Occupant density impact on building maintenance: Data-driven approach for university buildings

COVID-19 IMPACT ON UNIVERSITY BUILDINGS MANAGEMENT: A DATA-DRIVEN APPROACH TO MAINTENANCE ISSUES

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Abstract

Emergency conditions due to the COVID-19 pandemic altered the buildings use, thus affecting their planned management. Several public buildings were often left empty or occupied by a limited occupants' number, impacting maintenance needs and activities. This research adopts a data-driven approach to evaluate the COVID-19 pandemic impact on maintenance activities of a set of university buildings. Experimental data about occupants' presence and maintenance work orders (WOs) before and during the pandemic phases were collected. Results show how the reduction of occupants' number in the lock-down phase impacted the number, but not the typologies, of WOs. Then, WOs number grew back and reached pre-COVID-19 levels despite the limited occupants' number. The pandemic also seemed to alter the end-users' urgency perception of the necessity of maintenance activities, moving towards more negative sentiment scores. A model for occupants' density-WOs number correlation is also provided to support maintenance needs assessment by building decision-makers.

Keywords

COVID-19, Pandemic, Facility management, urgency perception, maintenance, data-driven approach

1. Introduction

When the World Health Organization (WHO) declared COVID-19 as a pandemic, citizens around the globe were asked to remain home to support social distancing measures, and then to reduce the fast spreading of the contagion [1,2].During lock-down periods, several public spaces such as restaurants and places of worship were closed [3], while the regular access to public and private offices, industries and schools was not allowed or significantly limited [4], requiring a quick transition towards different organization models and consequently stress on private and public organizations [1].

The practice of smart working increased, extending, to a large amount of population, flexible and remote-access work models [5]. Schools and Universities also reduced (or even suspended) didactic activities, implementing parallel in-situ and remote lessons to grant enough flexibility for the students in respect to the pandemic evolution and measures adopted in each country [6]. A tangible effect of these changes was the lowering and the shift of energy consumptions [7–9]. For instance, recent research shows that the mean energy demand decreased in a range of 14.3 to 18.7% in a Swedish district comprising residential buildings, offices, schools and retail shops [10]. On the contrary, COVID-19 lock-down measures caused an increase in domestic energy consumption [11].

Nevertheless, despite the very limited number of occupants, especially during strict lock-down phases, each public and private organization adopted specific countermeasures and safety protocols in their own buildings still open to the public to grant the effectiveness of measures suggested by WHO [1]. Management strategies based on individual safety measures and working protocols (e.g. social distancing, wearing a facemask, team arrangement and crowd density control) [12] were combined to building operation solutions, such as those concerning thermal control and proper management of the building equipment and services such as Heating, Ventilation and Air Conditioning (HVAC) systems, and elevators.

ASHRAE published specific Guidelines on March 2020, arguing the necessity to increase the amount of outdoor air in ventilation systems, disable demand-controlled ventilation (DCV), improve the level of the central air filter, keep the system running longer, and if possible, 24 hours a day, 7 days a week [13]. The consequence was the necessity to adopt variable operational plans for HVAC systems and services, depending on the allowed occupants' number during the different period of the pandemic, with a strong effect on facility management activities. Meanwhile, elevators were recognized to be significant closed environments for the contagion spreading because of their dimension and recurring use by occupants. The normal elevator operation was then altered, and the alternative use of stairs was promoted. Car capacity limitations were introduced in several countries [14].

As a consequence, pandemic obliged buildings owners and managers to change operational and maintenance plans, mainly in view of the increase of HVAC requirements and the reduction of other types of services, with possible impact on building Operation and Maintenance (O&M) cost and maintenance strategies [13].

It is important to consider that already today, O&M cost impacts about 75% of the overall buildings' costs during their life cycle [15–17] and that the pandemic could cause structural changes in future maintenance needs with a possible crisis of already adopted maintenance strategies [18–20]. Methods proposed along the time to increase the efficiency of the maintenance plans could then require improvements [21–23], bearing in mind the lesson learned with the pandemic event.

Despite the drama caused by the pandemic, with over two million deaths over the world to date, COVID-19 then can become an important occasion to understand how a pandemic event can affect the use of buildings and the related maintenance plans. Data-driven approaches can be used to estimate the effects of such conditions on the building management and maintenance issues, and then to share analyzed data with facilities and building decision-makers and contractors, thus promoting them to implement informed and optimized strategies [2,24,25]. Existing methods to collect information on maintenance, and to analyze and improve the effectiveness of the related strategies, could be used for this purpose [25–30]. These methods comprise automated inspection [31–36], intelligent control [17,24,37–39], natural language processing methods [40–48] and sentiment analysis methodologies [16,49,50]. However, to the authors' knowledge, to date, no information is available in the literature on the effect of the COVID-19 pandemic on buildings' O&M procedures.

In order to provide one of the first contributions in this field, this research analyzes the impact of the COVID-19 pandemic on the maintenance activities of a set of university buildings, thanking to data analysis on a real case study. These buildings host both offices and educational spaces and represent a significant case-study in the public buildings' context. Work Orders (WOs), that are the maintenance requests from end-users (i.e. occupants) solved by maintenance staffs, were analyzed comparing their trends before and during the COVID-19 pandemic, basing on text and data mining approaches [16]. Experimental data on daily effective occupants' presence and WOs were collected for 34 months. Data about the perception of maintenance activity by occupants were also analysed [16,49,55]. Finally, according to the pursued data-driven approach, WOs in the two different periods (before and during the pandemic) were compared to evaluate changes in the O&M actions and to define correlations between the WOs and the occupants' presence, thus providing the bases for automated tools for maintenance needs assessment and prediction.

