Multimorbidity Clustering of the Emergency Department Patient Flow: Impact Analysis of New Unscheduled Care Clinics

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ABSTRACT

Background: In France, the number of admissions to emergency departments doubled between 1996 and 2016, leading to overcrowding. To cope with the resultant overcrowding, redirecting patients to new healthcare services is a viable solution, to spread demand more evenly across available healthcare delivery points, and render care more efficient. The goal of this study was to analyse the impact of opening new unscheduled care services on variations in patient attendance at a large emergency department.

Methods: We performed a before-and-after study investigating the use of unscheduled care services in the Aube Department (Eastern France), focusing on emergency department attendance of Troyes Hospital. We applied a hierarchical clustering based on co-occurrence of diagnoses, to divide the population into different multimorbidity profiles and study their temporal trends. A multivariate logistic regression model was constructed to adjust the period effect for appropriate confounders.

Results: In total, 120,718 visits to the emergency department were recorded over a 24-month period (2018-2019), and 14 clusters were identified accounting for 94.76% of all visits. The before-and-after analysis showed a decrease of 57.95 visits per week in 7 specific clusters, while the consumption of unscheduled health care services increased by 328.12 visits per week.

Conclusions: Using an innovative and reliable methodology to evaluate changes in patient flow through the emergency department, our results could help to inform public health policy regarding the implementation of unscheduled care services, to ease pressure on emergency departments.

Keywords: Emergency Medical Services, Cluster Analysis, Multimorbidity Patterns, Retrospective Studies, Health Services Research

BACKGROUND

In France, admissions to Emergency Departments (ED) doubled between 1996 and 2016, increasing from 10 to 20 million visits annually, corresponding to an average growth of 3.5% per year [1]. This has led to overcrowding and saturation of EDs, with negative repercussions on quality of care [2] and on working conditions for healthcare professionals. Given the complex, systemic nature of this problem, expanding ED capacity and employing more staff are insufficient solutions [3]. Only a detailed study of healthcare needs, including analysis of patient flow and patient expectations, will enable the development of adequate solutions for healthcare delivery [4–7]. While EDs can re-organize internal procedures to optimize patient flow and delivery of care [8, 9], such changes do not stem the ever increasing tide of patients coming to the ED. Redirecting "avoidable" ED visits towards other healthcare services, notably Unscheduled Care Services (UCS), which are alternative clinics that can treat patients with low acuity conditions [10–15], is therefore one of the main responses proposed by current reforms [16, 17].

To evaluate the impact of new UCS on demand for ED care, it is necessary to quantify patient inflow and characterise the dynamics of patient flow through the ED [18, 19]. Most previous studies in this field have focused on a global evaluation of avoided ED visits and the resultant economical savings due the lower cost of UCS [10–15]. Segmentation of the complex patient flow using a classification of ED visits could help to characterize the nature of patient profiles avoided, and consequently, better understand temporal variations in ED attendance [20].

In this regard, the analysis of multimorbidity patterns is an appropriate tool to model the complexity of patients in terms of the diversity and statistical co-occurrences of their health conditions [21–25]. Usually applied on populations of complex and chronic patients in a high multimorbidity context, many opportunities still reside to extend this analysis on broader contexts like diseases trajectories of patients [26, 27].

In this context, segmenting the overall ED patient flow using the diagnoses from the visits and disease clusters, could be an innovative and original approach to evaluating the structure of, and trends in ED

129 patient flow [22, 28, 29]. We hypothesized that modelling the profiles of patients attending the ED
130 could enable more detailed analysis of the impact of UCS on ED attendance. The aim of this study
131 was thus to investigate the impact of opening new UCS on patient flow through the largest ED in the
132 Aube Department (France).

133 **METHODS**

134 ***Study design and population***

135 We performed a before-and-after study of the consumption of unscheduled care in the Aube
136 Department in Eastern France, particularly at the ED of the hospital of Troyes. The event of interest
137 that changed the organisation of delivery of unscheduled care in Troyes was the opening between
138 October and November 2018 of two new UCS, offering services akin to convenient care clinics [30].

139 The population under study was the whole population of patients attending the ED of Troyes hospital
140 from 01 May 2017 to 28 April 2019. Troyes hospital is the largest hospital in the Aube Department,
141 with a population of 310,000 inhabitants and a medical density of 234.1 physicians per 100,000
142 inhabitants that is in the lowest quarter of the Departments in France. The hospital has 442 medical
143 beds, 127 surgical beds, and 63 beds dedicated to gynecology/obstetrics. In 2018, there were a total of
144 62,082 ED visits, and an average rate of use of 250 to 330 visits per 1,000 inhabitants within the
145 hospital's catchment area. With >45,000 annual ED visits, according to national statistics [31], the ED
146 of Troyes hospital is classed as having a very high volume of activity. The 2-year study period was
147 chosen to account for seasonal variations each year, without being impacted by the restructuration of
148 the ED circuit that was introduced nationally in 2016 [9].

149 ***Measured Variables***

150 The primary endpoint was the difference in patient flow, measured in visits per week, before and after
151 the opening of two new UCS, at the level of subgroups formed using clustering methods.

152 Three major types of information were recorded:

- Information about the patient stay, visit identifier, patient identifier, date of arrival at the ED and in subsequent wards, and the triage circuit followed at arrival. The triage circuit can be either the long circuit (normal evaluation and management), or the short (fast-track) circuit, i.e. a pathway for assessment and treatment of low-severity patients (usually minor injuries or benign medical conditions). We recorded discharge destination from the ED, patient status using the Patient State (PS) classification previously developed by our group [9] and indicating patient severity. Finally, if the patient was admitted to the hospital, the primary diagnosis was recorded according to the International Classification of Diseases 10th revision (ICD10).
- Information about prescriptions, including medication, biological and radiological examinations.
- Socio-demographic data about each patient, namely: age, sex, and area of residence (i.e. town or postal code).

