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THE CITY CHALLENGES AND EXTERNAL AGENTS.
METHODS, TOOLS AND BEST PRACTICES

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The cover image is a train passes a rail road crossing that is surrounded by flooding caused by rain and melting snow in Nidderau near Frankfurt, Germany, Wednesday, Feb. 3, 2021. (AP Photo/Michael Probst)

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Covid-19 pandemic and activity patterns in Milan. Wi-Fi sensors and location-based data

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Abstract

The recent development of location detection systems allows to monitor, understand and predict the activity patterns of the city users. In this framework, the research focuses on the analysis of a sample of aggregated traffic data, based on the number of mobile devices detected through a network of 55 Wi-Fi Access Points in Milan. Data was collected over 7 months (January to July 2020), allowing for a study on the impact of the Covid-19 pandemic on activity patterns. Data analysis was based on merging: (i) time series analysis of trends, peak hours and mobility profiles; (ii) GIS-based spatial analysis of land data and Public Transport data. Results showed the effectiveness of Wi-Fi location data to monitor and characterize long-term trends about activity patterns in large scale urban scenarios. Results also showed a significant correlation between Wi-Fi data and the density distribution of residential buildings, service and transportation facilities, entertainment, financial amenities, department stores and bike-sharing docking stations. In this context, a Suitability Analysis Index is proposed, aiming at identifying the areas of Milan which could be exploited for more extensive data collection campaigns by means of the installation of additional Wi-Fi sensors. Future work is based on the development of Wi-Fi sensing applications for monitoring mobility data in real time.

Keywords

Urban mobility; Traffic data; Wi-Fi sensors; GIS analysis; Covid-19 pandemic.

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1. Introduction

Urban Informatics (Foth et al., 2011) provides innovative assessment tools and metrics to support an effective planning of mobility services, within an evidenced-based and multi-disciplinary approach. Thanks to the recent development of advanced ICT solutions and the increasing availability of digitally widespread data sources, Big Data is becoming a valuable support to unveil hidden mobility patterns in the cities (Batty, 2013; Crist et al., 2015): "[...] as representing measures of the 'pulse' of a city, as a measure of locational focus that moves in space and time but correlates in diverse ways with the substrata of the city which change much more slowly, such as population and employment densities and related infrastructures" (Batty, 2010, p.576).

In particular, the development of location detection systems allows to monitor, understand and predict the travel behavior of city users, considering both micro (e.g., road intersections) and macro scale scenarios (e.g., large transport infrastructures) (Xhafa et al., 2017). These include the following techniques for data collection:

- images stream analysis and acquisition systems (Buch et al., 2011): AI and computer vision techniques for processing a sequence of photographs or a video clip collected through CCTV cameras or drones;
- radio frequency systems based on Wi-Fi or Bluetooth technology (Sapiezynski et al., 2015): antenna type sensors for scanning wireless devices through the media access control (MAC) address (i.e., *unique identifier of each network device*);
- cell network data acquisition systems (Becker et al., 2013): data derived from subscriber identity modules (SIM cards) and cell network technology;
- software development kit, Beacon and bid stream systems (Lin & Hsu, 2014): data derived from Global Positioning System (GPS) signal of navigation devices and Apps for smartphones;
- Occupancy Detection Systems (Odat et al., 2017): light pulse type remote detection techniques, including Laser Imaging Detection and Ranging (LIDAR) and passive infra-red (PIR) sensors.

Nowadays, monitoring traffic data has become even more crucial for the activity of transport planners and decision makers, considering the need to investigate the unprecedented effects of disruption of the Covid-19 pandemic on urban mobility and to assess the effectiveness of immediate and longer-term actions that cities have developed to respond to the crisis (Coppola & De Fabiis, 2020; European Platform on Sustainable Urban Mobility Plans, 2020). In just a few months the nation-wide lockdown and post-lockdown phases have drastically changed citizens behaviors and mobility patterns related to the cities, neighborhoods and streets in which they live (Deponte et al., 2020; Zecca et al., 2020). Taking advantage of a preliminary work already presented by the authors[1], the current paper is based on the analysis of a large sample of structured proprietary data gathered during a 7-month period (January to July 2020) through a network of 55 Wi-Fi sensors distributed in several department stores, shops and public services in Milan (Italy). The objective of the analysis is twofold. First, the research aimed at testing the effectiveness and reliability of Wi-Fi technology to collect aggregated data about activity patterns in large scale urban scenarios. In this framework, the number of mobile devices detected per day per hour during the entire period of reference was analyzed to estimate the effects of the Covid-19 pandemic on activity patterns. In particular, a time series analysis on trends, peak hours and mobility profiles was executed to compare results between the Pre-Covid-19 period (from January 1st to February 22nd, 2020) and the lockdown Phase 0, 1, 2 and 3 (from February 23rd to July 31st, 2020). Second, the research aimed at correlating the number of detected mobile devices (i.e., *time-variant data*) with the density distribution of relevant land and Public Transport data (i.e., *time-invariant data*), such as building typologies, green areas, amenities and Public Transport. Given the unprecedented effects of the adopted containment measures on urban dynamics (e.g., restricted mobility, partial opening or closures of public services, etc.), the proposed GIS-based analysis aimed at understanding which areas of the city were more

[1] See: https://research.systematica.net/journal/monitoring-big-traffic-data-through-wi-fi-sensors-the-evolution-of-the-lockdown-phases-in-milan/

resilient during the evolution of the lockdown phases, considering the variation of Wi-Fi data during the entire period of reference. Moreover, the results of the analysis were used to define a *Suitability Analysis Index* (Santos & Moura, 2019), aiming at identifying the areas of Milan which could be exploited for more extensive data collection campaigns by means of the installation of additional Wi-Fi sensors. The paper proposes a review of relevant applications and scientific contributions focused on the use of the Wi-Fi technology for collecting data about activity patterns in urban areas (namely traffic data), in order to provide a preliminary assessment of its advantages and limitations. Then, it presents the enabling data and methodology which sets the current work, and the results of time series analysis of Wi-Fi data and GIS-based analysis of location-based data. The paper concludes with final remarks about the achieved results and future work.

