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Abstract:

The evaluation of new assessment units can identify areas of improvement for healthcare services. The South Warwickshire NHS Foundation Trust (SWFT) wants to evaluate a new Paediatrics Assessment Unit (PAU), the analysis is yet to begin. A comprehensive understanding of key performance indicators, including patient waiting times, length of stay (LOS), analysis of times series, and diagnosis severity is required for this service evaluation. This project aimed to analyse relevant performance indexes and describe in more detail the role of the PAU in supporting a high-quality paediatric emergency service. For this reason, data sources from different supplies such as the SWFT analytics team, operational managers, medical staff, and online platforms were gathered. The data was analysed by applying descriptive statistics for patients' characteristics and Welch's two-sample t-tests for examining changes in waiting times and LOS among others. In addition, I analysed patient reviews for assessing satisfaction. The study period included the COVID pandemic. Waiting times and LOS indicators increased, but the PAU has played a pivotal role as a healthcare provider for infants and toddlers. Furthermore, there was positive patient feedback regarding the Accidents and Emergency (A&E) and the paediatric unit. The results underlined the importance of taking patients' experience, internal managerial, external factors, and data perspectives limitations into account when evaluating health services.

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1. Introduction

Ever since the creation of the National Health Service (NHS) Act 1946, it has endured success and shared social commitment with the motivation to supply good, strong and reliable healthcare (Brain, J. 2022). In 2019, the NHS published its long-term plan. In this plan, there is a commitment to improve emergency care "*The NHS will reduce pressure on emergency hospital services as well as an action in response to the complex challenges of delivering 21st-century healthcare and building a resilient recovery from the recent COVID pandemic*" (Longtermplan.nhs.uk., 2019).

The pressures on urgent and emergency care services continue to dominate the headlines and are a daily concern for many patients using the services and the healthcare professionals who work in the NHS. The annual number of emergency attendances and admissions has been steadily increasing over many years. In accordance with this, prior to the COVID pandemic, the South Warwickshire NHS Foundation Trust (SWFT) had considered opening a Paediatric Assessment Unit (PAU) to reduce overcrowding in the Accidents & Emergencies department (A&E) and improve patient care.

However, during the COVID pandemic, concerns regarding overcrowding in the A&E department increased. Therefore, the SWTF intervened by establishing a PAU during the COVID pandemic. This action was aligned with national strategies, including the delivery of Same Day Emergency Care (SDEC). The PAU also aims to reduce admissions to the hospital by providing high quality SDEC thereby freeing up hospital beds for more critically ill patients. In the PAU SDEC, *patients presenting at the hospital with relevant conditions can be rapidly assessed and treated without being admitted to a ward (England, N. 2022).*

In more detail, this intervention was for alleviating capacity issues in the A&E and avoid children with minor illnesses to stay unnecessarily in the A&E. The PAU is located in the Warwick Hospital, adjacent to the paediatric ward. It is a 6-bed facility and became fully operational with the department assessing its first patient on January 12th, 2021. The service is designed to provide efficient care for infants, toddlers, children and young people under 16 years old who require urgent medical attention in Warwickshire and may not require hospital admission.

Patients can be referred by their GP (General Practitioners), no ambulance as paediatrics should be ambulatory, NHS 111, and A&E to be admitted to the unit, and then assessed by a proper

clinician promptly (Swft.nhs.uk. 2022). Exclusions on admissions are being applied for emergency transfer for resuscitation\stabilisation, isolation to prevent cross-infection and COVID positive or suspected. Additionally, the PAU was stablished to increase the capacity of the children's ward, so that clinicians could refer children directly to the unit for assessment, reducing the number of paediatric patients that had to be assessed by the paediatric team in the A&E. Furthermore, co-locating the PAU next to the children's ward enabled the inpatient paediatric team to work efficiently. (Swft.nhs.uk.,2022).

Generally, overcrowding and delays in A&E departments can compromise patient care. Establishing a PAU, and reducing the number of paediatric attendances at the A&E department, should reduce the likelihood of overcrowding and delays in the A&E. This could improve outcomes for patients not admitted to the PAU. Earlier studies revealed a major cause of morbidity and mortality cases is due to delays in the A&E diagnosis and treatment. Addressing this problem will have practical benefits for the PAU department at the SWFT and contribute to the understanding of future improvements (Rcpch.ac.uk., 2022).

Despite these beliefs, the PAUs effectiveness and appropriateness need to be evaluated, monitored, and assessed, especially at the post-intervention stage. Doing this analysis will contribute to the constant improvement required for the quality of healthcare services at the trust. This evaluation needs ongoing improvement and revision since the implementation has been approximated rather correct, and post-analysis has been found difficult to carry out. Prior to this evaluation there were also concerns that the PAU was not working efficiently and effectively. In view of these concerns, SWFT was keen for the PAU to be evaluated. The goal of this study is to generate insights in response to the evaluation of the PAU at the SWFT by extracting and manipulating data resources from the three principal platforms: Lorenzo, evolve (e-records), and IWantGreatCare[1] forum.

[1] Reviews of Warwick Hospital - Page - iWantGreatCare

1.1 Study aims and objectives:

As the Warwick hospital established a new PAU, understanding whether the specific performance indicators have been achieved was required. This study assessed the improvement in delivering patient care. Therefore, the following dissertation objectives were:

1. To establish the added value of the PAU on ameliorating the pressure of the A&E.

2. To determine how the patients' demand is satisfied with the service provided at the PAU/ A&E.

1.2 Methods

This study utilized the statistical examination of key performance indicators and outcomes between the A&E and the PAU. Those included an analysis and comparison of the following in the PAU & A&E: patient demographics description, time taken for a patient to be seen by a clinician/doctor, time of patient arrival and discharge in the A&E & PAU, referral type, discharge time, length of stay (LOS). Additionally, the use of time series analysis approaches to explain underlying patterns. Lastly, the application of sentiment analysis helped to determine patients' satisfaction.

1.3 Dissertation outline

This dissertation has the following structure:

1. Section 1 provides a brief introduction to the topic and the research objectives formulation.
2. Section 2 highlights relevant literature review to provide an overview of current knowledge.
3. For Section 3, the methodologies used are presented including data processing techniques, descriptive, statistical analyses, and sentiment analysis approaches.
4. Section 4 outlines the analysis of the results obtained through the process.
5. Section 5 suggests potential limitations and future research activities.
6. Section 6 summarizes the findings.

2. Literature review

2.1 key performance measures for A&E, evaluation and interventions

As has been previously reported in the literature, overview and significance of paediatric patients' studies reveal a range of 20%-30% of the visits A&E's are paediatric patients. These patients are significant because they stand for a large volume of patients (nearly one-third of all A&E visits), and because of the often-complex issues and risks to paediatrics. Although, most Paediatrics A&E visits are due to minor or benign conditions. Children and infants tend to have an increased vulnerability to illness and injury, including susceptibility to infections, and respiratory problems. (Sharon E, Mace. 2001).

There is a significant amount of published research regarding the impact of the implementation of rapid assessment units and the role of a PAU in providing exemplary healthcare services. A preliminary literature review shows and several studies suggest that the addition of these units has helped hospitals separate emergency rapid assessment from A&E services and has also helped alleviate the excessive burden on the A&E. Additionally, it is widely emphasized that overcrowding in the emergency department (ED) negatively affects patient outcomes, limits effective treatment for time-sensitive conditions such as pneumonia and sepsis, and reduces the safety and timeliness of care (Miake-Lye IM, et al. 2017).

Those research studies involve the evaluation of A&E's in countries such USA, Australia, New Zealand, among others. Since this study includes an end-to-end implementation of a Data mining project, it follows the CRISP-DM (Cross Industry Standard Process for Data Mining) method as the standard framework for data mining tasks (Wirth, R. and Hipp, J. 2000). In context, earlier observation studies have assessed the effect effectiveness of dedicated facilities (observation units) for patients who require short-course treatment and frequent reassessment, then they are monitored by dedicated staff. It has been identified that the aim here is to free up A&E space and resources for patients who are acutely ill (Hung, Geoffrey R. MD. et al. 2009) by avoiding the use of inpatient beds for short stays. A considerable number of studies have reported the effectiveness of such solutions (Hung, Geoffrey R, MD. et al. 2009 and Sharon E, Mace. 2001), and emphasised the importance of monitoring LOS, patient flow and admissions records.

Research studies have gone beyond these indicators when examining how to improve the service in A&Es. The papers published by Ardagh, M., et al. 2022 ; Li D, Abeywickrema M., et al 2021 highlight the importance of acquiring new medical staff to improve patient care. Interestingly, studies show extending the opening hours is not operationally efficient. Ardagh, M., et al. 2022 study showed that there was a significant improvement in the average waiting times to see a doctor when an additional nurse and doctor were rostered.

Most studies evaluate the performance of one-day rapid assessment units in comparison to previous practice of managing the patients in the A&E. However, few studies which focused on key performance indicators of these will prove to be particularly helpful during this research. A study of a unit in a busy London hospital, which primarily focused on the patient waiting times, concluded that about 63% of the patients in the department were seen by a clinician within 4 hours of being in the unit (M, Dunstan.et al. 2015). Dunstan, (2015) further explains that the provisioning of rapid assessment within few hours of patient being in the PAU will help further the RCS guidelines of improving emergency aid. Fearon et al. (2016) also focused on the waiting time KPI, and percentage of patients (69%) seen by a clinician within the first hour of arrival in a hospital in Ireland.

Another study focused on analysing whether rapid assessment units lead to a reduction in unnecessary hospital admissions (Reeds. et al., 2020). Reeds. et al. (2020) cited that about 44% of the referrals made to PAU were at once discharged and helped in reducing the admissions to the hospital. Further, reduced admissions also improved patient care efficiency, and patient experience and helped in cost reduction. Research on the referral of patients from various sources is also relevant to this dissertation. Research conducted on the PAU of an Ireland hospital revealed that most referral sources in both the A&E & rapid unit were GP referrals (Boyle, E., et al. 2012). The same study also posited that the presence of PAU helped significantly divert patients from A&E to the unit.

Research from Monash University, published in 2022, identified the importance of monitoring time series data to measure the increase in volume (number of patients) and age-specific rates of presentations to public hospital emergency departments (EDs), as well as any patterns in LOS; and to describe trends in ED utilisation. Furthermore, understanding patient's characteristics in the relation to median LOS and several patient demographic and clinical factors for all presentations were categorised according to age group, sex, referral source, type of transport to

the ED, Australasian Triage Scale (ATS) category which the level of immediately life-threatening, clinical diagnosis, ED LOS and discharge destination.

Broadly speaking, LOS has been considered by a series of recent studies as a quality indicator that stands for one of the most important performance measures in emergency departments. In a study carried out in Germany by Otto, R., et al. (2021) they stratified the LOS by (1) patient-related, (2) organizational-related and (3) structure-related factors. Average LOS for all patients was 3h 28 min (95% CI 3 h 27 min–3 h 29 min). LOS increased with patients' age and was shorter for walk-in patients compared to medical referrals was also found LOS was dependent on patient-related factors (age), disease-related factors (presentation complaint and triage level), and organizational factors (weekday and admitted/non-admitted status) (Otto, R., et al. 2021). As mentioned in this academic paper, these findings are determinant for the development of management strategies to enhance patient flow through the ED and thus prevent overcrowding.

One method employed by NJ Creasey, et al. 2015 carried out a study in a PAU which arose out of necessity and occupied a small space with limited privacy. The results emphasized on the long waiting times some children had to go through and proved that longer stays (>4–6 h) are inappropriate. Within the areas for improvement included consultant cover at peak times, facilities and space, waiting times to see a decision maker, early discharge/admission planning, and even parental information which contemplates patient's feedback. Although studies have been conducted by many authors, this problem is still insufficiently explored because of no patient's feedback for assessing quality health care, and the comparison for waiting times by gathering patient's characteristics presenting similar age, diagnosis and CABS score based on vitals in children at admission for prediction of severity of illness and outcome are not clearly presented in the literature.(Hassan, M.and David, K. 2006).

However, when having an ongoing increase in the demand of patients coming from different channels, it is essential to evaluate the effectiveness of new departments based on a timeframe basis as well as their connection to other units. The evaluation of the effectiveness of a rapid assessment zone to mitigate emergency department pressure has come to a wide awareness in the healthcare sector. The Emergency Medicine Journal (Bullard, M., et al.2022) evaluates this by gathering and reporting numeric data on at least one the following outcomes: (LOS; time in min from patient arrival to departure from the A&E), physician initial assessment (time in min from patient arrival to being seen by a doctor) and proportion of patients who left without being seen. Then, using a 2-sample t-test for continuous variables with a normal distribution mentioned by

(Jared S. Anderson, et al.,2020), mean, the standard deviation to compare between having no rapid assessment zones and having them, a comparative before and after intervention suggested by Tsai , VW. Sharieff ,GQ,. et al. (2012). The latter also states that rapid medical assessment is an effective way to improve patient flow, plus minimize the left without being seen (LWBS) rates in a paediatric emergency department (ED). A decrease in the LWBS rate allows the ED to provide health care to these potentially high-risk patients.

Following what it has been researched above, emergency department operation metrics and metrics were involved by Shari, J, Welch., et al.(2011) to improve the timeliness and efficiency of emergency care. ED Characteristics were identified including Acuity (Patients receiving codes of level 4 or 5 are high acuity; those receiving codes of 1 or 2, low acuity), admission rate (Percentage of ED visitors who are admitted as inpatients, Paediatric rate (Percentage of ED visitors younger than 18 years), Infant paediatric rate (Percentage of ED visitors younger than 2 years). Time intervals:

- ED LOS: Arrival time to departure time
- Arrival to treatment space time
- Admit decision to departure time: Decision to departure time
- Treatment space to provider time: Treatment space time to providers contact time

After having performed systemic literature, it was found that many studies tested the effect of an improvement intervention by analysing use measures as described above. However, there exist certain research projects that have included additional resources and data to be abstracted. For instance, Dr Paul Shekelle, Director of Evidence-based Synthesis Program (ESP) in Los Angeles, carried out an investigation in 2017 titled “Effectiveness of Interventions to Improve Emergency Department Efficiency (Miake-Lye IM, et al.2017). The study will be discussed below.

