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Research article

Mapping COVID-19's potential infection risk based on land use characteristics: A case study of commercial activities in two Egyptian cities

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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

The contagious COVID-19 has recently emerged and evolved into a world-threatening pandemic outbreak. After pursuing rigorous prophylactic measures two years ago, most activities globally reopened despite the emergence of lethal genetic strains. In this context, assessing and mapping activity characteristics-based hot spot regions facilitating infectious transmission is essential. Hence, our research question is: How can the potential hotspots of COVID-19 risk be defined intra-cities based on the spatial planning of commercial activity in particular? In our research, Zayed and October cities, Egypt, characterized by various commercial activities, were selected as testbeds. First, we analyzed each activity's spatial and morphological characteristics and potential infection risk based on the Centre for Disease Control and Prevention (CDCP) criteria and the Kriging Interpolation method. Then, using Google Mobility, previous reports, and semi-structured interviews, points of interest and population flow were defined and combined with the last step as interrelated horizontal layers for determining hotspots. A validation study compared the generated activity risk map, spatial COVID-19 cases, and land use distribution using logistic regression (LR) and Pearson coefficients (rxy). Through visual analytics, our findings indicate the central areas of both cities, including incompatible and concentrated commercial activities, have high-risk peaks (LR = 0.903, rxy = 0.78) despite the medium urban density of districts, indicating that urban density alone is insufficient for public health risk reduction. Health perspective-based spatial configuration of activities is advised as a risk assessment tool along with urban density for appropriate decision-making in shaping pandemic-resilient cities.

1. Introduction

COVID-19, a highly contagious respiratory illness, was identified in December 2019 in Wuhan, China, and it quickly spread to become a global pandemic [1,2]. COVID-19 has profoundly impacted public health, economies, and daily life worldwide, prompting governments and health organizations to implement various measures to curb the spread of the virus, including lockdowns, travel

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restrictions, and social distancing guidelines [3,4]. This ongoing pandemic has highlighted the miscalculations and powerlessness of all sectors in dealing with health crises, including city planning and the built environment [5,6]. However, it has given policymakers, architects, and urban planners a glimpse into forecasting post-pandemic planning by rethinking the critical role of planning rationality and how to be proactive rather than reactive, along with building contingency strategies for shaping pandemic-resilient cities under increasing genetic mutations [7,8].

Land uses especially commercial activity, are among many high-risk activities that increase or decrease infection risk due to exposure to prolonged infected aerosolized concentrations indoors and the high friction between asymptomatic or pre-symptomatic individuals [9,10]. The pandemic has significantly impacted commercial activity and human behavior, including lockdowns and social distancing guidelines, and accelerated the shift toward online shopping to avoid large crowds in enclosed spaces [11,12]. As a result, many retailers have had to adapt by offering more flexible options such as curbside pickup, home delivery, and online ordering [11,13]. At the same time, there are still many consumers who prefer the experience of shopping in physical stores, as it allows them to see and touch products before making a purchase [14,15]. After nearly three years of fighting against COVID-19, countries worldwide have hastily intervened to restructure the weaknesses and dysfunction of commercial activities to balance health and the economy [16]. The designer Landlord stated, "If malls do not reinvent themselves, there will be no mall of the future," and suggested outdoor area-based innovative designs to motivate customers to return without growing concern and dilute the virus concentration [17,18]. Many cities have intervened moderately in planning commercial activity spatially by exploiting marginalized spaces and inaccessible regions and shutting streets, alleys, parking lanes, and sidewalks in front of vehicular traffic [19,20]. In addition, they tried to create more recreational parklets to enable outdoor dining and safe shopping, along with other preventive measures [21,22]. On the other hand, some cities have pursued radical interventions through redistributing host-brand pop-up stores and neoteric markets on the city outskirts, implementing high-frequency alleviation policies in city centers, and polycentric development, or so-called "15-min cities", such as Delhi and Paris [23,24]. New York and Miami experimented with a tactical urbanism application strategy to create adaptive solutions immediately by promoting contemporary commercial center designs that move away from generic big-box designs towards more open-air concepts and seamless integration across the surrounding urban fabric [24,25].

In medicine, "diagnosing the illness is half the way to the cure," underscoring the importance of early detection to develop targeted strategies that can lead to successful recovery and improved health outcomes [19,26]. Based on this example, urban decision-makers and planners see identifying pandemic-risk locations and hotspots as half the way to shaping resilient and sustainable cities [16,27]. Although some studies have used GIS and spatial analysis techniques to visualize the spatial distribution and patterns of COVID-19 spread [28,29], no studies have focused explicitly on mapping infection risk based on land use characteristics, especially commercial activities. Furthermore, developed countries have applications, periodically updated data, and advanced tools to define the potential risk of activities regularly, and many publications use these in their analysis; in developing countries, it may be more complicated and need to be illustrated. COVID-19 potential infection risk mapping based on commercial activities involves a comprehensive analysis of spatial and demographic factors to identify areas where the risk of virus transmission is heightened due to various commercial operations. By scrutinizing factors such as the density of commercial establishments, their proximity to residential zones, transportation hubs, and the nature of activities conducted within them, this mapping approach aims to pinpoint locations susceptible to increased virus spread [27,29].

Hence, our research question is: how can the potential hotspots of COVID-19 risk be defined intra-cities based on the spatial planning of commercial activity? For this question, two cities, Zayed and October, Egypt, were selected as a case study. Our methodology first defines all methods in the literature review for mapping potential pandemic risks and selecting the appropriate method for our cases. Second, applying the chosen methodology to case studies by analyzing commercial activities' spatial and morphological characteristics and the infection risk potentiality of each activity based on the criteria of the Centre for Disease Control and Prevention using the Kriging Interpolation Method; and third, defining population density and flow analysis using Google Mobility and semi-structured interviews. Finally, the previous steps are combined as interrelated horizontal layers, followed by a validation study comparing the generated activity risk map and spatial COVID-19 cases. Our approach for mapping COVID-19 infection risk based on commercial activities could be a strategic tool that informs public health policies and urban planning decisions, fosters a safer environment in the face of ongoing pandemic challenges, and rearticulates contingency plans by spatially predicting the spread of other contagious viruses.

2. Literature review

2.1. Defining and controlling the COVID-19 pandemic transmission spatially

Controlling and defining the COVID-19 pandemic transmission spatially involves implementing strategies that consider geographical factors to prevent or limit the spread of the virus within specific areas [22,30]. Based on previous articles, many ways of controlling pandemic transmission have been defined as follows: Pursuing rigorous prophylactic health measures, which include implementing targeted lockdowns and restrictions in areas with high infection rates [23,31]. This can involve closing non-essential businesses, limiting gatherings, restricting movement in and out of the area, establishing quarantine and isolation facilities, continuing testing and vaccination, enforcing travel restrictions, and implementing rigorous screening measures at entry points—monitoring movement between regions to prevent the virus from spreading across geographical boundaries [22,32]. Urban density can be a factor in lowering the causative pathogen of COVID-19 transmission risk, which has been the subject of heated discussion throughout the pandemic's spreading phases [7,8]. Several studies have explored the relationship between urban density and the prevalence of contagious diseases, including COVID-19. A study in Tehran, Iran, analyzed data to understand the link between urban density and COVID-19 infection and death rates. The study found that Tehran's heterogeneous urban pattern allowed for examining possible associations between density and the intensity of virus transmission [8]. Another study emphasized the impact of large and densely populated cities on the spread of COVID-19, highlighting the high infection rate and population movement in densely populated areas that have contributed to the rapid transmission of the disease [7,33]. Factors such as population density, income, race, built-environment factors (e.g., road density, building density), and environmental factors (e.g., air pollution, humidity, temperature) have been found to influence the spread of COVID-19 [6,22]. Research has also shown that urbanization and population density levels affect the spatial distribution of COVID-19 cases. A study found that areas with higher urbanization and population density levels were more likely to be COVID-19 hotspots during the early epidemic phase, demonstrating that urbanization and population density can be risk factors for spreading the disease [34,35].

Spatial distribution and activity morphology are substantial variables in controlling infection cases based on zoning and risk assessment, considering factors such as population density, healthcare infrastructure, and previous infection rates to determine high-risk areas [5,36]. The spatial shifting pattern of the COVID-19 pandemic in the United States has been studied, revealing the importance of understanding the spatial distribution of cases to inform control measures [37]. Spatial and spatio-temporal epidemiological approaches have been proposed to inform COVID-19 surveillance, involving analyzing the disease's spatial patterns and temporal trends to identify high-risk areas and implement targeted interventions [38]. Studies have focused on the spatial decomposition of the infection probability of COVID-19, aiming to identify spatial differences and clusters of cases. The spatial distribution characteristics of COVID-19 have been analyzed in specific areas, such as Beijing [39]. Using spatial analysis techniques like Moran's I index and LISA (Local Indicators of Spatial Association), researchers have identified clustered patterns in the distribution of cases [40]. Ren et al., 2020 observed that the very high-risk infection zones in Beijing and Guangzhou contained hazardous activities and proximity to hotspots [41]. On the other hand, a study of the spatial compatibility or discrepancy between business density and pandemic risk in Macau revealed that urban density-based traditional planning control needs to be improved to downsize infection risks when considering the geographical distribution of business activities [16]. Finally, the built environment can contribute to and mitigate the risk of COVID-19 transmission. Factors such as housing conditions, indoor air circulation, and community design can influence the spread of the virus [5,6]. Also, mobility has great effects on reduction. For example, Najmeh et al. (2021) demonstrate the riskiest places surrounding the hospitals using an MLP-ANN in Tehran City. The implementation results revealed a meaningful relationship between the distance from the hospitals and patient density. The RMSE and R measures are 0.00734 and 0.94635 for [0–500 m], while these are 0.054088 and 0.902725 for [500–1000 m], respectively. These values indicate the role of distance to central hospitals in COVID-19 treatment [42].