Statistical analysis

A multimorbidity clustering method was developed and applied to determine the spectrum of patient profiles according to clinical characteristics. The detailed method is available online as Supplementary Methods S1 – Additional File 1. Using the co-occurrences of ICD10 diagnoses with block level representation, we applied a Hierarchical Agglomerative Clustering (HAC) [32] with a new measure of similarity, namely the relative risk :

$$\mathrm{RR}_{ij} = \frac{p_{ij}}{p_i p_j} \quad (1)$$

where p_{ij} designates the probability of diagnoses i and j co-occurring in sets of patients 'visits less than 6 months apart , and p_i and p_j are the marginal probabilities of occurrences that are used to weight the relation [33]. Here, the number of clusters was determined by the maximisation of a membership ratio (MR) criterion:

178 $$MR = \frac{RR_{intra}}{RR_{inter}} \quad (2)$$

179 where RR_{intra} designates the average of the relative risk of a block with the other blocks of its cluster,
180 and where RR_{inter} designates the maximum average of the relative risk of a block with a cluster other
181 than its own. Using this criterion, clusters were obtained, ordered by the size of the patient population
182 concerned and named based on analysis of the blocks of diagnoses content. Relevant information was
183 summarized using means and standard deviations, median and quartiles, and number and percentage.
184 The content of the blocks of diagnoses and the values of RR_{intra} and RR_{inter} for each cluster were also
185 analysed.

186 Differential analysis was performed on the rates of weekly ED visits before and after the opening of
187 the UCS, to identify clusters showing a significant decrease, using Fisher's F test for linear trends. The
188 significance level used was $p<0.05$ and the sign ± is used to indicate the standard deviation of a
189 temporal series in conjunction with its mean. A multivariate logistic regression model of the
190 probability of a visit belonging to a cluster on the decline, was constructed, adjusting for confounders.
191 The final model was selected using backward selection, based on minimisation of the Akaike
192 Information Criterion (AIC) [34]. The equation of the model retained was:

193 $$\text{Logit}(p) = \alpha + \omega Pe + \gamma R + V'\rho + X'\beta \quad (6)$$

194 where p is the probability of belonging, alpha is the constant, Pe is the period (before or after), R
195 indicates whether the visit was followed by readmission within 7 days, V is a visit-related information
196 vector including the triage circuit and the quantity of prescriptions of drugs and exams, and X is a
197 patient-related vector, including the age category, sex, and patient status at arrival at the ED.

198 In parallel, data regarding unscheduled ambulatory care from all healthcare establishments in the
199 Department was recorded based on the statistics of the national health information database. Overall
200 trends in patient flow were studied for the period 2016 to 2019 and put in perspective with the results
201 of our analyses.

202

203 **RESULTS**

204 During the 2-year study period, 120,718 visits to the ED were recorded, involving 75,279 patients;
205 114,391 of these visits (94.76%) were retained for the present analysis (see Figure 1). These involved
206 72,666 patients (96.53%), a total of 150 blocks of diagnoses, 2750 complete ICD10 diagnostic codes
207 and an average of 1.47±0.96 diagnostic occurrences per patient. A total of 6,199 visits (5.16%),
208 involving 5459 patients (7.25%), were excluded from the clustering analysis due to missing ICD10
209 diagnostic codes, and a further 208 (0.17%) because of an insufficient number of occurrences of the
210 block, defined as a minimum of 10 for the purposes of this study.

211 Cluster analysis aggregated the 114,391 visits into 14 clusters. The populations of these clusters
212 ranged from 1,807 to 14,232 patients (see Table 1, Supplementary Table S2 – Additional File 1 and
213 Figure 2). The overall MR was 1.67, with a RR_{intra} value of 1.54, and a RR_{inter} value of 0.92. Clusters 1
214 and 3 were the most heterogeneous, with local MRs of 1.23 and 1.34, in contrast with other clusters
215 where the MR was above 1.62. Most of the clusters were characterized by the heterogeneity of the
216 groups in terms of age, with standard deviations ranging from 20.96 to 28.86 years.

217 Clusters 1 and 3 were largely composed of older populations, with an average age of 58.44 and 49.51
218 years respectively. They were characterized by chronic diseases and symptoms related to aging. In
219 these clusters, we noted a high rate of use of medications, biological tests and radiological
220 examinations with a mean of 4.58 and 3.25 drugs respectively: as well as 2.79 and 2.15 biological tests
221 and 1.48 and 1.35 radiological examinations respectively. In addition, management times were longer
222 than in other clusters, with averages of respectively 261.33, and 233.90 minutes. Hospital admission
223 rates further to the ED visit were also the highest, at 44%, and 33%, and involved a lower rate of
224 patients with PS1 status (namely outpatients with moderate medical treatment), at respectively 53%
225 and 65%. They were the only clusters with more marked use of the long triage circuit, with usage
226 ratios (short circuit to long circuit) of 0.36 and 0.61.

227 Cluster 2 comprised a majority of women (69%) while clusters 5, 7, 9, 10, 13 comprised a majority of
228 men (proportions between 57 and 62%). Cluster 2 is related to gynaecological problems (related to

229 pregnancy, menstruation) and digestive problems. Clusters 5, 7, 9, 10, 13 were characterised by
230 trauma and at-risk behaviours.

231 Cluster 4 is characterised by seasonal infectious diseases and a young population with an average age
232 of 20.77 years. In particular, this cluster comprised 6,286 visits with patients aged under 5 years,
233 accounting for 43.84% of the total visits in this cluster, and 49.60% of all visits by under 5s across all
234 clusters. The visits in this cluster were characterised by a shorter waiting time than all of the other
235 clusters, at an average of 43.81 minutes. The rate of patients with PS1 status was 87%, i.e. higher than
236 11 of the other clusters, while the use of the fast-track (short) circuit was 3.89 times more frequent
237 than use of the long triage circuit.

238 Numerous clusters had health problems that were predominantly trauma-based, namely clusters 5, 7,
239 8, 10, 12, 13, 14 and indirectly, clusters 1, 3, 6, 9**.** 28.61% of the ED visits resulted in diagnoses from
240 Chapter XIX, *Injury, poisoning and certain other consequences of external causes*. Furthermore, there
241 was a limited number of diagnosis blocks in most of them, ranging from 1 to 2, with a high number of
242 individual diagnostic codes, ranging from 45 to 304 for clusters 5, 7, 8, 10, 11, 13 and 14.