A key conclusion reached during Dr Paul Shekelle’s study was that a minor number of studies have reported the types of data needed to fully assess the effectiveness of efficiency improvement interventions. Affirming that very few studies have reported utilization, cost, and quality of care outcomes together. The following two maps display the improvement in the LOS and wait time by 11 types of interventions subsequently:

1. Physician Triage
2. Expand Nurse Scope of Practice
3. Fast Track
4. Point of Care Testing
5. information technology (IT)
6. Rapid Assessment Unit
7. Medical Scribe
8. Team Triage
9. Care Teams
10. Observation Unit
11. Other

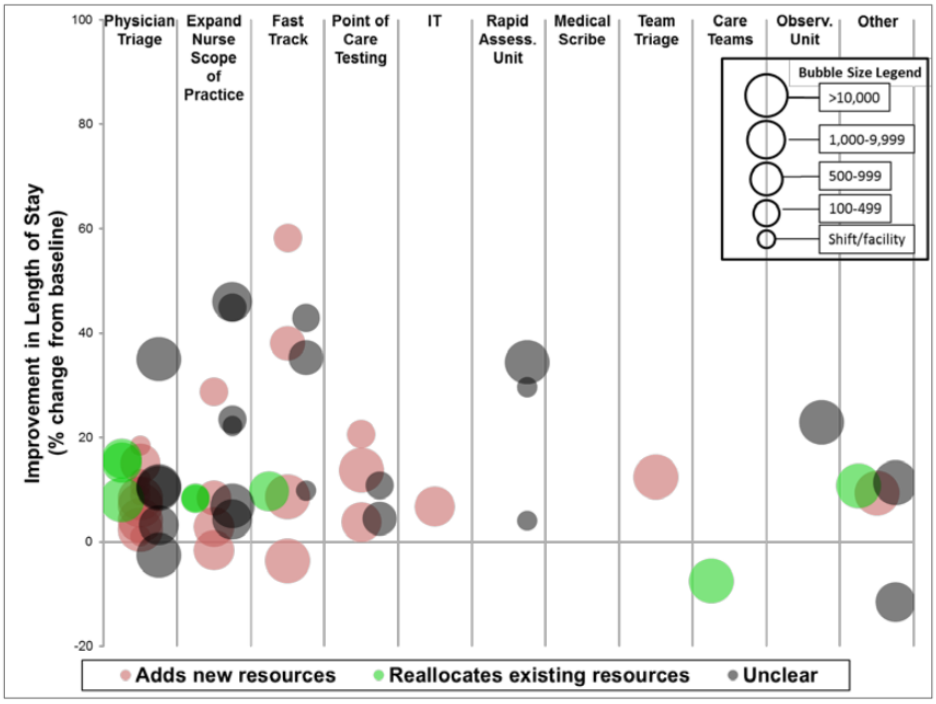

Figure 1. Evidence Map Displaying Improvement in LOS taken from Miake-Lye IM, et al. (2017).

Most studies that reported changes in LOS (n:67) improved mean LOS by between 10 and 40 minutes (e.g., Fernandes ,CM., et al. 1996; Day, TE., et al.2013; Rodi ,SW.,et al.2016). The results show that Fast Track and Nurse Scope of Practice interventions had the highest frequency of studies that were able to yield improvements greater than 30%. Whether Rapid assessment units reported LOS outcomes is unclear (Figure 1).

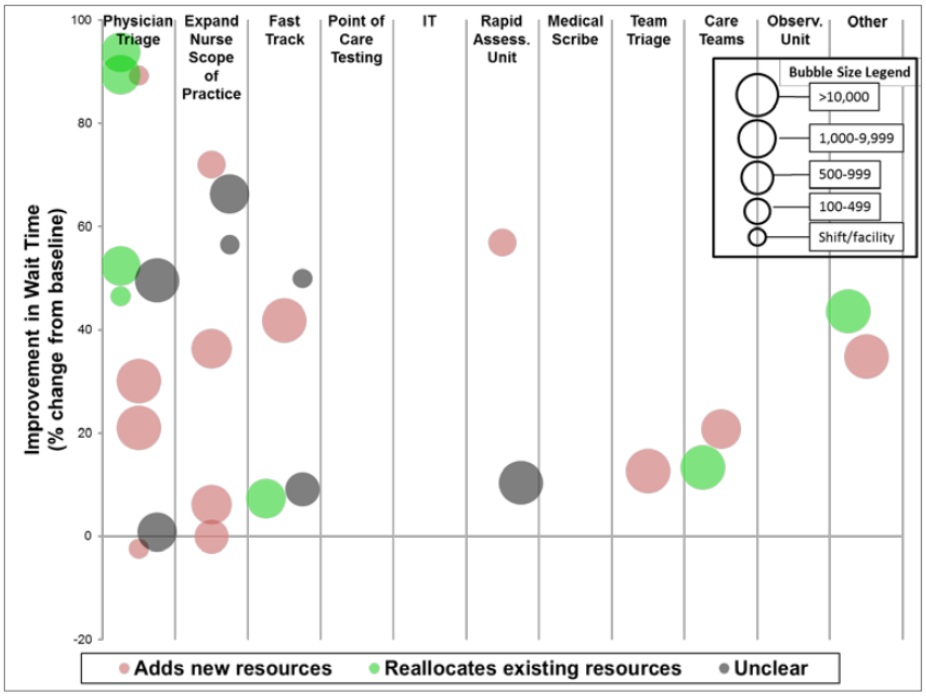

Figure 2. Evidence Map Displaying Improvement in Wait time taken from Miake-Lye IM, et al. (2017).

Improvements in wait time tended to range between 10 and 40 minutes (figure 2). Studies with a physician triage and additional nurses as interventions had the highest improvements, of more than 60% by reallocating existing resources. Rapid assessment unit resources interventions reported lower effects on Wait Time. Essentially, expanding the size of the ED is a clear fix for overcrowding, however, this is often costly and impractical. For decision-makers with resource constraints, more accurate reporting of resource requirements is imperative. (Miake-Lye IM, et al. 2017)

2.2 Text Mining and Sentiment Analysis Techniques

Opinion mining or sentiment analysis has recently come to the interest of many industries and fields. As said by Robinson, J. 2022. When human readers approach a text, we use our understanding of the emotional intent of words to infer whether a section of text is positive or negative. To begin performing this technique, tidy text format is a necessary and powerful way to make handling data easier and more effective. This is defined as a table with one token per row, a token is most often a single word per row. Packages such dplyr, tidyr, and broom are used, then to allow the manipulation and exploration of the text. These include word frequencies and sentiment analysis. Stine, R,A. (2019) represents the evolution of the field as a three-phrase process summarized as below:

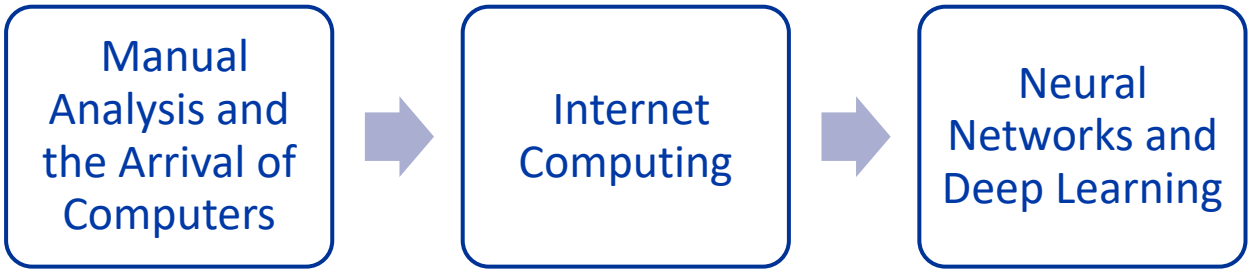

Figure 3. Phases of development of sentiment analysis based on Stine, R,A. (2019).

The first phase was stimulated by technological progress but predates modern computers. The bast quantity of documents that could serve as for identifying features in the text that might predict an opinion required human input, such as supplying a list of key words to be counted. … In the second phase, the rapid growth of computers and storage expanded the counting task. Rather than counting a few predetermined words, it became possible to count them all… Lately, the third phase of sentiment analysis began in the past decade with the appearance of practical methods for applying deep learning to NLP. Stine, R,A. (2019).

Robinson, J.2022 suggests a process of sentiment analysis chart that uses tidytext. It supplies a way to explore attitudes and opinions expressed in texts. Text mining offers tools such as sentiment analysis to understand the changes in customer's/patient's attitudes, which can give the basis for identifying positive or negative reviews. In the following figure a step-by-step sentiment analysis approach is displayed:

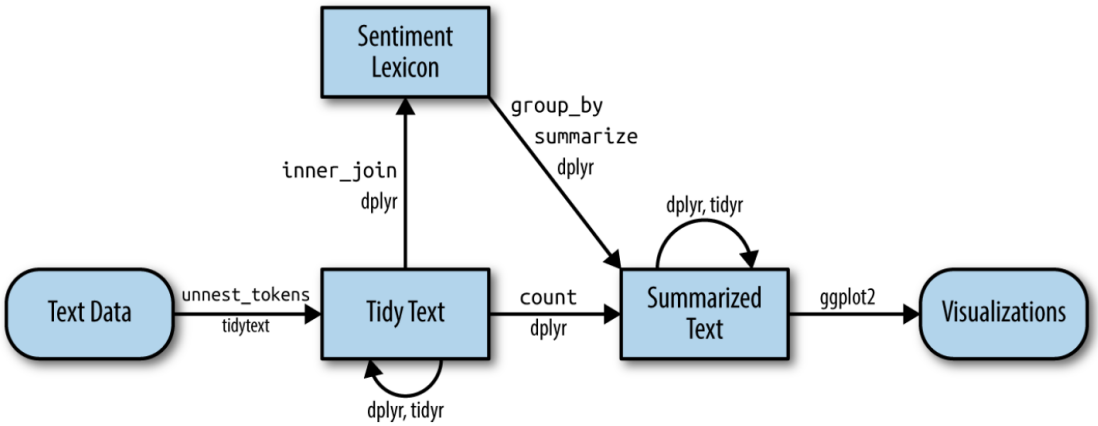

Figure 4. Flowchart for sentiment analysis taken from Robinson, J. 2022.

Text Data must be prepared, clean, and converted to the proper format. After having developed the needed format by using dplyr, tidyr, and broom among other packages for the text data, which is called Tidy Text, it is joined and matched with the sentiment lexicon or dictionary methods that hold a list of words and their respective sentiment categorization or level of sentiment. Moving on through the process, while selecting the rightest dictionary type is subjective and depends upon the text structure once it is decided summarizing and visualization approaches come next on the flow.

A series of recent studies has indicated as Stine, R,A. (2019) that sentiment analysis or opinion mining aims to assign an opinion or emotional label to text. Frequently, it is to examine whether the text expresses a positive or negative opinion often called polarity. The most widely used form of opinion mining assumes that the text of a website/document/form presents a collection of information of some entity by the customer/patient, such as the opinion of a customer/patient expressed in a product review/service subsequently. More systematic and theoretical analysis is needed for extracting the reviewer's intention from what may be a brief, sarcastic comment making sentiment analysis a challenging problem in natural language processing (NLP). Excellent reviews of NLP include Jurafsky ,D. and Martin ,JH. 2009; Manning ,CD. and Schutz ,H. 1999 ;W,T, Lin,.et al.2011.

Earlier studies have shown that the most direct approach to sentiment analysis which relies on a dictionary, or lexicon, that assigns positive or negative labels to a list of predetermined words is

the oldest and simplest. The predominance of these marked words decides the opinion assigned to a record. For example, Kumar, C.S.P., 2021 conducted experiments on the proposed approach using NHS England, NHS Choices, Hospitals, Patient Comments and Ratings, and patients expressing their experiences over social media. The proposed approach defined a new domain-specific dictionary and uses this in sentiment scoring to enhance the overall sentiment classification on patient authored text (Kumar, C.S.P et al. 2001). Additionally, Agarwal ,A, Xie B. et al. 2011; Gohil ,S. Vuik ,S. Darzi, A. 2018; Kouloumpis, E,.et al. 2011 carried out a Twitter health care research quantitative method of sentiment analysis for the free-text messages (tweets) using AFINN dictionary.

By citing and exploring the structure of the dictionaries, it is possible to describe that the Bing dictionary (Hu M, Liu, B. 2004), as explained by several authors and widely used, is the simplest and perhaps the best known. It contains 6,788 words as positive or negative. As it has been examined, the Bing dictionary has far more negative than positive word types (4,782 vs. 2,006). The AFINN (Nielsen, FA. 2011) has fewer types but assigns a numerical sentiment range from −5 to +5 to types rather than a category. The remaining dictionaries (NRC, Loughran) hold a more diversified list of emotions to word types. Rather than just labelling words as positive or negative, these categories include anger and joy (Mohammad, SM, Turney, PD. 2013) and litigious (Loughran and McDonald. 2011, which is oriented toward business applications).

3. Methodology

The definition of key indicators performances and understanding of the PAU role within the Warwick hospital are important activities. This section contains the description of the approaches performed for both datasets (A&E and PAU), and patients' reviews.

3.1 Dataset 1: A&E Paediatrics and Dataset 2: PAU Data (inpatient)

This methodology was developed to determine the benefit of having established the PAU. The collected information involved primarily quantitative resources but also touched upon descriptive qualitative methods. As the client provided data resources directly, those were extracted, manipulated, and analysed as a primary data analysis resource. For data processing, this project followed the CRISP-DM (Cross Industry Standard Process for Data Mining) method (Wirth, R. and Hipp, J., 2000) (Please refer to Figure 5). Further, R Studio was the main tool.

