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Frequent attendance at the emergency department shows typical features of complex systems: analysis of multicentre linked data

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ABSTRACT

Objective,

Frequent attendance at the ED is a worldwide problem. We hypothesised that frequent attendance could be understood as a feature of a complex system comprising patients, healthcare and society. Complex systems have characteristic statistical properties, with stable patterns at the level of the system emerging from unstable patterns at the level of individuals who make up the system.

Methods

Analysis of a linked dataset of routinely collected health records from all 13 hospital trusts providing ED care in the Yorkshire and Humber region of the UK (population 5.5 million). We analysed the distribution of attendances per person in each of three years and measured the transition of individual patients between frequent, infrequent and non-attendance. We fitted data to power law distributions typically seen in complex systems using maximum likelihood estimation.

Results

The data included 3.6 million attendances at EDs in 13 hospital trusts. 29/39 (74.3%) analyses showed a statistical fit to a power law; 2 (5.1%) fitted an alternative distribution. All trusts' data fitted a power law in at least one year. Differences over time and between hospital trusts were small and partly explained by demographics. In contrast, individual patients' frequent attendance was unstable between years.

Conclusions

ED attendance patterns are stable at the level of the system, but unstable at the level of individual frequent attenders. Attendances follow a power law distribution typical of complex systems. Interventions to address ED frequent attendance need to consider the whole system and not just the individual frequent attenders.

What this paper adds

What is already known on this subject

Frequent attendance at the Emergency Department by some individuals is a ubiquitous problem.

Frequent attendance is typically thought of as a problem of particular individuals, but similar patterns are seen in many naturally occurring complex systems.

Complex systems typically display measurable features including heavy-tailed distributions of events such as power law distributions.

What this study adds

Power laws or power-law-like distributions were seen in attendance patterns at almost all EDs examined and remained stable over time.

These findings suggest that ED frequent attendance is a system-level phenomenon as well as an individual one; it requires system as well as individual solutions.

Introduction.

The problem of frequent attendance – patients repeatedly attending the ED although it may not be the most appropriate place for them - is a major challenge for emergency medicine[1]. While frequent attendance appears to be ubiquitous [2], frequent attenders comprise a heterogeneous group with complex needs[3 4], which for many comprise a mix of physical, mental and social problems[5 6]. While frequent attendance may at first appear to be a simple concept, it becomes less certain on closer inspection: definitions based on a threshold number of cases are abitrary[7], definition of attendances for lower acuity problems[8 9] is challenging, and the decisions patients make about use of emergency care are complex,[10] reflecting personal and social factors[11 12]. Furthermore, interventions aimed at frequent attenders, such as case management, which often appear effective at the level of the individual patient, appear less effective in controlled trials and populations [13 14]. This has led some commentators to argue that frequent ED attendance represents a consequence of problems in wider social systems[15].

While ED frequent attendance is ubiquitous [2], the population of frequent attenders is constantly changing. Studies in emergency medicine [16 17] have demonstrated that frequent attendance by an individual is a relatively unstable state: many frequent attenders in one time period become infrequent attenders in the next, and vice versa.

In this study we approached the problem of ED frequent attendance from the perspective of a complex system comprising ED patients, staff and the wider social setting [2 18]. Complex systems comprise many components and their interactions[19]. Through these interactions, they generate – and are also constrained by - behaviours at the system level. The process by which system-level behaviours emerge from individual interactions, without external or top-down control, is referred to as self-organisation [19]. A widely used example is that of a flock of birds such as starlings which creates complex geometric patterns in flight from the apparently simple interactions of individual birds. Complex systems usually display order and stability at the level of the whole system while containing apparent disorder and instability at the level of the individual components. When examined statistically, complex systems show skewed distributions with a "heavy tail" containing high and very high values. There are several types of heavy-tailed distribution, but the one that has received most attention in relation to complex systems is the power law distribution [20]. Box 1 describes power laws and the characteristics of power law distributions.