2.2. COVID-19 potential infection risk mapping methods based on land use characteristics

Identifying the virus-infected areas and the likelihood of its acquisition spatially is divided into mathematical analysis and spatial methods [7,38]. In the first method, studies have used numerical health data for each region to predict the number of infected and death cases using the exponential smoothing method, deep learning models, compartmental models, and autoregressive moving average models. These methods are suitable for cities with daily updated and announced specific infection data to predict infection probability mathematically [43,44]. However, these methods ignore urban characteristics and potential outbreaks spatially. The other method most appropriate for urban planners is visualizing potential risks based on urban characteristics and human mobility [37,45]. Cell phone data has been used in studies to determine the potential risk of cholera and has recently been applied to define the spatial-temporal prefoliation of COVID-19 transmission in the United States, Sao Paolo, and Rio de Janeiro, Brazil, and, most recently, in Macau, China [46,47]. The most recent study in Tel Aviv, Israel, recommended using Google Community Mobility data, which is available for most countries online and may help predict outbreaks [48].

Studies have shown the increasing relevance of geospatial technologies, particularly for infectious disease surveillance and modeling strategies. GIS has been extensively used in analyzing, visualizing, and detecting disease patterns [28,37]. A recent review found that among the 869 studies included, one-fourth used GIS mapping techniques. One study proposed a risk assessment and prediction model for COVID-19 based on spatiotemporal geographic epidemiological data, an LR model, and geographic detectors [49]. The study considered the resident population, the floating population, and all urban spatial factors that may affect the spread of the epidemic in geographical space. Another study proposed a risk-based assessment framework for analyzing COVID-19 risk in areas, using integrated hazard and vulnerability components associated with this pandemic for effective risk mitigation. The study was conducted in a region administered by the Jaipur Municipal Corporation (JMC), India [50]. Based on the current understanding of this disease, they hypothesized different COVID-19 risk indices (C19Ri) of the wards of JMC, such as proximity to hotspots, total population, population density, availability of clean water, and associated land use and land cover, and calculated them using a GIS-based multicriteria risk reduction method. Najmeh et al. (2021) reviewed the most promising categories of GIS-based solutions in this domain by dividing the solutions into ten classes, including spatio-temporal analysis, SDSS approaches, geo-business, context-aware recommendation systems, participatory GIS and volunteered geographic information (VGI), internet of things (IoT), location-based service (LBS), web mapping, satellite imagery-based analysis, and waste management [51]. Hamid Reza et al., 2020 analyzed the risk factors of coronavirus outbreaks to identify the areas with a high risk of infection and to evaluate the infection behavior in Fars Province, Iran, using a GIS-based machine learning algorithm (MLA) and support vector machines (SVM) [52]. In contrast, the daily observations of infected cases were tested in the polynomial and the autoregressive integrated moving average (ARIMA) models to examine the patterns of virus infestation in the province and Iran.

3. Characterization of the case study

In Egypt, a developing country in North Africa, new satellite cities have a unique experience in shaping fragmented commercial services away from city centers and oriented towards the suburbs [53] (see Fig. 1 a). These emerging cities present a distinct approach to urban development by strategically reshaping the distribution of commercial services and diverging from the traditional commercial activities concentrated in central urban cores. Instead, they are decentralizing and reorienting these services towards suburban areas, which became the preferred places for shopping and entertainment pre- and post-COVID-19 outbreak [54,55]. Egypt's 6th of October City (populations of 2.40 million people) and Sheikh Zayed City (0.91 million people) are ideal locations to investigate the spatial correlation between the COVID-19 infection and commercial land use characteristics. Furthermore, addressing two cities simultaneously avoids drawing case-specific conclusions. Comparing and contrasting the experiences of multiple cities can provide a broader perspective and allow for a more nuanced understanding of land use's role in influencing infection risk. Our selection is based on the clarity of service centers' hierarchy and the plurality of mall morphological characteristics (see Fig. 1 b and c). The hierarchy typically encompasses various scales, from neighborhood-level centers to larger regional centers, which became shopping cities in a densely populated region called the Greater Cairo Region (GCR). At the same time, the plurality of these characteristics indicates the diversity in how malls are designed and structured, which includes factors like mall size (large shopping malls, small stores, and outdoor malls), layout, architectural style, incorporation of green spaces, outdoor areas, and integration with public transportation [56].

4. Data and methods

4.1. Study data

This study focuses on the two Egyptian cities and examines the effects of the distribution pattern of commercial activities on potential COVID-19 risk. For this purpose, many data points were collected from various sources, including governmental databases, customer data, and census data. To analyze the effects of the distribution pattern of commercial activities, the researchers employed

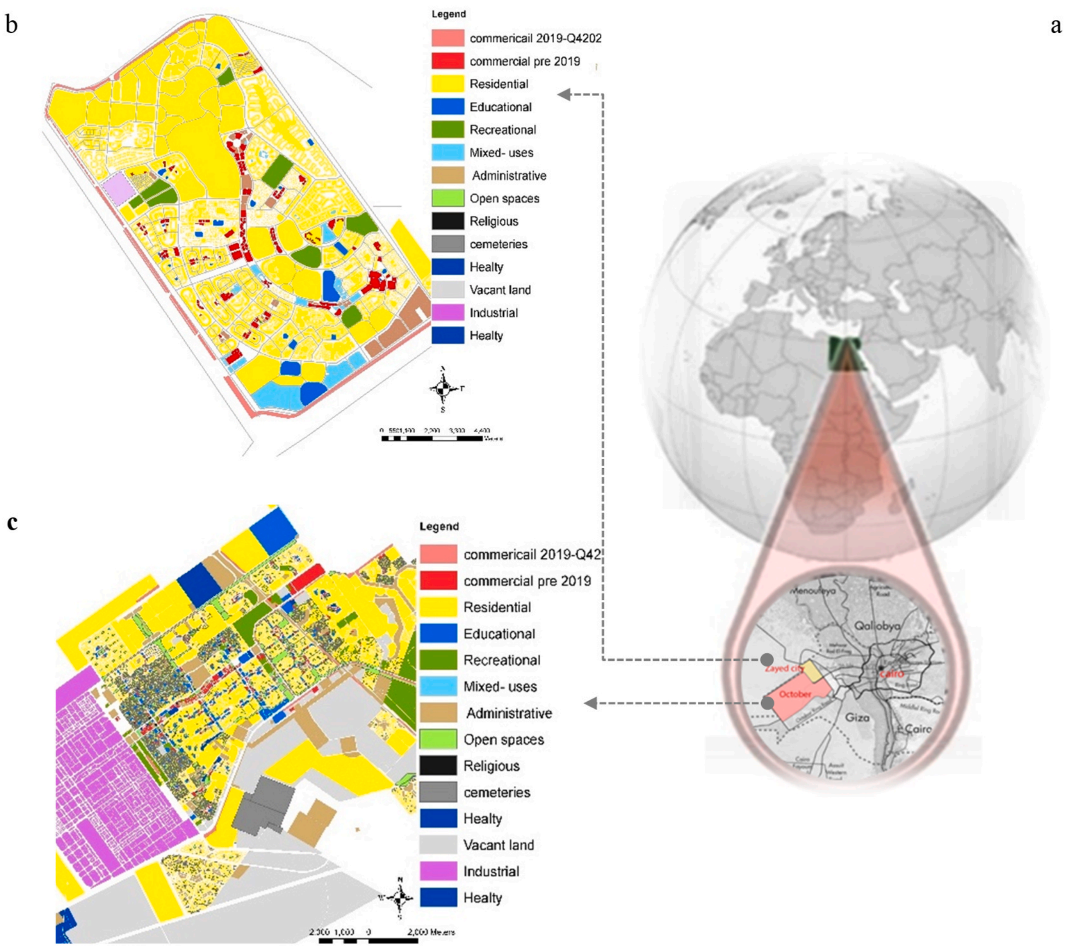

Fig. 1. (a) Locations of the two cities, (b) Land uses of Sheikh Zayed City, (c) Land uses of October City.

Geographic Information Systems (GIS) to map out the locations of different types of businesses, such as retail stores, restaurants, entertainment venues, and service providers. These maps were then overlaid with population density data to identify areas where commercial activities are densely concentrated and coincide with high population densities. The study also considered factors like transportation networks and accessibility, as these influence the movement of people and the potential for virus spread. By examining indoor and outdoor commercial spaces, the researchers aimed to assess how varying environments impact infection risk. The data collected from platforms and location-based services provided insights into consumer behavior, which helped the researchers understand patterns of movement and interactions within commercial areas. These insights were further enriched by qualitative data collected through surveys and interviews with local businesses and residents, shedding light on perceptions and experiences of infection risk and preventive measures. Our data is divided into three categories as follows.