243 The before-and-after analysis shows a significant overall decrease of 32.65 visits per week for the 14
244 clusters (2.93%, F-test, p=3.55E-02) and a specific decrease of 57.95 visits per week in 7 clusters
245 (13.59%, F-test, p=1.92E-10). As illustrated by Figure 3 and described in Table 2, Clusters 3, 5, 7, 9,
246 10, 13, 14, were associated with this decrease with significant downward trends (illustrated in). The
247 specific decrease corresponds to a loss of 0.083 visits per patient over a period of 2 years. The before-
248 and-after analysis also showed a significant (F-test, p=6.20E-03) increase of 17.44 visits per week
249 (10.27%) in cluster 1 and a non-significant (F-test, p=0.48) increase of 17.56 visits per week (13.19%)
250 in cluster 4.

251 Structural analysis of the 6,199 visits without diagnostic codes showed a non-significant increase of
252 2.37 visits per week (F-test, p=0.64). They went from an average of 58.18 visits per week in the
253 "before" period to 60.57 in the "after" period. More than two thirds (4266 visits, 68.82%) of these

visits involved patients who left without waiting for the medical examination. The other patients (1853 visits, 21.18%) could not be diagnosed due to lack of information or to the nature of stay.

The average number of ED visits decreased by 29.37 visits per week (2.5%), from 1168.66±76.62 visits per week before the opening of the USC, to 1139.29±51.83 visits per week afterwards, with a significant linear trend (F-test, p=1.61E-06). Unscheduled care in the Department increased significantly by 328.12 visits per week (14.75%, F-test, p =4.25E-04) during the study period. Additional analysis of the national healthcare information database illustrated by Figure 4, showed that in the first 6 months after the opening of the UCS, unscheduled care went from a baseline of 2225.13±258.43 visits to 2553.25±261.27 visits per week. This increase was mainly due to the opening of the UCS, where attendance was 189.5±62.54 visits per week during this period. Using this volume as reference, the ratio of the specific cluster decreases observed in the ED to the increase in the UCS was 30.58%.

The multivariate analysis shows that the probability of belonging to one of the 7 clusters with a significant reduction decreased after the opening of the UCS. As illustrated by Table 3 with an odds ratio (OR) of 0.83 (95%CI [0.81, 0.86]), this corresponds to a reduction in these clusters after the opening of the UCS. The ORs of the different variables indicate that the population concerned is less subject to weekly readmissions (OR 0.65, (95%CI [0.61, 0.68]), more often males, with an OR of 0.70 (95%CI [0.68, 0.72]) for female gender. This population also had a more moderate disease state, with an OR of 1.23 (95%CI [1.18, 1.27]) for PS1 status, older age, with an OR of 1.41 (95%CI [1.77, 1.97]) for the age category 75 years and older, and greater need for radiological examinations, with an OR of 1.47 (95%CI [1.45, 1.49]).

DISCUSSION

Our results show a decrease in the probability of belonging to 7 clusters after the opening of unscheduled care services (UCS). The reduction predominantly involved patient profiles linked to trauma and trauma-related symptoms. This drop is in line with the type of patients managed by the UCS in question. Our findings further show a non-significant increase in infectious diseases and a

280 significant increase in general symptoms of chronic conditions. These increases partially compensate
281 the decrease in visits of the 7 clusters mentioned earlier. Temporal trends in patient profiles of these 2
282 clusters are mainly due to seasonal variations, notably during the winter periods of epidemic and
283 overcrowding of ED services, rather than representing a true trend related to the opening of UCS.
284 Consequently, the implementation of UCS is associated with a change in patient flow to the ED, but
285 the more pronounced increase in passage through the UCS, which was of greater magnitude than the
286 reduction in ED visits, suggests that the UCS may also have diverted the flow of patients that would
287 have been treated by appointment-based care otherwise.

288 Our study applied a novel method of analysing multimorbities by clustering the general population of
289 ED patients. To the best of our knowledge; and based on the review of Padros-Torres et al.[22], where
290 most studies focus on complex patient and chronic diseases [21–25], this is the first time that analysis
291 of multimorbidity patterns has been used to cluster healthcare visits in a temporal analysis, and in this
292 specific population . With our novel method, we extend the usage of theses methods to a global
293 population with a low multimorbidity context and with a comprehensive clustering that was able to
294 classify the vast majority of ED visits (92.93%).

295 Previous studies investigating the impact of UCS have reported substantial reductions in "avoidable"
296 ED visits, as well as cost reductions [11–15]. Using a questionnaire, Moe et al measured the impact of
297 an after-hours clinic in terms of avoided ED visits and cost savings, and found that 36.8% of patients
298 attending the after-hours clinic would otherwise have gone to the ED if the clinic had not been
299 available [11]. In their study investigating the use of convenient care clinics (CCCs) outside of typical
300 office hours, Patwardhan et al [13] found that among over 2.6 million encounters, in the absence of
301 CCCs, 4.5% of all patients would have gone to the ED for weekend and after-hours encounters and
302 3.15% for weekday encounters during office hours, and respectively 29.39% and 27.34% would have
303 gone to an urgent care centre. In our study, the observed rate of 30.58% is similar to these literature
304 reports. In a before-and-after study of monthly ED visit frequency after implementation of an after-
305 hours clinic, Jones et al reported a mean of 49.28 fewer semiurgent patient visits per month to the ED
306 [15]. With an average reduction of 57.95 visits per week, corresponding to a reduction of 13.59% in

307 the 7 clusters with significant decreases, and a reduction of 4.96% of all ED visits, our findings are in
308 the same range as these previous reports. The observed success can be explained by the large
309 proportion of "avoidable" visits among those attending the ED. These patients are often characterised
310 by low acuity and high vulnerability [5, 35, 36], and re-directing them towards sites of care other than
311 the ED yields cost savings. One of the major obstacles to greater success of UCS is likely the
312 behaviour of patients, some of whom may prefer to go to the ED because they do not know that
313 alternatives exist, or because there is no financial incentive inciting them to try less costly care options
314 first [4, 37–40]. In this regard, information campaigns or the introduction of co-payment fees for ED
315 visits can be helpful in limiting "avoidable" ED attendance. However, unscheduled consultations
316 remain a weak link in the delivery of programmed healthcare, and are more difficult to manage. The
317 creation of care sites specifically for unscheduled care calls on public demand for such services that
318 can result in an increase of overall costs and new problems of saturation and overcrowding. As
319 improving access to primary care seems to be insufficient [41, 42], other solutions remain to be found
320 to limit social vulnerability and improve the general health of the population [38, 43].