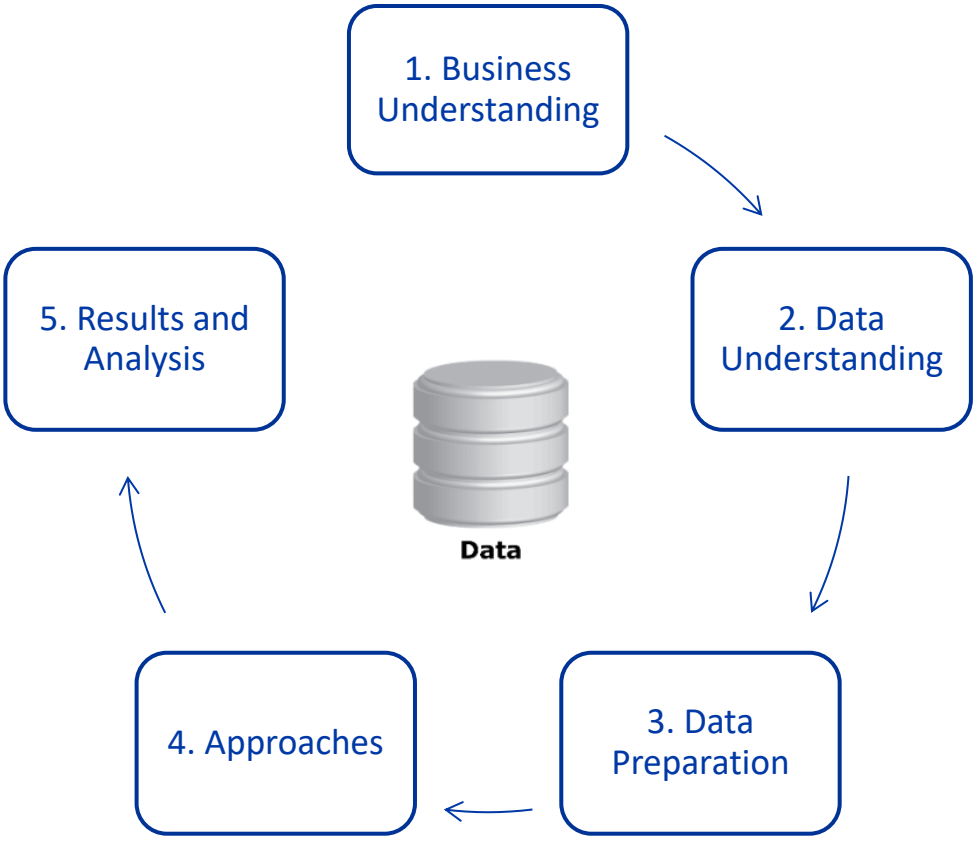

Figure 5. Process Diagram based on CRISP-DM

1. **Firstly, the business understanding:**

To begin with the business understanding, the problem statement, the validation of the approaches carried out, and all necessary clarifications were gathered by arranging meetings and discussions with staff and Consultants at the hospital. (See appendix)

2. **As a second stage, data understanding:**

The data was provided by the Information & Performance team of the TRUST. Firstly, Dataset 1: A&E patients from 01/01/2019 to 31/03/2022 (241174 patients to which 47284 correspond to < 16 years old) was collected, and its variables are as follows:

Variable	Description
Arrival Date	Patient arrival time and date
Age on arrival	Patient's Age
Patient Gender	Female and Male
Arrival > Initial Assessment	Elapsed time between Arrival and Initial assessment (minutes) (blank: unattended patient)
Arrival > Triage	Elapsed time between Arrival and triage (minutes) ((blank: unattended patient))
Arrival > Treatment	Elapsed time between Arrival and treatment (minutes) (blank: unattended patient)
Arrival > DTA	Elapsed time between Arrival and DTA (DECISION TO ADMIT) (minutes) (blank: unattended patient)
Arrival > Departure	Elapsed time between Arrival and Departure (minutes) (blank: unattended patient)
Diagnosis	Diagnosis Description
Acuity	Level of urgency
Admission Source	Referral type
Admitted	Y:yes, N:no

Admitting speciality	Admission speciality
Local patient Number	Identifier
Referred to Service	When the patient came to ED, were they referred to
Month Ending	Month of admission

Table 1. Dataset 1: A&E patients

Following the table above, each patient who walks into the A&E goes through the stages illustrated in figure 6. Describing and exploring those phases was needed, then these relevant KPIs were used as measures for assessing the establishment of the PAU were determined as follows:

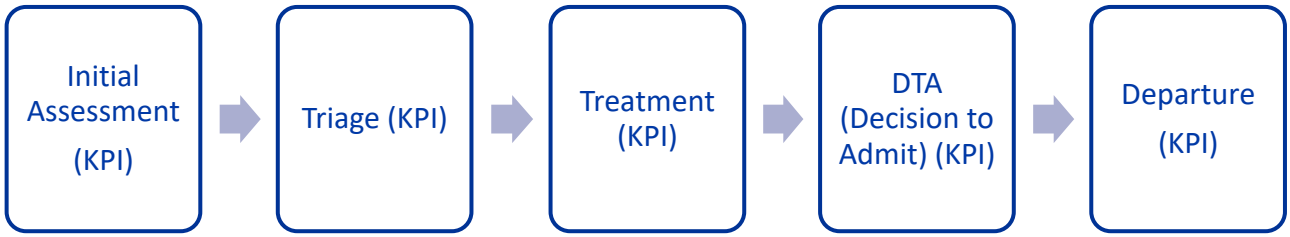

Figure 6. Patient flow stages A&E (KIP's)

Additionally, since the valuation of healthcare services can also be developed by identifying patient characteristics, a second database was introduced. The new database provided details for descriptive analysis, operational characteristics analysis, and assessing LOS for the PAU. This new dataset stored inpatient information for the PAU from 06/04/2020 to 30/06/2022 with a total of 4916 observations. The explanation for each variable is in table 2.

Variable	**Description**
Financial year	Fiscal year yyyy/d format
Financial month number	Month encoding 1 to 12
Month ending	Month ending date for each patient visit d/m/yyyy format
LOS	LOS for inpatient
Admission method group description	Admission method

Admission method hospital provider Spell description	Admission method specific description
Admission method hospital Provider spell	Admission code
Specialty group	Non-Paediatric/ Paediatrics
Treatment function code at admission	Treatment encoding
Age on admission	Age
Child	Grouping age 13 - 16, 17 and over, 3 to 5, 6 - 12 and Under 3 years
Main primary diagnosis	Main Diagnosis
Diagnosis description	Description for Diagnosis
Diagnosis main grouping	Description for main diagnosis
Start date hospital provider spell	Arrival date at PAU
Start time hospital provider spell	Arrival time at PAU
Discharge time hospital provider spell	Discharge time from PAU
Local patient number	Unique identifier
Priority type description	Level of emergency

Table 2. Dataset 2: PAU Data (inpatient)

3. Thirdly, data preparation

After identifying the measures for evaluation (KPI), the specification for pre- and post-implementation dates was completed. At least three months gap were included within the intervention for settling purposes, and to avoid seasonality effects, as suggested by several studies. The periods before and after were as follows:

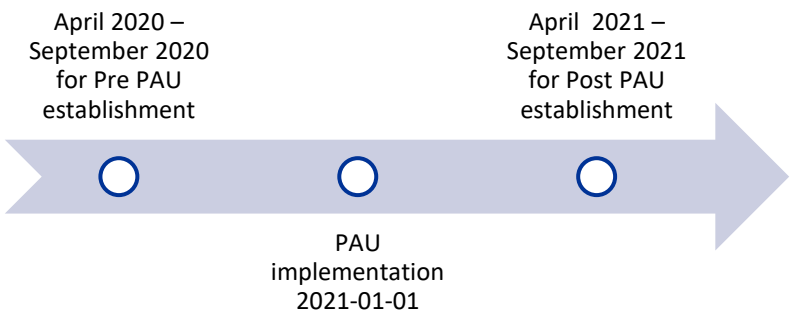

Figure 7. Pre and Post implementation

The figure above reflects two periods: from April 2020 to September 2020 (6 months) for the period before the establishment of the PAU and from April 2021 to September 2021 for the Post PAU establishment. Filters were applied before performing any statistical approach and analysis. These filters were decided based on the specific characteristics that PAU patients possess. The extractions were:

- To take patients younger than 16 years old since the PAU is exclusively for infants, children, and teenagers.
- To filter admission times from 10 am to 8 pm since the PAU opens from 10 am and admits the last patient at 8 PM.
- To filter by standard-level emergency care (regime/therapy) and non-urgent-level emergency care (regime/therapy) since the PAU only deals with those sorts of acuities.

(Note: There was no need to filter by day because the PAU opens every day)

4. Following our methodology, our fourth phase is called "Approaches"

- Null hypothesis significance testing (NHST) and estimation approach

Performing the analysis for each KPI began. It started with the creation of five data frames for each KPI while removing NAs. Besides that, a new dummy variable called implementation was inserted containing the number 1 for after or 0 for before PAU. Then, to examine those evaluation measures, independent samples null-hypothesis significance testing (NHST) (Howell, D,C. 2017) shall have been applied to continuous data (where p-value < 0.05 is statistically significant). A

Welch's test was run since its assumptions are that the comparison is for two independent means, and the variances are unequal.

The **KPI's** included were a total of 5:

1. Arrival > Departure (minutes)
2. Arrival > DTA (minutes)
3. Arrival > Treatment
4. Arrival > Triage
5. Arrival > Initial Assessment

Subsequently, Null hypothesis significance testing (NHST) formula was applied:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{s_{\bar{x}_1 - \bar{x}_2}} = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Howell, D,C. (2017)

Where the variables are:

Symbol	Description
$\bar{x}_i$	The mean of the sample i
$s_{\bar{x}_1 - \bar{x}_2}$	The standard error of the difference in sample means
s_i	The standard deviation of sample i
n_i	The number of observations in the sample i

NHST assumes hypothesis such:

- Null Hypothesis: The difference between mean of **KPI** after PAU implementation (implementation1) and before PAU implementation (implementation0) is zero.
- Alternate Hypothesis: The difference between mean of **KPI** after PAU implementation (implementation1) and before PAU implementation (implementation0) is NOT zero.

Following this testing, linear regression model for **KPI** and implementation of PAU as independent variable was created as below:

$$z.\boldsymbol{KPI} = \beta_{Intercept} + \beta_{implementation} \times implementation + \epsilon$$

Cumming, G. and Calin-Jageman, R. (2016) ; Cumming, G. (2014)

The summary lm() output contains an NHST of whether the coefficient is zero or not.

Furthermore, estimation approach (Cumming, G. and Calin-Jageman, R. 2016; Cumming, G. 2014) for calculating confidence intervals for each **KPI** was run. The estimation approach was carried out and took a 98% confidence interval range. Since the confidence interval range is between 95% CI [lower-upper], it tells us how confident we can be that our estimate coefficient for implementation1 will fall into that range depending on how wide our interval is. Additionally, it was important to mention how narrow the interval was and whether it did not include zero. Here we made a model object m.**KPI.**by.implementation and then use emmeans to get confidence intervals for **KPI** for PAU implementation and non-implementation and pairs () and confint() to contrast the implementation and no implementation.

- Descriptive analysis and Time series:

The application of time series analysis and examination of patterns were used for specific purposes. This approach covered explanations behind trends based on qualitative information from medical staff and recent official resources such as NHS websites, newspapers, and governmental information.

- Assessing LOS

To verify whether the LOS at the PAU was due to patient-related circumstances or organizational (Otto, R., et al. 2021), a comparison between similar patients admitted to the PAU was made. For this approach, 32 patients were selected randomly while applying eight filtering steps. Their characteristics filtered were:

- Emergency admission method.
- Pediatrics specialist.
- 0 years old.

- Respiratory diagnosis.
- Acute upper respiratory infection (most common diagnoses).
- Urgent priority.
- Accident and emergency admission method.
- Admission date from 2020 to 2021.

Subsequently, their Paediatric Early Warning Score (PEWS) was obtained by using their local hospital number on the records platform. PEWS score holds vital signs and observations essential to assess child's clinical status. This score provides a range from 0 (low severity) to 6+ (highest severity) depending on patient vital signs such heart rate, respiratory rate, temperature, among others (see appendix). Then, LOS within similar severity of illness was evaluated.

As a result, a Table 3 was created which included variables such:

- LOS in minutes.
- First ward of stay
- Admission method
- Admission date
- Start time when admitted
- Local patient number
- LOS in hours
- Description PEWS form
- New ID for security purposes

	LOS in mins	FIRST_WARD_STAY_NAME	ADMISSION_METHOD_HOSPITAL_PROVIDER_SPELL_DESCRIPTION	ADMIT_DATE
1	180	PAA	Accident and emergency	2020-05-03
2	281	PAA	Accident and emergency	2020-05-03
3	8	PAA	Accident and emergency	2020-05-27

START_TIME_HOSPITAL_PROVIDER_SPELL	LOCAL_PATIENT_NUMBER	LOS in hours	DescriptionPWESFORM	NEWID
16:30:00		3	0	1
10:09:00		5	-0	2
04:07:00		0	0.5	3

Table 3. PEWS score

5. **Our last step for this methodology is Results and Analysis:** Those will be covered in section 4

3.2 Text analytics–reviews

On the other hand, IWantGreatCare is an independent organization. This platform is available for measuring patient experience and outcomes, storing over six million healthcare reviews across 28 countries worldwide. From this website, reliable and transparent Warwick hospital reviews from patients were extracted. Hence, using these valuable resources to assess a patient's experience during their stay was plausible for this study. Text mining insights were developed in this scenario for generating insights into patients' satisfaction.

Further, patients' comments analysis was done through sentiment analysis. It is the process of extracting the emotions of the author of a text at the time of writing it. This text mining technique has recently been used to examine a large amount of qualitative data, often called a type of text analytics. The steps for this technique were 5 based on Robinson, J. 2022: preparing the dataset, cleaning data, preparation analysis, finding sentiment, and choosing the dictionary, and finding dominant and positive words. (See figure 8).

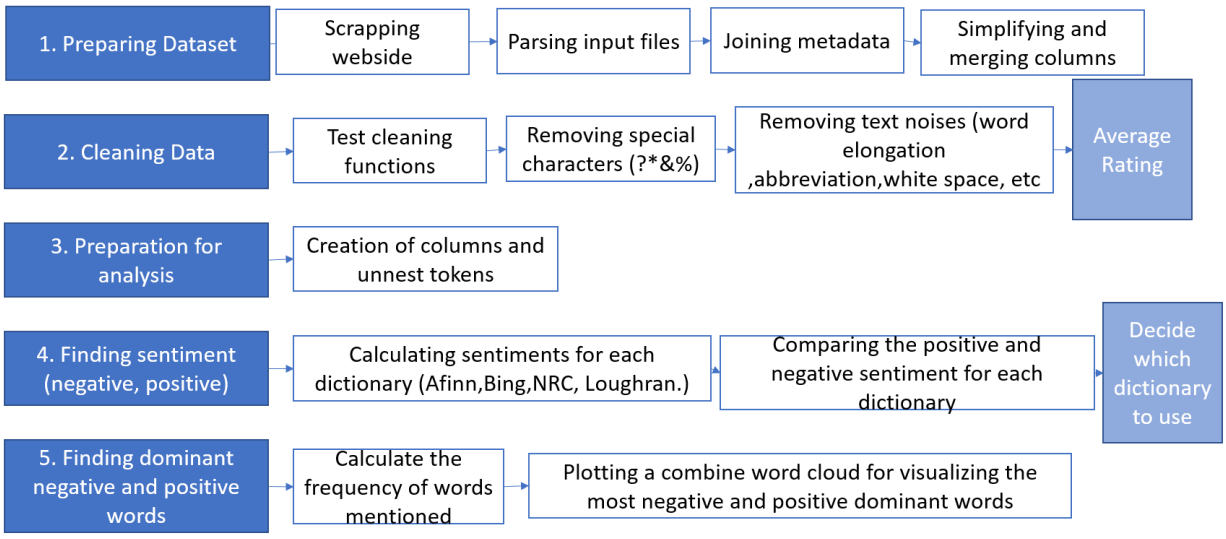

Figure 8. Method for sentiment analysis based on Robinson, J. 2022

To explain in detail figure 8, we have the following steps:

1. **Preparing Dataset**

As shown on figure 8, preparing Dataset is the beginning of the process. Raw data was converted to rds format. Collapsed text like reviews per SKU was split into different columns using separate and pivot longer functions. 9,263 and 967 reviews from A&E and Paediatrics A&E respectively were kept after omitting duplicated or missing data. Likewise, through web scrapping 16,370 from A&E and 2,850 from Paediatrics A&E reviews were extracted. So, two data sets were obtained where variables include: rating (from 1 to 5 stars), date and reviews.

