of the total variance. The items loaded to MR1 were P6 (Absence of crowd management forces at the stores) and P5 (Proper precautions not being taken at stores). Factor MR3 is named as *supply-side disruption*. It explained 13% of the total variance. The items loaded to MR3 were P1 (Limitations imposed on buying), P7 (Fluctuation in opening and closing timings of shops), and P2 (Some regular items not available). The factor MR2, named as *excessive pricing*, explained 12% of the total variance. The item loaded to MR2 is P3 (Increased cost on some items).

Table 7
Factor pattern matrix for rotated loadings.

Sr. no	Items of measurement	Notation	MR1 (16%)	MR 3 (13%)	MR 2 (12%)
1	Absence of crowd management forces at the stores	P6	**0.85**	0.32	0.05
2	Proper precautions not being taken at stores	P5	**0.65**	0.25	0.06
3	Limitations imposed on buying	P1	−0.02	**0.55**	0.06
4	Fluctuation in opening and closing timings of shops	P7	0.19	**0.47**	0.03
5	Some regular items not available	P2	0.05	**0.43**	0.26
6	Increased cost on some items	P3	0.21	0.20	**0.96**
7	Restrictions on payment mode	P4	0.29	0.33	0.21
8	Issues not sorted within 2 weeks	P8	0.23	−0.04	0.11
9	Risk of getting infected	P9	0.25	0.39	0.01
		MR1	MR3	MR2	
	SS loadings	1.42	1.17	1.05	
	Proportion Variance	0.16	0.13	0.12	
	Cumulative Variance	0.16	0.29	**0.41**	
	Proportion explained	0.39	0.32	0.29	
	Cumulative Proportion	0.39	0.71	1.00	

Cumulative variance have been shown in bold for easrier understanding and noticing

Table 8
Residual test results.

Indicators	Values
Root Mean Square of the Residuals (RMSR)	0.02
Tucker Lewis Index (TLI)	0.953
Root Mean Square Error of Approximation (RMSEA)	0.043

Internal reliability analysis gave the value of Cronbach alpha value for all the 9 items as *0.71* (should be >0.6 as per Butts & Michels, 2006), which is satisfactory. The reliability of subscales was also found out. Cronbach alpha for the factor supply-side disruption is 0.72; 0.62 for dynamic pricing and 0.57 for a perceived threat.

Descriptive analysis on the data collected suggest that consumers did not prefer visiting stores for buying essential commodities during the lockdown. More inclination towards online shopping, government-imposed restrictions and pandemic driven anxiety could be the major reasons for this shift. The results of factor analysis demonstrate a considerable explanatory data that can be used in future studies. This will enable retail marketers to prioritize their resources effectively and efficiently. For instance, vendor side disruption was majorly because of the consumer's perceived risk while physically visiting stores for shopping. Therefore, vendors and governmental bodies should make sure of a safe environment thus, ensuring a stress-free shopping experience for consumers.

9.2. *Online shopping*

Table 9 shows the list of items that were used to assess the online shopping experience of respondents. Bartlett's test results gave a P-value <0.05, and the KMO value obtained is *0.83* (>0.5). Thus, the success of both sphericity and KMO tests makes the data suitable for factor analysis. The parallel analysis test suggests that the observed eigenvalues higher than their corresponding random eigenvalues are more likely to form significant factors. Accordingly, Fig. 15 suggests the retention of 3 factors.

After conducting factor analysis using 3 factors and rotating them by the 'varimax' method. Table 10 shows the loadings of items on different factors. The three factors used in factor analysis were named as vendor distrust (VD), supply-chain disruption (SD) and order-placing difficulty (OD). These three factors explained *52%* variance in the data. Table 11 shows the residual test results. The root mean square of residuals is *0.03*, which is in the range of acceptance of closer to zero. The root mean square error of approximation (RMSEA) is *0.06* showing a good model fit as the value is more than 0.05. The Tucker–Lewis index (TLI) here is *0.948*, while the cut off for TLI is 0.9, so is acceptable.

The factor MR1, named as *vendor distrust*, explained *25%* of the total variance. The items which were loaded highly to MR1 were Q6 (high delivery charges), Q5 (fear of getting poor quality item), Q7 (some orders getting canceled), and Q3 (increased prices of some items). Factor

Table 9
Items used in the questionnaire (online shopping).