321 *Limits*

322 The present study also has some limitations. Firstly, there is potential for selection bias in the
323 population of the city of Troyes. Nevertheless, this bias is minimized by previous reports in the
324 literature showing that our population is representative of the national population [31]. Secondly, the
325 choices made for our clustering approach with a block level representation of the diagnostic on a
326 global and non-stratified population also limits the accuracy of the clusters in terms of population
327 health problems. However, this approach achieves better statistical representativeness with a relevant
328 and coherent set of diseases cluster for the entire population. Indeed, these choices obviate the need for
329 a high number of lower quality clusters with pattern redundancies that would render the results
330 difficult to interpret and read. Thirdly, in this study, there was no control group unaffected by the
331 opening of UCS. The conditions of access to healthcare data from other Departments, and the
332 specificity of the local context precluded us from using a design that might limit this bias.

333

CONCLUSION

In this study, we propose an original and reliable method for assessing changes in patient flow through different healthcare delivery services that can be extrapolated to several contexts. It requires only the existence of a system for labelling diagnoses, so that their co-occurrence can be measured in the patients' records. It has been shown to be efficacious when patients are characterised according to hierarchical codes such as the ICD10 diagnostic system, and can also be successfully applied to study temporal trends in relation to a specific event, even in the absence of a control group. This methodological approach is fully in line with current thinking on public health policy, aiming to reorganise the relationships between primary care and emergency departments, with a view to improving the functioning of EDs by boosting the offer of unscheduled and/or non-urgent care. The implementation of new unscheduled care services was accompanied by a decrease in ED visits among multiple patient profiles, in line with the type of patients cared for by the new services. This new distribution of healthcare delivery therefore had a concrete impact and helped to optimise patient flow through the different sites of care.

358 **LIST OF ABBREVIATIONS**

359 ED: Emergency Department

360 HAC: Hierarchical Agglomerative Clustering

361 ICD: International Classification of Diseases

362 RR: Relative Risk

363 MR: Membership Ratio

364 UCS: Unscheduled Care Services

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DECLARATIONS

Ethics approval and consent to participate

This study was performed in compliance with national legislation regarding epidemiological studies (declaration N°2203674v0, dated 24/07/2018). Since the study was wholly observational and used only anonymized data, neither ethics approval nor a specific written informed consent from participants was required in France for this retrospective database study. In accordance with French ethical directives, the requirement for written informed consent was waived because the study was strictly observational, and all data were blinded. (ref : French Public Health Code. Article R. 1121-2. [http://www.legifrance.gouv.fr]). According to the French Public Health Code, this research not needed an ethical committee (ref :French Public Health Code. Article R. 1121-2. [http://www.legifrance.gouv.fr]). . The study is conducted according to the legal representant of medical information: it was declared with the national registry of health research under the number N°1113130319. Patients were informed that the study was being carried out through the hospital's registry of ongoing studies.

Consent for publication

Not applicable

Availability of data and materials

The main dataset containing the patient's exact stay with arrival date, ID number, stay number, age, gender, diagnoses, and other information described in the methods section cannot be made publicly available due to its confidential nature. Access is restricted by law to researchers that have complied with national legislation regarding epidemiological studies. It can be made available from the corresponding author on reasonable and legal request.

All analyses and data management were performed using R version 3.5.2. The code of the clustering method, with intermediate tables for testing, is available upon request and requires for execution the open software RStudio with 3 libraries: tidyverse, lubridate, reshape2.

404 ***Competing interests***

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409 ***Author's contributions***

410 JC, DL, AW, FMC, FY and SS designed the study. SS, DL, TM, GS contributed to the acquisition of

411 data. JC conducted the statistical analysis. JC, TM, GS, HQ, AD, DL and SS contributed to drafting

412 the article or revising it critically for important intellectual content. All authors read and approved the

413 final manuscript.

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Tables

Table 1 – Characteristics of the 14 clusters

Cluster name	1 : General symptoms of chronic conditions	2 : Digestive disorders, pregnancy, menstruation	3 : General symptoms and mental disorders	4 : Infectious diseases	5 : Head Trauma	6 : Mental disorders and at-risk behaviours	7 : Hand and Wrist Trauma
Population : n(%)	14151 (19%)	13982 (19%)	12202 (17%)	11150 (15%)	10318 (14%)	9535 (13%)	6293 (9%)
Age, mean±standard deviation	58.44 (+-26.98)	36.51 (+-23.11)	49.51 (+-28.88)	20.77 (+-24.78)	31.00 (+-25.81)	38.60 (+-22.55)	32.21 (+-20.95)
Females, n(%)	8345 (46%)	12936 (69%)	7560 (53%)	7036 (49%)	4810 (43%)	6080 (50%)	2597 (38%)
Visits, n(%)	18020 (16%)	18617 (16%)	14241 (12%)	14271 (12%)	11220 (10%)	12075 (11%)	6755 (6%)
Number of visits per patient	1.27	1.33	1.17	1.28	1.09	1.27	1.07
Waiting time, minutes; median (Q1-Q3)	47.68 (21.75-99.62)	59.30 (29.22-111.06)	57.65 (27.25-117.53)	43.81 (22.97-77.12)	59.27 (30.25-105.23)	44.06 (18.10-93.90)	58.83 (30.90-105.27)
Duration of management, minutes; median (Q1-Q3)	261.33 (144.43-403.46)	160.18 (48.00-313.63)	233.90 (101.99-379.34)	64.69 (31.25-153.80)	70.17 (39.02-130.03)	137.10 (61.12-280.97)	70.65 (43.38-113.80)
Number of medications, mean±standard deviation	4.58 (+-5.63)	2.58 (+-3.90)	3.25 (+-4.44)	1.32 (+-3.09)	1.06 (+-2.18)	1.66 (+-2.93)	1.17 (+-1.73)
Number of biology exams, mean±standard deviation	2.79 (+-2.20)	1.91 (+-1.96)	2.15 (+-2.17)	0.73 (+-1.49)	0.19 (+-0.79)	1.19 (+-1.90)	0.11 (+-0.49)
Number of radiological exams, mean±standard deviation	1.48 (+-1.18)	0.54 (+-0.87)	1.35 (+-1.33)	0.31 (+-0.71)	0.96 (+-1.13)	0.85 (+-1.16)	0.98 (+-0.94)
Number of blocks of diagnoses	42	28	8	20	1	15	1
Number of ICD10 diagnostic codes	513	482	157	284	105	330	52
Ratio of short circuit to long circuit	0.36	1.26	0.61	3.89	14.76	1.91	93.55
Patients in PS1 status, n(%)	9636 (53%)	14364 (77%)	9211 (65%)	12429 (87%)	10479 (93%)	8705 (72%)	6294 (93%)
Number admitted to hospital, n(%)	7873 (44%)	3918 (21%)	4764 (33%)	1748 (12%)	626 (6%)	2678 (22%)	368 (5%)
Rate of readmission within 7 days (%)	5.26%	9.29%	5.48%	6.45%	3.39%	6.72%	3.88%