The implication of thinking of ED attendance as a complex system behaviour, is that frequent attendance may need to be seen as part of a continuum of attendance rather than a discrete problem. Thus, responses to frequent attendance may need to consider not just the individual frequent attenders, but the factors at interpersonal and societal levels which drive all attendance[12]. Without addressing the whole system, stopping individual frequent attenders may only result in new frequent attenders taking their place.

We hypothesised that a regional urgent and emergency care system would show typical features of a complex system: specifically, it would show a stable pattern of frequent attendance which followed a power law distribution.

BOX 1

Power law distributions

In a power law distribution, the probability of an event of magnitude X follows the equation $P_{(X)}=kX^{-\alpha}$ where k is a constant and α is termed the power law scaling parameter. For such a power law distribution, the probability of an event of magnitude at least X ($P_{(x \geq X)}$) approximates to $kX^{(1-\alpha)}$. This represents the complementary cumulative distribution function and if plotted on logarithmic axes it produces a straight line.

Consider a power law distribution with a lower threshold of 1, and with parameters k=1 and α=3. If X = 2, then $P_{(x \geq X)}$ = 0. 25. Thus the median of the distribution is 1 and the interquartile range is 1 to 2. As X increases, $P_{(x \geq X)}$ diminishes: using the parameters above, for X = 4, $P_{(x \geq X)}$ = 0.0625; for X=10, $P_{(x \geq X)}$ = 0.01. While the probability of values for X which are far above the upper quartile is low, it is not negligible. For instance, using the example above, for X = 100, $P_{(x \geq X)}$ = 100^{-2} = 0.0001. Thus, in a large sample of tens of thousands, the tail of this distribution would likely include several occurrences of X≥100. This presence of extreme values is referred to as the "heavy tail" of the distribution. It includes values for X which would be extremely improbable in a gaussian or exponential distribution with similar interquartile range.

Power laws can be fitted to empirical data and their scaling parameters estimated. Fitting power laws to different sets of data permits comparison of their scaling parameters.

Methods

Study Design

We carried out an analysis of routinely collected healthcare data for all ED care in the Yorkshire and Humber region of the UK, comprising 5.5 million residents over 3 consecutive years from April 2014 to March 2017.

Patient and public involvement

No patients were involved.

Data sources

We used a dataset extracted from the "Connected Health Cities: Data linkage of urgent care data" study (known as the "CUREd research database") [21]. This covers all EDs in the Yorkshire & Humber region.

Ethics and permissions

The CUREd database has approval from a National Health Service (NHS) Research and Ethics Committee, overseen by the NHS Health Research Authority's Research Ethics Service, and from the NHS Health Research Authority (HRA), directly, to receive health and social care data without patient consent for patients of emergency and urgent care services in Yorkshire and Humber. The Leeds East REC granted approval (18/YH/0234) and, subsequent to receiving a recommendation to approve from the Confidentiality Advisory

Group (18/CAG/0126, previously 17/CAG/0024), the NHS HRA provided approval for English health and care providers to supply identifiable patient data to the study.

Data extracted

The data used in the study comprised de-identified data extracted from routinely collected information on every ED attendance in the region, with all attendances for each individual patient linked by a single pseudonymised ID. We included all attendances at a type 1 ED (i.e. a consultant led 24-hour service with full resuscitation facilities and designated accommodation for the reception of accident and emergency patients) by adults aged 18 or more at the time of attendance. Attendances were grouped by individual patient and by hospital trust. We used hospital trusts rather than individual EDs because they typically serve a distinct geographical population. While many trusts have only one ED, some trusts serve a conurbation with more than one ED and patients may visit either. Patients were categorised by age band (18-34, 35-54, 55-69, 70-84 and 85+), sex and by deprivation. The measure of deprivation was the Index of Multiple Deprivation (2015) for England. Patients were grouped into quintiles of deprivation relative to the entire English population. The distribution of patients by IMD quintiles in the data was not even; this reflects both the demography of Yorkshire and Humber generally – with more people living in deprived areas than the English average - and greater ED use by people of lower sociodemographic status.