Items (notation)	Measurement
Q1	Limitations on amount of buying online
Q2	Some regular items not available online
Q3	Increased prices of some items
Q4	No delivery slot available
Q5	Fear of getting poor quality item
Q6	High delivery charges being applied
Q7	Some orders were canceled
Q8	Not able to place order because of high demand
Q9	Issues not sorted within 2 weeks

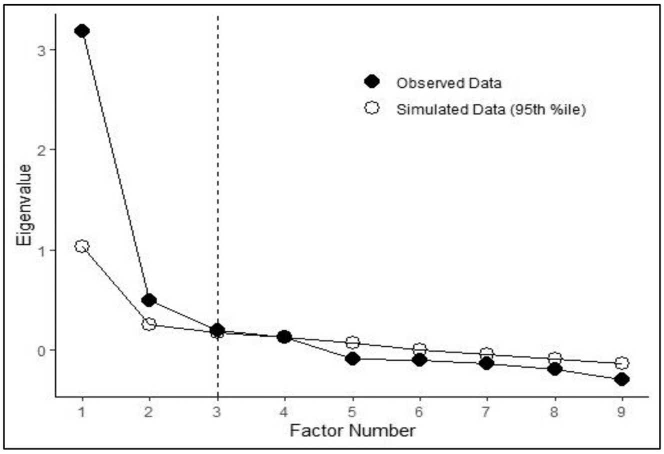

Fig. 15. Parallel analysis scree plot (online shopping).

Table 10
Factor pattern matrix for rotated loadings.

Sr. no	Items of measurement	Notation	MR1 (25%)	MR2 (17%)	MR3 (10%)
1	High delivery charges being applied	Q6	**0.82**	0.08	0.00
2	Fear of getting poor quality item	Q5	**0.69**	0.22	0.02
3	Some of the orders getting canceled	Q7	**0.51**	0.26	**0.41**
4	Increased prices of some items	Q3	0.50	0.28	0.02
5	Some regular items not available online	Q2	0.18	**0.97**	0.15
6	Limitations imposed on amount of buying items online	Q1	0.32	0.33	0.10
7	Not able to place online order due to higher demand	Q8	0.48	0.28	**0.66**
8	Delivery slot not available	Q4	0.40	**0.41**	0.44
9	Issues not sorted out within 2 weeks	Q9	−0.11	0.00	0.29
			MR1	MR2	MR3
	SS loadings		2.21	1.50	0.92
	Proportion Variance		0.25	0.17	0.10
	Cumulative Variance		0.25	0.42	**0.52**
	Proportion explained		0.48	0.32	0.20
	Cumulative Proportion		0.48	0.80	1.00

Cumulative variance have been shown in bold for easrier understanding and noticing

Table 11
Residual test results.

Indicators	Values
Root Mean Square of the Residuals (RMSR)	0.03
Tucker Lewis Index (TLI)	0.948
Root Mean Square Error of Approximation (RMSEA)	0.06

MR2 is named as *supply-chain disruption*. It explained *17%* of the total variance. The items loaded to MR2 were Q2 (some regular items not available online) and Q4 (delivery slot not available). The factor MR3, named as *order-placing difficulty*, explained *10%* of the total variance. The highly loaded items to MR3 were Q8 (not able to place the order online due to high demand) and Q7 (some of the orders getting canceled).

Internal reliability analysis is conducted, which produced Cronbach's alpha value (α) for all 9 items as 0.8 (significant if $\alpha > 0.6$ as per Butts & Michels, 2006), which is satisfactory. Subsequently, the reliability of subscales is also found out. Cronbach alpha for factor vendor distrust (MR1) is 0.75, for supply chain disruption (MR2) is 0.64, and for order-placing difficulty (MR3) is 0.59. All of them were found to be satisfactory, i.e., were greater than or equal to 0.6.

Although, online shopping gained popularity during lockdown, disruptions were seen at final vendor node there too. The results of factor analysis suggest that the factor 'vendor distrust' has major impact on disruptions experienced in online shopping. Therefore, online shopping service providers should build systems that are more reliable, user friendly and affordable to common people.

10. Discussion and policy suggestions

The data collected cover 20 states in India, indicating wide geographical applicability of the study findings. The initial spread in India was slow, and the people in India were exposed to information overload from China, Europe, the USA, and other affected countries with COVID-19, where cities and regions were placed under lockdown to control the spread of the disease. As the number of cases rose by early March, so did the social anxiety. Anecdotes on toilet-paper shortage and empty supermarket racks from the worst-hit countries urged some consumers in India to prepare, including hoarding essential commodities, for the possible replications of these events in other countries. The Junta curfew and the subsequent sudden announcement of a 3-week pan-India lockdown with very short notice created uncertainty and anxiety in the minds of consumers, store owners, transporters, and suppliers. This study focuses on consumers' responses to these events regarding essential commodities.