- **Spatial distribution of commercial activities:** updated GIS maps, satellite maps, strategic reports, and spatial distribution of commercial activity based on the New Urban Communities Authority (NUCA) were collected and processed as shown in Table 1 [54,57]. The resultant data covered the physical analysis of commercial uses and spatial distribution, commercial density, commercial attraction and concentration of public green spaces, and urban district density. We added new field data called "activity risk," which ranked approximately 982 activities from 0 to 10 based on the Centers for Disease Control and Prevention (CDCP) criteria [37,46], WHO, speeches, lectures, and websites.
- **Mobility data:** Collecting mobility data concerning COVID-19 involves gathering information about the movement of individuals, both within specific geographic areas and between locations. This data is valuable for understanding how people's mobility patterns impact the spread of the virus, defining hotspot places, and informing policymakers about the extent of people's commitment to implementing public health responses and policies. Many techniques for understanding human mobility dynamics between places and their interactive gravity are available in developed countries, such as cell phone data, footprint intelligence platforms, taxi data, subway smart cards, social media data, and geotagged tweets. Our study used aggregated human mobility data from February 15, 2020, to August 7, 2022. This dataset was obtained from Google Mobility for the region and is based on over 1.2 million Egyptian users, demographically and socioeconomically representative of the two cities' populations. In addition to data from a questionnaire, semi-structured interviews and on-site and online purchasing data were also collected; finally, on annual and quarterly reports of companies and institutions that declare the volume of their customer interactions. The dataset comprises daily and hourly movement patterns within and between uses and preferred shopping locations after COVID-19. Phone cell data regarding national security is not available in Egypt. During the mobility analysis, we consider health measure data gathered from official Egyptian journals and the Ministry of Egyptian Health, which illustrate health policies that affect lockdown and reopening activities, infection risk reduction, and how citizens apply health measures.
- **Cities' COVID-19 cases:** Given the sensitivity of health-related information and the privacy concerns associated with COVID-19 patient data, obtaining comprehensive and accurate data can be complex. We exerted every effort to bring the daily COVID-19 cases of each city from the Ministry of Health, but we only got the 6th of October city through the quarantine hospital in October, which is classified as secret and not for publishing. The patient's name, dates of birth and death, and residential location are all classified as data. Access to Zayed City data was so tough and unavailable, but only one city can be used for validation of the risk mapping model, especially two selected cities that are neighboring each other.

4.2. Proposed method

As shown in Fig. 2, a comprehensive method was carried out, starting with an analysis of commercial activity spatially and morphologically and a quantification of all infection risks: First, classify commercial activities into different categories based on their characteristics (indoor vs. outdoor activities, high customer density vs. low customer density, proximity to residential areas, and transportation hubs). Second, ranking the potential for exposure to COVID-19 within different types of commercial activities based on CDCP criteria, considering factors such as close interactions, duration of exposure, crowded spaces, and environmental factors that impact virus transmission within commercial spaces as well as the size and layout of spaces, including distancing measures. Third, analyzing people's movement between commercial activities and their potential interactions. Fourth, risk weighting and scoring involve combining exposure assessment, environmental factors, mobility patterns, and compliance to assign risk scores and weight different factors based on their significance in contributing to potential transmission. Fifth, utilize GIS to visualize the infection risk on a spatial map and highlight areas with high-risk concentrations. Sixth, validate the model using available COVID-19 case data or proxy indicators by comparing predicted risk scores with actual case patterns. Finally, translate the findings into actionable

Table 1
Data descriptions.

Data type	Date	Format	Source of Data	Derived Data
Updated GIS maps, Census data, and Risk of commercial activities (ranked from 0 to 10)	2021	Geospatial database PDF files	NUCA, CDCP, WHO	Spatial concentration of activity and Activity risks
Human mobility	2020, 2021, 2022	Excel data, Geospatial database	Google Mobility, Survey, Reports	Descriptive data (graphics) about POI, Flow of people, and Hotspots
COVID-19 cases in 6th October city	2022	unpublished Documents	Quarantine hospital	Mapping risk spatially for the validation process

Table 2
Commercial activity's risk level is based on CDCP and reports using point-kriging method.

Risk	Commercial activity	Rank
Low risk (0–3 points)	•Getting takeout from a restaurant	1
	•Getting daily necessities through grocery shopping	3
	•Eating at a restaurant with a garden, roof, or open street (less than 10 people per hour)	3
	•Specialized stores (phones, sporting goods and equipment, electronic devices, clothes, materials, etc.) with adequate physical distancing	2
	•E-commerce-dependent shops only/Mobile shopping	0
Medium risk (4–7 points)	•Eating outdoors at a restaurant with adequate physical distancing	4
	•Fast-food spots and beverage kiosks with adequate physical distancing and ventilation	4
	•Malls surrounded by open spaces for physical distancing	6
	•Shops with walking and hiking places in busy downtown	5
	•Small malls in sparsely populated districts	7
High risk (8–10 points)	•Eating indoors at multistorey restaurants or going to casinos	7
	•Eating outside in an area surrounded by risky activities or densely packed areas	8
	•Malls with theatres or concert venues (increases with crowds, singing, and chanting)	9
	•Multistorey commercial centers with a specific direction of movement	7
	•Going to hair salons, barbershops, gyms, bars, etc.	10
	•Central megamalls surrounded by activities of high frequency (administrative, educational, health, religious, mixed-use, etc.)	9

recommendations for urban planning and public health, identify areas of concern and high-risk commercial categories, and propose targeted interventions and guidelines to mitigate infection risks.

- ***A descriptive analysis of the characteristics of commercial activity:*** The locations of the two cities and commercial uses were determined and geographically described using two methods. First, the nearest neighbour index (NNI) defines the aggregation and diffusion of activity, where NNI is the nearest neighbour, $\mathrm{Min}(\mathrm{d_{ij}})$ is the distance from commercial centers, N is the number of stores, and i is the average of the total distances, using Equation.1. Second, kernel density estimation (KDE) or spatial conglomeration analysis is used to define the activity intensification rate and the spatial correlations and interactions between different commercial categories [58]. KD^E is the kernel density, h_i is the dispersion rate, xi is the average of the distances, i is the nuclear density function, and k is a spatial weighting, using the Equation.2 [59]:

$$\boldsymbol{NNI} = \sum_{i}^{n} \frac{\boldsymbol{Min}\left(\mathrm{d_{ij}}\right)}{\boldsymbol{N}} \tag{1}$$

$$KDE = \sum_{i=1}^{n} \frac{1}{h^2} k\left(\frac{xi^{-C}i}{h_i}\right) \tag{2}$$

- ***Quantifying the degree of activity risk in transmitting infection:*** Based on the CDCP data, the degree of activity risk in transmitting infection was defined and mapped into categories typically ranging from low-risk to high-risk activities, considering proximity, duration, and the potential for respiratory droplet transmission, as shown in Table 3, using the point-kriging method. Kriging is achieved by estimating the value at an unknown point using known values at nearby locations. The predicted value, Kriging estimator Z(u), is based on a combination of basic linear regressions, as shown in Eq. (3) [46]. Using Z(u) is a powerful interpolation method that takes advantage of spatial autocorrelation and provides both interpolated values and estimates of uncertainty, making it a preferred choice when accurate and reliable spatial predictions are needed compared to other interpolation methods under certain conditions. Kriging considers the spatial autocorrelation in the COVID-19 data and provides estimates of uncertainty and interpolated values if the spatial correlation structure is reasonably defined through variogram analysis. This contrasts with methods like nearest neighbour interpolation, which can result in "blocky" or unrealistic characters.

$$D(u) = \sum_{i=1}^{n} hz(u_i) \tag{3}$$

where u and u_i respectively indicate the location vectors for estimation point and neighboring data points at the number of data points, n. In addition, h are kriging weights which are estimated as solutions of the kriging system to minimize the variance of the estimator.

- ***Defining hotspot or point of interest (POI):*** The urban population density and detected hotspot patterns are calculated as shown in Eq. (4) [46]. Collected movement data, which includes areas with concentrated movement, and areas with high population density might include commercial areas, transportation hubs, public spaces, and other gathering points.

$$E_{(F)} = \sum\nolimits_{I=1}^{n_1} MNxS(\acute{\imath}) \tag{4}$$

Table 3
Commercial uses in both cities before and after 2019. The corresponding pictures show the diversity in commercial centre morphology in the two cities.

Categories	Sheikh Zayed City						6th October City					
	Pre-2019			From 2019 to 2021			Pre-2019			From 2019 to 2021		
	Number	% Green space	Morphology	Number	% Green space	Morphology	Number	% Green space	Morphology	Number	% Green space	Morphology
Megamalls	8	12	Indoor services, distributed in city centre location	0	0	outdoor services, distributed along arterial roads and peripheries areas	6	16	Indoor services, distributed in city centre location	3	34	outdoor services, distributed along arterial roads and peripheries areas
Restaurant-indoor, fast-food spots, beverage kiosks (FB)	261	5		23	10		153	2		44	16	
Entertainment activities	34	14		6	45		92	3		6	34	
Restaurant-outdoor	12	21		364	71		23	12		398	78	
Grocery stores and department stores (DS)	122	12		65	23		–	–		87	32	
Culture, sporting goods and equipment stores (CSS)	21	10		14	5		32	9		11	5	
Daily necessity stores (DNS)	34	7		17	23		54	8		21	43	
Restaurant-takeout	121	4		73	38		145	5		15	31	
Places for walking and hiking in busy downtown	0	0		3	94		0	0		5	91	
Administrative buildings and banks (ASB)	431	9		24	21		101	6		39	15	
Buildings under construction during **the** survey (BC)	0	–		197	–		0	–		254	–	