2. **Cleaning Data**

Moving onto the second step, review text data was tokenized for this analysis. Anomalies removed were:

- Emotions: emoticons, grades, and ratings are replaced with corresponding.
- Spelling Mistakes: Spelling in the text was checked using the Hunspell package.
- Suggested words to correct the text. Those last ones were revised and corrected manually
- Special characters, numbers and double spaces.

3. **Preparation for analysis**

This third stage involved the creation of columns with the words extracted from the reviews and then ready for unnesting tokens.

4. **Finding sentiment (negative, positive)**

In this evaluation stage represented as number four on the mentioned figure, four dictionaries have been considered (Afinn, Bing, loughran and Nrc) to compare between them and determine the one worth highest detectability/coverage of words' polarity.

5. **Finding dominant negative and positive words**

Lastly, the fifth approach was to find the most dominant words and their frequency of mention to create the word cloud plot.

4. Results and Analysis

The study aims to establish the added benefit of the PAU for the A&E and determine how the patients' satisfaction has been met. The first section of this chapter outlines the results obtained from data and time series analysis. And the second section, sentiment analysis presents the reviews collected from the IWantGreatCare website.

4.1 Data and time series analysis

There were several approaches that served to determine the added value of the PAU. These are statistical tests to assess relevant KPIs, explanatory analysis for patients' characteristics, and time series for trend analysis.

Null hypothesis significance testing (NHST) assumes normally distributed variables. Skewness is present as shown on the distribution of every KPI variable in figure 9. However, since the number of records is considerable, running a NHST hypothesis testing and estimation approach was suitable.

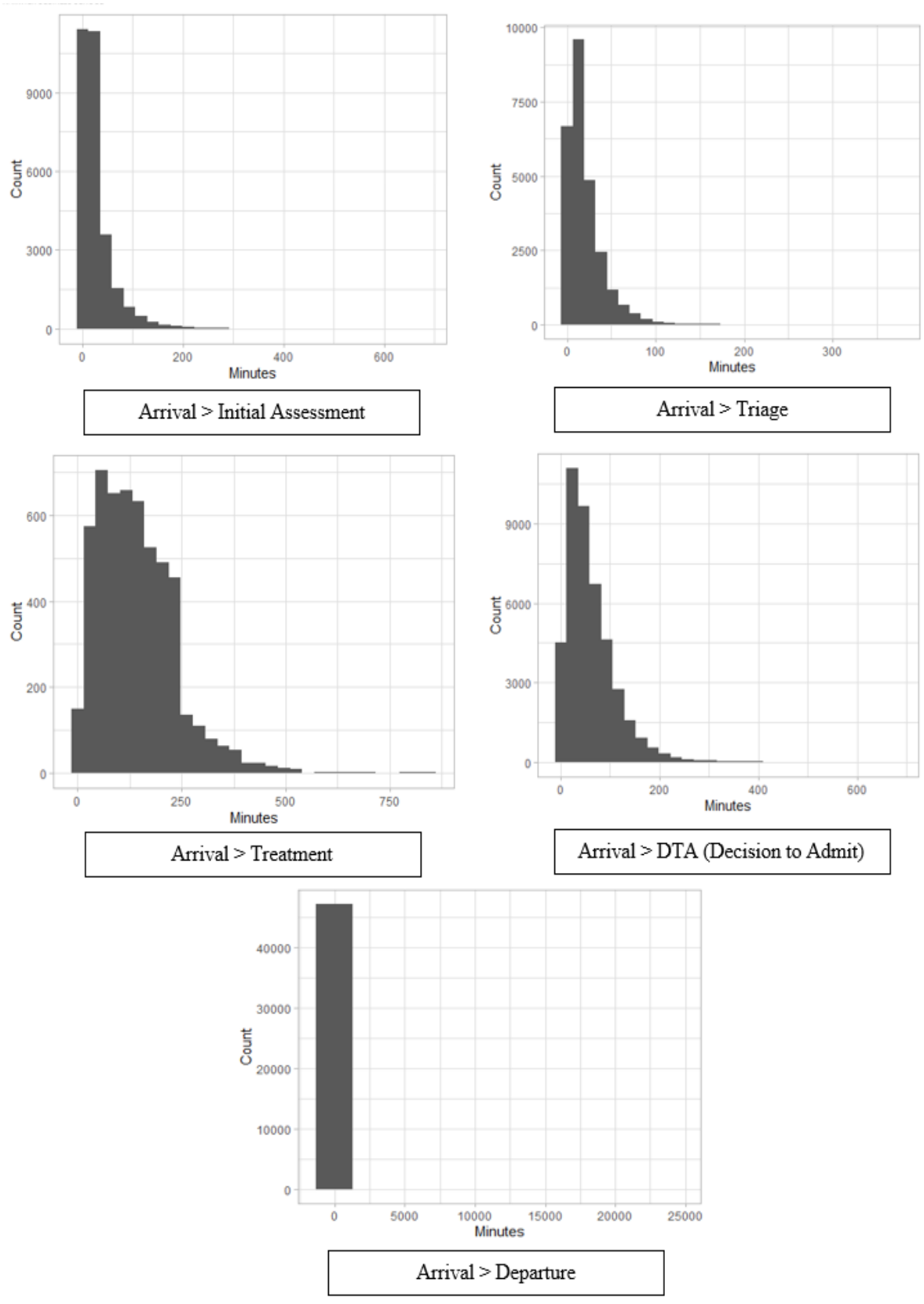

Figure 9. Distribution of the 5 KPIs

After checking the distribution for each KPI, the results from the t-test (NHST) along with Estimation approach techniques were generated to verify whether the waiting times: Departure, DTA (decision to admit), treatment, triage, and Initial assessment had a similar or different average waiting times before and after the PAU. The results revealed the next 5 bullet points:

- For Departure KPI:

Welch Two Sample t-test	
t	-14.629
df	1688.5
p-value	< 2.2e-16
95 percent confidence interval	
-15.07184	-11.57973
Sample Estimates:	
mean in group 0	mean in group 1
16.56921	29.895

Interpretation: The mean of Arrival > Departure (minutes) after PAU implementation (implementation1) and before PAU implementation (implementation0) is NOT zero. $t(1688.5) = -14.629, p < 0.00.$

Therefore, the t=test tells us that we should accept the Alternate hypothesis and the data is statistically significant. However, the waiting times for departure did not significantly improve post-intervention but increased.

Summary lm()				
Residuals:				
Min	1Q	Median	3Q	Max
-124.24	-43.76	-9.50	31.76	491.76
Coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	98.756	2.102	46.99	<2e-16 ***
implementation1	43.480	2.972	14.63	<2e-16 ***
Signif. Codes:	0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			
Residual standard error: 63.23 on 1808 degrees of freedom				
Multiple R-squared: 0.1058, Adjusted R-squared: 0.1053				
F-statistic: 214 on 1 and 1808 DF, p-value: < 2.2e-16				

Interpretation: The summary () output contains an NHST of whether the coefficient is zero or not. Given the results we find that the effect of implementation (implementation1) on the Departure (time) is NOT zero. However, waiting times did not reduce. $t(1808) = 14.63\ .p < .00$

Estimation approach

Here we make a model object m.Departure.by.implementation and then use emmeans to get confidence intervals for the Arrival > departure waiting times for PAU implementation and non-implementation and pairs () and confint() to *contrast* the implementation and no implementation.

Estimation Approach							
implementation	emmean	SE	df	lower.CL	upper.CL		
0	98.8	2.1	1808	94.6	103		
1	142.2	2.1	1808	138.1	146		
Confidence level used: 0.95							
contrast			estimate	SE	df	lower.CL	upper.CL
implementation0 - implementation1			-43.5	2.97	1808	-49.3	-37.7
Confidence level used: 0.95							
	coefficients	2.5 %	97.5 %				
(Intercept)	98.75580	94.63383	102.87777				
implementation1	43.47956	37.65021	49.30891				

Interpretation reporting 95% confidence interval difference: The mean in Departure waiting times for no implementation is 98.8 95% CI. The mean in Departure waiting times for implementation is 142.2 95% CI. This difference in means is significantly different from zero, but implementation did not reduce waiting times overall. (See Figure 10 for confidence intervals by implementation and contrast).

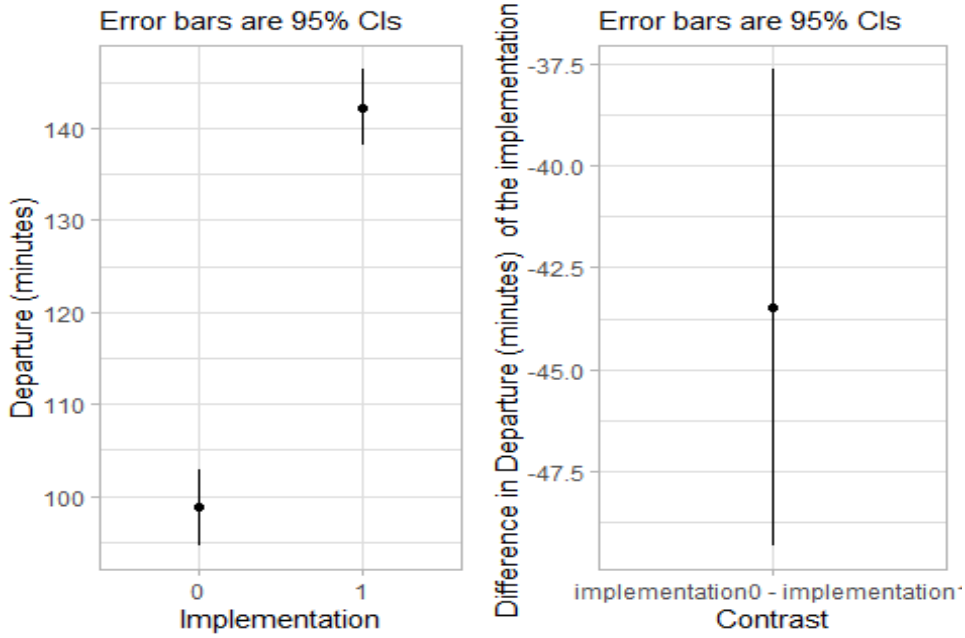

Figure 10.Confidence intervals and contrast for Departure

- For DTA KPI

Welch Two Sample t-test	
t	-9.3995
df	314.34
p-value	< 2.2e-16
95 percent confidence interval	
-109.42	-71.54
Sample Estimates:	
mean in group 0	mean in group 1
82.907	173.3888

Interpretation: The mean of Arrival > DTA (decision to admit) (minutes) after PAU implementation (implementation1) and before PAU implementation (implementation0) is NOT zero. $t(314.34) = -9.3995, p < 0.00$

Therefore, the t=test tells us that we should accept the Alternate hypothesis and the data is statistically significant. However, the waiting times for DTA did not significantly improve post-intervention but increased.

Summary lm()				
Residuals:				
Min	1Q	Median	3Q	Max
-162.39	-61.39	-14.91	42.61	459.61
Coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	82.908	8.641	9.594	< 2e-16 ***
implementation1	90.481	10.934	8.275	3.67e-15 ***
Signif. Codes:	0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			
Residual standard error: 94.27 on 315 degrees of freedom				
Multiple R-squared: 0.1786, Adjusted R-squared: 0.176				
F-statistic: 68.48 on 1 and 315 DF, p-value: 3.674e-15				

Interpretation: The summary () output contains an NHST of whether the coefficient is zero or not. Given the results we find that the effect of implementation (implementation1) on the DTA (decision to admit) time is NOT zero. However, it did not reduce waiting times. $t(315) = 8.275. p < .00$

Estimation approach

Here we make a model object m.DTA.by.implementation and then use emmeans to get confidence intervals for the Arrival > DTA waiting times for PAU implementation and non-implementation and pairs () and confint() to *contrast* the implementation and no implementation.

Estimation Approach

implementation	emmean	SE	df	lower.CL	upper.CL
0	82.9	8.64	315	65.9	99.9
1	173.4	6.70	315	160.2	186.6

Confidence level used: 0.95

contrast	estimate	SE	df	lower.CL	upper.CL
implementation0 - implementation1	-90.5	10.9	315	-112	-69

Confidence level used: 0.95

	coefficients	2.5 %	97.5 %
(Intercept)	82.90756	65.90535	99.90978
implementation1	90.48133	68.96825	111.99440

Interpretation reporting 95% confidence interval difference: The mean in DTA (decision to admit) waiting times for no implementation is 82.9, 95%CI. The mean in DTA (decision to admit) waiting times for implementation is 173.4 95%CI. This difference in means is significantly different from zero, but the implementation did not reduce waiting times overall. (See Figure 11 for confidence intervals by implementation and contrast).