1.1 Related Works

Wi-Fi technology is recognized as one of the most effective sensors for monitoring activity patterns, considering both outdoor and indoor scenarios. This is due to installation and maintenance costs, precision rate, energy consumption, robustness to weather and light conditions (Bernas et al., 2018), and compliance to the General Data Protection Regulation (GDPR) (National Centre for IoT and Privacy, 2020). Additionally, the ubiquity of Wi-Fi sensors in cities enable the collection of data with high spatial and temporal granularity (Kontokosta & Johnson, 2017). In recent years, numerous studies addressed potentialities and shortcomings of Wi-Fi technology to enhance the existing traffic monitoring infrastructure, including the following:

- Transport for London (2019) conducted an extensive pilot research on Wi-Fi data collection and analysis to improve services. The study proved that Wi-Fi technology could enable more efficient planning and management of the transport infrastructure;
- Sapiezynski et al. (2015) investigated the possibility to accurately track students' movements on campus with a reduced number of existing Wi-Fi APs, due to low variability of activity patterns, and discussed the implications on user's privacy;
- Bellini et al. (2017) proposed a methodology to select existing Wi-Fi APs at optimal locations in order to produce accurate OD matrices, daily users' mobility behaviors analyses and forecasting;
- Kontokosta and Johnson (2017) estimate types of residents based on activity patterns of users connecting to the Wi-Fi network, with the aim to create a real-time census of the city;
- Soundararaj et al. (2020) used Wi-Fi probe requests to identify footfall patterns in retails, with a focus on methods to validate data;
- Kostakos et al. (2013) proposed an integration of magnetic loops traffic sensors with the existing Wi-Fi infrastructure to monitor cities in near real-time.

Among the limitations of Wi-Fi technology, it has to be noted that it does not allow to disaggregate data among different means of transportation (e.g., private motorized vehicles, cyclists, pedestrians, etc.). The capability of this technology to detect mobile devices depends on its connection features, its battery level and actual usage. The accuracy of Wi-Fi data can be also influenced by background noise due to fixed devices and systematic errors due to the device's orientation. Furthermore, the possibility to estimate traffic data is limited by the possibility to detect multiple mobile devices per users, leading to an oversampling error (Soundararaj et al., 2020).

2. Enabling Data and Methodology

Thanks to the collaboration with the Wi-Fi service provider FreeLuna[2], a large sample of proprietary data was collected through a network of 55 Wi-Fi sensors (see Fig.1 and Tab.1) from the beginning of January 2020 to

[2] See: https://www.futur3.it/en/

the end of July 2020. First, the proposed time series analysis was focused on the number of mobile devices detected per day per hour through the Wi-Fi sensors, in order to highlight trends, peak hours and mobility profiles during the entire period of reference. Then, results were compared against an extensive GIS-based analysis focused on relevant land and Public Transport data (see Tab.1), which were retrieved, sorted and filtered from geoportals and open data repositories. This information was analyzed to design a multi-layer map of Milan and to estimate the spatial distribution of each dataset considering the localization of the Wi-Fi Access Point (APs).

Fig.1 The location of the 55 Wi-Fi APs, with related radius of action (r = 80 m) and catchment areas (r = 280 m)

From a general point of view, the proposed GIS analysis was based on various attributes and characteristics of the urban area surrounding each Wi-Fi sensor. To do so, raw data related to the urban scale were extracted about surrounding areas of each Wi-Fi AP (see Fig.2 and Fig.3). A catchment area with a radius of 280 m (circular buffer areas of 0.246 km^2) was designed, considering the radius of action of installed Wi-Fi sensors (80 m) and the travel distance allowed from place of residence within the restricted territories during the lockdown Phase 1 (200 m), according to the national regulation enforced by the Italian Government[3].

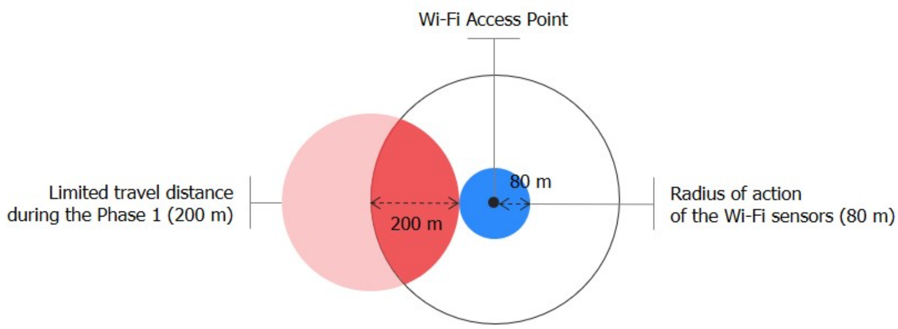


Fig.2 The catchment area surrounding each Wi-Fi AP is based on the radius of action of the Wi-Fi signal (r = 80 m) and on the travel distance allowed within the restricted territories during the lockdown Phase 1 (r = 200 m)

Data analysis was based on counting the number of mobile devices (e.g., smartphones, tablets, notebooks, etc.) detected per hour per day by means of the 55 Wi-Fi APs. A preliminary data validation allowed us to discard the Wi-Fi data collected from a few malfunctioning APs, characterized by an irregular signal. The clean data set consists of a total of 111,100,558 mobile devices, representing in an aggregated manner the traffic

3 See: http://www.governo.it/it/coronavirus-misure-del-governo

data (TD) observed in Milan during the entire period of reference and constituted by various means of transportation. Then, the time series of Wi-Fi data was post-processed and analyzed focusing on trends, peak hours and mobility profiles.