Analysis of characteristics and stability of ED use at system level

We carried out analyses at the level of the whole region (in order to examine the effects of age and socioeconomic status) and at the level of individual hospital trusts (to look for geographic variation). For each year we aggregated all attendances per patient and calculated the complementary cumulative distribution function, defined as the proportion of patients whose total number of attendances was equal to or greater than each number of attendances between 1 and the largest recorded. We then plotted this distribution with logarithmic axes. Plots showed data broken down by year and by either age band, socioeconomic status, or hospital trust. The technique of using logarithmic axes in this way means that a power law distribution appears as a straight line with a slope of one minus the scaling parameter. A larger power law scaling parameter indicates a steeper slope and a shorter tail to the distribution, while a smaller scaling parameter indicates a gentler slope and a longer tail.

We fitted power law distributions to data using maximum likelihood estimation with the poweRlaw package[22] for R. We carried this out in four steps: inspection of plots; identification of best-performing minimum attendance number; fitting of distributions and estimation of confidence intervals. In step 1, we inspected plots of the data to find a plausible range of possible values for the minimum attendance number to use in the power law fitting (i.e. the number of attendances above which the shape of the distribution on logarithmic plots became linear). In step 2, we found the best-performing minimum attendance number by comparing the maximum likelihood fitting of the data to a power law starting at each value in the range of minimum attendance numbers from step 1. We then used this minimum attendance number as the lowest eligible number of attendances per patient for inclusion in the next two steps. In step 3, we tested the fit of the data to a power law using the Kolmogorov-Smirnoff test. We extracted the scaling parameter for the distribution and estimated p-values for the Kolmogorov-Smirnoff test by bootstrapping following the approach recommended in Clauset[23] with 500 iterations. Where the p-value of the Kolmogorov-Smirnoff test was >0.05 we labelled the distribution as indistinguishable from a power law. When a distribution of data looked like a power law on the logarithmic plot, but the p-value of the fit was <0.05 (i.e. the distribution differed significantly from a power law at some point) we compared the fit between a power law and two other distributions – the Poisson and lognormal - to find the distribution which best fitted the data. This comparison used a log likelihood ratio test [23]. We labelled these distributions as similar to a power law. Finally, in step 4, we calculated 95% confidence intervals for each power law scaling parameter by bootstrapping with 400 iterations. We estimated the Monte Carlo Error (MCE) arising from the bootstrapping procedure[24]. Further details about power-law fitting and the choice of minimum threshold are in supplementary materials.

For the main analyses we used 12-month periods (April-March for each year in the data). We estimated power law scaling parameters for data split by year and additionally split by hospital trust, patient age or socioeconomic deprivation. We initially included all patients with complete data in each analysis but subsequently excluded patients over 70 from some of the analysis because the data for this group did not resemble a power law over the majority of the distribution. Finally we examined 6-month periods (beginning in April and October) in order to test for stability in the face of seasonal variation in demand.

Results

Over the three years there were a total of 3,864,081 type 1 ED attendances. The total volume increased over the three years from 1,263,149 attendances (830,046 patients) in Year 1 (2014-15) to 1,310,167 (850,443 patients) in Year 3 (2016-17). This represents an increase in attendances and patients attending of 3.7% and 2.5% respectively between the first and third years.

The 13 hospital trusts varied substantially in size and demographics. Table 1 lists characteristics of each hospital trust including size of population served; number of ED patients; their median age and the percentage of patients in the most deprived quintile of the UK population. Some trusts covered a mix of urban and rural settings, while others served major conurbations with high levels of deprivation.