2. Materials and methods

2.1. Building classification and occupants' presence

The analyzed building stock comprises 23 buildings of the Polytechnic University of Marche, placed in Ancona (Italy), and was selected as a significant case study because it includes offices, educational spaces, and laboratories. The Gross Floors Area (GFA) of the overall building stock is about 152000 m^2. These buildings normally (i.e. in no-pandemic contexts) host a population of about 16.000 students and about 1600 workers (permanent and non-permanent staff: teaching staff, researchers including PhD and post-doc fellows, technicians, administrative workers).

Figure 1 shows the localization in the urban context and the aerial view of the main university campuses and faculties, while Table 1 summarizes the main characteristics of each related building (i.e. year of construction/rehabilitation, GFA [m^2], number of floors, overall number of seats in classrooms for educational buildings), also classifying the buildings according to their main intended use.

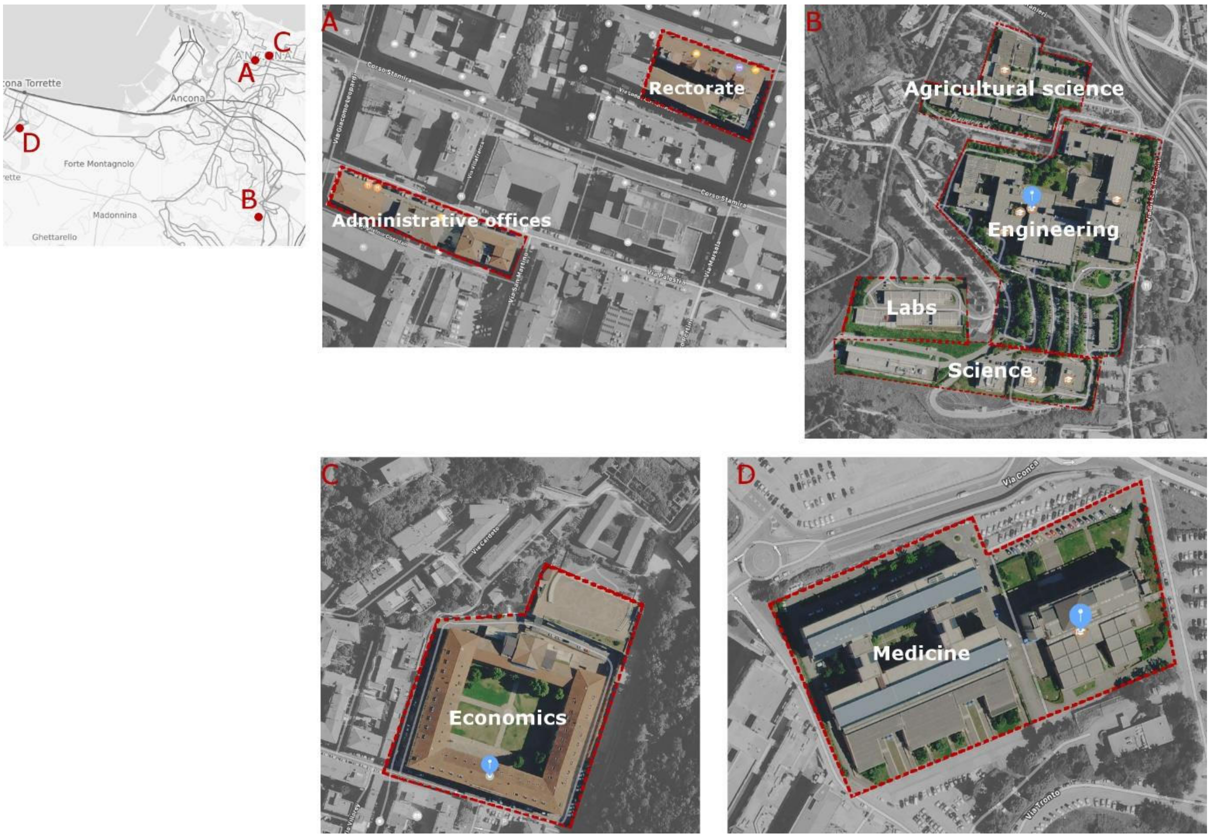

Figure 1 Building stock of the Politechnical University of Marche considered in this work: general map of Ancona, Italy (left, background from Open street maps) with the position of each campus/faculty shown in Table 1, and related aerial views (right, background from Google maps).

Data on daily occupants' presence in each building of the university have been collected for 34 months, from January 2018 to October 2020.

During the whole monitored period, the workers' access was allowed through a personal badge, thus ensuring the direct collection of the workers' number for each building. Restrictions to the workers' access have been provided during the COVID-19 period, but the use of the personal badge always allowed to precisely monitor the number of workers inside the buildings.

Data on students' number have been collected differently before and during the pandemic. Before the COVID-19 pandemic (from January 2018 to February 2020), educational buildings were attended by students depending on the hosted didactic activities. During the lesson's periods (September-December and March-June), the number of on-site students depended on the lessons timetable organization. For each course, the effective number of enrolled students in each course, weighted by the mean percentage of non-frequenting students, was calculated. During the exam periods (July-August and January-February), data from the exam University database, which collects the daily presence of each enrolled student at each course exam, were considered to calculate the number of on-site students.