Indicator	Data typology	Parameter	Data Source	Year
Traffic Data	Wi-Fi APs position	-	FreeLuna	2020
	Timestamp (YYYYMMDDhh)	-	FreeLuna	2020
	Counted mobile devices	TD	FreeLuna	2020
Land Data	Residential Buildings	ReB	Geoportal Lombardy Region	2012
	Administrative Buildings	NReB_Ad	Geoportal Lombardy Region	2012
	Commercial Buildings	NReB_Co	Geoportal Lombardy Region	2012
	Industrial Buildings	NReB_In	Geoportal Lombardy Region	2012
	Service and Transportation	NReB_ST	Geoportal Lombardy Region	2012
	Green Areas	GA	Geoportal Lombardy Region	2012
	Education Amenities	A_Ed	Geoportal City of Milan and OpenStreetMap	2020
	Entertainment Amenities	A_En	Geoportal City of Milan and OpenStreetMap	2020
	Financial Amenities	A_Fi	Geoportal City of Milan and OpenStreetMap	2020
	Shops	A_Sh	Geoportal City of Milan and OpenStreetMap	2020
	Department Stores	A_DS	Geoportal City of Milan and OpenStreetMap	2020
	Sustenance Amenities	A_Su	Geoportal City of Milan and OpenStreetMap	2020
Public Transport Data	Bike-sharing Stations	PT_Bi	Geoportal City of Milan	2020
	Subway Lines	PT_Su	Geoportal City of Milan	2020
	Tram Lines	PT_Tr	Geoportal City of Milan	2020
	Bus Lines	PT_Bu	Geoportal City of Milan	2020

Tab.1 The list of proprietary and open datasets that were analyzed and merged for understanding the impact of the lockdown phases on activity patterns in Milan

The proposed GIS data analysis was based on extracting a series of location-based data from the areas surrounding each Wi-Fi AP, focusing on:

- Land Data (Geoportal of Lombardy Region[4]; Geoportal of the City of Milan[5]; OpenStreetMap[6]):
  - Residential buildings (ReB), administrative (NReB_Ad), commercial (NReB_Co), industrial buildings (NReB_Co) and service and transportation facilities (NReB_ST);
  - Green areas (e.g., parks, public gardens, flowerbed) (GA);
  - Amenities: education (A_Ed) (e.g., school, University, library, etc.), entertainment, arts and culture (A_En) (e.g., museum, cinema, etc.), financial (A_Fi) (e.g., ATM, bank), healthcare (A_He) (e.g., hospital, pharmacy, etc.), shops (A_Sh), department stores (A_DS) and sustenance (A_Su) (e.g., bar, restaurant, etc.);
- Public Transport Data (Geoportal of the City of Milan): bike sharing docking stations (PT_Bi), subway lines (PT_Su), tram lines (PT_Tr) and bus lines (PT_Bu).

The dataset, composed by punctual, linear and areal vectors, was analyzed through density-based calculation on catchment areas. For the purpose of comparing the various indicators among them, each one has been normalized on a 0-1 scale, creating Z-scores that follow the normal distribution of the values. The following step has involved the calculation of a series of correlations (using Pearson's Correlation Coefficient) between

4 See: http://www.geoportale.regione.lombardia.it/en/home
5 See: https://geoportale.comune.milano.it/sit/
6 See: https://www.openstreetmap.org/

the normalized values of density for each indicator. The problem of accounting for autocorrelation of the variables included in this study was then considered by implementing a modified t-test of spatial association derived from the work of Clifford et al. (1989). This is mainly based on the corrections of the sample correlation coefficient between two spatially correlated variables and requires the estimation of an effective sample size. The modified t-test helped to adjust Pearson's correlation coefficients and the respective p-values, removing the variables whose p-value was no more significant if accounting for autocorrelation.
All the significant correlation coefficients were then included in the calculation of the Suitability Analysis Index (SAI). This was essentially based on a weighted summation of the normalized density values of the variables proposed in this study (taking into account autocorrelation results) and on the use of the open sourced H3 hexagonal grid presented by Uber Engineering in 2018[7]. This was aimed at identifying the areas of Milan which could be exploited for more extensive data collection campaigns of traffic data by means of the installation of additional Wi-Fi sensors.

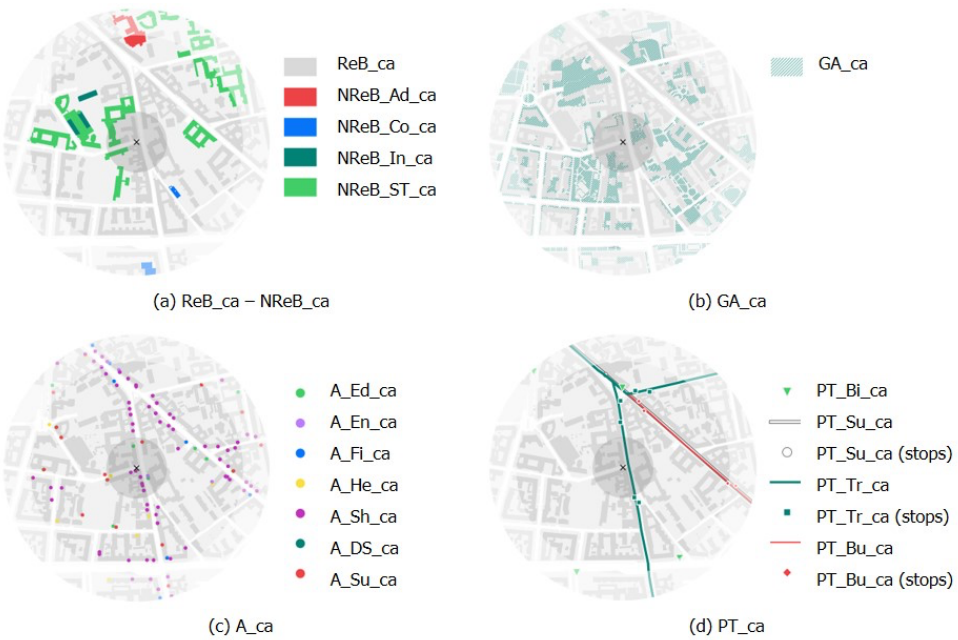


Fig.3 An exemplification of the procedure applied to extract the land and Public Transport data on catchment areas

3. Results

3.1 Time-series analysis

The analysis was aimed at identifying significant variations in the number of mobile devises detected through the Wi-Fi sensors during the Pre-Covid-19 period and the lockdown Phase 0, 1, 2 and 3. The definition of the lockdown phases is based on the containment measures enforced by the local and national governments, which gradually prohibited any movements to, from and within the restricted territories to contrast the spread of contagion[8]. A series of information related to the timeline of the lockdown phases are described below:

- pre-Covid-19 period (from January 1st, 2020, to February 22nd, 2020): The Covid-19 virus was first confirmed to have spread to Italy on January 31st, 2020. A cluster of cases was detected in the Lombardy Region on February 21st, 2020;