Visualisation of ED use at system level

Figure 1 shows the distribution of attendances per patient on logarithmic axes. Plots shown are for Year 2, but plots for each year are shown together in the upper part of supplementary figure 1. Figure 1a shows data points aggregated across all hospital trusts. The linear relationship between the log number of attendances and the log probability of a patient having that number or more – particularly between 3 and 30 attendances is indicative of a power law distribution. Figure 1b shows the data split by deprivation quintile. The gradient becomes shallower as deprivation increases and the relative difference between deprivation levels increases with the number of attendances. Thus 5 or more attendances occur in approximately 1.2% of attendees from the least deprived quintile compared to 4% from the most deprived, for 10 or more attendances the respective proportions are 0.12% and 6% and for 50 or more attendances, 0.001% and 0.01%. Figure 1c shows the data split by patient age: in this figure, the lines representing patients aged 70-84 and 85+ can be seen to curve differently from the straight lines of the other age groups. Figure 1d is a simplified version of Figure 1c with patients split into those aged under 70 years and those aged 70 and over. This highlights that the distribution for patients aged over 70 is convex on the logarithmic axes and does not have the linear appearance of a power law until a minimum attendance number of around 10. This distribution has a shorter tail. In summary, for all groups except patients aged over 70 individual attendance patterns appeared on visual inspection to fit a power law.

Estimation of power law fitting

From observation of the data and preliminary testing of model fit, we found that the best-performing minimum value of attendance for power law fitting was 3; this value was used in all subsequent model fitting. Table 2 shows the results of analysis of power law fitting at the level of year and hospital trust. The data were indistinguishable from a power law in 29/39 instances. Of the remaining 10 instances, 8 were similar to a power law (they were a better fit to a power law than a Poisson distribution and there was no difference in fit between a power law and a lognormal distribution). The remaining two instances showed better fit to a lognormal distribution. They were from the same trust, but data from that trust in the remaining year was indistinguishable from a power law. Plots of data from this trust (M) show minor deviations from a power law in years 1 and 3 but the overall pattern is still clearly heavy-tailed (lower part of supplementary figure 1). Data pooled across trusts was indistinguishable from a power law in 7/15 analyses split by year and deprivation quintile and 3/9 analyses split by year and age group. In all remaining analyses, data were similar to a power law. As 61/63 distributions analysed were indistinguishable from, or similar, to a power law distribution we included all of them in comparisons of power law scaling parameter.

Table 3 summarises three measures of ED attendance by deprivation quintile and age group. The total numbers of attendance for deprivation reflect both increased prevalence of socioeconomic deprivation in the region (quintiles are for the whole population of England not just Yorkshire and Humber) and increased ED use by the most socioeconomically deprived. The power law scaling parameter is inversely related to socioeconomic deprivation. In terms of the plots in figure 1 a smaller scaling parameter equates to a shallower slope, meaning that the probability of a patient having a given number of attendances is higher, and the probability of having no further attendances is lower. Monte Carlo Error estimates were consistently small (<0.002) suggesting that the confidence intervals around the power law scaling parameters in table 3 were robust.

Table 3 also permits assessment of trends in ED attendance. The number of attendances increased over time in all subgroups apart from those aged 18-34. The power law scaling parameter decreased (i.e., greater probability of high attendance) except for the highest and lowest socioeconomic deprivation groups. The finding of little change in the most deprived is surprising given that much of the perception about ED capacity has focused on unnecessary attendance in this group [6].

Figure 2 examines the variation in power law scaling parameters between hospital trusts. Figure 2a shows the variation between years within trusts. While there is clear variation between trusts, there is relatively little year to year variation within trusts. In figure 2b the scaling parameter for a single year (Year 2) is plotted against the proportion of patients in the most deprived population quintile. It suggests that at least part of the variation between trusts is attributable to population differences. Analysis in shorter periods found no consistent seasonal pattern between semesters (supplementary figure 2).

Discussion

Summary of principal findings

This study confirmed the hypothesis that ED attendance patterns follow power law distributions. These findings were consistently present across 13 hospital trusts and were stable over several time periods. The findings suggest that frequent attenders are not a discrete group of patients to be considered separately from others, but rather represent one part of a continuous and uninterrupted distribution of attendance.

Limitations

Despite the size of population served it is possible that some of the features we observed were local rather than general phenomena, however the consistency of findings across a very socioeconomically diverse region suggests a generalisable process. While data did not provide a precise fit to a power law in every analysis – particularly when aggregating across hospital trusts, the absence of a better fitting distribution in almost all cases suggested that this lack of fit may be explained by local 'noise' in the data rather than a fundamental misapplication of the model. We fitted the power law distribution only to patients with at least 3 attendances. This use of a lower (and sometimes higher) threshold for power laws is widely recognised due to finite sample effects[23]. In this case a threshold of 3 allowed us to include all patients who met the lowest possible threshold for frequent attendance[25].