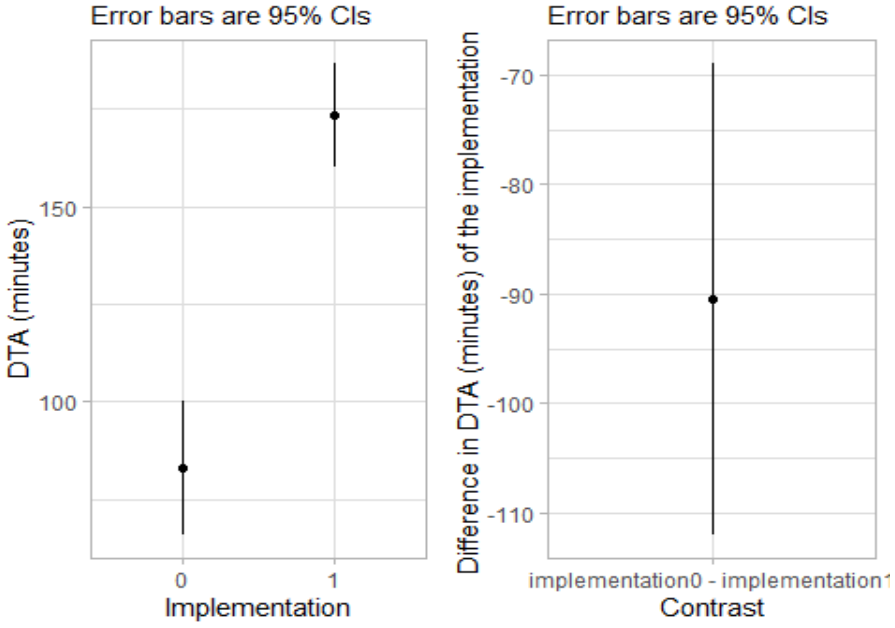

Figure 11. Confidence Interval and Contrast for DTA

- For treatment KPI

Welch Two Sample t-test	
t	-18.351
df	1334.6
p-value	< 2.2e-16
95 percent confidence interval	
-40.18874	-32.4261
Sample Estimates:	
mean in group 0	mean in group 1
49.6926	86

Interpretation: The mean of Arrival > treatment (minutes) after PAU implementation (implementation1) and before PAU implementation (implementation0) is NOT zero. $t(1334.6) = -18.351, p < 0.00$

Therefore, the t=test tells us that we should accept the Alternate hypothesis and the data is statistically significant. However, the waiting times for treatment did not significantly improve post-intervention but increased.

Summary lm()				
Residuals:				
Min	1Q	Median	3Q	Max
-80.000	-27.693	-5.693	19.000	304.000
Coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	49.693	1.412	35.18	<2e-16 ***
implementation1	36.307	1.988	18.27	<2e-16 ***
Signif. Codes:	0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			
Residual standard error: 39.55 on 1582 degrees of freedom				
Multiple R-squared: 0.1742, Adjusted R-squared: 0.1737				
F-statistic: 333.7 on 1 and 1582 DF, p-value: < 2.2e-16				

Interpretation: The summary () output contains an NHST of whether the coefficient is zero or not. Given the results, we find that the effect of implementation (implementation1) on the treatment (time) is NOT zero. However, it did not reduce waiting times. $t(1582) = 18.13. p < .00$

Estimation approach

Here we make a model object m.DTA.by.implementation and then use emmeans to get confidence intervals for the Arrival > DTA waiting times for PAU implementation and non-implementation and pairs () and confint() to *contrast* the implementation and no implementation.

Estimation Approach							
implementation	emmean	SE	df	lower.CL	upper.CL		
0	49.7	1.41	1582	46.9	52.5		
1	86.0	1.40	1582	83.3	88.7		
Confidence level used: 0.95							
contrast			estimate	SE	df	lower.CL	upper.CL
implementation0 - implementation1			-36.3	1.99	1582	-40.2	-32.4
Confidence level used: 0.95							
	coefficients		2.5 %	97.5 %			
(Intercept)	49.6926		46.92211	52.46310			
implementation1	36.3074		32.40896	40.20583			

Interpretation reporting 95% confidence interval difference: The mean in treatment waiting times for no implementation is 49.7, 95% CI. The mean in treatment waiting times for implementation is 86.0, 95% CI. This difference in means is significantly different from zero, but the implementation did not reduce waiting times overall. (See Figure 12 for confidence intervals by implementation and contrast).

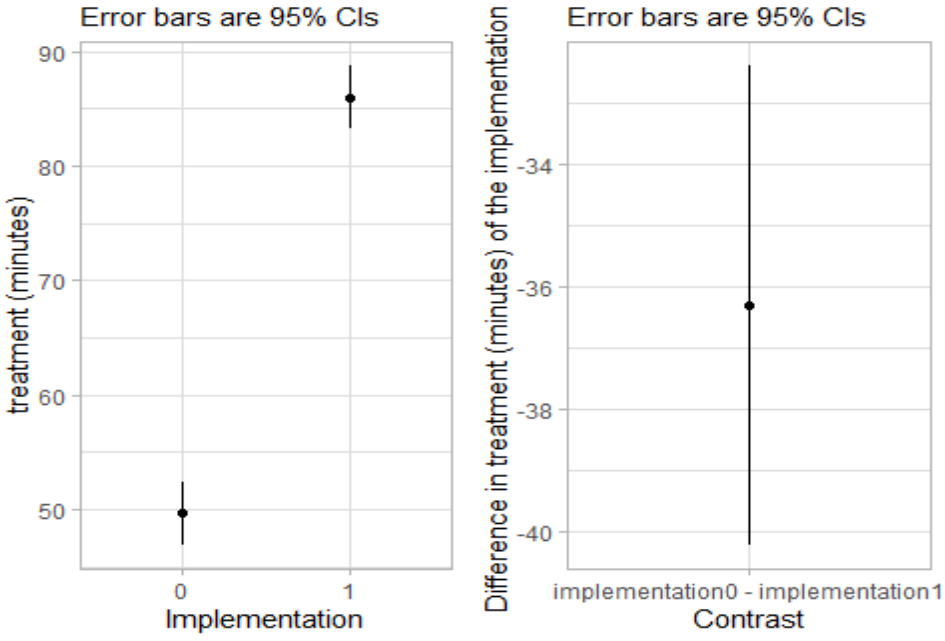

Figure 12. Confidence Intervals and Contrast for treatment

- For triage KPI

Welch Two Sample t-test	
t	-14.972
df	1721.3
p-value	< 2.2e-16
95 percent confidence interval	
-14.35946	-11.03305
Sample Estimates:	
mean in group 0	mean in group 1
16.56575	29.262

Interpretation: The mean of Arrival > triage (minutes) after PAU implementation (implementation1) and before PAU implementation (implementation0) is NOT zero. $t(1721.3) = -14.972, p < 0.00$

Therefore, the t=test tells us that we should accept the Alternate hypothesis and the data is statistically significant. However, the waiting times for triage did not significantly improve post-intervention but increased.

Summary lm()				
Residuals:				
Min	1Q	Median	3Q	Max
-29.262	-12.566	-4.262	8.434	161.738
Coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	16.5657	0.6273	26.41	<2e-16 ***
implementation1	12.6963	0.8658	14.66	<2e-16 ***
Signif. Codes:	0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			
Residual standard error: 18.87 on 1903 degrees of freedom				
Multiple R-squared: 0.1015, Adjusted R-squared: 0.1011				
F-statistic:215 on 1 and 1903 DF, p-value: < 2.2e-16				

Interpretation: The summary () output contains an NHST of whether the coefficient is zero or not. Given the results we find that the effect of implementation (implementation1) on the triage (time) is NOT zero. However, it did not reduce waiting times. $t(1903) = 14.66. p < .00$

Estimation approach

Here we make a model object m.triage.by.implementation and then use emmeans to get confidence intervals for the Arrival > triage waiting times for PAU implementation and non-implementation and pairs () and confint() to *contrast* the implementation and no implementation.

Estimation Approach							
implementation	emmean	SE	df	lower.CL	upper.CL		
0	16.6	0.627	1903	15.3	17.8		
1	29.3	0.597	1903	28.1	30.4		
Confidence level used: 0.95							
contrast			estimate	SE	df	lower.CL	upper.CL
implementation0 - implementation1			-12.7	0.866	1903	-14.4	-11
Confidence level used: 0.95							
	coefficients	2.5 %	97.5 %				
(Intercept)	16.56575	15.33549	17.79600				
implementation1	12.69625	10.99823	14.39427				

Interpretation reporting 95% confidence interval difference: The mean in triage waiting times for no implementation is 16.6, 95% CI. The mean in triage waiting times for implementation is 29.3, 95% CI. This difference in means is significantly different from zero, but implementation did not reduce waiting times overall. (See Figure 13 for confidence intervals by implementation and contrast)

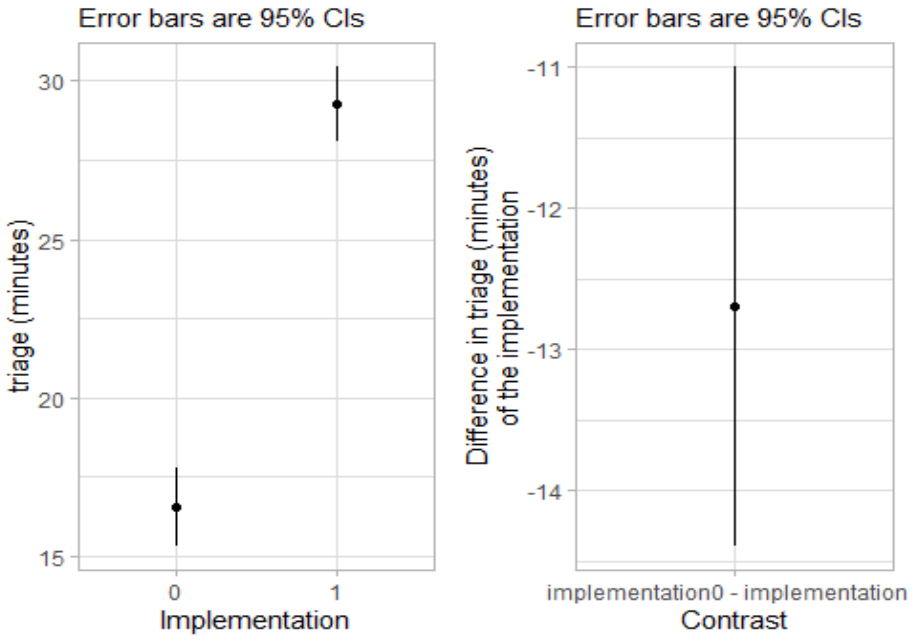

Figure 13. Confidence Intervals and Contrast for Triage

- For Initial Assessment KPI

Welch Two Sample t-test	
t	-14.969
df	1661.8
p-value	< 2.2e-16
95 percent confidence interval	
-15.07184	-11.57973
Sample Estimates:	
mean in group 0	mean in group 1
16.56921	29.895

Interpretation: The mean of Arrival > initial assessment (minutes) after PAU implementation (implementation1) and before PAU implementation (implementation0) is NOT zero. $t(1661.8) = -14.969, p < 0.00$

Therefore, the t=test tells us that we should accept the Alternate hypothesis and the data is statistically significant. However, the waiting times for initial assessment did not significantly improve post-intervention but increased.

Summary lm()				
Residuals:				
Min	1Q	Median	3Q	Max
-28.895	-12.569	-4.569	8.431	161.105
Coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	16.5692	0.6610	25.07	<2e-16 ***
implementation1	13.3258	0.9118	14.61	<2e-16 ***
Signif. Codes:	0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1			
Residual standard error: 19.86 on 1901 degrees of freedom				
Multiple R-squared: 0.101, Adjusted R-squared: 0.1005				
F-statistic:213.6 on 1 and 1901 DF, p-value: < 2.2e-16				

Interpretation: The summary () output contains an NHST of whether the coefficient is zero or not. Given the results we find that the effect of implementation (implementation1) on the assessment (time) is NOT zero. However, it did not reduce waiting times. $t(1901) = 14.61. p < .00$

Estimation approach

Here we make a model object m.initial_assessment.by.implementation and then use emmeans to get confidence intervals for the Arrival > initial assessment waiting times for PAU implementation and non-implementation and pairs () and confint() to *contrast* the implementation and no implementation.

Estimation Approach							
implementation	emmean	SE	df	lower.CL	upper.CL		
0	16.6	0.661	1901	15.3	17.9		
1	29.9	0.628	1901	28.7	31.1		
Confidence level used: 0.95							
contrast			estimate	SE	df	lower.CL	upper.CL
implementation0 - implementation1			-13.3	0.912	1901	-15.1	-11.5
Confidence level used: 0.95							
	coefficients	2.5 %	97.5 %				
(Intercept)	16.56921	15.27286	17.86557				
implementation1	13.32579	11.53748	15.11410				

Interpretation reporting 95% confidence interval difference: The mean in initial assessment waiting times for no implementation is 16.6, 95% CI. The mean in assessment waiting times for implementation is 29.9, 95% CI. This difference in means is significantly different from zero, but implementation did not reduce waiting times overall. (See Figure 14 for confidence intervals by implementation and contrast)

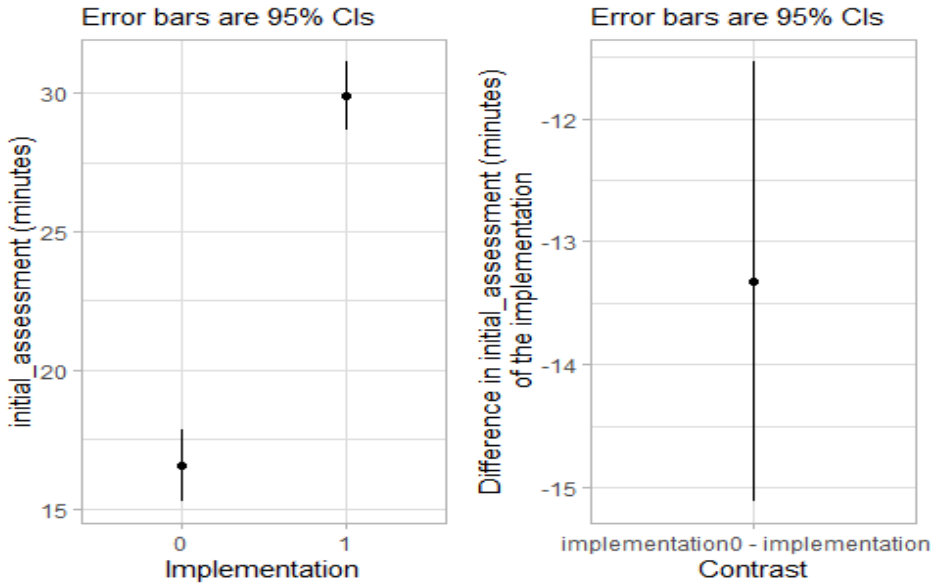

Figure 14. Confidence Intervals and Contrast for Initial Assessment

After carrying out Null Hypothesis testing for mean difference and estimation approach, the results concluded that the intervention of setting up a 6-bed PAU with 1 (Nurse) staffing did not improve waiting times at any stage of the patient flow. Instead, waiting times increased dramatically after implementation. Initial assessment and triage pre- and post-resulted in a much smaller range difference than other stages. Regarding the confidence intervals, the most critical stages appear to be "decision to admit" and treatment because of their difference in the confidence intervals.