During the first phase of COVID-19 pandemic (from the 3rd of March to the 31st of August 2020), students did not have access to the university buildings, because of Italian national regulations for contagion limitation supporting the full "lock-down" strategies. Full remote access to didactic activities and exams were provided using digital platforms. Therefore, the number of on-site students was very limited, considering that only few of them obtained specific authorizations to reach university, i.e. to conclude thesis work. Thus, the on-site students' number was calculated basing on the authorization process data.

During the second (second half of June to August 2020, as a "partial lock-down" phase) and third (September and October 2020, as a "partial reopening" phase) COVID-19 phases, the university buildings partially reopened to students attending exams and lessons. The student's presence was monitored through a specific APP, named *UnivpmAgenda*, introduced to track the effective presence of students as imposed by national regulations. Each student had to book in advance, generate a QR-code and register the presence with this code on tablets at the entrance of the buildings. Thus, during the COVID-19 pandemic, the students' number was calculated thanks to booking systems data.

Basing on the sum between the workers' and students' number, the daily occupants' number was calculated for each building of the campus. Then the occupants' number was averaged on a monthly basis and considering the reference periods ("mean daily occupant's number"): before COVID-19; during COVID-19; and during each COVID-19 phase ("lock-down", "partial lock-down" and "partial reopening"). Finally, the occupants' density (people/m^2) was calculated as the ratio between the mean daily occupants' number (excluding holidays) and the GFA.

Main building intended use	**Campus/faculty**	**Building**	**Year of Construction / Rehabilitation**	**GFA [m^2]**	**Number of floors**	**Classroom Seats**
Administration	RECTORATE	RECT	1976	1560	6	-
	ADMINISTRATIVE OFFICES	ADM_OB12	1976	1200	4	-
		ADM_OB8	1976	1620	4	-
Educational & Research	SCIENCE FACULTY	S1	1997	2700	3	458
		S2	2004	2700	3	45
		S3	2008	2700	3	144
	MEDICINE FACULTY	EUS	1995	16400	7	1214
		MUR	2008	7400	6	1410
	ENGINEERING FACULTY AND LABS	AMA	1990	2750	1	670
		B1	1990	8505	6	610
		B1Bis	1990	2916	3	360
		B2	1990	10206	3	220
		B3A	1990	5103	3	1710
		B3B	1990	5670	4	868
		B4	1990	8748	3	331
		B5	1990	11664	3	410
		BAS	2005	5052	3	1508
		PMS	1990	2592	4	212
		TOW	1990	3564	11	140
	ECONOMICS FACULTY	EC	1996	20400	4	2761
		AB1	1982	3000	4	-

	AGRICULTURAL SCIENCE FACULTY	AB2	1982	1470	2	1025
		AB3	2002	350	1	262

Table 1 Main characteristics of the analysed buildings.

2.2. Maintenance work orders analysis

The maintenance Work Orders (WOs) produced for 34 months (from January 2018 to October 2020, hence before and during the COVID-19 pandemic) have been collected in collaboration with the facility management contractor (ANTAS). They were then analyzed, obtaining the temporal distribution of anomalies and faults in the buildings' components and systems and the related maintenance (including repairing and replacement) interventions.

WOs from the end-users are organized into 7 types of interventions depending on the equipment/system/component to be maintained:

1. *"electrical"*, including lighting, power systems, local area networks and internet accesses;
2. *"building components"*, referring to building construction components, such as walls, doors, windows;
3. *"HVAC"*, referring to Heating, Ventilation, Air Conditioning and Cooling units;
4. *"plumbing"*, including sanitary systems;
5. *"fire"*, including all the fire safety equipment (fixed and moveable) and building components;
6. *"dialer alarm"*, including all the alarm systems (e.g. security, fire, control of all the building systems);
7. *"elevator"*, including all the related parts, such as cabins, motors and their equipment.

A total number of 10281 WOs was processed considering the whole 34 months-long period. As for occupants' presence, WOs data were divided into two main blocks to compare trends before (January 2018 to February 2020) and during (march-October 2020) the COVID-19 pandemic. Furthermore, a random sample of each data-block (and of each sub-block referred to each COVID-19 phase) has been considered to obtain data frames characterized by the same length and the same proportion of end-users' requests by type.

WOs were essentially exchanged by e-mail from the end-users to the technicians involved in the maintenance activity. Since each WO process begins with the reporting of anomalies or faults by non-technical personnel, the information provided consists of unstructured textual data including the personal perceptions about the importance and urgency of the reported anomaly. Thus, text mining and sentiment analysis [55–57] on the WOs sentences have been performed through the "Orange" machine learning and data visualization python tool (version: 3.26; https://orangedatamining.com/). Sentences were translated into English language and preliminary treatment of the textual information has been performed [55,58–60]. For each sentence, VADER (Valence Aware Dictionary for sEntiment Reasoning) scores were calculated. VADER methodology comprises the calculation of four "sentiment" scores (positive, negative, neutral, compound). The compound score is a synthetic score computed by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive) [61,62]. WOs were also analyzed in terms of three levels of severity (low, medium and high) [16], depending on the presence of a list of the most frequent related words in textual communication. High severity words are typically used when an immediate repair or action is required (e.g. urgent, safety, emergency, alarm, fire). On the contrary, the words related to low severity are the ones used when a repair or action can be postponed and planned (e.g. have a look, change, verify, clean, paint). Finally, requests not classified in any of the previous categories are defined as of medium severity [16].