Relationship to other research

A review of published studies to 2017 documented heavy tailed distributions in use from over 20 EDs but only one tried fitting a power law distribution[2]. None of these studies was large enough to examine the impact of demographic features on these patterns. The study places research into ED frequent attendance alongside a wider body of quantitative work about complex systems. While complex systems science is increasingly contributing to other areas of medicine[26], it has only rarely been used to address pressing problems of health system use[27].

Implications

The approach we have used for fitting power laws and related distributions to ED data has implications for measurement and for understanding of the problem of frequent attendance. The fitted parameters provide a new objective measure by which to quantify patterns of ED use. They can potentially be used to provide a means for identifying when and under what circumstances systems change (or deviate from) their distribution, including in evaluating new interventions to manage demand.

Our findings demonstrate a difference between older frequent attenders and others in that the power law features were not observed. This suggests that frailty-related frequent attendance is different from that seen in younger adults and may be better understood at the level of the individual patient rather than the whole system.

Thinking of ED use as a complex system has important implications: first, frequent attendance needs to be seen as part of a continuum of attendance rather than a discrete problem of exceptional individuals. Second, the approach described here can be used to evaluate interventions to reduce frequent attendance in the ED which takes a whole system view[28]. While a solution for an individual may benefit that person, if it simply means that another patient occupies their place in the power law distribution of attendance, then the emergency medicine system will be no better off. Third, the very stability of complex systems, which we have demonstrated in ED use, makes them challenging to change. The power law behaviour observed in the behaviour of individuals within a system is also seen in systems as they respond to change. Most changes have little effect (the system buffers them), but a few result in marked change (the system is transformed). If interventions to reduce demand on the ED are interventions in complex systems, one would expect most interventions addressing ED frequent attendance to have small effects. However one would also expect a few interventions to have larger effects [29], potentially leading to pressure to adopt them elsewhere even though the benefits may have been more to do with local contextual factors. Finally, because frequent attendance can be seen to be just one part of a continuous spectrum of attendance, strategies to reduce reattendance should consider the effects of processes which occur in many consultations: these may include defensive safety netting ("come back if you have any concerns") and unthinking emphasis on patient satisfaction (much of which derives from business models designed to generate ongoing demand).

Conclusion

This study found compelling evidence that frequent attendance at the emergency department can be understood as representing a complex system. The concepts and analytic tools used here can be used to design, evaluate and model interventions to address frequent attendance, in order to ensure that they do more than replacing one high-using individual with another.

Contributorship

CB and SM proposed the study, TS prepared the dataset. CB conducted the analysis in discussion with JL and PO. All authors contributed to interpretation of the data and editing the manuscript

Funding Information

NIHR Applied Research Collaboration, Yorkshire & Humber supports the CUREd database. No specific funding was obtained for the analysis reported here.

Competing interests

There are no competing interests for any author

Ethics Statements

The CUREd database has approval from a National Health Service (NHS) Research and Ethics Committee, overseen by the NHS Health Research Authority's Research Ethics Service, and from the NHS Health Research Authority (HRA), directly, to receive health and social care data without patient consent for patients of emergency and urgent care services in Yorkshire and Humber. The Leeds East REC granted approval (18/YH/0234) and, subsequent to receiving a recommendation to approve from the Confidentiality Advisory Group (18/CAG/0126, previously 17/CAG/0024), the NHS HRA provided approval for English health and care providers to supply identifiable patient data to the study. The study complies with the common law of duty of confidentiality owed by health professionals in regard to information provided by patients in the course of clinical care; the General Data Protection Regulation as enacted in the UK by the Data Protection Act 2018; and, where applicable, the Statistics and Registration Service Act 2007.