[7] See: https://eng.uber.com/h3
[8] See: http://www.governo.it/it/coronavirus-misure-del-governo

- phase 0 (from February 23rd, 2020, to March 8th, 2020): Milan was defined by the local government as a "yellow zone". The Duomo Church, the Scala theatre and other cultural sites were temporally closed, as well as schools and Universities; bars and clubs closed at 6 pm;
- phase 1 (from March 9th, 2020, to May 3rd, 2020): Milan was defined by the Italian government as a "red zone" (along with the entire Lombardy Region). In order to avoid gatherings, the access to green areas, educational, entertainment, sport, sustenance, religious and commercial public services was banned (apart from tobacco shops, food and do-it-yourself department stores). Public Transport capacity was reduced to 25% to allow social distancing. Any movement was prohibited to and from the restricted territories, as well as within the territories themselves. Apart from health and emergency reasons, the travel distance allowed from the place of residence was limited to 200 m;
- phase 2 (from May 4th, 2020, to June 14th, 2020): Gradual easing of the lockdown containment measures, as the epidemic curve was in a downward phase. Green areas, sustenance, commercial and religious public services were reopened, but strongly limited to a fixed quota of accesses and services hours. Public Transport capacity was kept at 25%;
- phase 3 (from June 15th, 2020, to July 31st, 2020): Further easing of the containment measures. Entertainment public service were reopened. Public Transport capacity was increased to 50%.

The analysis of Wi-Fi data trends (see Tab.2 and Fig.4) was based on the total and average number of mobile devices detected per day through the entire network of Wi-Fi sensors, from January 2020 to July 2020. Data analysis highlighted a significant difference between the datasets related to the Pre-Covid-19 period and the lockdown phases, caused by the evolution of the containment measures put in place to contrast the spread of contagion. The results of a series of independent samples t-tests[9] (two-tailed) showed a significant difference between the average number of mobile devices detected per day during the Pre-Covid-19 period and the lockdown Phase 0 ($t(66) = 7.583$; $p < .01$), Phase 1 ($t(106) = 31.857$; $p < .01$), Phase 2 ($t(93) = 21.254$; $p < .01$) and Phase 3 ($t(98) = 15.004$; $p < .01$).

Further data analysis was based on the calculation of the percentage difference between the moving average of the number of detected mobile devices (MA, time period: 3 days) and the cumulative average of values (CA, time period: 7 months). This allowed us to smooth out short-term fluctuations of data and to highlight long-term trends (see Fig.4), such as: (*i*) the downsized amount of traffic volumes observed during the first week of January, 2020, due to the holidays; (*ii*) the stable trend of data during the Pre-Covid-19 period; (*iii*) the gradual downward trend of data during the lockdown Phase 0; (*iv*) the flattened traffic volumes during Phase 1 (total lockdown); (*v*) the gradual increase of traffic data during Phases 2 and 3, due to the easing of the containment measures.

Phases	Time period	Total	Average	SD	Trend
Pre-Covid-19	From 01/01/2020	56,273,763	843.091	1,610.054	--
Phase 0	Until 08/03/2020	10,239,857	528.210	907.143	-37%
Phase 1	Until 03/05/2020	8,437,822	141.186	690.046	-83%
Phase 2	Until 14/06/2020	13,235,535	279.195	736.948	-67%
Phase 3	Until 31/07/2020	22,913,563	440.942	1,064.999	-48%

Tab.2 The total number of mobile devices detected during the Pre-Covid-19 period and the lockdown Phase 0, 1, 2 and 3, with daily average and standard deviation. The table shows the percentage decrease of each lockdown phase compared to the Pre-Covid-19 period

9 All statistics presented in this paper have been performed by using the software IBM SPSS Statistics v.27 and R v.4.0.5 (Spatial Pack), and they have been conducted at the $p < .01$ level.

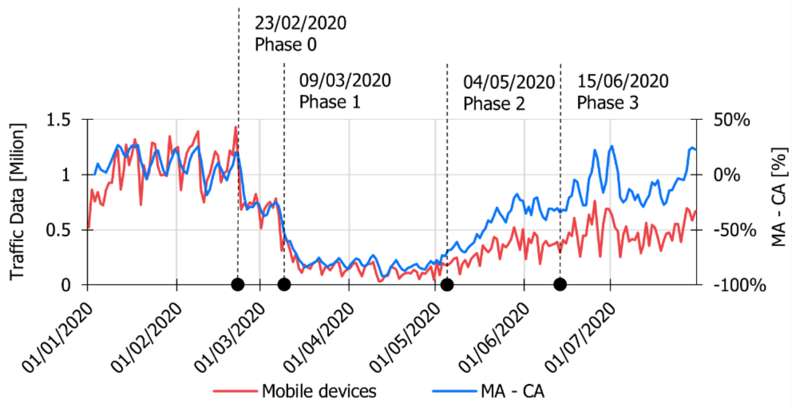


Fig.4 The number of mobile devices detected per day during the Pre-Covid-19 period and the lockdown Phase 0, 1, 2 and 3, and the percentage difference between the moving average (MA) and the cumulative average of values (CA)

3.2 Circadian rhythm and mobility profiles

The number of detected mobile devices was further analyzed to characterize peak hours (i.e., *circadian rhythm of the city*) (see Fig.5). Results showed that the Pre-Covid-19 period was characterized by peak hours in the working days afternoon (highest peak hour on Friday afternoon at 5 pm) and on Saturday evening and Sunday afternoon. Phase 0 was characterized by an overall decrease of traffic volumes, with relative peak hours in the afternoon. Phase 1 was characterized, instead, by a flattened temporal distribution of values during the entire week. Phases 2 and 3 were characterized by an increase of traffic volumes.