Correlations between building characteristics, occupants' density and number and type of WOs, were performed using both parametric and non-parametric tests through the statistics language "R" (version: 4.0.3) [63] and the "stats" package (https://cran.r-project.org/package=STAT). Analyses were carried out on data relating to the whole analysis period, and to the pandemic phases. The Shapiro–Wilk normality test was first used to test the normality hypothesis of the related distributions [64]. The Pearson's coefficient has been considered for normally-distributed samples to measure the presence of a linear correlation between the occupants' density and the number of WOs per square meter. This correlation has been mainly considered to make these two data comparable in terms of the building dimension, expressed by the GFA. Furthermore, the Spearman's rank has been adopted, to investigate the association between all the paired data, thus including also those that could be not considered as normally distributed.

Finally, a regression model has been developed between monthly WOs and occupants' density through a Matlab routine (version: 2020a), to provide maintenance prediction rules depending on the occupants' presence.

3. Results and discussion

3.1. Occupants' presence before and during COVID-19 pandemic

According to the experimental data on the occupants' presences,

Figure 2 shows the occupants' density in the whole buildings stock for the whole 34 months-long period. Until February 2020 (included), the occupants' density is mainly influenced by the didactic activities. We can observe a sinusoidal trend depending on the alternate lessons and exams periods.

As expected, from March to June 2020, the drastic density values reduction is due to the full lock-down period in Italy. After a localized lock-down in some areas of Lombardia and Veneto regions, a generalized lock-down approach was introduced on the 5th of March. All schools and universities were closed, and didactic activities were remotely performed using digital platforms. On the 22nd of March, industries were stopped, while public and private offices were closed. Only at the end of April, when the Rt index fell below 0.5 some activities were reopened. The occupants' density in this period was mainly due to the workers' presence, although most of them could have restricted access because of national lock-down rules.

Year	Month	Occupation density (People/m2)	Period	Opening type
2018	1	0.042	pre-covid	FULL OPENING
	2	0.035		
	3	0.064		
	4	0.059		
	5	0.079		
	6	0.043		
	7	0.031		
	8	0.013		
	9	0.049		
	10	0.073		
	11	0.077		
	12	0.066		
2019	1	0.039		
	2	0.044		
	3	0.076		
	4	0.067		
	5	0.072		
	6	0.036		
	7	0.033		
	8	0.012		
	9	0.057		
	10	0.092		
	11	0.090		
	12	0.086		
2020	1	0.043		
	2	0.043		
	3	0.004	covid	LOCK-DOWN
	4	0.004		
	5	0.004		PARTIAL LOCK-DOWN
	6	0.002		
	7	0.006		
	8	0.001		PARTIAL REOPENING
	9	0.016		
	10	0.020		

Figure 2 Occupation density averaged for each month, during the 34 months-long considered period (January 2018 to October 2020), by also distinguishing the opening phases with respect to COVID-19 pandemic.

In June 2020, national regulations suspended the strict lock-down, but overcrowding limits were maintained to grant WHO measures application, including remote-access strategies for didactic

activities. In July 2020, density values increased again due to the on-site exams' activities. The occupants' density in August 2020 was quite low as in the previous years, due to summer holidays.
Finally, in September 2020, density values grow up in comparisons to the previous months, since national regulations allowed educational organizations to start on-site activities limiting the number of students for each classroom. Anyway, the occupants' number remained lower than in 2018 and 2019, as students were able to choose whether to attend on-site classes or follow them by digital platforms.
The overall data trend relating to COVID-19 period reflects the timing of contagion spreading and safety strategies implementation, such as that detected in the Asia region [65] or other areas [7,66–72].

Campus	**Building**	**GFA [m^2]**	**Mean daily occupants' number [persons]**		
			FULL OPENING (January 2018 – February 2020)	**During COVID19 (March-October 2020)**	**Variation %**
AGR	AB1	3000	375	44	*-88%*
	AB2	1470	807	124	*-85%*
	AB3	350	211	14	*-93%*
ECO	EC	20400	2071	297	*-86%*
ENG	AMA	2750	491	43	*-91%*
	B1	8505	428	54	*-87%*
	B1Bis	2916	245	34	*-86%*
	B2	10206	157	26	*-83%*
	B3A	5103	1,315	154	*-88%*
	B3B	5670	655	71	*-89%*
	B4	8748	238	31	*-87%*
	B5	11664	299	38	*-87%*
	BAS	5052	1,137	142	*-88%*
	PMS	2592	156	16	*-89%*
	TOW	3564	102	20	*-81%*
MED	EUS	16400	891	97	*-89%*
	MUR	7400	1,016	129	*-87%*
SCI	S1	2700	371	51	*-86%*
	S2	2700	157	21	*-86%*
	S3	2700	169	23	*-86%*

Table 2 Mean daily occupants' number on the whole period before (FULL OPENING) and during the COVID-19 pandemic for each building.

Table 1 Table 2 shows the mean daily occupants' number of students and workers for each educational and research building, before and during the pandemic (whole period from March to October 2020). These buildings are shown because of occupants' presence differences are maximized with respect to the administrative ones, due to the prevalence of educational spaces in the GFA and students' number and use, as discussed above. Table 3 resumes the related values for each campus of the university, and for the whole university, by distinguishing the values for the three COVID-19 emergency phases as in Figure 2 and their variations in respect to full opening conditions. Table 2 and Table 3Table 2 confirm the abovementioned trends, by stressing how small differences in building use existed between strict and partial lockdown (ranging from about -95 to -70% of occupants' number depending on the COVID19 emergency phase and on the considered campus).