Table 1 Characteristics of hospital trusts and ED attenders

Trust population served		ED patients in 2015-16		
Hospital Trust	Number[1] (thousands)	Number (thousands)	Most deprived[2]	Median Age
A	161	27	3%	52
B	476	79	14%	50
C	160	31	23%	50
D	428	65	56%	42
E	789	111	40%	42
F	578	65	40%	47
G	538	109	34%	45
H	456	77	30%	45
I	245	43	38%	47
J	427	74	34%	48
K	332	67	31%	49
L	265	42	39%	46
M	583	78	43%	46

ED Emergency Department

[1] Estimated from NHS data for populations of corresponding clinical commissioning groups. This does not include patients who are seen at an ED but whose home address is outside the corresponding area.
[2] Proportion of ED patients whose postal code was in the most deprived 20% of the English population based on the Index of Multiple Deprivation 2015

Table 2 Fit of power law distribution to data from each hospital trust by year

Hospital Trust	Year 1				Year 2				Year 3			
	Scaling Parameter[1]	KS [2] p-value	LRT[3] p-value	Distribution	Scaling Parameter	KS p-value	LRT p-value	Distribution	Scaling Parameter	KS p-value	LRT p-value	Distribution
A	3.65	0.09		Power Law	3.65	0.07		Power law	3.59	0.14		Power law
B	3.56	0.23		Power Law	3.52	0.00	0.53	Uncertain	3.46	0.08		Power law
C	3.66	0.46		Power Law	3.84	0.30		Power law	3.73	0.82		Power law
D	3.41	0.23		Power Law	3.41	0.12		Power law	3.40	0.10		Power law
E	3.37	<0.01	0.38	Uncertain	3.35	0.02	0.50	Uncertain	3.34	0.19		Power law
F	3.48	0.02	0.10	Uncertain	3.41	0.66		Power law	3.29	0.23		Power law
G	3.65	0.01	0.89	Uncertain	3.63	0.00	0.35	Uncertain	3.63	0.04	0.17	Uncertain
H	3.67	0.38		Power law	3.59	0.69		Power law	3.52	0.38		Power law
I	3.57	0.26		Power Law	3.59	0.33		Power law	3.56	0.18		Power law
J	3.66	0.29		Power law	3.59	0.63		Power law	3.62	0.29		Power law
K	3.46	0.10		Power Law	3.48	0.47		Power law	3.49	0.86		Power law
L	3.55	0.04	0.26	Uncertain	3.49	0.14		Power law	3.59	0.85		Power law
M	3.48	<0.01	<0.01	Lognormal	3.46	0.08		Power law	3.48	0.03	0.02	Lognormal

[1] Scaling parameter for power law fit for all patients with 3 or more attendances.
[2] Kolmogorov Smirnoff test p-value (if >0.05 indicates data indistinguishable from a power law)
[3] Likelihood Ratio Test p-value (only applied if data not indistinguishable from a power law; if >0.05 indicates no difference in fit between lognormal and power law distribution)

Table 3 ED attendance characteristics by population deprivation quintile and age group

	Number of ED patients (thousands)			Attendances per ED patient			Power law scaling parameter (with 95% CI)[1]		
	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
Deprivation Quintile									
Most deprived	286	290	292	1.68	1.68	1.70	3.24 (3.21-3.27)	3.24 (3.22-3.27)	3.22 (3.19-3.25)
2	165	168	169	1.52	1.53	1.54	3.62 (3.57-3.67)	3.57 (3.52-3.61)	3.52 (3.48-3.57)
3	140	142	144	1.45	1.46	1.47	3.81 (3.74-3.87)	3.73 (3.66-3.79)	3.67 (3.61-3.74)
4	136	138	139	1.41	1.42	1.43	3.95 (3.88-4.02)	3.87 (3.8-3.94)	3.84 (3.76-3.91)
Least deprived	96	97	99	1.36	1.37	1.37	4.06 (3.96-4.17)	4.05 (3.93-4.15)	4.14 (4.04-4.25)
Age group							3.54 (3.51-3.57)	3.51 (3.48-3.54)	3.49 (3.46-3.52)
18 to 34	279	280	277	1.51	1.51	1.51	3.4 (3.37-3.44)	3.37 (3.34-3.4)	3.35 (3.31-3.38)
35 to 54	241	243	242	1.47	1.48	1.49	3.53 (3.49-3.57)	3.54 (3.49-3.59)	3.46 (3.42-3.5)
55 to 69	137	143	147	1.45	1.46	1.47	3.24 (3.21-3.27)	3.24 (3.22-3.27)	3.22 (3.19-3.25)
70 to 84	122	125	130	1.62	1.64	1.65			
85+	51	52	54	1.77	1.80	1.83			
Total	830	843	850				3.50 (3.48-3.52)	3.48 (3.46-3.50	3.46 (3.44-3.48)