Table 1 (continued) – Characteristics of the 14 clusters

Cluster name	8 : Spine disorders	9 : Occulomotor disorders	10 : Lower limb trauma and hemopathy	11 : Arthropathies	12 : Chest trauma and at-risk behaviours	13 : Shoulder and arm trauma	14 : Cutaneous infections and wounds
Population : n(%)	3455 (5%)	3038 (4%)	3007 (4%)	2601 (4%)	2084 (3%)	1822 (3%)	1799 (2%)
Age, mean±standard deviation	45.51 (+-22.58)	39.44 (+-23.83)	36.02 (+-23.82)	45.81 (+-25.40)	45.93 (+-23.60)	40.97 (+-26.87)	33.21 (+-21.12)
Females, n(%)	2060 (55%)	1254 (39%)	1381 (43%)	1304 (48%)	1129 (47%)	834 (43%)	857 (44%)
Visits, n(%)	3756 (3%)	3226 (3%)	3201 (3%)	2738 (2%)	2386 (2%)	1919 (2%)	1966 (2%)
Number of visits per patient	1.09	1.06	1.06	1.05	1.14	1.05	1.09
Waiting time, minutes; median (Q1-Q3)	62.00 (32.06-111.47)	55.23 (29.30-94.68)	59.78 (31.32-107.80)	60.62 (32.57-110.72)	54.35 (26.26-99.12)	48.65 (21.92-92.75)	58.58 (32.33-103.68)
Duration of management, minutes; median (Q1-Q3)	125.00 (55.37-275.53)	44.13 (23.28-90.58)	89.43 (53.47-146.97)	94.52 (44.72-222.18)	105.10 (44.50-252.83)	104.36 (61.55-177.15)	64.10 (31.37-132.08)
Number of medications, mean±standard deviation	2.56 (+-3.89)	0.66 (+-1.78)	1.51 (+-2.62)	2.02 (+-3.81)	2.08 (+-3.74)	2.21 (+-3.22)	1.32 (+-2.67)
Number of biology exams, mean±standard deviation	0.76 (+-1.34)	0.20 (+-0.92)	0.35 (+-1.04)	0.96 (+-1.85)	1.09 (+-1.76)	0.40 (+-0.99)	0.59 (+-1.31)
Number of radiological exams, mean±standard deviation	1.12 (+-1.42)	0.18 (+-0.56)	1.25 (+-1.20)	1.18 (+-1.37)	1.26 (+-1.43)	2.03 (+-1.52)	0.23 (+-0.56)
Number of blocks of diagnoses	2	11	2	2	9	1	8
Number of ICD10 diagnostic codes	118	94	45	304	113	30	123
Ratio of short circuit to long circuit	2.70	13.44	17.60	3.45	2.49	18.14	8.06
Patients in PS1 status	3034 (81%)	3053 (95%)	2767 (86%)	2246 (82%)	1900 (80%)	1594 (83%)	1583 (81%)
Number admitted to hospital, n(%)	670 (18%)	148 (5%)	413 (13%)	466 (17%)	441 (18%)	301 (16%)	360 (18%)
Rate of readmission within 7 days (%)	4.77%	3.84%	4.90%	4.57%	8.38%	4.48%	7.48%

Table 2 – Before-After Analysis of the weekly visits for each cluster

Cluster name	Before UCS opened (mean ± SD)	After UCS opened (mean ± SD)	Difference (%)	P*
1 : General symptoms of chronic conditions	169.74 ± 25.48	187.18 ± 23.49	17.44 (10.28%)	6.20E-03
2 : Digestive disorders, pregnancy, menstruation	181.50 ± 14.22	175.68 ± 14.22	-5.82 (-3.21%)	6.63E-01
3 : General symptoms and mental disorders	140.99 ± 14.84	129.32 ± 15.06	-11.67 (-8.27%)	5.27E-05
4 : Infectious diseases	133.12 ± 39.93	150.68 ± 31.75	17.56 (13.19%)	4.82E-01
5 : Head Trauma	113.87 ± 16.76	92.89 ± 12.89	-20.98 (-18.42%)	2.33E-06
6 : Mental disorders and at-risk behaviours	118.41 ± 17.48	112.14 ± 16.37	-6.27 (-5.29%)	2.37E-01
7 : Hand and Wrist Trauma	68.04 ± 11.25	57.36 ± 8.68	-10.68 (-15.70%)	3.02E-03
8 : Spine disorders	35.79 ± 6.65	37.75 ± 5.34	1.96 (5.48%)	1.66E-01
9 : Occulomotor disorders	32.25 ± 6.00	28.00 ± 5.93	-4.25 (-13.18%)	1.29E-02
10 : Lower limb trauma and hemopathy	32.43 ± 7.95	26.75 ± 6.60	-5.68 (-17.53%)	1.22E-03
11 : Arthropathies	26.95 ± 5.64	25.43 ± 6.13	-1.52 (-5.64%)	8.85E-01
12 : Chest trauma and at-risk behaviours	22.66 ± 5.21	24.61 ± 5.49	1.95 (8.60%)	7.53E-02
13 : Shoulder and arm trauma	19.47 ± 4.45	16.07 ± 4.58	-3.40 (-17.47%)	4.60E-03
14 : Cutaneous infections and wounds	19.33 ± 5.29	18.04 ± 3.76	-1.29 (-6.69%)	1.19E-02
Total	1108.66 ± 72.71	1076.18 ± 49.76	-32.48 (-2.93%)	3.55E-02
Total for negative trends	425.74 ± 34.94	368.04 ± 27.84	-57.70 (-13.55%)	1.92E-10