Campus	FULL OPENING	LOCK-DOWN	PARTIAL LOCK-DOWN	PARTIAL REOPENING
AGR	1393	72 (-95%)	125 (-91%)	432 (-69%)
ECO	2071	133 (-94%)	198 (-90%)	692 (-67%)
ENG	5552	274 (-95%)	465 (-92%)	1411 (-75%)
MED	1908	119 (-94%)	187 (-90%)	446 (-77%)
SCI	697	42 (-94%)	75 (-89%)	208 (-70%)
TOTAL	**11621**	**640 (-94%)**	**1050 (-91%)**	**3189 (-73%)**

Table 3 Mean daily occupants' number in pre- (FULL OPENING) and during-COVID-19 phases for each campus and related percentage variations in respect to the full opening scenario.

3.2. Work orders before and during COVID-19 pandemic

Figure 3 shows the monthly number of WOs from the end-users and the contextual occupants' density during the monitoring period of 34 months (from January 2018 to October 2020), for each type of WO and considering the whole building stock.

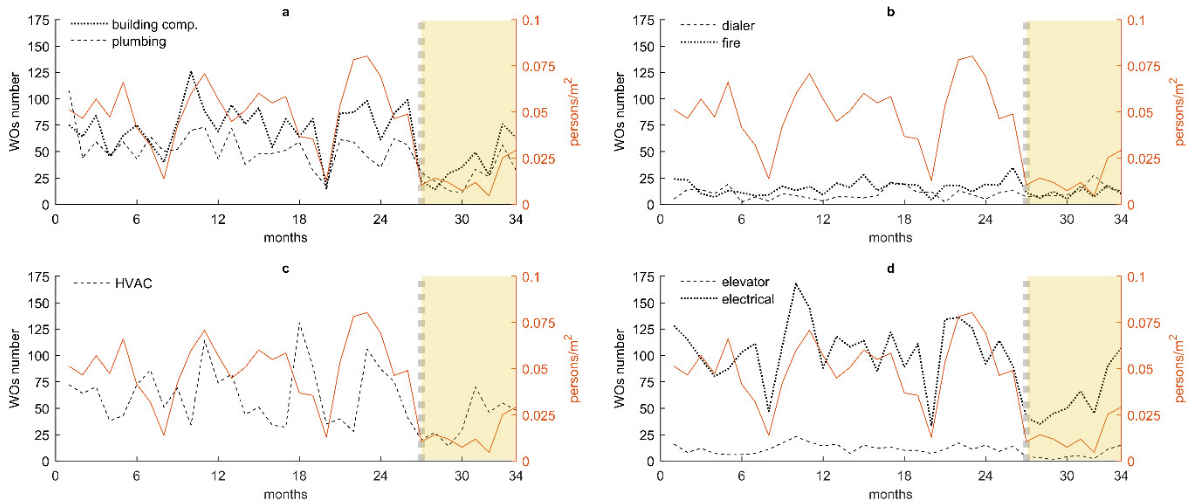

Figure 3 Monthly WOs number (black line, left y-axis) in comparison with occupants' density (red continuous lines, right y-axis) before and during the pandemic (month 1 is January 2018; COVID-19-related period stressed by the yellow area), for the whole building stock, considering the following WO

typologies: a) building components and plumbing; b) dialer alarm and fire; c) HVAC; d) elevator and electrical.

The comparison of the monthly WOs number before and during the pandemic reveals a general WOs reduction due to the starting of strict lock-down measures on March 2020 (month 27). The maximum reduction ranges from -5 to -70%, depending on the WOs type. This reduction is associated with the occupants' density decrease of about -94% (see Table 3). The most important reduction characterizes Elevator WOs (-70%), probably due to both a limited use as high-exposure closed environments [14] and to the lowest occupants' density [54].

However, differences between the campus of the university exist, considering the percentage variations in the mean monthly number of WOs before and during COVID-19, as shown in Table 4.

The analysis of these data underlines the different activities carried out in the university campus/faculty. It is worth noticing that WOs concerning "*Fire*" and "*Dialer alarm*" in the Agriculture Science Faculty grew because of interventions performed during the pandemic period. Such interventions concerned fire equipment and related building components (e.g. restoring extinguishers and fire doors), and other building systems (leading to requests due to their control alarms activation).

	AGR	**ECO**	**ENG**	**MED**	**SCI**
Building components	-35%	-63%	-66%	-61%	-40%
Dialer alarm	1580%	0%	-28%	-26%	0%
Electrical	-40%	-64%	-65%	-56%	-52%
Elevator	-100%	-87%	-70%	-53%	-38%
Fire	168%	-94%	-65%	-49%	13%
HVAC	-63%	-37%	-65%	-46%	-49%
Plumbing	100%	-60%	-66%	-70%	-44%

Table 4. Percentage variation of the mean monthly number of WOs for each campus during COVID-19 with respect to pre-COVID-19 period.

Table 5 shows the proportion of WOs before and during the pandemic, among the considered typologies.

Type	**PRE-COVID-19**	**DURING-COVID-19**
Building components	22.27%	20.60%
Dialer alarm	3.07%	6.53%
Electrical	31.87%	30.80%
Elevator	3.00%	2.80%
Fire	4.80%	5.60%
HVAC	18.13%	19.33%
Plumbing	16.87%	14.33%
Total	100%	100%

Table 5. Proportion of WOs in pre- and during-COVID-19.