[1] Power law fitted to data from patients aged under 70 and with 3 or more attendances in a year, 95% confidence intervals estimated by bootstrap sampling.

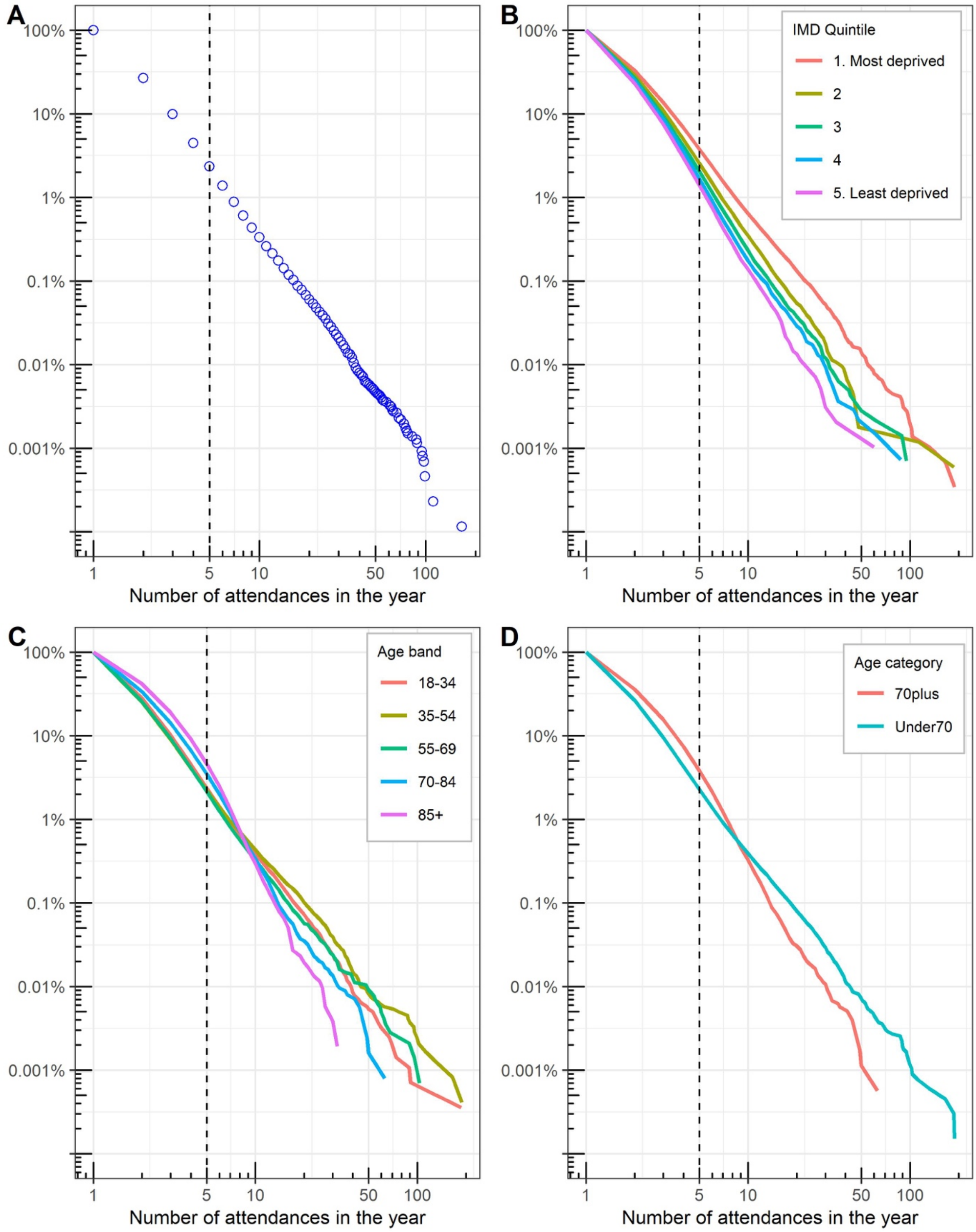

FIGURE 1

Figure 1 Distributions of ED attendance. Axes represent number of attendances in a year and the proportion of patients ED attenders who make at least that number of attendances. Figure 1A represents all patients in one year (using points to indicate spacing of values), Figure 1B shows data split by socioeconomic deprivation status, and Figure 1C by age group. Figure 1D is a simplified version of 1C. Figures 1B-1D