However, these results needed further examination to consider huge external impacts such as COVID-19, and lockdowns in the Warwickshire area. Moreover, patients' specific characteristics are yet to be analyzed to understand the PAU role within the hospital for Pediatrics.

Two indicators to understand patients' characteristics are as follows: (Shari ,J, Welch,.et al.2011)

- The pediatric rate relates to the Percentage of A&E visitors younger than 16 years of 241176 total patients. In our case, 42294 are younger than 16 years old, meaning that 17% of the patients from the A&E are pediatrics across the years of study.
- At the same time, the Infant pediatric rate stands for the Percentage of A&E visitors younger than three years old. 241176 patients whose age is less than three years old. In total, 17484 are younger than three years old, so 7.2% is the infant rate for this period. This number also represents nearly 41% of pediatric patients (42294).

Figure 15 depicts the age on arrival < 16 years old at the A&E. By exploring this distribution, the interpretation was that most patients age 0 to 3 years old while 5 to 10 years old children account for a smaller number. The mean is seven years old.

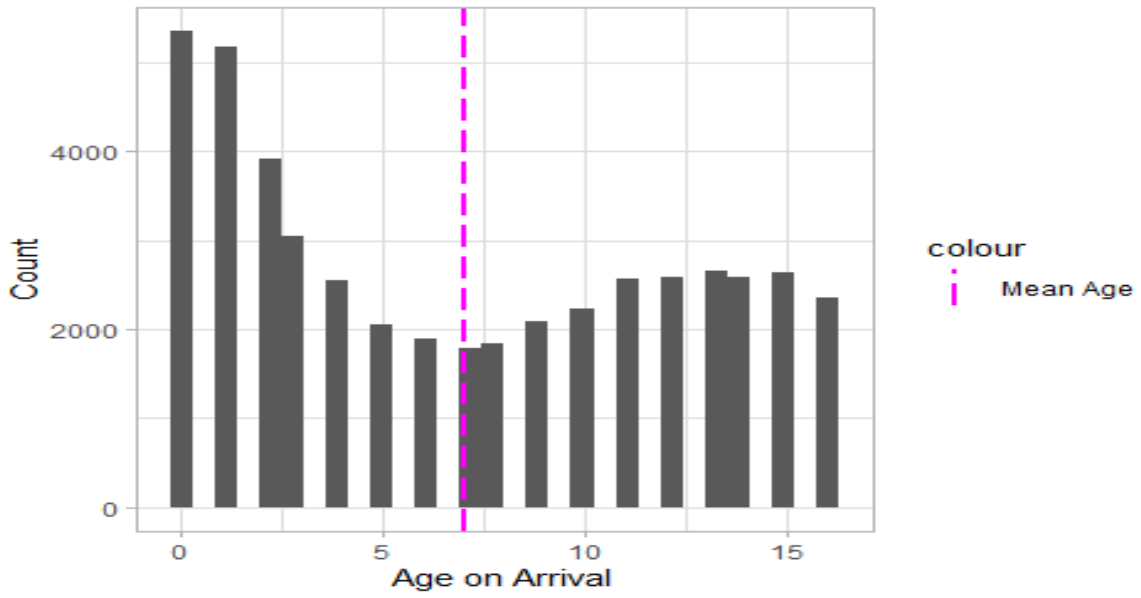

Figure 15. Distribution of Age in the A&E for Paediatrics

Moreover, about patients' gender contrast. As pictured in figure 16, there has been a higher percentage of Male patients while female corresponds to a minority group. The figure also exhibits the evident increasing trend in the number of patients from 2019 to 2022 overall, specifically from 2021.

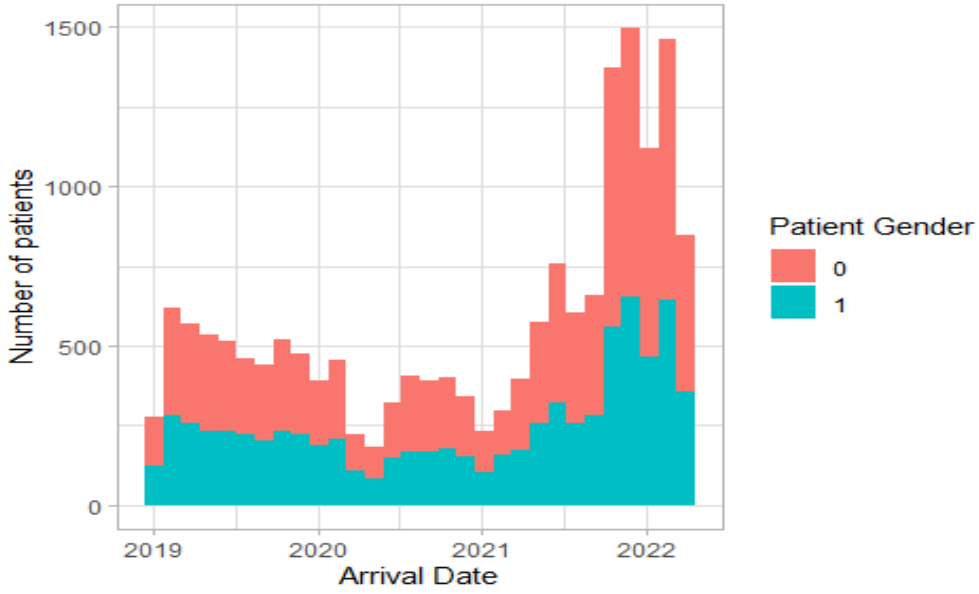

Figure 16. Patients by Gender in the A&E for Paediatrics

Additionally, regarding operational factors, the A&E operates daily. A time series plot (Figure 17) of the number of Pediatrics patients from 2019 to 2022 by day was introduced to describe operational details through the years of study. The number of patients on the y-axis against the years of study grouped by each day. This exploration revealed that Monday and Sunday are the busiest days for the A&E. Note that attendance started to rise in the middle of 2021 onwards, as shown and proven in Figure 17.

Figure 17. Time Series for Paediatrics patients by Weekday

Likewise, the opening hours are 24 hours a day. To evaluate peak hours when there is the highest number of attendees, a distribution of the number of patients at each time from 12 pm to 12 am by weekday was plotted. Then, the busiest hours of the day for the A&E start at 8 am and go on until 11 pm approximately. Therefore, it is not operationally efficient to open a 24-hour PAU since the demand of patients before 7 am and after 8 pm is not significant. (Figure 18).

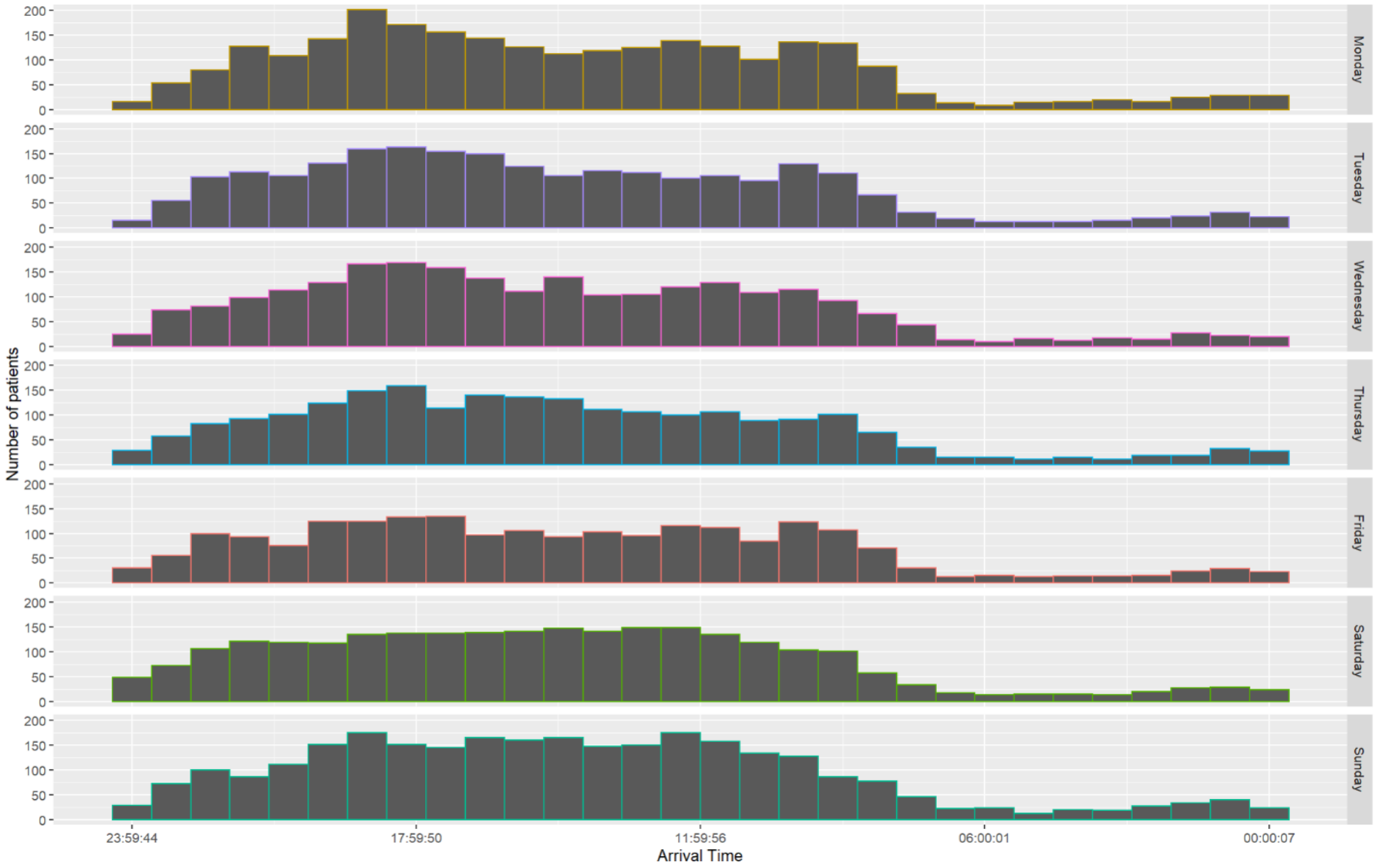

Figure 18. Distribution of patients at each Arrival Time by weekday

The previous tests and exploratory analysis revealed that the waiting times and the number of patients were soaring progressively. For further revision, time series analysis was utilized to explain the circumstances that led to those dramatic changes. This analysis will be presented before diving into inpatient data details.

Additional explanations for the next graphs are: a magenta vertical line that points at the date the first COVID case was reported in Warwickshire, a dark blue as for the PAU data was set up, and finally, two dashed light blue lines standing for the period March to July 2021 on which England began leaving lockdown. (Baker, C., et al.2021; coronavirus.data.gov.uk.n.d;www.ons.gov.uk. n.d.)

Figure 19 displays how the waiting times in minutes for each KPI have behaved from 2019 until 2022. The time series reflect that Arrival > Initial Assessment (minutes) have increased from 2019 to 2022 (figure 19), especially surging from around 2021 middle of the year. These graphs also show that there were no changes in waiting times at the very start of the pandemic in the UK.

As the pandemic surged, lockdowns were put in place. Afterwards, in July 2021, when lockdown restrictions were lifted the A&E waiting times rose rapidly. Establishing the PAU may have reduced the pressure on the A&E department, but it was not preventing an increasing waiting time during the pandemic, as shown on the graph. However, DTA (Decision to admit) seems to be less affected by the pandemic.

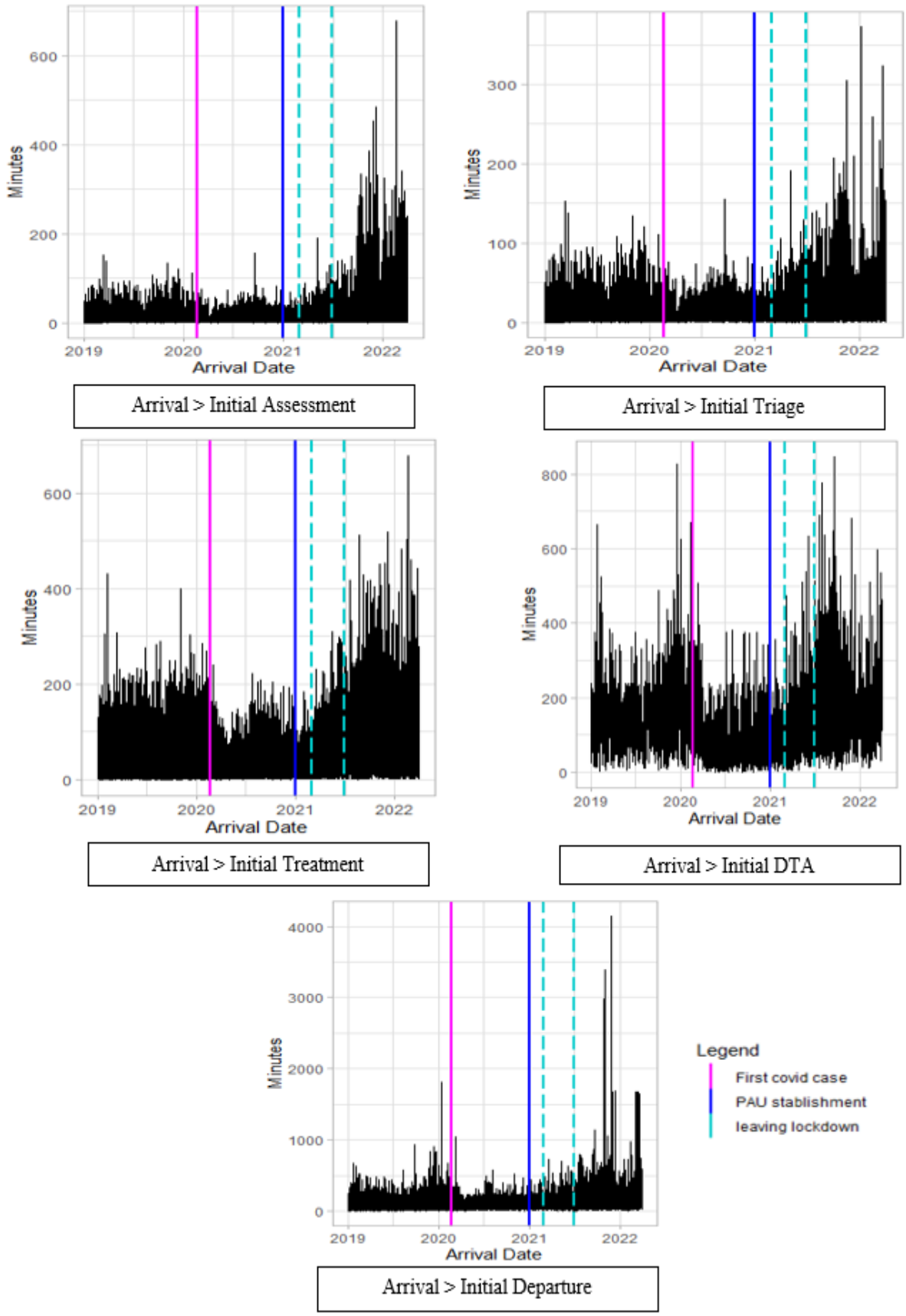

Figure 19. Time series contrast for each KPI

As described above, the waiting times have risen, especially after the leaving lockdown periods. As the number of patients attending at the A&E increased, then the A&E performance declined. So, following up with time series analysis, Figure 20 compares three-time series graphs. First, the number of COVID cases in Warwickshire, then the number of COVID patients at the Warwick Hospital, and the number of non-COVID patients that came into the A&E between Jan 2019 to March 2022.