"*Electrical*" and *"building components*" typologies have the greater WOs number, both before and during the pandemic, mainly because of their largest and widespread number of installed appliances/elements in respect to the GFA. On the contrary, a reduced number of WOs is performed in the category "*elevator*", because numerically less relevant. However, it is noteworthy that a minor WOs number does not imply minor importance of the maintenance operation: for instance, an elevator's fault has a relevant impact on building operation, compared with a lamp's fault, even if this could be more frequent. The proportion relating to "*building components*", "*electrical*", "*plumbing*" and "*elevator*" WOs decreased during the pandemic. Occupants directly interact with these building components and systems, thus increasing their maintenance needs. The reduction of occupants' number could have decreased the related proportion of WOs. On the contrary, WOs on "*HVAC*" slightly grew, essentially because of the increased operational and maintenance requirements during the pandemic and of the increased risk perception of end-users relating to contagion spreading in case of limited indoor ventilation (Guo et al., 2021; Shin & Kang, 2020). Data on "*Fire*" and "*Dialer alarm*" WOs were mainly affected by the aforementioned issues in the Agricultural Science Faculty buildings interventions.
Finally, important differences in WOs from end-users exist considering the different COVID-19 phases previously defined in Figure 2. Figure 4 shows the monthly mean of WOs number in respect to the global GFA before COVID-19 and during the three pandemic phases. This visualization aims to show the aforementioned impact of the WOs types in respect to the dimension of the buildings.

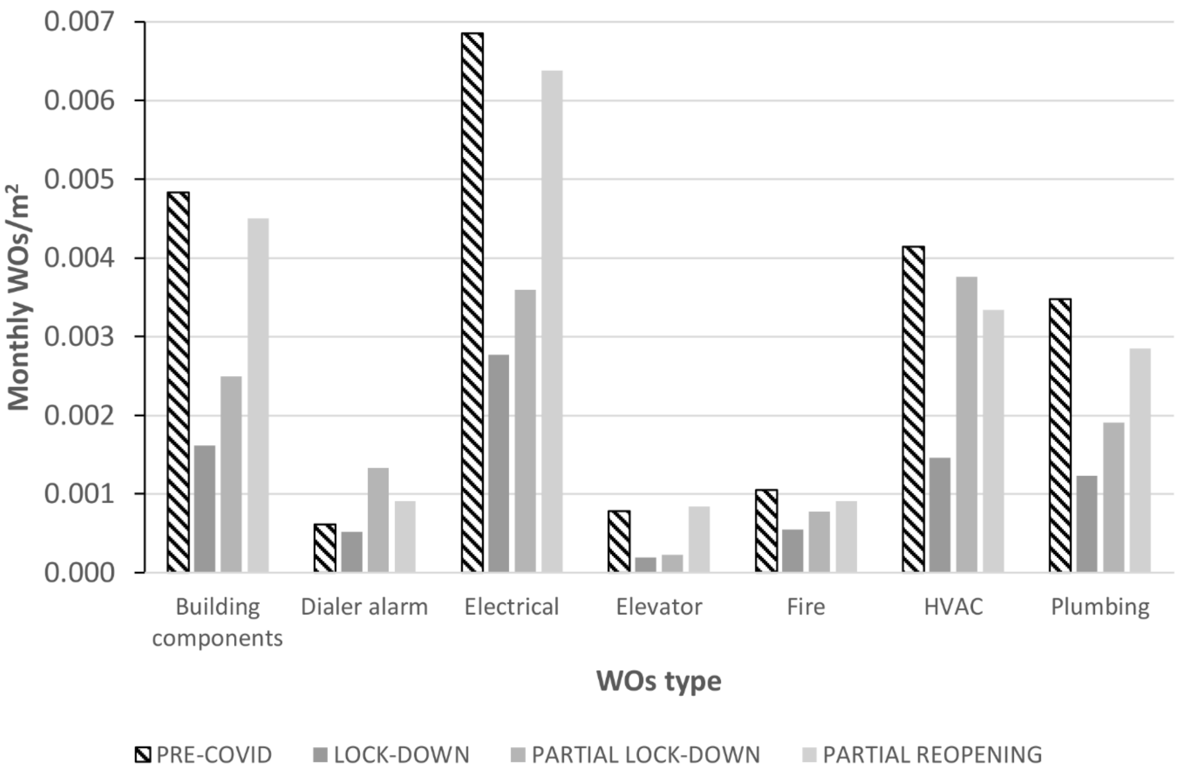

Figure 4 Monthly mean of WO number per GFA (m^2) during each analyzed period and considering the whole building stock.

During the first phase (strict lock-down), the number of WOs similarly falls by -62% for each WOs type (mean value for all the types). During the second phase (partial lock-down), we observe an upswing in the WOs number, according to the less strict limitations in the buildings access, as discussed above. The mean reduction is about -35% compared to the pre-COVID-19 period. Finally, during the third period, the number of WOs increases, thanking to the partial reopening of university buildings for exams and lessons, thus reaching a mean reduction of only -9% in comparison with the pre-COVID-19 situation.

3.3. Work orders severity level

Sentiment analysis has been performed to understand how the end-users' perception of the maintenance activities represented by WOs changed during the COVID-19 pandemic, through VADER sentiment polarity scores (compound) as shown in Figure 5 and Table 6.