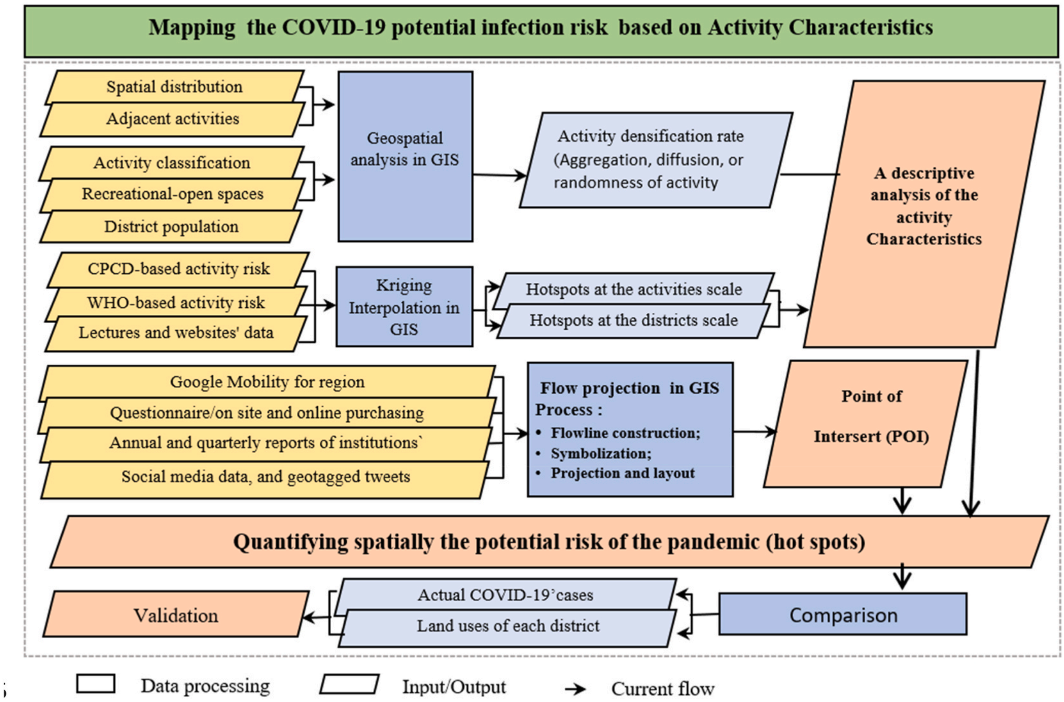

Fig. 2. Flow chart for data processing and methods.

where $E_{(F)}$ is the active population in each pattern, $S(i)$ is the active population represented by ith category in the thermodynamic diagram, *MN* is the area size of the ith category, and n_1 is the number of categories. In the interim, we computed the density of urban morphology and identified patterns of hotspots using Eq. (5) [46], where, v_L is the urban morphological density, M^i is the urban footprint, and A_qJ is the size of a hotspot pattern. Ultimately, we employed bipolar coordinates and harnessed visual analytics, a prevalent tool in environmental studies. This enabled us to create interconnected thematic maps for comprehending spatiotemporal hotspot dynamics.

$$v_L = \frac{M^i}{A_q J} \tag{5}$$

- ***Validation study:*** Conducting a validation study to assess the accuracy of COVID-19 potential infection risk mapping based on land use characteristics involves comparing the predicted risk with actual observed COVID-19 cases. Include sensitivity: the proportion of actual COVID-19 cases correctly identified as high-risk areas on the map. Positive/Negative Predictive Value (PPV/NPV) is the proportion of high- or low-risk areas on the map corresponding to actual COVID-19 cases [60].
- ***Correlation Coefficient:*** Correlation study are used to explore the strength and direction of the relationship between potential COVID-19 risk regions (hotspots) and characteristics of land uses in the region using the Pearson correlation coefficient (rxy) and multivariate mathematical methods of regression (MMR) and named the LR Algorithm [61,62], using Eqs (6) and (7).

$$r_{xy} = \frac{\sum(x_i - x)\ \sum(y_i - y)}{\sqrt{\sum(x_i - x)^2}\ \sqrt{\sum(y_i - y)^2}} \tag{6}$$

$$\rho_1 = \frac{1}{1 + e - (B_0 + B_1 v_1 + B_2 v_2 + \ldots \cdot + B_n v_n)} \tag{7}$$

Where, ρ_1 is the likelihood of an event occurring, B_0 has a constant value, B_1. B_n are regression coefficients, v_1. v_n are independent parameters (land uses or activities), and x, y denotes the mean of x, y.

5. Results and discussion

5.1. A descriptive analysis of the commercial activity characteristics

The spatial distribution of activity in both cities depends on two pillars: first, zoning ordinances that isolate employment locations, shopping and services, and housing locations from each other and are intrinsically linked to transportation systems, and second, pedestrian-centered neighborhoods within a 5-min walk and simultaneously increasing expanses of mixed-use land. Under the e-commerce evolution, activity location became a sub-issue during choice, and most commercial activities began to spread away from central areas towards peripheral regions with low rental fees. We explained this spatial planning of activity by analyzing each city's nearest neighbour index (NNI) and kernel density estimation (KDE).

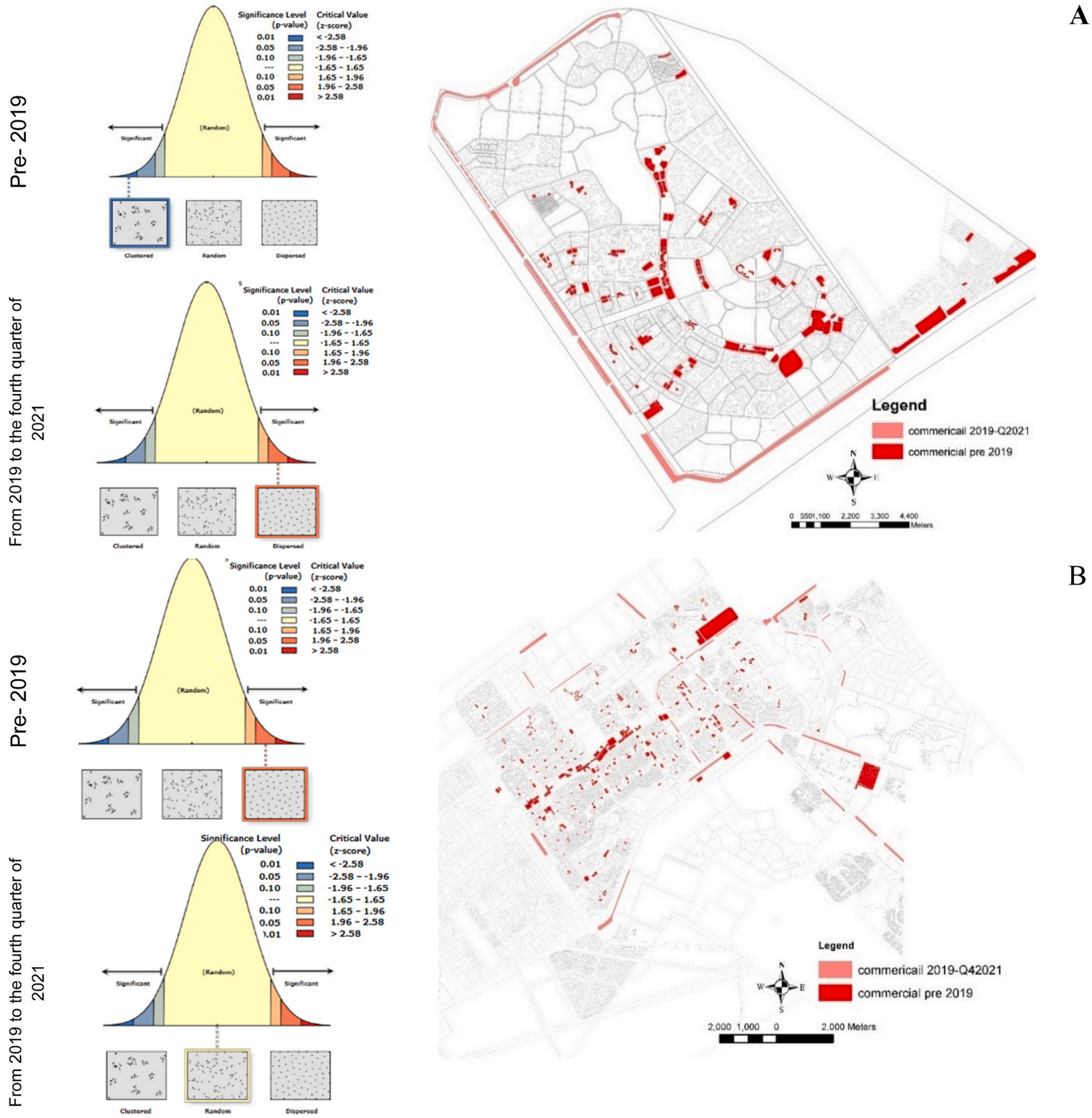

Fig. 3. Results of the nearest neighbour analysis of both cities (A, Zayed City, and B, October City).

- **Nearest neighbour index (NNI) of commercial uses:** The commercial centers in the two cities exhibited different spatial patterns. When observing the historical configuration of commercial use, we found that commercial activity concentrated in the city centre, which formed a monocentric urban structure (MUS) at its inception, shifted into polycentric or fragmented urban structures from 2000 to 2015. Three years ago, NUCA realized a new commercial pattern, "multipolar" or "finger's urban structure/container philosophy," constituting a horizontally dispersed pattern, as shown in Fig. 3 (A and B). Before 2019, the NNI (0.34, 0.31), less than 1.0, showed a compact pattern. From 2019 to Q4-2021, the NNI (1.07, 1.43), which was more than 1.0, indicated a random pattern in October City, whereas it indicated a dispersed pattern in Zayed City.
- **Kernel density estimation (KDE) analysis of commercial uses:** Land development initiatives in both cities have relocated malls and low-profit specialty stores from the center to the periphery, distributed along the arterial roads. Among the different commercial typologies are fast-food spots, beverage kiosks, daily needs, and department stores, which are characterized by convenient spaces for outdoor seating, spaces between dining tables, sportive touristic walkways, a promenade for visitors' strolls, bike lanes, and a unique competitive advantage generated by their geographical proximity to residents. These are followed by administrative buildings, banks, sporting goods, and equipment stores, which have the lowest aggregation, as shown in Fig. 4 (A and B), Table 3. Open spaces positively correlate with new commercial stores, where Pearson's correlation coefficient is 0.872 and 0.907 in Zayed and October, respectively. On the other hand, the spatial distribution of new malls post-2019 is negatively correlated with population density, where $rxy = -0.366$ and -0.606 in Zayed and October, respectively. Through the analytical description of the emerging commercial pattern, the two cities, each with a single core, are progressively turning into scattered commercial ribbons.