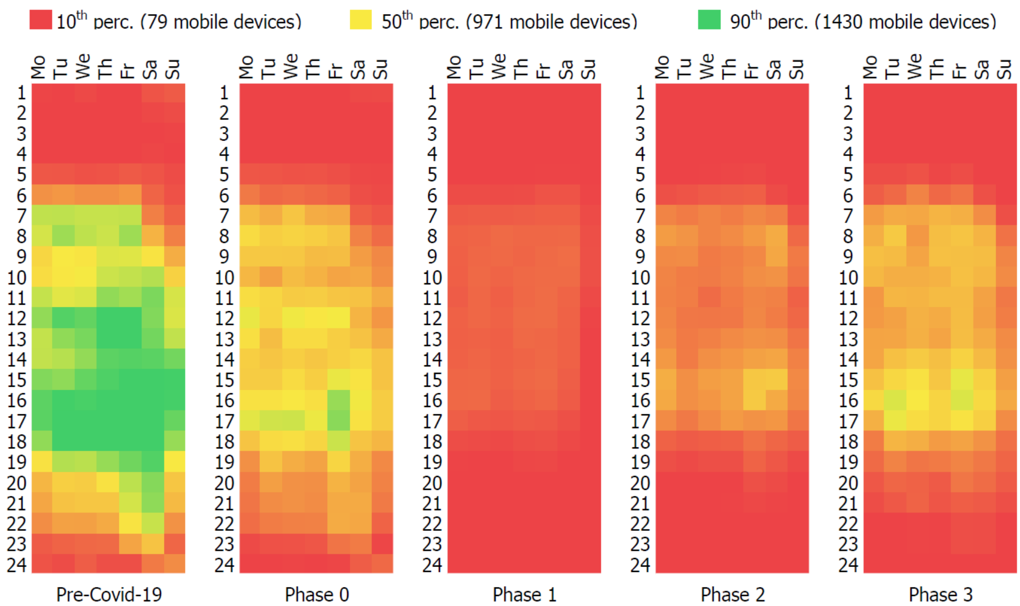
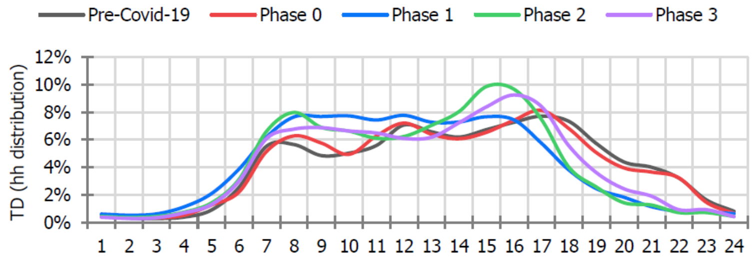
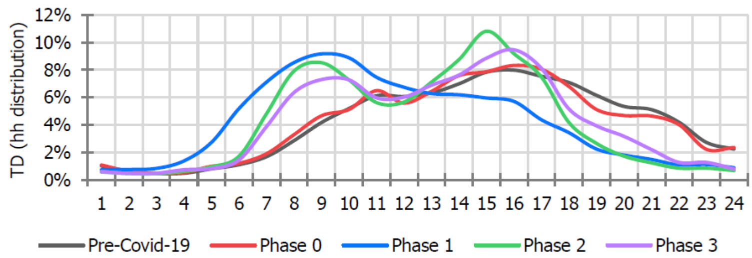


Fig.5 Peak hours per hour per day during the Pre-Covid-19 period and the lockdown Phase 0, 1, 2 and 3. Colour palette refers to the percentile frequency distribution of values for the Pre-Covid-19 period

The analysis of weekdays mobility profiles was based on the segmentation of the lockdown phases and on the calculation of the average hourly distribution of values (see Fig.6). Results highlighted consistent peaks for the Pre-Covid-19 period and all the phases (e.g., home-to-work and home-to-school mobility patterns, occasional demand related to leisure trips, etc.), exception made for the Phase 1. The flattened profile of Phase 1, from 8 am to 4 pm, is due to the absence of daily commuting and occasional leisure related trips. On the contrary, the analysis of weekends mobility profile highlighted an emerging phenomenon related to Phase 1, whose profile is an inverted copy of the one depicted for the Pre-Covid-19 period: whereas the latter showed a PM peak and a growing demand before noon, the former presented an AM peak and a decreasing demand after noon.



(a) Weekday profiles



(b) Weekend profiles

Fig.6 The (a) weekdays and (b) weekends average distribution of the number of detected mobile devices during the Pre-Covid-19 period and the lockdown Phase 0, 1, 2 and 3

3.3 Spatial analysis of land and Public Transport data

The proposed extensive GIS-based analysis[10] was executed to calculate the density distribution of building typologies, green areas, amenities and Public Transport located within the catchment areas surrounding each Wi-Fi AP (see Fig.3 and Tab.3).

Data	Measure	Average	SD	Pre-Covid	P0	P1	P2	P3
ReB_ca	[m^3/km^2]	6,177,670.273	2,115,604.956	•	•	•	•	•
NReB_Ad_ca	[m^3/km^2]	176,588.110	290,185.320	•	•	~	•	•
NReB_Co_ca	[m^3/km^2]	458,238.290	410,745.312	•	•	~	~	•
NReB_In_ca	[m^3/km^2]	72,873.005	170,419.409	•	•	~	•	•
NReB_ST_ca	[m^3/km^2]	903,631.974	1,071,623.767	•	•	~	•	•
GA_ca	[km^2/km^2]	0.150	0.116	•	•	x	•	•
A_Ed_ca	[No./km^2]	20.822	18.742	•	x	x	x	x
A_En_ca	[No./km^2]	10.042	12.003	•	x	x	x	•
A_Fi_ca	[No./km^2]	24.071	22.473	•	•	~	•	•
A_He_ca	[No./km^2]	21.339	11.781	•	•	•	•	•
A_Su_ca	[No./km^2]	181.786	75.624	•	•	x	~	~
A_Sh_ca	[No./km^2]	726.923	396.651	•	•	x	~	~
A_Ds_ca	[No./km^2]	29.461	57.364	•	•	~	•	•
PT_Bi_ca	[No./km^2]	8.934	6.604	•	•	•	•	•
PT_Su_ca	[No./km^2]	2.141	2.802	•	•	~	~	~
PT_Tr_ca	[No./km^2]	21.265	23.394	•	•	~	~	~
PT_Bu_ca	[No./km^2]	31.233	23.665	•	•	~	~	~

Tab.3 The density distribution of building typologies, green areas, amenities and Public Transport on catchment areas, and their closure/opening during the Pre-Covid-19 period and the lockdown Phase 0, 1, 2 and 3 (i.e., • open; ~ partially open; X closed)

[10] All GIS-based analyses presented in this paper have been performed by using the software QGIS v.3.16.1.