For each series, the linear trend of the 2-year study period has been tested using Fisher's F test and resulting in a p-value. - SD : Standard deviation ; * Fisher test on linear trend (F test)

Table 3 - Logistic regression model showing the factors associated with the probability of belonging to decreasing clusters

Variable	OR*	95%CI **	p ***
"After" period (reference: Before)	0.83	[0.81,0.86]	1.57E-38
Readmission within one week	0.65	[0.61,0.68]	9.02E-57
Female gender	0.70	[0.68,0.72]	1.00E-177
PS1 status	1.23	[1.18,1.27]	0.00E+00
Short circuit through ED	2.25	[2.17,2.34]	0.00E+00
Age category (Reference: 25-50 years)			
0 - 10 years	0.75	[0.72,0.78]	0.00E+00
10 - 25 years	1.18	[1.14,1.22]	0.00E+00
25 - 50 years	-	-	-
50 - 75 years	1.20	[1.16,1.25]	0.00E+00
75 years and over	1.41	[1.35,1.48]	0.00E+00
Number of biological exams (per additional exam)	0.82	[0.81,0.83]	2.03E-188
Number of radiological exams (per additional exam)	1.47	[1.45,1.49]	0.00E+00
Waiting time (per additional hour)	1.00	[1.00,1.00]	6.25E-47
Duration of management (per additional hour)	1.00	[1.00,1.00]	5.00E-09

* OR: Odd Ratio
** CI: Confidence Interval
*** Wald test (z-test)
AUC = 0.7
Hosmer-Lemeshow test : X^2=1584.6 , p-value < 2.2e-16

Figure legends

Figure 1 – Visit selection flow chart from the RESURGENCES database

Figure 2 – Distribution of blocks of diagnoses in the 14 clusters – Each cluster is represented by a unique colour. The volume of each area is proportional to the number of patients affected by the given block of diagnoses during the study period. The label of each block can be found at: https://www.icd10data.com/ICD10CM/Codes or in Supplementary Data Table S3 – Additional File 1

Figure 3 – Trends in clusters before and after the opening of UCS – The numbers of weekly admissions are represented with boxplots where the middle line indicates the median, the boxes delimit the quartiles. The upper and lower whisker extends from the hinge to the largest and smallest (resp.) value no further than 1.5 * IQR from the hinge. (where IQR is the inter-quartile range, or distance between the first and third quartiles).

Figure 4 - Trends in unscheduled care in the Aube Department, December 2015 – December 2019 – The numbers of weekly admissions is represented using lines for each type of unscheduled care surrounding the ED of Troyes. Ambulatory care is all the unscheduled consultations performed for the most part by general practitioners and nurses in the Aube territory via the *SOS Médecin* association and the *Permanence Des Soins Ambulatoires* (PDSA) registred in the *Système Nationale des Données de Santé* (SNDS, the national health information database).

Additional File 1 content

Supplementary Methods S1 – The detailed method used to cluster multimorbidity patterns is presented. The method is also compared to the literature.

Supplementary Table S2 – Diagnostic content and quality indicators of the 14 clusters - Clustering result of the method presented in Supplementary Methods S1 with the data presented in the present Methods section with detailed information on the cluster, their content, and their quality.

Supplementary Data Table S3 – Labels of the ICD10 Blocks - Content of each block from the International Classification 10th revision