5.2. Quantifying commercial activity risk degree in transmitting infection based on the CDCP criteria

In this step, the commercial activity risks in both cities were geocoded by GIS from highest to lowest based on CDCP criteria and infectious disease experts, as shown in Table 2. We ranked the low-risk category from 0 to 3, which refers to restaurants and small and open shops, which are characterized by ventilation due to their small size or the successive frequency of customers with less likelihood of face-to-face contact, such as takeout restaurants, e-commerce-dependent shops, grocery stores, and small shops with adequate ventilation and physical distancing. The medium-risk category ranges from 4 to 7, with many people congregating in outdoor places with adequate physical distancing, such as malls surrounded by adequate open spaces for physical distancing or eating outdoors at a restaurant. The high-risk category from 8 to 10 includes commercial activities with direct contact without adequate ventilation and physical separation, such as hair salons, eating indoors at a restaurant, and visiting casinos, malls with theatres, or concert venues, where risk increases with larger crowds or singing and chanting. Additionally, gyms have a risk of being in a closed place and another risk related to metabolism and increased breathing during exercise, which doubles the probability of infection risk. As shown in Fig. 5

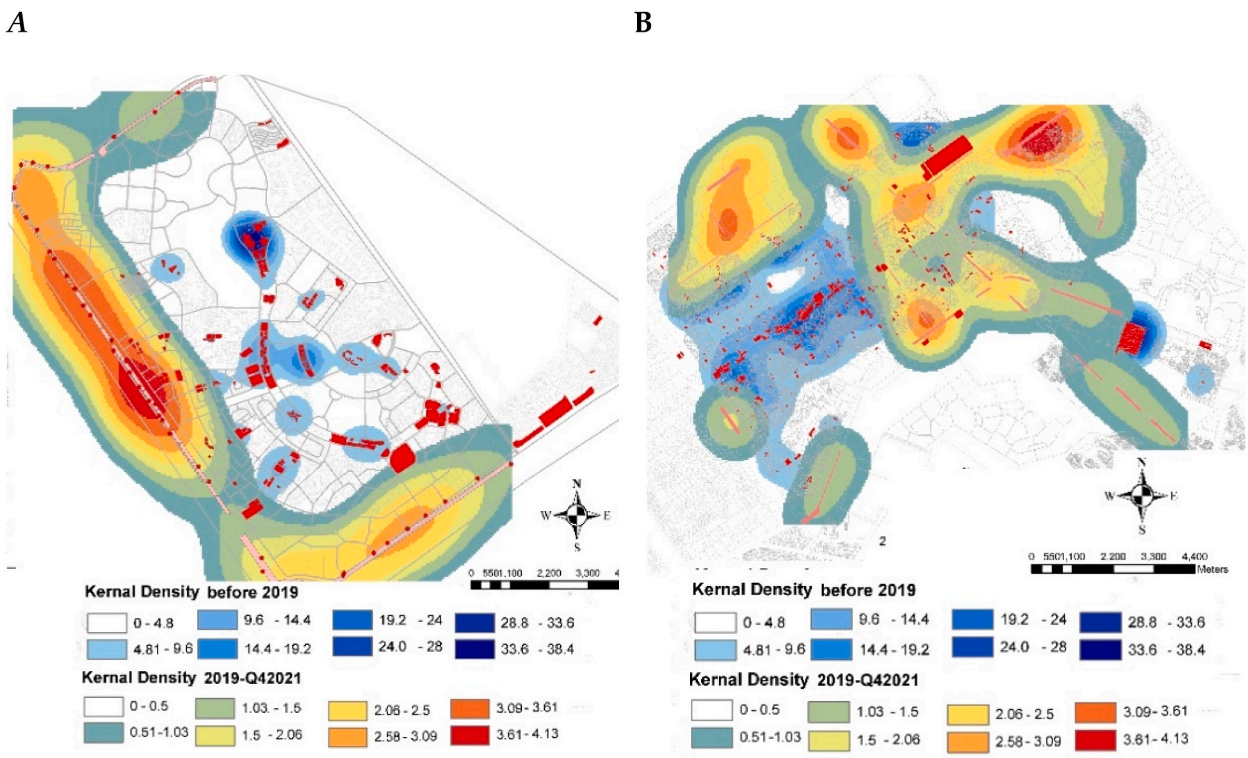

Fig. 4. Commercial activity morphology and kernel density estimation (KDE) (A, Zayed City, and B, October City).

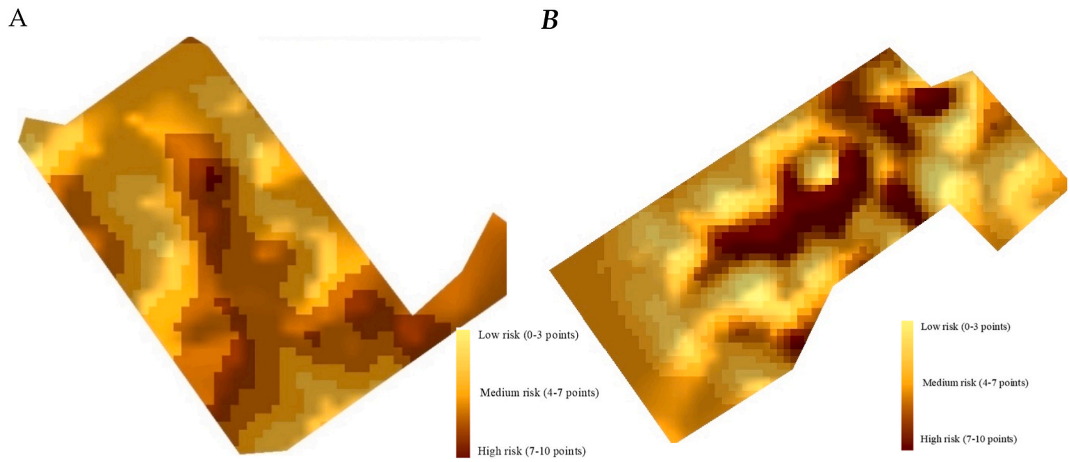

Fig. 5. Classified regions based on the spatial concentration of activity risk in both cities using the kriging Interpolation method in GIS (A, Zayed City, and B, October City).

(A, and B) and Fig. 6 (A, and B), most high-risk activities are concentrated in city centers, which indicates that their distribution is based on economic and market forces without considering the health dimension. The risk decreases as we head to the subcentres and marginalized areas.

5.3. *Characterization of shopper's behavioural network after COVID-19*

The COVID-19 pandemic has significantly impacted various aspects of society, including shopping behaviours, accelerating the adoption of online shopping and e-commerce, and making shoppers more reliant on digital platforms to purchase goods and services. Also, health and safety concerns became paramount for shoppers, and consumers became more conscious of physical spaces. To determine customer trends and flows, as follows.

- **Google Mobility:** These statistics indicate that at the beginning of the pandemic, the two cities were almost entirely on lockdown, and services were available only online except for necessary services and adherence to all precautionary measures. After approximately five months, the epidemic's severity began to subside, accompanied by the partial reopening of commercial activities for a specific time. Due to customers' anxiety, residents began to resort significantly to malls with open spaces in peripheral areas or inside neighborhood centers, and there was a slightly increasing influx of customers to megamalls. Starting in 2022, customers returned to their old shopping habits before the outbreak, disregarding the healthy aspects and preventive measures, which may pose a potential outbreak risk, as shown in Fig. 7 (A,B).
- **Semi-field survey and shopping reports:** These methods were used to cover some missing data and spatially determine the point of interest in both cities post-COVID-19, rush hours in these places, and the concentration of people all day. Our survey investigated shoppers' behavior changes, shopping motivation, preferred locations, duration, frequency rate, and identity of shopping centers post-COVID-19. Our main questions are: (1) What are the preferred locations for shopping? (2) What is the preferred time to shop post-COVID-19? (3) How much time do you spend at malls? (4) What is the purpose of going to malls? Nine hundred fourteen samples were taken face-to-face in March 2021; 104 were conducted on-site in May 2022, and an online questionnaire with 532 samples was completed in May 2022. All samples were selected in different places and on different days, with some demographic criteria. An updated annual shopping report was also utilized, indicating online and on-site services. We found that with

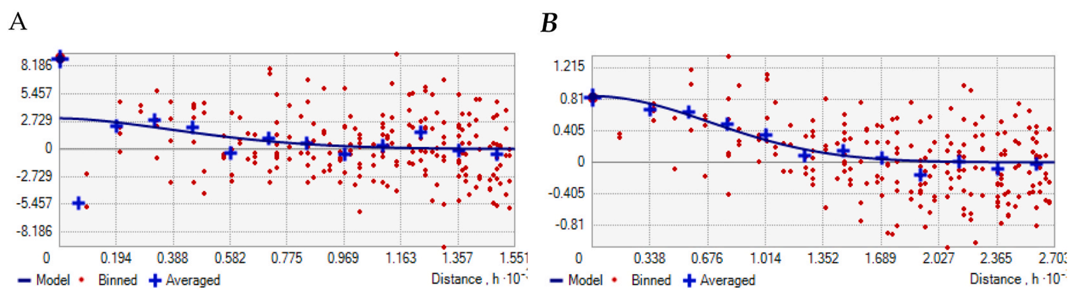

Fig. 6. Covariance modeling (semivariogram model) and its original data (point). They all pointed to a concentration of relatively high-risk commercial areas in the middle of the debtors' territory, represented by blue (averaged); (A, Zayed City, and B, October City).