In this study, Clifford and Richardson (1989) effective sample size adjustment method was used to account for spatial autocorrelation in the Pearson's Correlation Coefficient, employing spatial correlation matrices for each variable to jointly measure the dependence between the number of detected mobile devices, namely traffic data, and the density distribution of building typologies, green areas, amenities, Public Transport (see Fig.7 and Tab.4). The results of the analysis showed:

- strong, positive correlation between the density distribution of department stores (A_DS_ca) and the traffic data collected during the Pre-Covid-19 period (R^2 = 0.575; r = 0.761; n = 52; $p < 0.01$), Phase 0 (R^2 = 0.484; r = 0.696; n = 52; $p < 0.01$), Phase 1 (R^2 = 0.259; r = 0.509; n = 52; $p < 0.01$), Phase 2 (R^2 = 0.492; r = 0.701; n = 52; $p < 0.01$) and Phase 3 (R^2 = 0.521; r = 0.722; n = 52; $p < 0.01$);
- moderate, positive correlation between the density distribution of residential buildings (ReB_ca) and the traffic data collected during the Pre-Covid-19 period (R^2 = 0.202; r = 0.449; n = 52; $p < 0.01$), Phase 0 (R^2 = 0.125; r = 0.354; n = 52; $p < 0.05$), Phase 1 (R^2 = 0.143; r = 0.379; n = 52; $p < 0.01$), Phase 2 (R^2 = 0.185; r = 0.430; n = 52; $p < 0.01$) and Phase 3 (R^2 = 0.138; r = 0.371; n = 52; $p < 0.01$);
- moderate, positive correlation between the density distribution of Service and Transportation facilities (ReB_ca) and the traffic data of the Phase 1 (R^2 = 0.137; r = 0.371; n = 52; $p < 0.01$);
- Moderate, positive correlation between the density distribution of entertainment, arts and culture amenities (A_En_ca) and the traffic data of the Pre-Covid-19 period (R^2 = 0.423; r = 0.643; n = 52; $p < 0.01$) and Phase 3 (R^2 = 0.296; r = 0.544; n = 52; $p < 0.01$);
- moderate, positive correlation between the density distribution of financial amenities (A_Fi_ca) and the traffic data of the Pre-Covid-19 period (R^2 = 0.138; r = 0.372; n = 52; $p < 0.05$) and Phase 1 (R^2 = 0.109; r = 0.331; n = 52; $p < 0.05$);
- weak, positive correlation between the density distribution of bike-sharing docking stations (PT_Bi_ca) and the traffic data of Phase 1 (R^2 = 0.094; r = 0.306; n = 52; $p < 0.05$);
- moderate positive correlation between the density distribution of education amenities (A_Ed_ca) and the traffic data collected during the Pre-Covid-19 period (R^2 = 0.152; r = 0.390; n = 52; $p < 0.05$). However, it has to be noted that this result was excluded from the analysis, since schools and Universities were permanently closed during the entire period of reference.

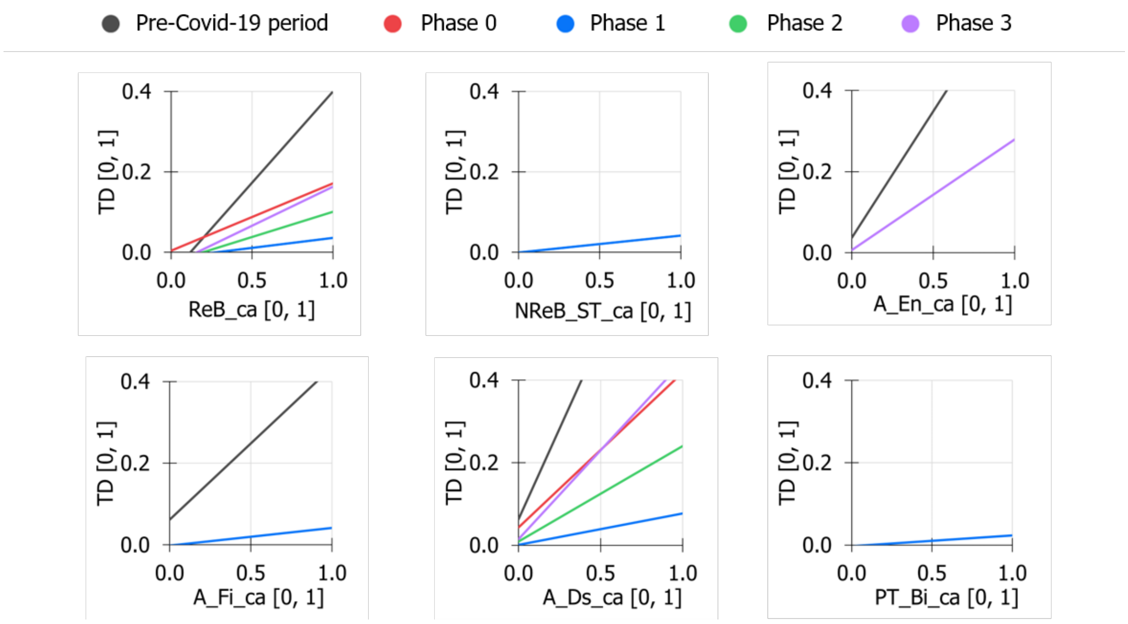


Fig.7 Linear trend lines show (when applicable and significant) the correlation results between Wi-Fi data (TD) and the land and Public Transport data extracted on catchment areas (z values in a range between 0 and 1)