Figures

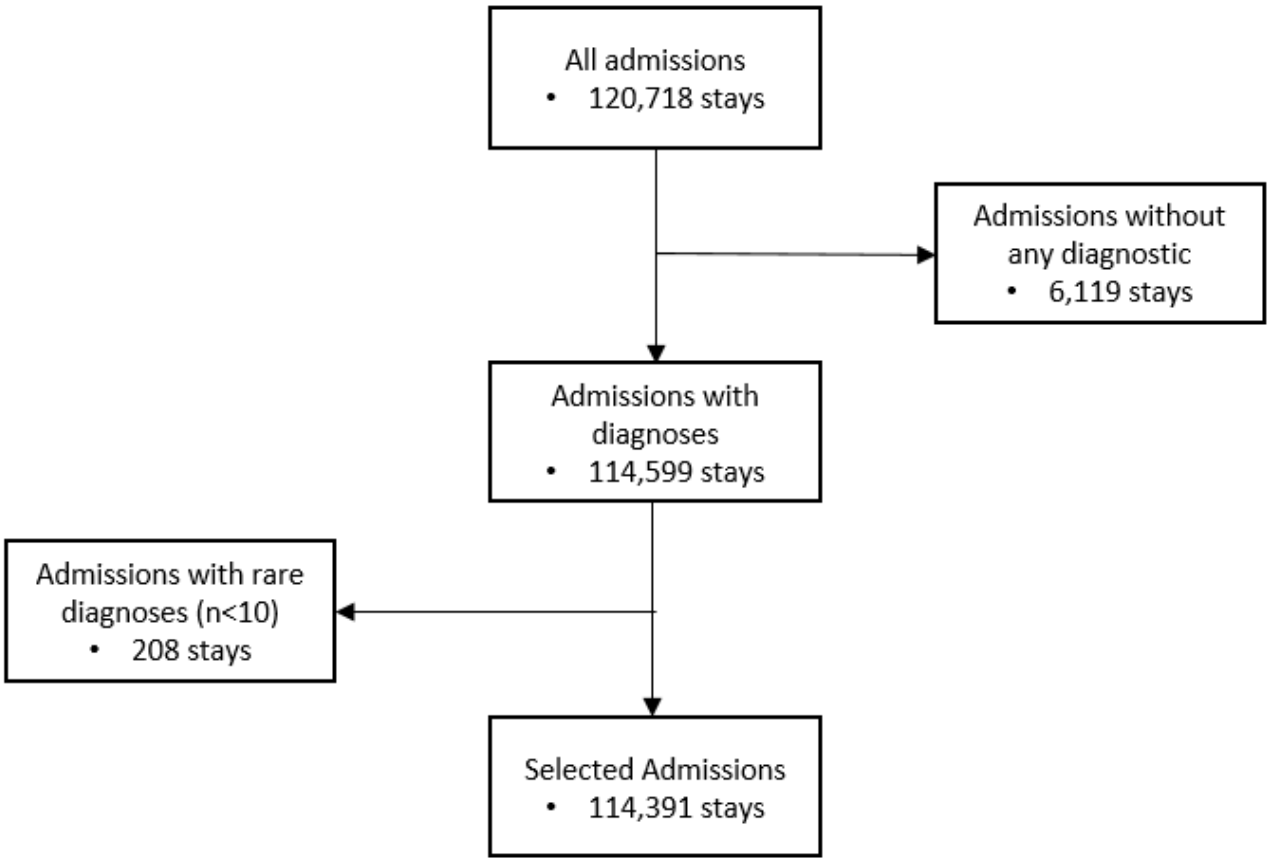
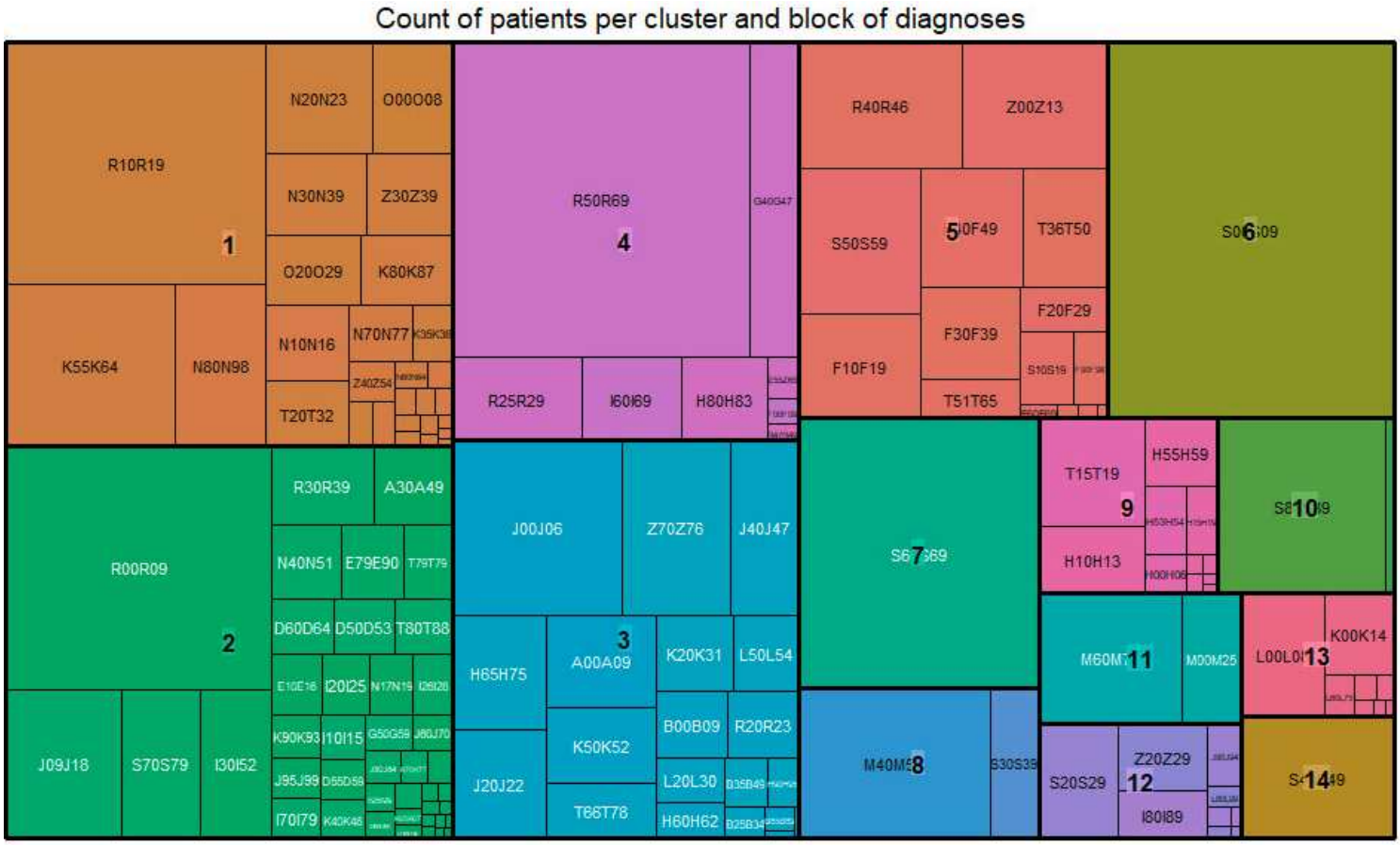