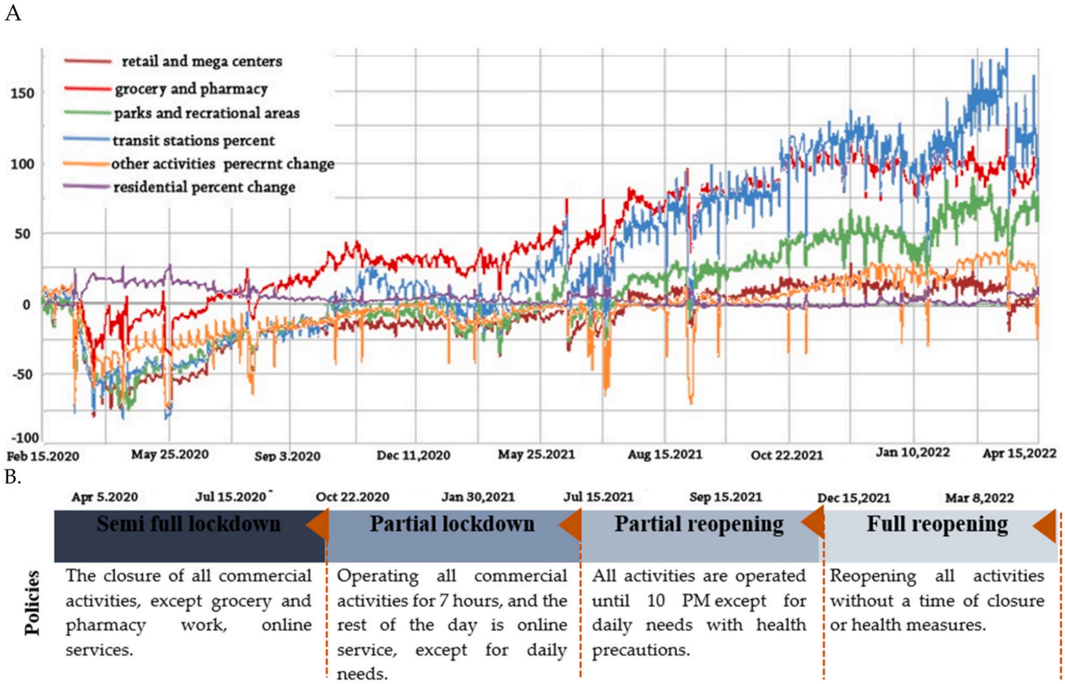

Fig. 7. A. Flow mobility and fluctuations in both cities from Q1 of 2020 to Q1 of 2022 and (B) the policies affecting mobility fluctuations.

fluctuations in the pandemic and the lockdown-reopening cycles, which remained oscillatory in September and October, people relied on online purchases more often than usual. Approximately 76 % of customers placed online orders for delivery between March 2020 and June 2020 in large malls, with a gradual decline to 38 % between August and September 2021 due to the easing of restrictions. Conversely, in small commercial centers with open spaces, home delivery decreased to 17 % compared to 81 % on-site purchasing, as residents took advantage of it to leave their homes for shopping and picnics during the quarantine. 80.4 % of the customers spent 1–2 h during one visit to the megamalls, and there was great reluctance among customers, fearing infection risk. In addition, customers in local and small centers were entertainment customers who attributed more importance to shopping as a leisure activity. When assessing the preferred commercial form, approximately 74 % preferred new shopping streets with

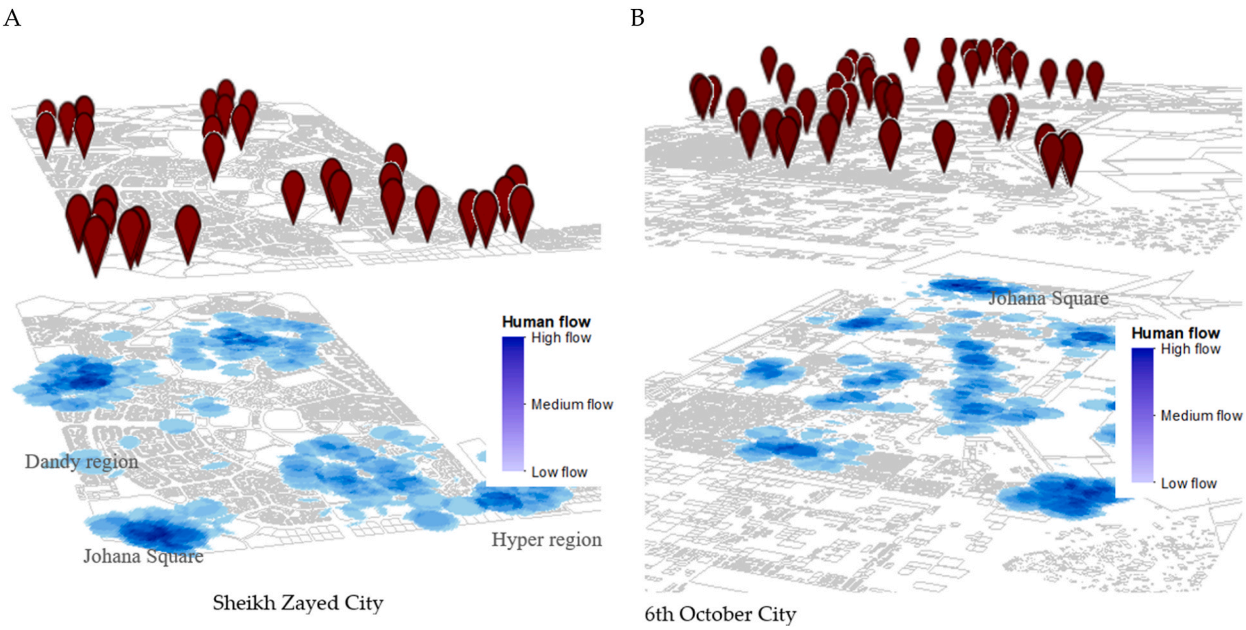

Fig. 8. Human mobility analysis of both cities and points of interest (A, Zayed City, and B, October City).

recreational areas or outdoor spaces in both cities. Furthermore, greenery-dependent peripheral malls and small local centers became more attractive than central megamalls after the pandemic. Asked about the preference reasons, most respondents mentioned the positive aesthetic role in keeping precautionary distances in contrast to the megamalls, indicating the necessity of transforming the urban metabolic lifestyle to be local in the neighborhood context rather than commuting large distances. According to unpublished paper reports in late 2021, the most intense hotspot areas in the two cities were the megamall areas, which are focused on the arterial axis with Hyper Mall, Dandy Mall, and Americana, and the touristic center in Zayed City. In addition to the commercial centers on the central axis, the Mall of Arabia, the Mall of Egypt, and the sixth commercial district in October, these areas represented the highest daily frequencies in 2021, with 72 % of the total daily frequencies in contrast to their decline to 24 % in 2020, which reached 1 % on some days, as shown in Fig. 8 (A, and B).

5.4. Quantifying spatially and mapping the potential risk of a pandemic

A set of interrelated horizontal maps was generated, as shown in Fig. 9. Through visual analytics, we found that the high-risk peaks were in both cities' centers, reflected by concentrated mega malls, compacted mixed-use activities such as gyms, hair salons, theatres, and indoor gathering activities that are adjacent to administrative services and indoor restaurants, insufficiently open spaces, and proximity to public transport stations (hotspot areas). This result suggests that the city center has become a hub of contagious transmission because of the activity densification driven by the market, regardless of the health factors in planning. It is striking that these activities are in low-density neighborhoods (the neighborhoods of the upper classes), but the customer flow is very high, especially from the residents of the outlying areas of the city. The pandemic risk declines to a medium degree towards the neighborhoods in peripheral regions, illustrating that the pandemic spreading is decreasing as you move from the more densely populated and central parts of the city toward the less densely populated peripheral neighborhoods. This could be due to lower population density, reduced human interaction, and potentially less frequent movement of people in these areas. However, it's important to note that the risk is still considered moderate; there is still a level of risk, but it's somewhat lower than in the central areas. It's also worth mentioning that this statement is a generalization and might not apply uniformly to all cities or regions, as various factors such as local demographics, healthcare infrastructure, and government policies can influence the pandemic risk across different areas. It is striking that this category intersects with high and medium density, despite finding the same activities in the first category, characterized by prevalently dispersed small commercial services with sufficient space to provide outdoor services and take health measures. Similarly, a low-risk peak appears at city edges with dispersed outdoor linear services, including outdoor restaurants, malls, takeout restaurants, and beverage shops. This category intersects with medium density and high human flow. We can deduce that high-risk peaks are