Data	TD_Pre-Covid-19	TD_Phase 0	TD_Phase 1	TD_Phase 2	TD_Phase 3
ReB_ca	0.449**	0.354*	0.379**	0.430**	0.371**
NReB_Ad_ca	0.002	0.002	-0.037	-0.025	0.020
NReB_Co_ca	-0.168	-0.176	-0.142	-0.164	-0.018
NReB_In_ca	0.109	0.192	-0.003	0.013	0.118
NReB_ST_ca	0.326	0.149	0.371**	0.222	0.253
GA_ca	-0.085	-0.021	n/a	-0.171	-0.082
A_Ed_ca	0.390*	n/a	n/a	n/a	n/a
A_En_ca	0.643**	n/a	n/a	n/a	0.544**
A_Fi_ca	0.372*	0.206	0.338*	0.259	0.253
A_He_ca	-0.130	-0.145	-0.002	-0.069	-0.125
A_Su_ca	0.156	0.061	n/a	0.135	0.104
A_Sh_ca	0.274	0.231	n/a	0.254	0.197
A_Ds_ca	0.761**	0.696**	0.509**	0.701**	0.722**
PT_Bi_ca	0.253	0.112	0.306*	0.216	0.226
PT_Su_ca	0.289	0.164	0.154	0.133	0.174
PT_Tr_ca	0.047	-0.015	-0.047	-0.087	-0.063
PT_Bu_ca	-0.003	0.093	-0.054	0.121	0.060

Tab.4 Corrected Pearson's coefficient and adjusted p-values related to the correlation results between traffic data and the land and Public Transport data extracted on catchment areas (. Correlation is significant at the .01 level; *. Correlation is significant at the .05 level)**

3.4 Suitability Analysis Index

Focusing on the number of mobile devices detected during the Pre-Covid-19 period, the executed correlation analysis showed that some of the considered land and Public Transport data were effective indicators of higher Wi-Fi data, with reference to residential buildings (ReB_ca), education amenities (A_Ed_ca), entertainment amenities (A_En_ca), financial amenities (A_Fi_ca) and department store (A_Ds_ca). This was further analyzed to identify the areas of Milan which could be suitable for more extensive traffic data collection campaigns. Thus, a Suitability Analysis Index (SAI) was defined through the density distribution of relevant data on the entire territory of Milan:

$$\sum_{k=1}^{0} = {}_{K\_ReB}\, ReB(ce) + {}_{K\_A\_Ed}\, A\_Ed\ (ce) + {}_{K\_A\_En}\, A\_En(ce) + {}_{K\_A\_Fi}\, A\_Fi(ce) + {}_{K\_A\_DS}\, A\_DS(ce)$$

The proposed index was calculated through the weighted summation of normalized density distribution of values (z values in a range between 0 and 1) on the H3 hexagonal grid proposed by Uber Engineering in 2018. Among the several resolutions available for the H3 grid, the current work adopted the one characterized by cells with an average diameter of the circumscribed circle of 395 meters, in line with the commonly known comfortable walkable distance of 5 minutes (Buhrmann et al., 2019). The constant parameters K_ReB (corresponding to 0.15), K_A_Ed (corresponding to 0.15), K_A_En (corresponding to 0.15), K_A_Fi (corresponding to 0.15) and K_A_DS (corresponding to 0.4) were weighted by discretizing the r results of spatial autocorrelation analyses[11] (Lee Rodgers and Nicewander, 1988) (see Tab.4), in order to accentuate the impact of A_DS on SAI (∑ constant parameters = 1). Results (see Fig.8) showed the areas of Milan which could be effectively exploited for extensively monitoring high traffic data by means of the installation of additional Wi-Fi sensors (areas characterized by SAI ≥ .8). The granularity and widespread coverage of results showed the suitability of both central and peripheral areas of the city, as well as the overlap of the modeled data with the major transport infrastructures.

[11] The constant parameters related to strong (K_A_DS) and moderate correlation results (K_ReB, K_A_Ed, K_A_En and K_A_Fi) respectively correspond to .4 and .15.

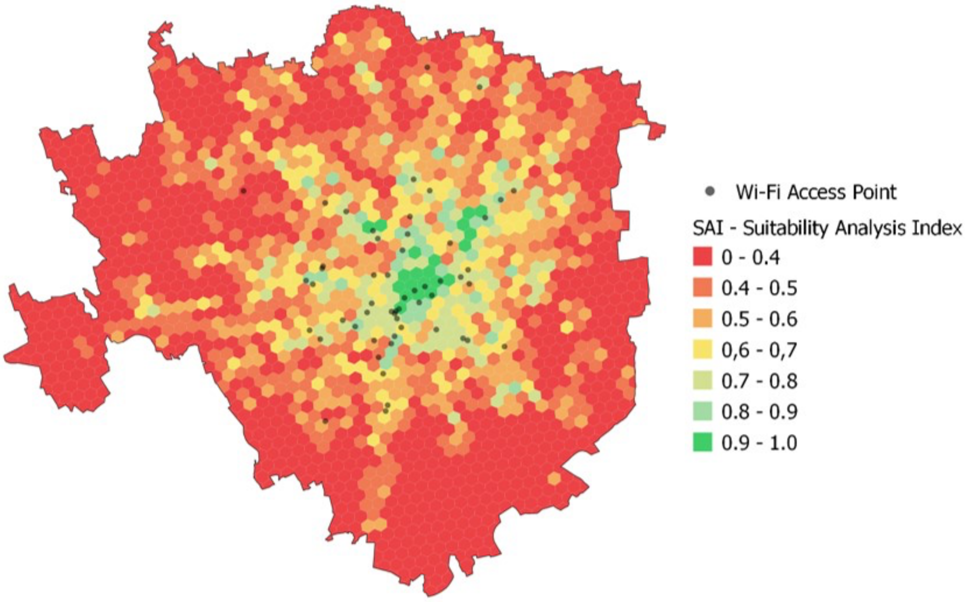


Fig.8 The map shows the results of proposed Suitability Analysis Index, aimed at identifying the areas of Milan which could be suitable for the installation of additional Wi-Fi sensors to collect traffic data (areas characterized by SAI ≥ .8)

4. Discussion

The development of location detection systems (e.g., image stream, radio frequency, cell network, bid stream, light pulse techniques) enables to monitor, understand and predict the mobility patterns of the city users. In particular, Wi-Fi technology is recognized as one of the most effective sensors for monitoring activity patterns with high spatial and temporal granularity (e.g., installation and maintenance costs, precision rate, energy consumption, robustness to weather and light conditions, compliance to the GDPR). However, the capability of this technology to collect reliable traffic data is limited by systematic under sampling and oversampling errors (Soundararaj et al., 2020) and by the difficulties in distinguishing traffic flow typologies (e.g., vehicular, pedestrian, etc.).