Figure 1

Visit selection flow chart from the RESURGENCES database



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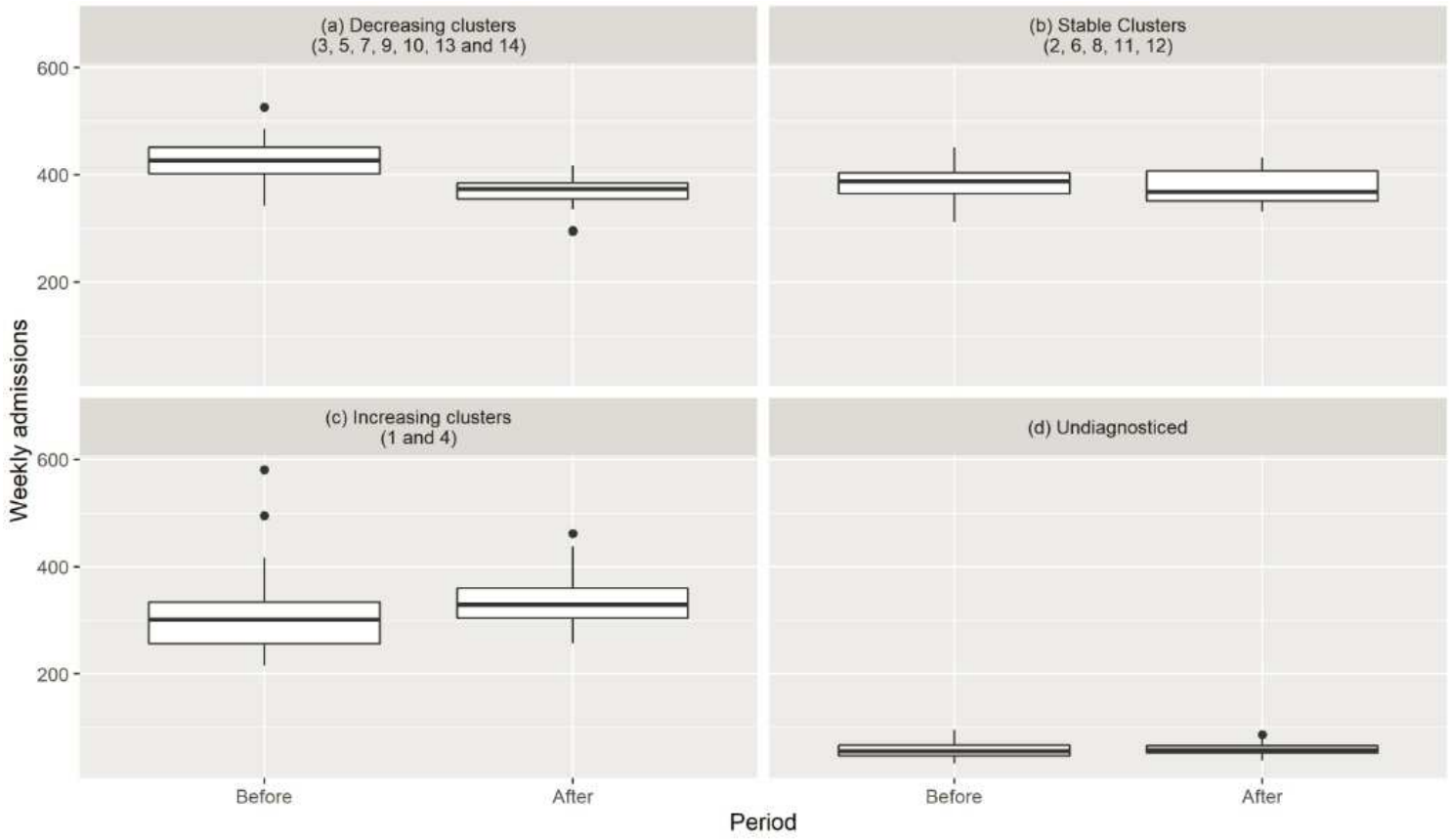

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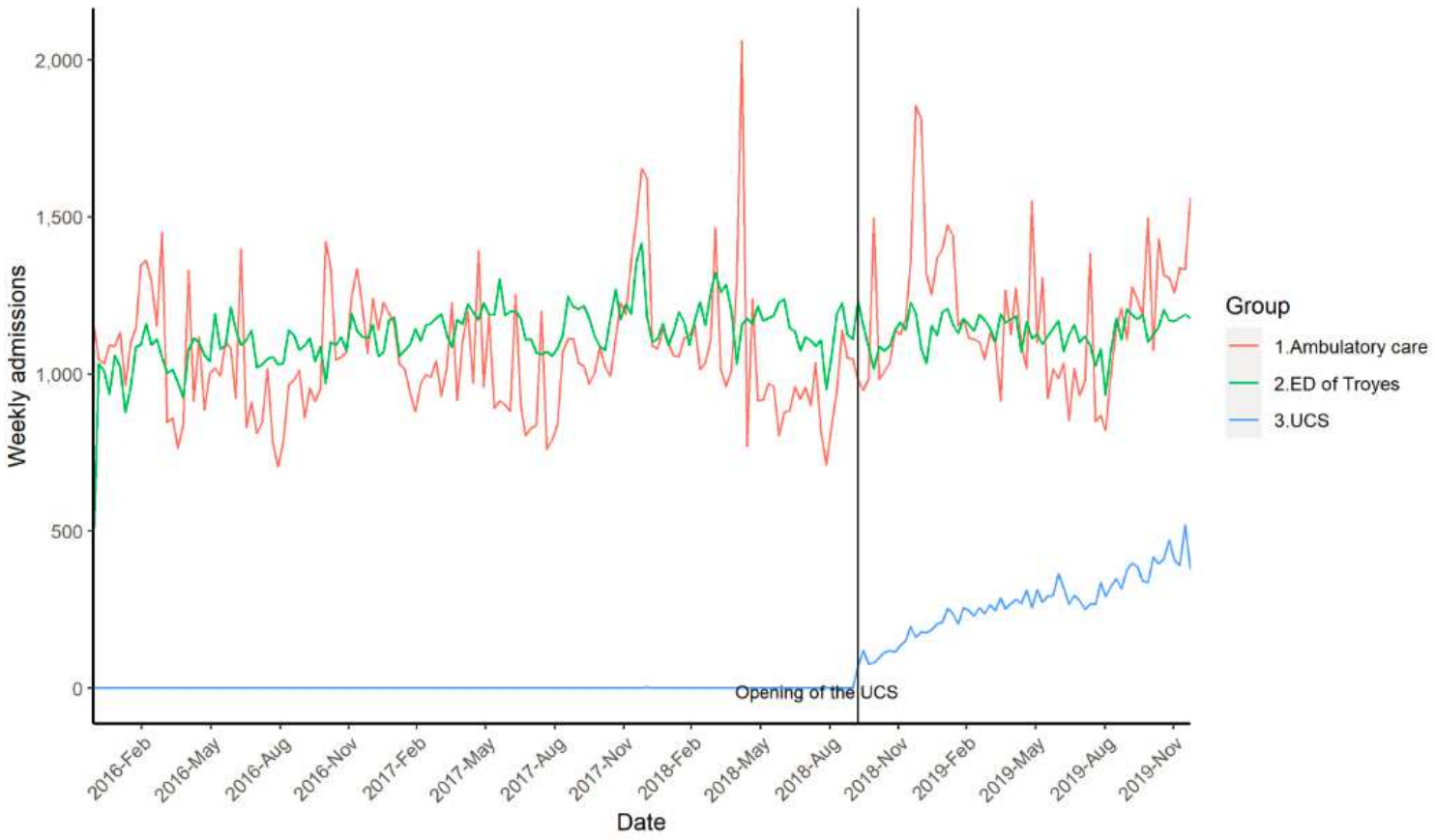

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Supplementary Files

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