use lines rather than points to reduce crowding of the data. Dashed line at 5 attendances indicates a commonly used threshold for frequent attendance.

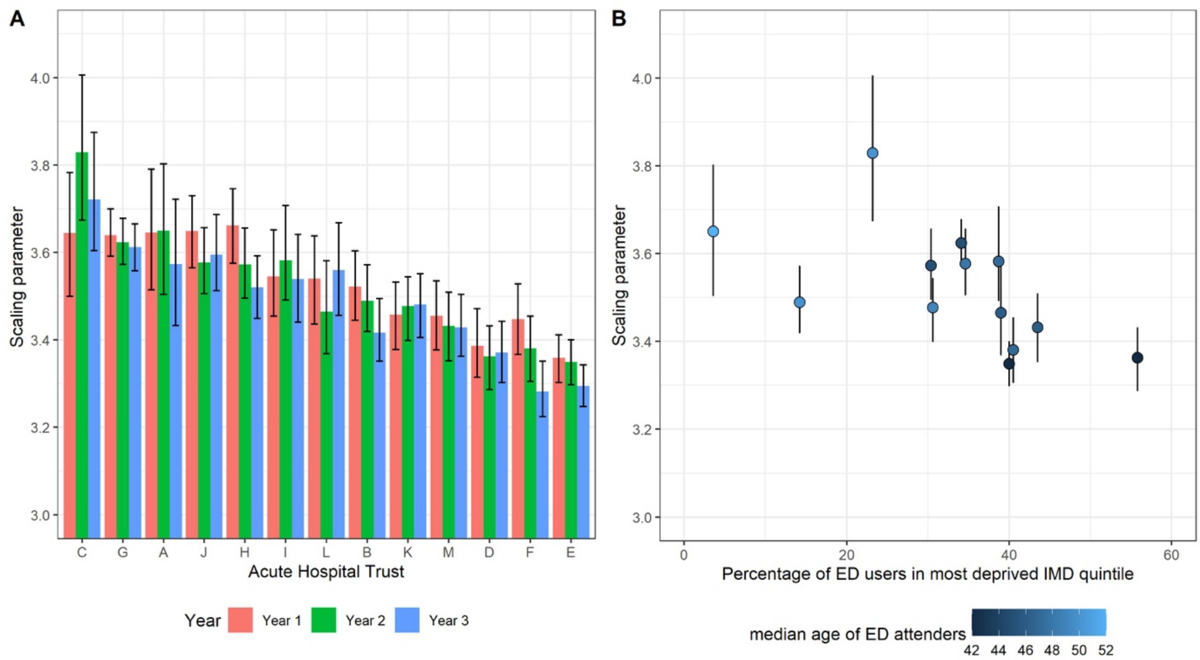

FIGURE 2

Figure 2 Variation in power law scaling parameter by hospital trust.
Figure 2A shows the year to year variation for each hospital trusts ordered by scaling parameter. Figure 2B shows the relationship between power law scaling parameter, socioeconomic deprivation and median patient age for each hospital trust. Error bars in both plots indicate 95%confidence intervals.

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