The behavioral changes reported in this study are the combined effect of the pandemic and the lockdown. It is concluded that the frequency of visiting stores for both perishable and non-perishable commodities reduced during the pandemic (Fig. 3). A primary reason for this behavior is the fear of getting infected. It is natural that when consumers want to reduce the frequency, they will purchase considering longer future needs. The extra purchase is also a preparation for a possible quarantine. Close to 50% of consumers purchased groceries, considering a future period of more than 1 month. Another reason for hoarding commodities is the fear of their shortage in the near future. The critical factors for in-store purchasing that resulted from these situations are perceived fear/risk, supply-side disruptions, excessive pricing. The knowledge that such exigencies are likely can motivate policymakers to ensure sufficient supply of essential commodities at the final vendor nodes to instill confidence in consumers, thereby controlling excessive purchase. Enforcement measures that control opportunist pricing would also benefit, as excessive pricing is a critical factor. The factors that disrupted online purchasing are vendor distrust, supply-side disruption, and order-placing difficulty. Vendor distrust being the major factor, retailers as well as online shopping service providers should build systems that are more reliable, user friendly and affordable to common people.

The share of online purchasing of groceries is <20% in India; thus, some limited vendors can be trusted for the quality and pricing of commodities. Like the in-store purchase, online stores were also affected by supply disruptions. The limited number of well-recognized vendors were not prepared to handle the drastic rise in demand. Considering the rapid growth in online order and their importance during emergencies, businesses and policymakers must make conscious efforts to maintain and improve the multi-modal nature of purchase options.

The fear of infection, restriction on the travel, and the disruptions at the organized retail stores shifted many to the local *kirana* stores. Although they are facing stiff competition from organized retail stores, *kirana* stores still are the key final node vendors of essential household commodities for the people from all income groups. They have proven to be very effective in an emergency, but most of them lack the convenience of electronic payment and online ordering. It is suggested that necessary support should be provided by the government to improve their efficiency and improve their reach. This will also encourage walking, reduce longer trips, and is efficient in many dimensions, including that of the environment and employment. The persistent ignorance of pedestrian-friendly infrastructure has been degrading the walkability in Indian cities. It is vital, especially in anticipation of emergencies, but not limited to them, to create walkable neighborhoods where day-to-day subsistence need not depend on motorized mobility.

11. Conclusions

In this study, data related to consumers' responses concerning essential commodities during and before the pan-India lockdown was collected using an online questionnaire. The data were collected from 20 states in India, but responses are restricted from those who can read and write English and use the internet. The questionnaire included three broad sections, one each for socio-economic characteristics, before lockdown purchase activity, and during lockdown purchase activity. Overall, data from 733 households were collected, though a few optional questions were left unanswered by some respondents. Thus, the number of data-points varies across different components of our analysis. Descriptive analyses are presented with reference to frequency of purchasing, type of stores visited, mode of payment, trip length distribution, mode of travel, and panic and excessive buying. The effect of income group on these attributes is also assessed. Factor analysis was performed to identify the factors that express the experience of consumers during lockdown for in-store and online purchasing of essential commodities.

Fear of infection and lockdown restrictions caused a reduction in the frequency of essential purchase but resulted in panic and excessive buying. The increasing share of organized retail stores reversed during the lockdown because of their inability to cater to the excessive demand and the proximity of *kirana* stores. Short trips of <1 km increased during the lockdown, and walk is found to be a popular mode of travel across all income groups. Two-wheelers are the primary choice for the group I (income less than INR 50,000) and group II (income between INR 50,000 to 200,000) respondents, whereas walk is the most preferred by group III (income greater than INR 200,000). The distribution fitting to the trip length distribution revealed that the exponential distribution is the best fit for the before lockdown travel for in-store purchase, whereas gamma distribution is the best fit during the lockdown. The behavior of the consumers is found to be influenced by income group. The factor analysis identified perceived fear/risk, supply-side disruption, and excessive pricing as disruptive factors for in-store purchasing. The factors affecting online purchasing are vendor distrust, supply-side disruptions, and difficulty in placing orders.

The findings from the study point to suggestions that will help manage emergencies in pandemic situations like COVID-19. A few important suggestions are 1) ensuring sufficient (more than what is usually available) supply of essential commodities to instill confidence, 2) enforcement to avoid opportunist pricing, 3) making retail store operators and consumers follow the rules such as social distancing and wearing masks, 4) improving walkability in cities, 5) facilitating local *kirana* stores for electronic payment and online ordering, 6) convincing organized retail stores to enhance their in-store purchase and online ordering capabilities. The findings can also be useful in developing urban freight demand models for emergencies. Developing a comprehensive emergency freight demand model analyzing different disruption scenarios is the need of the hour and can help in tackling such emergencies effectively in the future.

CRediT authorship contribution statement

Gopal R. Patil: Conceptualization, Methodology, Writing – review & editing, Supervision. **Rutuja Dhore**: Data curation, Formal analysis, Writing – original draft. **B.K. Bhavathrathan**: Methodology, Writing – review & editing. **Digvijay S. Pawar**: Methodology, Writing – review & editing. **Prasanta Sahu**: Methodology, Writing – review & editing. **Asim Mulani**: Data curation.

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