On this figure, after leaving the lockdown (March to July 2021) and January 2021, there is a trend surging in terms of the number of patients walking into the A&E department (non-COVID patients). On 8 March 2021, England began a phased exit from lockdown. A “cautious but irreversible” decision to ease lockdown restrictions began by lifting restrictions in all areas. (Baker, C., et al. 2021).

Prior to the pandemic, nearby hospitals provided emergency services for patients. However, in the middle of 2020, the Solihull Hospital (30 minutes away by car) stopped admitting emergency cases. Solihull Urgent Treatment Centre temporally closed. Closures had an impact on GPs (General Practitioners), West Midlands Ambulance Service, and other A&E departments. Hence, people who would normally attend Solihull Hospital had to commute to other places to get treatment, including some residents travelling to Warwick hospital for care (BBC, News,.2022;www.birminghamandsolihullccg.nhs.uk.n.d.). To summarize, previous statements explain why the number of patients had increased, consequently affecting the waiting times.

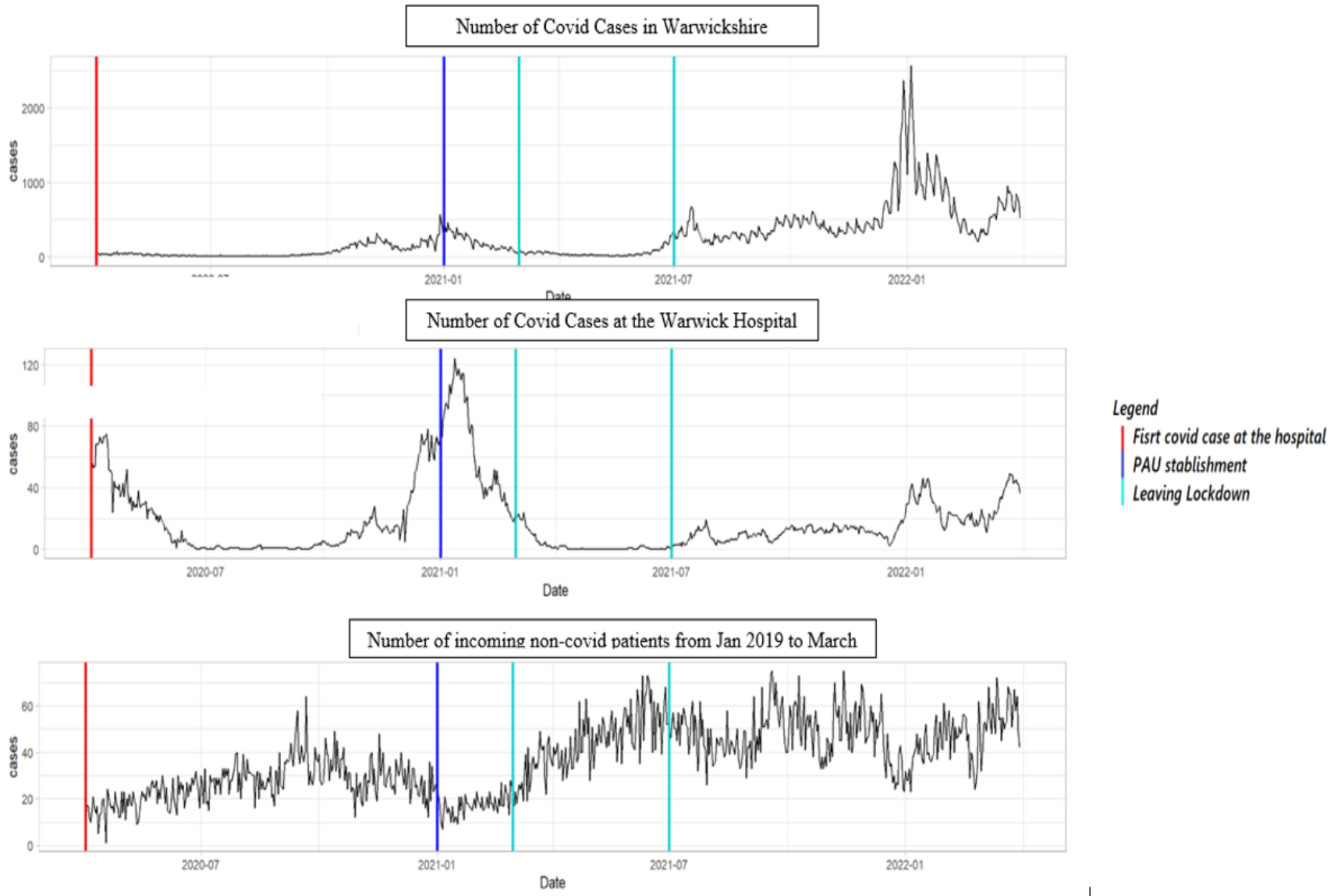

Figure 20. Time Series Contrast

As exploring inpatient details is also fundamental for this study, the dataset containing PAU attendees' specifications is now added. Figure 21 describes the distribution of Age on Admission. There is a considerable number of PAU patients whose age is between 0 and 4 while teenagers and 5 to 13 years old children constitute a lower percentage.

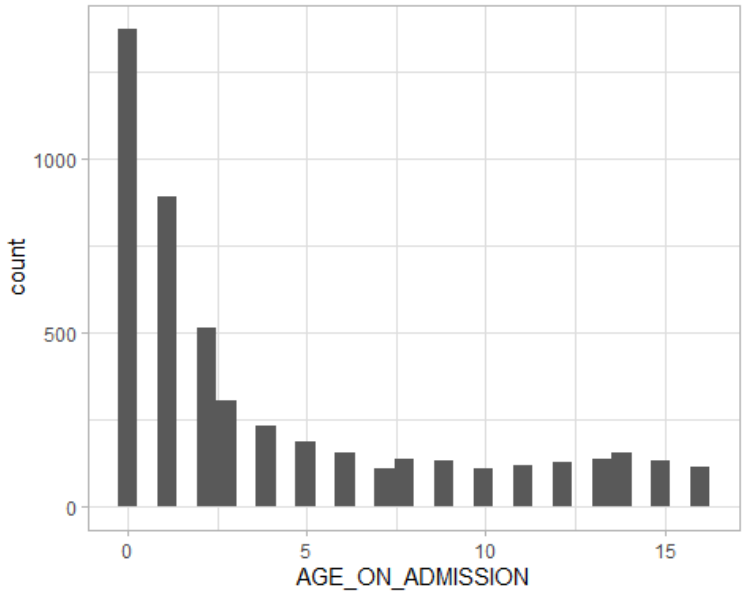

Figure 21. Distribution of the Age on Admission at PAU

Moving onto the distribution of patients through the years of operation, figure 22 represents the number of patients at each Arrival Date by age (0-16). Then, the PAU targeted those patients between 0 to 3 years old (infants and toddlers) to prevent complications in their health and cross-infection. Infants of 0 years old receive exceptional care in the hospital as they have been admitted to the PAU regularly.

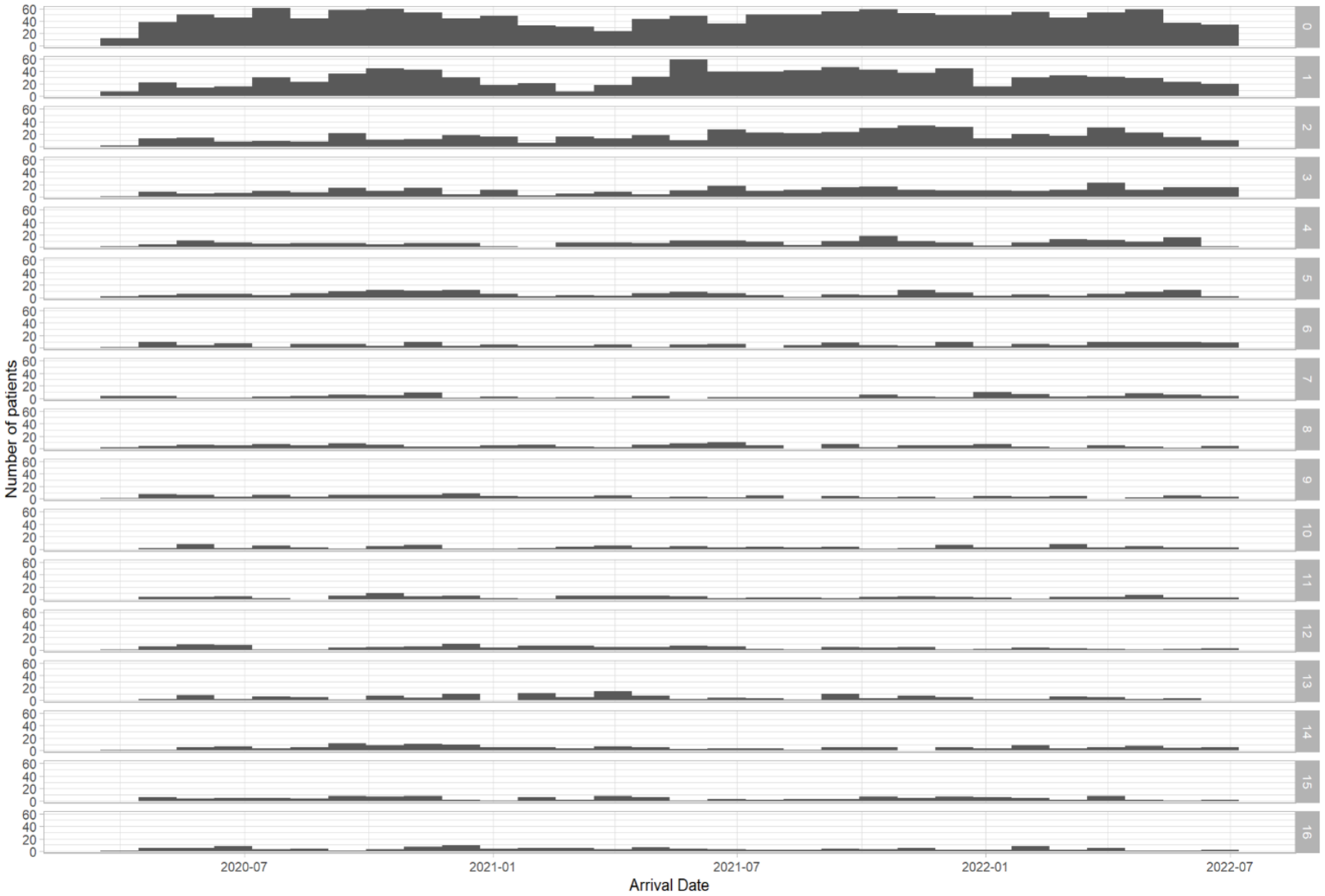

Figure 22. Number of patients at PAU by Age

As a general overview, the number of PAU admissions through the years has been steady. Figure 23 reflects the distribution of admissions at the PAU from 2020 to 2022 and the distribution of patients for non-urgent and standard emergency levels in the A&E. The latter is in the bottom right corner of the figure mentioned.

Admissions for PAU are between 0 to 200 patients monthly, as described in figure 23. In contrast, A&E paediatrics patients account for at least 1000 (Acuity level standard, non-urgent emergency, and arrival time between the PAU admission hours). The PAU is constantly admitting up to 200, around 20% of A&E paediatric patients. Even though the waiting times have not improved after post-implementation, this unit has been contributing with reducing the burden in the A&E.