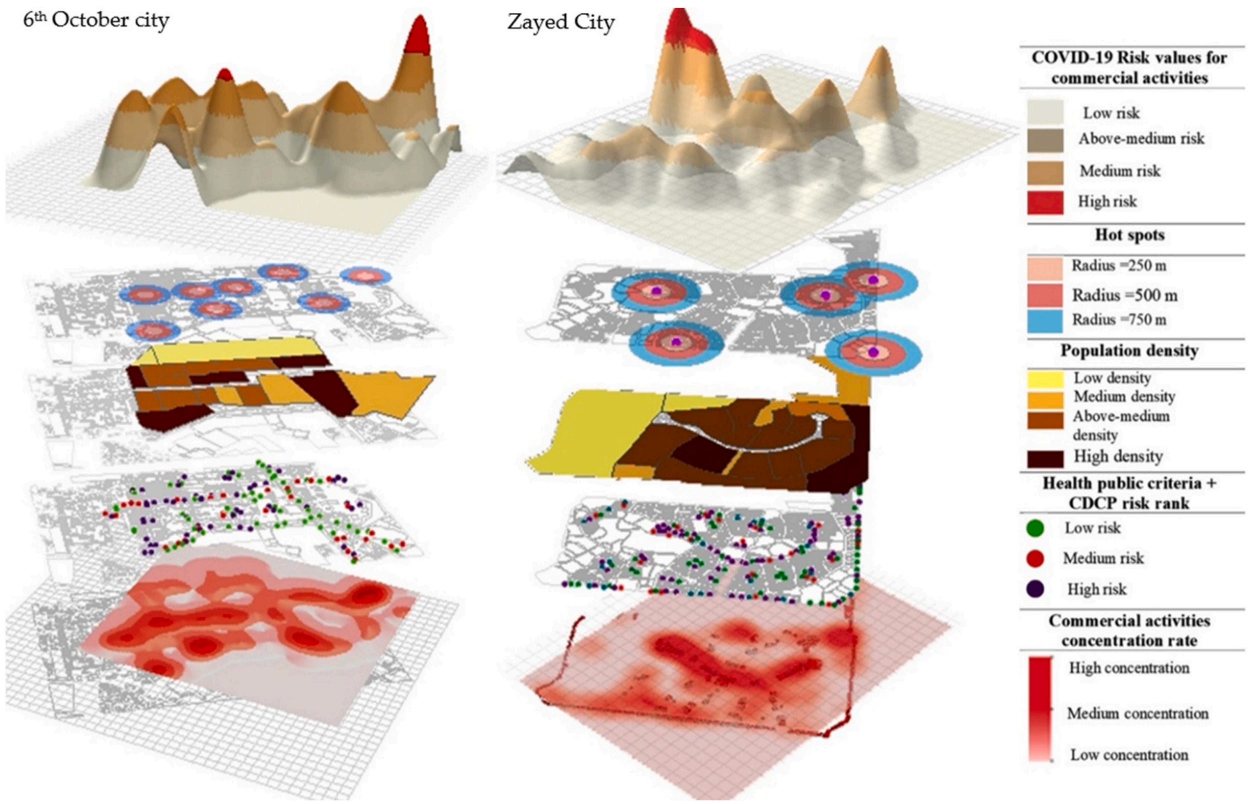

Fig. 9. Spatially quantifying and mapping the potential risk of a pandemic.

concentrated in city centers, which are characterized by high intensification of risky commercial activities with the high human flow and low population density (high classes), and then see a decrease when moving towards peripheral areas, which are characterized by dispersed activities with the medium flow and high population density (medium and low classes).

5.5. Validation study

In this study, the results obtained by spatially quantifying and mapping a pandemic's potential risk were compared with those obtained from realistic COVID-19 cases in each district. The results obtained from these two different methods were compared in Fig. 10 (a, b, and c). Pearson's correlation coefficient between two variables (COVID-19 and land use) was calculated, which equals 0.91 (statistically significant at the 0.05 level). The COVID-19 infection has the highest correlation with indoor restaurants and public transportation stations (0.82, 0.81), followed by banks and pharmacies (0.78, 0.75), as shown in Fig. 11 (a and b). We also used the LR algorithm using Equation (4) and (5) to describe the relationship between COVID-19 and activities in all cities. To evaluate the final risk maps, the prediction rate curve for LR is 0.903, showing that public transport stations in the 6th of October city, due to the overcrowding of passengers, have the most significant influence on the prevalence of COVID-19, followed by indoor restaurants, banks, pharmacies, and supermarkets. Decentralizing activities in both cities may be a more effective method of mitigating vulnerability risk.

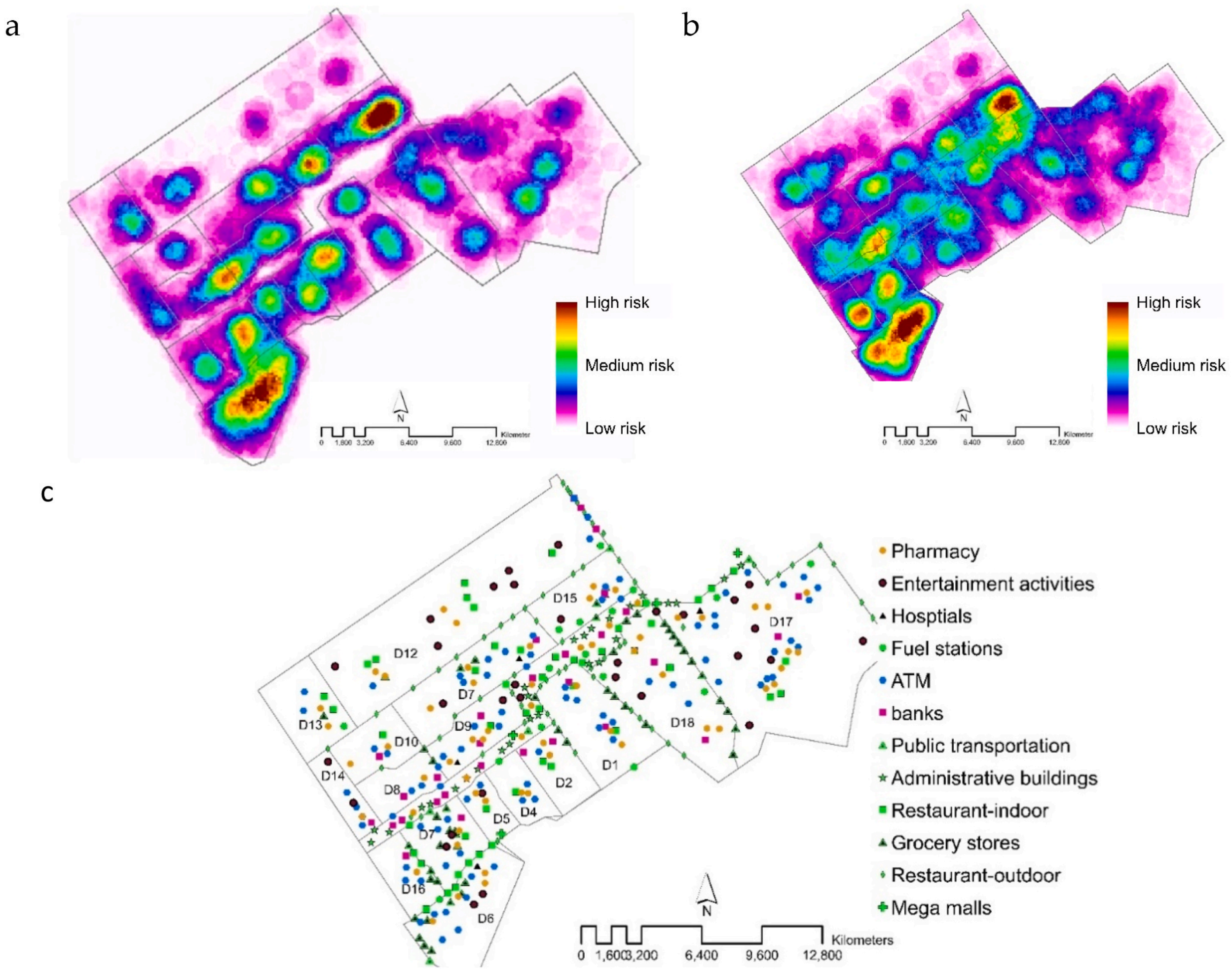

Fig. 10. (a) mapping the realistic hotspot of COVID-19 cases of 6th October; (b) mapping the potential COVID-19 infection risk based on activity characteristics using the Kriging interpolation method; (c) commercial land use of 6th October city.

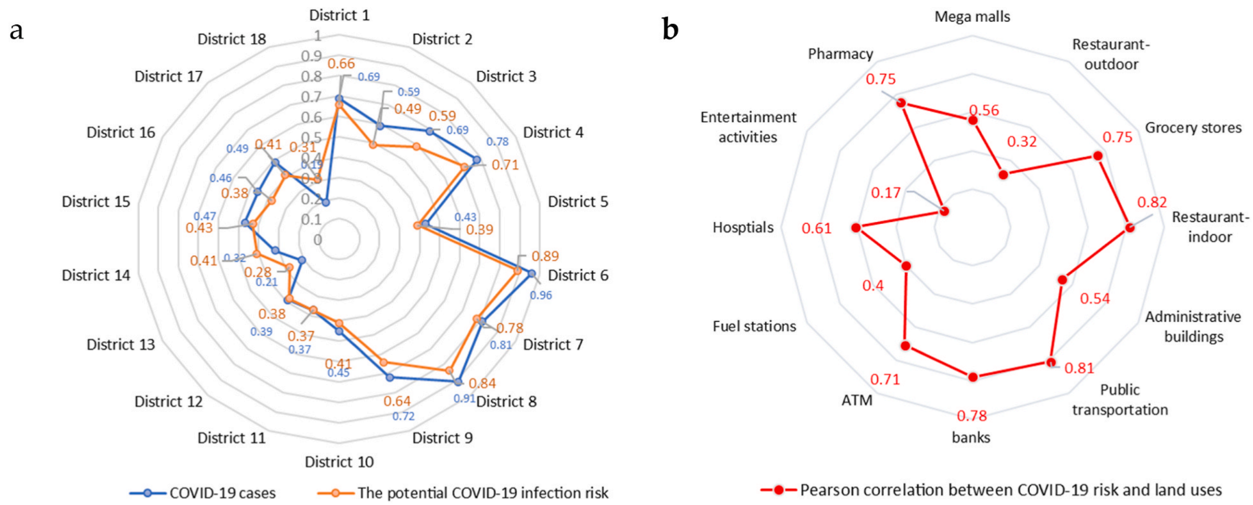

Fig. 11. (a) Validation of the potential COVID-19 infection risk based on activity characteristics and realistic cases, (b) Pearson's correlation coefficient between COVID-19 risk and city land uses.