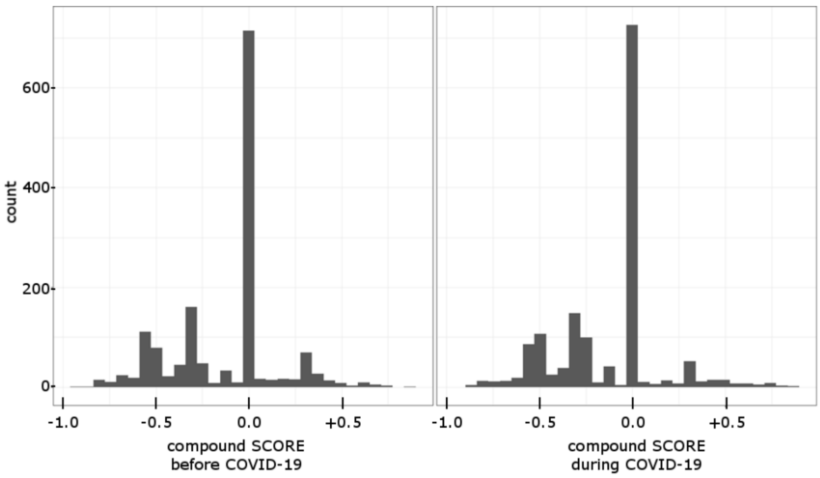

Figure 5 Sentiment polarity scores provided by VADER: before (left) and during (right) COVID

	Min	**25^{th} perc.**	**Mean**	**50^{th} perc.**	**75^{th} perc.**	**Max**
PRE-COVID19	-0.880	-0.318	-0.125	0.000	0.000	0.896
DURING-COVID19	-0.900	-0.340	-0.122	0.000	0.000	0.855

Table 6. Statistical description of compound score in VADER before and during COVID-19.

A slight shift of the "compound" score towards negative values, which is mainly shown by minimum, 25^{th} percentile-related and maximum values in Table 6

Differences in perceived severity exist considering the three COVID-19 phases. Before the pandemic, the percentage of "high severity problems" is 27.6% of the total, regardless of the WOs type. During the first strict lock-down phase, this percentage slightly increases up to 29.1%, probably due to the combination of two opposite factors. The lock-down phase caused a limited use of buildings and equipment, and therefore a reduction in the level of severity of WOs would have been expected. At the same time, however, the particular stressful situation may have created a more general increase in risk perception among occupants in building use.

This percentage additionally grows up to 34.4% in the second and third phases of the COVID-19 pandemic, characterized by partial lock-down and partial reopening, as in Figure 2. This reduction of restriction could have boosted a full awareness of the urgency of the problems to be solved thus justifying the sharp increase of WOs classified as "high severity" WOs. In general terms, this trend could be supported by the increased adoption of protective behaviours during the COVID-19 phases, which was associated with higher values of perceived severity and negative emotions [73].

However, the perceived severity varies with the WOs type. In general terms, similar trends are noticed before and during the pandemic in terms of "high severity" WOs types, as shown by Table 7. The increase of "*dialer alarm*" and "*fire*" values are mainly due to the impact of works in the Agricultural Science Faculty, as discussed above (see Table 5). As remarked above, "*HVAC*" WOs show a sligh increase of "high severity" WOs during the pandemic, thus suggesting how comfort issues in building use, generally associated to HVAC functioning, were summed to the the known correlation between these systems and the risk of contagion from the end-users' standpoint [13,74].

Type	**BEFORE**	**DURING**
Building components	22.90%	18.46%
Dialer alarm	9.88%	20.08%
Electrical	26.72%	20.08%
Elevator	1.29%	1.01%
Fire	12.16%	16.23%
HVAC	16.02%	16.23%
Plumbing	11.04%	7.91%
Total	**100.00%**	**100.00%**

Table 7. Proportion of "high severity" WOs by type, before and during COVID-19 pandemic.
Table 7.

3.4. Correlation between WOs and COVID phase

A preliminary Shapiro-Wilk test revealed that all the WOs typology data are normally distributed (p-value > 0.05) apart Dialer Alarm type, as shown by Table 8. To understand how occupants' density variation affected the quantity of WOs, a Pearson correlation test between monthly WOs and occupants' density was performed for each WOs type, and considering the whole 34-month long period. The dialer Alarm category was excluded due to the rejection of the null hypothesis of Shapiro-Wilk test.

	Building components	Dialer alarm	Electrical	Elevator	Fire	HVAC	Plumbing	Occupants’ density
W	0.96	0.93	0.95	0.98	0.95	0.95	0.96	0.95
p-value	0.31	0.03*	0.17	0.79	0.12	0.13	0.26	0.11
r	0.75	n.a.*	0.78	0.66	0.43	0.32	0.57	-

*Table 8. Shapiro-Wilk test results and Pearson’s correlation tests (r value as order coefficients) performed in respect of occupants’ density. Values lower than the threshold p-value (0.05) and thus not assessed (n.a.) by the Pearson’s correlation test are marked by *.*

Table 8 also shows the results of the Pearson correlation tests by means of the related r values, considering the mean monthly number of WOs per m^2, for each WOs type, and the related occupants’ density (people/m^2).

The highest r values characterize the correlation between occupants’ density and the following types: “*Building components*”, “*Electrical*”, “*Elevator*”, “*Plumbing*”. In this sense, the occupants mainly and directly interact with these building components and systems. On the contrary, a weak correlation appears for the “*Fire*” and “*HVAC*” WOs. In particular, for the “*HVAC*” WO, it should be noted that, during the lock-down phases, it was necessary to change the functioning of the ventilation systems, removing internal air recirculation and increasing airflow rates, as a precautionary measure in the WHO strategies context.

The Shapiro-Wilk test was repeated on the subset of data comprising only the pandemic period, thus demonstrating that data were non-normally distributed. Consequently, the Spearman’s test was performed on these data. According to the test, a positive association between “*Elevator*” WOs and occupants’ density (r=0.66) and between “*Plumbing*” WOs and occupants’ density (r=0.57) was shown during the COVID-19 phase. Such a result confirms the previous discussion on the general correlation trends of Table 4, Table 5 and Table 7. On the contrary, the Spearman’s r-values for “Building components” and “*Electrical*” are lower, probably due to the necessity to perform a continuous maintenance activity not depending on the number of people on-site.