In this context, the proposed study was based on the analysis of a large sample of data collected during a 7-month period (January to July 2020) through a network of 55 Wi-Fi sensors distributed in Milan. The research was firstly aimed at testing the effectiveness of Wi-Fi technology to gather aggregated traffic data in large scale scenarios. From a general point of view, the achieved results confirmed the effectiveness of this data collection method for characterizing the evolution of the lockdown phases and activity patterns. The robustness of the proposed analysis of Wi-Fi data trends among the lockdown phases is based on the use of the same set of sensors, which has been preliminary validated among few malfunctioning Wi-Fi APs.

However, the accuracy of the presented results could be limited by an under sampling error due to technical, territorial and social factors: (i) mobile devices' sensitivity (e.g., connection features, battery level, orientation, etc.); (ii) arbitrary location of the Wi-Fi APs with respect to the entire territory of the city of Milan, as distributed in several department stores, shops and public services; (iii) socio-demographics characteristics of the population related to mobile devices' ownership; and (iv) partiality of the considered sample size compared to total amount of daily trips related to number of inhabitants (1,242,120) and workers (1,016,790) of the city of Milan (ISTAT-Italian National Institute of Statistics, 2011). Furthermore, the reliability of the collected data could be limited by an over-sampled representation of the population linked to: (v) possibility of a user of carrying multiple devices; (vi) multiple probe requests from a single mobile device to a Wi-Fi AP; and (vii) background noise due to fixed devices (e.g., routers, desktop computers, etc.).

In order to mitigate oversampling inaccuracies, filtering and clustering procedures have been taken by the data provider by removing probe requests from fixed devices, as well as by associating consecutive probe requests to the correct user. However, data sampling is estimated by the provider at being 2-10% above ground truth. Thus, future steps of this research will be based on further developing of a methodology to filter out background noise and improve data accuracy. Moreover, taking advantage of previous works already performed by the authors[12], future work will be based on the use of computer vision techniques (Zhao et al., 2019) to cross check the validity of Wi-Fi-based traffic data through images stream acquisition systems. Existing CCTV infrastructures or ad hoc installed cameras could be coupled with Wi-Fi sensors, with the aim to obtain comparable analyses and a validation methodology on vehicles and pedestrian activity.

5. Conclusion and Future Work

Location detection systems are becoming a valuable support for the activity of transport planners and decision makers by unveiling hidden mobility patterns in cities. Nowadays, this has become even more crucial considering the unprecedented effects of disruption of the Covid-19 pandemic on urban mobility. In this context, the proposed study focused on the analysis of number of mobile devices detected through 55 Wi-Fi APs, placed in several shops, department stores and public services in the city of Milan. First, time series analyses unveiled relevant trends, peak hours and mobility profiles. Then, the number of mobile devices detected during the Pre-Covid-19 period and the lockdown Phase 0, 1, 2 and 3 was correlated to several city features, such as building typologies, green areas, amenities and Public Transport, through an extensive GIS-based analysis. Here, the main purpose was to understand which characteristics of the city would create resilient neighborhoods during the different phases of the Covid-19 pandemic.

Results showed that the concentration of both residential buildings (ReB_ca) and department stores (A_Ds_ca) was positively correlated with Wi-Fi data among all lockdown phases. The containment measures put into place during Phases 0, 1, 2 and 3 were based, in fact, on reducing or prohibiting any movements from place of residence, apart from health and emergency reasons and food shopping. Furthermore, results showed that the catchment areas characterized by the concentration of service and transportation facilities (NReB_ST_ca) and financial amenities (A_Fi_ca) were more resilient during the lockdown Phase 1, considering the relative distribution of Wi-Fi data. The increase of Wi-Fi data during Phase 1 around catchment areas characterized by the presence of bike-sharing docking stations (PT_Bi_ca) could be related, instead, with the city users' need to avoid crowded transport infrastructures by using safe and contactless travel options, such as cycling. Furthermore, the correlation analysis focused on the Pre-Covid-19 period showed that some of the considered land and Public Transport data were effective indicators of higher Wi-Fi data, with particular reference to the concentration of residential buildings (ReB_ca), education (A_Ed_ca), entertainment (A_En_ca) and financial amenities (A_Fi_ca), and department store (A_DS_ca). This analysis has notable implications for future applications, considering the possibility to forecast traffic data through time-invariant characteristics of the urban settlement. Thus, results were further analyzed to define a Suitability Analysis Index, aiming at identifying the areas of Milan which could be suitable for more extensive traffic data collection campaigns based on the installation of additional Wi-Fi sensors. Results of correlation analysis focused on the lockdown phases open up debate on the need to design cities to have a polycentric structure, with several and distinctive areas of attraction for the city users (i.e., *15-minute city concept*), in order to be resilient to extraordinary events such as the Covid-19 pandemic. Almost 70 years after Jacobs (1961) arguments for smaller and connected neighborhoods were published, the world is beginning to fully grasp the importance of mixed-use urban planning (Song et al., 2013). Such plans are also in keeping with the General Theory of Walkability proposed by Speck (2013), which states that the level of pedestrian friendliness of urban areas is directly related to their level of usefulness and attractiveness, pinned down in metrics of land-use mix, street

[12] See: https://research.systematica.net/journal/looking-with-machine-eyes-how-deep-learning-helps-us-read-our-cities/

connectivity and commercial density as well as poly-centricity to ensure service coverage within short walkable distances. Future work will be based on the development of Wi-Fi sensing applications for monitoring traffic data in near real time (Li et al., 2020), considering that the triangulation of APs enables both outdoor and indoor data collection (Soundararaj et al., 2020). The planned activity could support the management of crowd dynamics on occasion of big events (e.g., trade exhibitions, music, art and cultural festivals, sport events), characterized by the scarcely predictable impact of extraordinary touristic flows. In analogy with the pilot study proposed by Transport for London (2019), the application of the Wi-Fi technology to monitor traffic data in real time in mass-transit and gathering facilities could enable, in fact, to assess the contextual conditions of service, detect anomalies, avoid service disruption and guarantee the comfort and security of the users.

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Fig.5: Systematica Srl;

Fig.6: Systematica Srl;

Fig.7: Systematica Srl;

Fig.8: Systematica Srl.

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