6. Discussion and recommendations

6.1. Discussion and results

A comprehensive approach was implemented in our study, commencing with the spatial and morphological analysis of commercial activities and quantifying all infection risks. Initially, commercial activities were categorized based on their distinct attributes; subsequently, an assessment was made to rank the susceptibility to COVID-19 exposure within varying commercial activity types using CDCP criteria. Additionally, the study examined the patterns of individuals' movement between different commercial activities and the potential interactions that might arise. Risk weighting and scoring procedures amalgamated exposure evaluations, environmental variables, and mobility patterns, assigning risk scores and establishing weights for different factors. Leveraging GIS, the infection risk was visually portrayed on a spatial map, accentuating zones with high pandemic risk (hotspots). Available COVID-19 cases were employed to validate the model's accuracy, with predicted risk scores compared against realistic case distributions. Egypt's 6th of October City and Sheikh Zayed City were selected for applying methodology as ideal locations because of the clarity of service centers' hierarchy and the plurality and diversity of commercial activities' morphological characteristics (large shopping malls, small stores, and outdoor malls).

- Regarding the commercial activity characteristics in the two cities, under the evolution of e-commerce, activity location became a sub-issue during choice, and most commercial activities began to spread away from central areas towards peripheral regions with low rental fees. Before 2019, the NNI (0.34, 0.31), less than 1.0, showed a compact pattern. From 2019 to Q4-2021, the NNI (1.07, 1.43), which was more than 1.0, indicated a random pattern in October City, whereas it indicated a dispersed pattern in Zayed City. KDE analysis showed that open spaces positively correlate with new commercial stores, where Pearson's correlation coefficients are 0.872 and 0.907 in Zayed and October, respectively. On the other hand, the spatial distribution of new malls post-2019 is negatively correlated with population density, where $rxy = -0.366$ and -0.606 in Zayed and October, respectively. Through the analytical description of the emerging commercial pattern, the two cities, each with a single core, are progressively turning into scattered commercial ribbons.

- Commercial activity risks in both cities were geocoded using the Kinger interpolation method from highest to lowest based on CDCP criteria and infectious disease experts, ranking the low-risk category from 0 to 3, the medium-risk category from 4 to 7, and the high-risk category from 8 to 10. Our analysis revealed that most high-risk activities are concentrated in city centers, which indicates that their distribution is based on economic and market forces without considering the health dimension. The risk decreases as we head to the subcenters and marginalized areas.
- Regarding shoppers' behavioral networks after COVID-19, statistics indicate that the two cities were almost completely on lockdown at the beginning of the pandemic, and services were available only online. In 2022, customers returned to their old shopping habits before the outbreak, disregarding the healthy aspects and preventive measures, which may pose a potential outbreak risk. A semi-field survey was conducted to spatially determine the point of interest in both cities post-COVID-19. Our survey investigated shoppers' behavior changes, shopping motivation, preferred locations, duration, frequency rate, and identity of shopping centers post-COVID-19. We found that approximately 76 % of customers placed online orders for delivery between March 2020 and June 2020 in large malls, with a gradual decline to 38 % between August and September 2021 due to the easing of restrictions. Conversely, in small commercial centers with open spaces, home delivery decreased to 17 % compared to 81 % on-site purchasing, as residents took advantage of it to leave their homes for shopping and picnics during the quarantine. About 74 % of respondents

preferred new shopping streets with recreational areas or outdoor spaces in both cities. Furthermore, greenery-dependent peripheral malls and small local centers became more attractive than central megamalls after the pandemic. According to unpublished paper reports in late 2021, the most intense hotspot areas in the two cities were the megamall areas, which are focused on the arterial axis and represent the highest daily frequencies.

- A set of interrelated horizontal maps was generated by quantifying spatially and mapping the potential risk of the pandemic. Through visual analytics, we found that high-risk peaks are concentrated in city centers, which are characterized by high intensification of risky commercial activities with high human flow and low population density (high classes), and then see a decrease when moving toward peripheral areas, which are characterized by dispersed activities with the medium flow and high population density (medium and low classes). Hence, the urban density of districts was not correlated with transmission risk, but incompatible and concentrated commercial activities had the highest effect. This result revealed that the variables of spatial distribution (aggregation, diffusion, city centre, suburbs), morphology, the relationship with surrounding activities, and hotspots greatly influence potential infection outbreaks. In contrast, urban density has a low impact. These findings are significantly consistent with some publications highlighted previously in the literature review (Kim, 2021 [34]; Moldoveanu & Martin, 2022 [63]; Paez, 2020 [64]; Zhou et al., 2022 [46]).
- Quantifying and mapping a pandemic's potential risk were compared with those obtained from realistic COVID-19 cases in each district. Also, the land uses and hot spots were compared. We found that Pearson's correlation coefficient between the two variables equals 0.91, and the prediction rate curve for LR is 0.903, showing that restaurants, banks, pharmacies, and supermarkets in the 6th October city have the greatest influence on the prevalence of COVID-19.

6.2. Recommendations and perspectives for shaping pandemic-resilient cities

Despite COVID-19 repercussions triggering socio-economic damage, it can be a considerable opportunity to shape pandemic-resilient cities, or "Building Back Better," which involves a holistic approach considering various aspects of urban planning, infrastructure, healthcare, and social dynamics [5,24]. These recommendations aim to mitigate pandemic effects and not wait for another health crisis to alarm us, as COVID-19 may not be the last crisis. We suggest considering the health perspective during commercial activity planning as one of the sustainability goals rather than market-force-based traditional spatial distribution. Business activities should be shifted towards greener, smarter, and more dispersed services within walking distance of homes and all districts as independent, self-sufficient, and smart regions. Our suggestions and results may not be only for the pandemic but also for achieving a better environment and reducing the bill for other disasters that we are currently experiencing, as follows: first local malls are catalyzing a shift to easily accessible systems such as walking incentives, cycling, and low-occupancy vehicles, which reduce emissions. Second, viral epidemics are frequently incubated in peri-urban communities and transmitted to urban centers [19]. Local facilities may decrease the flow rate to the central regions, which face difficulties applying preventive measures. Third, reducing urban inequities allows for developing the new marginalized poles, generating massive economic returns, and supporting social sustainability (e.g., interactivity and generating work opportunities for district inhabitants). Finally, radical measures such as expanding street pavements, using nature-based solutions, and combining commercial activities with bike routes help quickly provide renewable ventilation, eliminate harmful airborne viruses, and maintain acceptable levels of social distancing. Another advantage is that they reduce the use of public and private automobiles and the associated GHG emissions, energy consumption, natural disasters, and climate change [65–69]. This transferable analysis indicates that health-based spatial activity planning is a precondition for pandemic-resilient urban planning. Returning to normalcy without learning from COVID-19's harsh lesson may mean passing up a once-in-a-lifetime opportunity to recognize inherent and interconnected environmental, economic, social, and interpersonal crises that predate the pandemic. Whatever shape the next health crisis takes, it will almost certainly be nothing more than a symptom of the same chronic problems with service distribution. As a result, our societies' political institutions must address not just the ongoing crisis but also the frequent, exceptional, and simultaneous crises.

7. Conclusions

Using the high-resolution spatial analysis of commercial activity, human mobility, and urban density, our study analyzes the potential COVID-19 infection risk based on commercial activity characteristics applied in two Egyptian cities under the hurried lifting of lockdown constraints, particularly when the healthcare system burden remains high worldwide. Our study reveals that the high density of commercial activities and the concentration of incompatible land uses correlate more with COVID-19 prevalence than urban density. Therefore, activity characteristics-based estimation is appropriate for assessing spatial heterogeneity for potential pandemic risks under rising new variants. Also, health criteria-based urban morphology can be a straightforward alternative for more effective resilience and disease reduction than urban density. Regardless of defining hot spots in two cities, decision-makers should use workable approaches and consider spatially high-risk peaks to control further COVID-19 transmission and shape pandemic-resilient cities.

The meticulous analysis of potential COVID-19 infection risk grounded in the distinctive characteristics of commercial activities bears profound significance for urban planners and policymakers. This correlation provides insights into the spatial dynamics shaping disease transmission, facilitating informed decisions and strategic interventions safeguarding public health and urban resilience. Understanding correlation can influence future urban planning decisions by encouraging designs that reduce the concentration of high-risk commercial activities, promoting layouts that prioritize health and safety in public spaces, and empowering authorities to allocate resources that align with the risk profile of various commercial settings. Our study faced limitations due to the lack of periodic and cell phone data about pandemic cases. Two medium-sized cities in the same country were analyzed; the risk probably differs in small and metropolitan cities. Future publications could study various global regions more thoroughly under the supervision of an immunological disease expert to determine the impact of each variable separately and eventually all variables. Finally, while this study applied the methodology to a commercial activity, other studies could use it for different activities.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author, [H.H].

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Ethics statement

"This article does not contain any studies with human participants performed by any of the authors".

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CRediT authorship contribution statement

Karim I. Abdrabo: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Mahmoud Mabrouk:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Data curation, Conceptualization. **Haoying Han:** Supervision. **Mohamed Saber:** Supervision. **Sameh A. Kantoush:** Supervision, Project administration, Funding acquisition. **Tetsuya Sumi:** Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e24702.

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