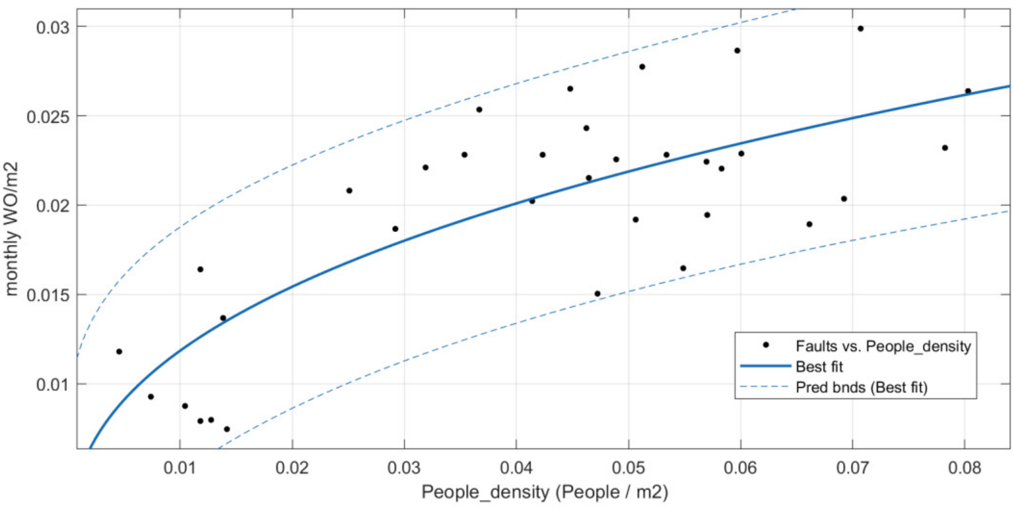

Figure 6 Fitting of Monthly WO/m2 and People density (People /m2)

Finally, Figure 6 shows the result of the fitting process performed to find a relationship between the occupants' density and the mean monthly WOs per m^2. Dotted lines are the confidence 90% bounds. According to a power-law approach (R = 0.61) as described in equation 1:

$y = a^x + b$ [1]

Where

y = mean monthly WO per m^2

x = occupants' density (People/m^2)

a = 0.0685

b = 0.3811

Considering that Table 5 shows that the shares of WOs typologies generated before and during the COVID-19 pandemic were almost the same (with percentage differences on average about 1.5%), the number of expected WOs for each WOs type could be derived by multiplying y (as in equation 1) for the expected percentages characterizing each WOs type (as in Table 5).

4. Conclusion

This research has shown the impact of the COVID-19 pandemic on maintenance activities in an educational context, by considering a university building stock composed of 23 buildings at the Polytechnic University of Marche, Ancona, Italy. Important building operation issues that characterized the different pandemic phases in terms of occupants' presence (students; teaching, technical and administrative staff) and maintenance work orders (WOs) were analyzed for this purpose. The occupants' density was calculated considering the effective building use and with respect to the total gross floor areas of the buildings stock. According to a data-driven approach, the effect of occupants' density on the WOs number and types was assessed, thus moving towards a predictive model to support building decision-makers in maintenance needs assessment.

From March until June 2020, we found a drastic reduction of the occupants' density, due to the strict lock-down strategy adopted in Italy. The mean occupants' density reduced in few days from 0.0547 to 0.0035 People/m^2. After this strict lock-down period, people density maintained low values if compared with the pre-COVID-19 situation, reaching 0.0123 people/m^2 in September-October 2020 (about 1/5 of the pre-COVID-19 value), when the university reopened and on-site lessons were allowed again, and just before the second infection wave in Italy.

WOs generated during these periods did not follow the same trend. Only in the first phase of the pandemic (strict lock-down period), we observed a relevant reduction, likewise to the reduction of in-situ occupants. Elevators are a significant example, since results show a significant correlation between occupants' density and WOs number. During the COVID-19 pandemic, suggested the occupants' limitation and the WHO-suggested restrictions on their use (as high-exposure closed environment) decreased their operation, and so the WOs number. On the contrary, other building systems needed a change in their functioning due to the WHO safety strategies, as for HVAC, thus pointing out a lower impact and correlation of occupants' density to the WOs number.

However, WOs reduced only in the first phase of the pandemic, when the lock-down measures actually stopped all the main activities at university. After these first months, WOs increased reaching almost the original values in October 2020 (-9% in respect to the pre-COVID-19 phase).

During the pandemic event, the severity perception of generated WOs also slightly changed. VADER sentiment analysis shows a shift towards negative scores, especially during the strict lock-down phase while the percentage of "high severity"-classified WOs increased too. This trend could be also due to a general increase in individuals' negative emotions and risk perception due to COVID-19 contexts. Anyway, further activities to evaluate such perception issues are needed.

Finally, the correlation between occupants' density and the mean monthly WO per m^2 has been performed, relying on experimental data, to derive a model able to describe the effect of the occupants' presence on the WOs needs, also in view of future variations in the on-site end-users' number due to emergency events. The cost of each maintenance intervention could be also included in the model, thus being useful also to estimate the expected maintenance costs and supporting decision-makers in both maintenance needs and cost assessment activities. In view of the above, this data-driven approach and the proposed predictive model could be extended to other kinds of buildings, as those open to the public, which use and functioning was and will be affected by closures due to COVID-19 contexts, as well as to other future pandemics.

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