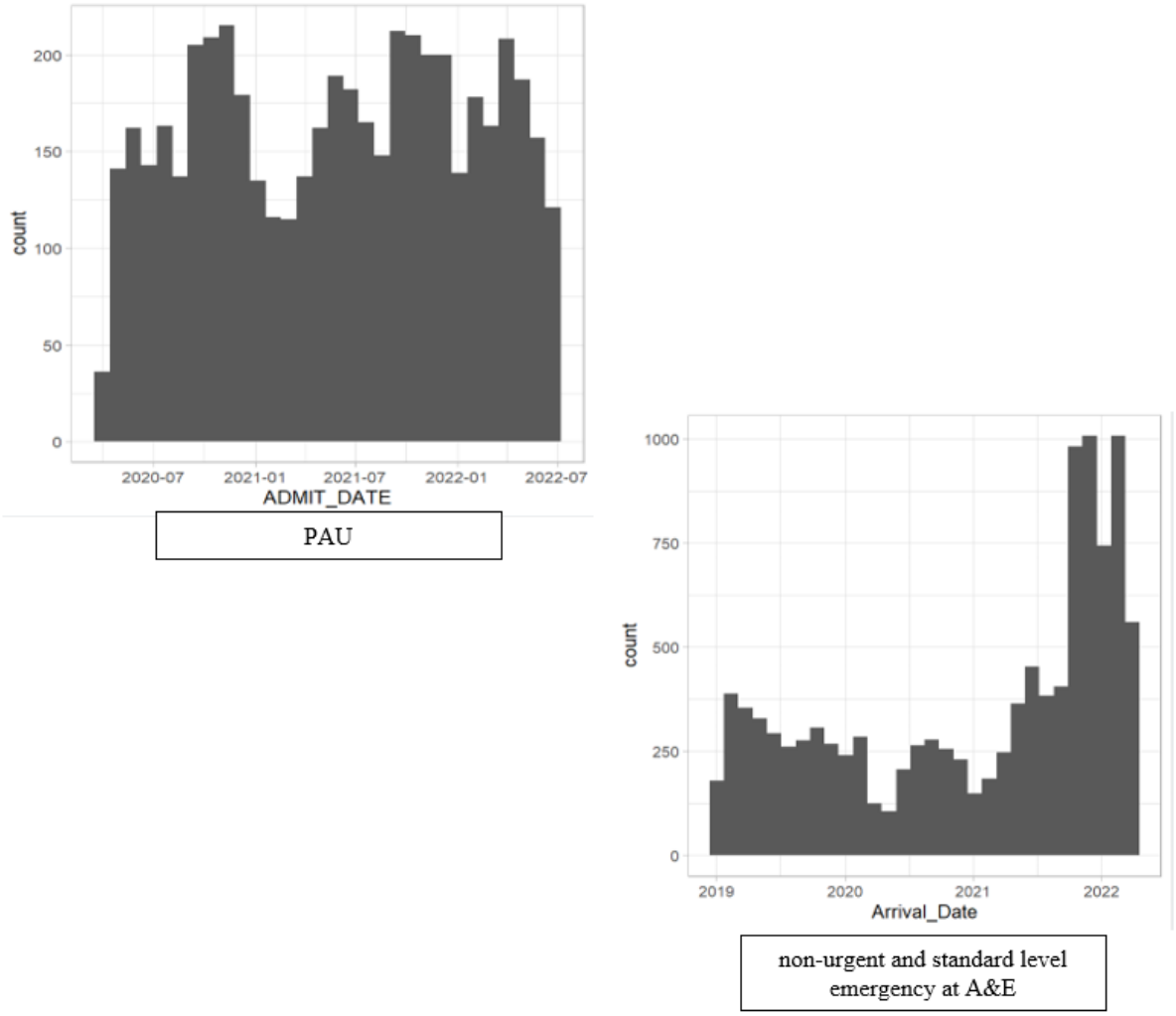

Figure 23. Distribution of admissions

Figure 24 reveals the earlier statement. The admission method for patients at the PAU was plotted as a proportion to verify the most common admission route for PAU patients. There is a slightly decreasing trend in the proportion of patients admitted into the PAU through the A&E. Even so, emergency admission method corresponds to one highest percentage followed by general practitioner referrals. Next, the latter shows an upward trend through the years of operation. As roughly 50% of the PAU patients have been admitted through the A&E, its burden has been reducing.

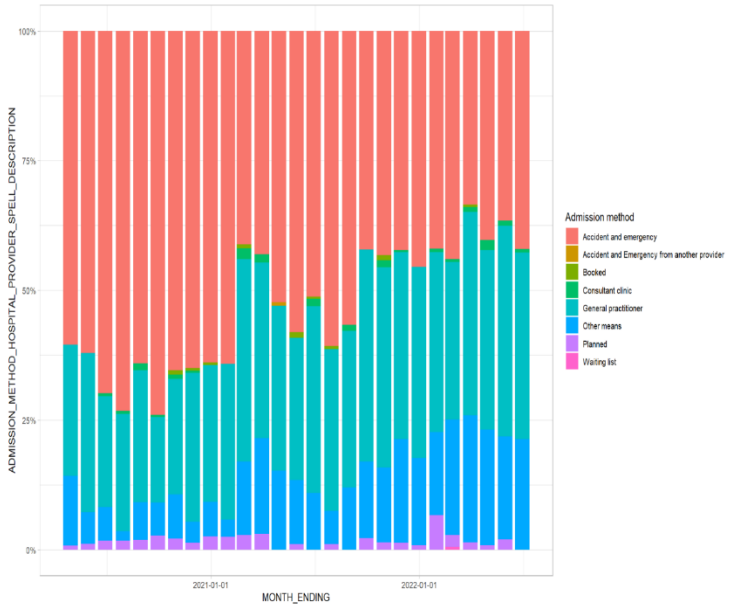

Figure 24. Proportion of admissions method at PAU

Within those admitted patients, the most common diagnosis is respiratory just before perinatal. Also, Viral infections are among the most suffered. Figure 25 shows the number of children per diagnosis.

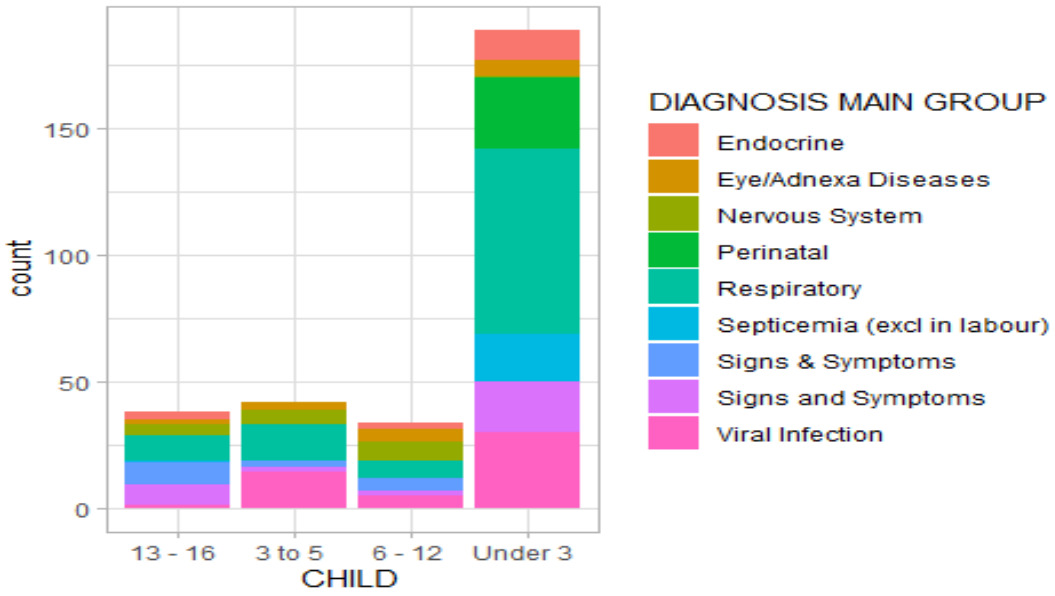

Figure 25. Distribution of Diagnosis main group by Age Category

Refer to appendix (Extra graphs) to view graphs of the number of patients through the years of study, Distribution of the number of patients at each Discharge Time by weekday for PAU, and Distribution of the number of patients at each Arrival Time by weekday for PAU.

Furthermore, to begin assessing LOS for inpatient data, given that:

- The most prevalent diagnosis is respiratory,
- PAU admitts 0-years-old patients frequently,
- PAU admission acuity is standard/low,
- Emergency department is the most frequent admission method

, 32 patients presenting those characteristics were randomly selected to assess LOS. A new data frame was created after having collected the PEWS (Paediatric Early Warning Score) for these patients. Its most relevant variables are in Table 4.

Patient Number ID	Admit Date	LOS in Hours	PEWS Description
1	2020-05-03	3	0
2	2020-05-03	5	-0 Form no filled
3	2020-05-27	0	0.5 little more pain
4	2020-06-09	0	0
5	2020-06-25	2	-0 Form no filled
6	2020-06-30	4	2 Critical
7	2020-07-27	1	0.5 Only temperature
8	2020-07-29	3	0
9	2020-08-11	2	1
10	2020-08-28	3	0.5 Temperature only
11	2020-09-05	1	1

12	2021-05-18	5	2
13	2021-05-20	2	1
14	2021-05-23	1	1
15	2021-05-28	8	1
16	2021-06-02	1	-0 Form no filled
17	2021-06-03	20	3 stay many hours
18	2021-06-29	3	0.5 Temperature only
19	2021-07-11	3	3
20	2021-10-17	1	3
21	2021-12-10	8	1.5

22	2022-01-19	2	2
New format pilot introduced 23	2022-03-08	4	2
24	2022-03-29	3	5
25	2022-04-08	3	4
26	2022-04-10	6	4.5
27	2022-04-11	2	1
28	2022-04-29	1	2
29	2022-05-08	2	1.5
30	2022-05-14	2	3
31	2022-06-08	14	3.5 stay long hours
32	2022-06-21	9	2.5 stay long hours

Table 4. Sample of 32 PAU patients

Following that, LOS at the PAU is, in most cases, consistent with the severity of illness and urgency. Also, over the last few months, the PAU has focused more on assessing and assisting patients between 0 to 3 years old presenting high PEWS scores.

Nevertheless, it was imperative to evaluate the LOS by (1) patient-related, (2) organizational-related and (3) structure-related factors. LOS is likely to be influenced by not only the severity of the illness (patient-related) but also organizational-related or structure-related factors. In some cases, for a few patients, their LOS differed even when presenting the same type of illness and severity (PEWS score). When the LOS is associated with a delay in treatment or assistance, and patients were not discharged rapidly there is likely to be an organizational-related or structure-related cause.

To summarise, since the PAU currently employs only one medical nurse, based on the results of this project, it is advised and recommended that the number of staff at PAU should increase while monitoring the patients' trends regularly. The PEWS score collection revealed inconsistencies for similar patients in terms of their LOS. Furthermore, although the waiting times are consistently increasing, the PAU has been pivotal in providing medical services to infants and toddlers in need, mainly presenting respiratory diseases. Hence, the importance of PAU in the provision of medical services for paediatric patients is significant.

4.2 Text analytics–reviews

Reviewing patient experience is a reliable practice to generate insights on the services offered. For this reason, sentiment analysis approach was used to establish patient satisfaction. Therefore, after extracting the reviews from the website "IWantGreatCare", the calculation for rating scores submitted by patients was calculated and plotted as a distribution bar chart. Figure 26 represents the distribution of the average rating from 1 as the lowest to 5 stars as an excellent satisfaction for emergency reviews and paediatrics. A vast number of comments were rated more than 4.5 out of 5.0. The average rating for the A&E reviews is 4.54, whereas the paediatrics unit is 4.53. Overall, a positive experience is shown. (Figure 26)

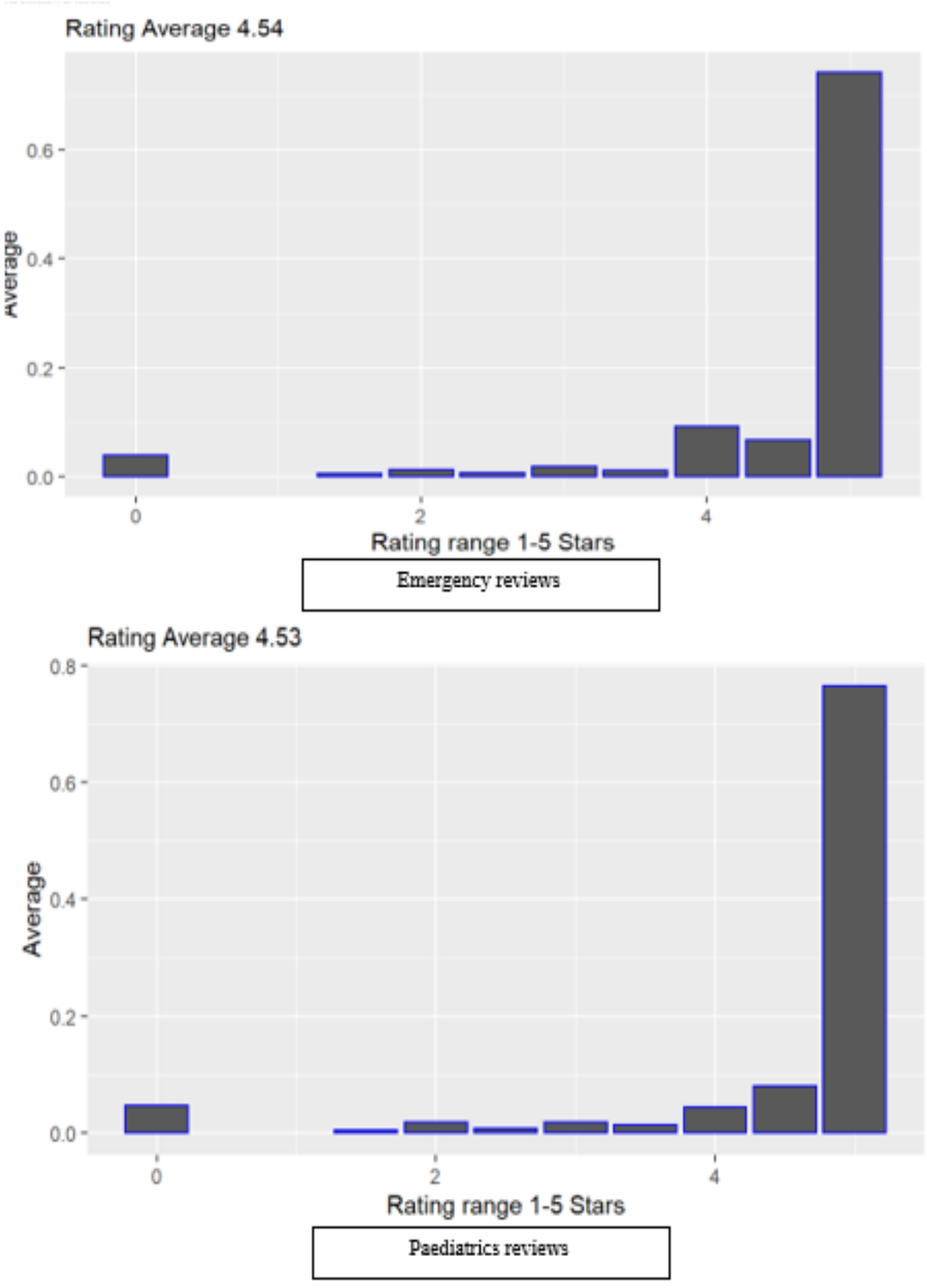

Figure 26. Distribution of the Average rating

Referring to our methodology for reviews text data, the results reflected:

Finding sentiment: Dictionary Coverage

Four dictionaries are available to find the highest coverage. They were bing, afinn, nrc and loughran. The type of sentiment was estimated for each dictionary using the obtained tokens. Figures 27 and 28 represent the total number of words on the y-axis, and the x-axis includes the dictionary. From this, the conclusion was that bing detected both positive and negative polarity for the higher number of words while Loughran had the least number of words. When it came to measuring polarity, note that Bing is slightly better.

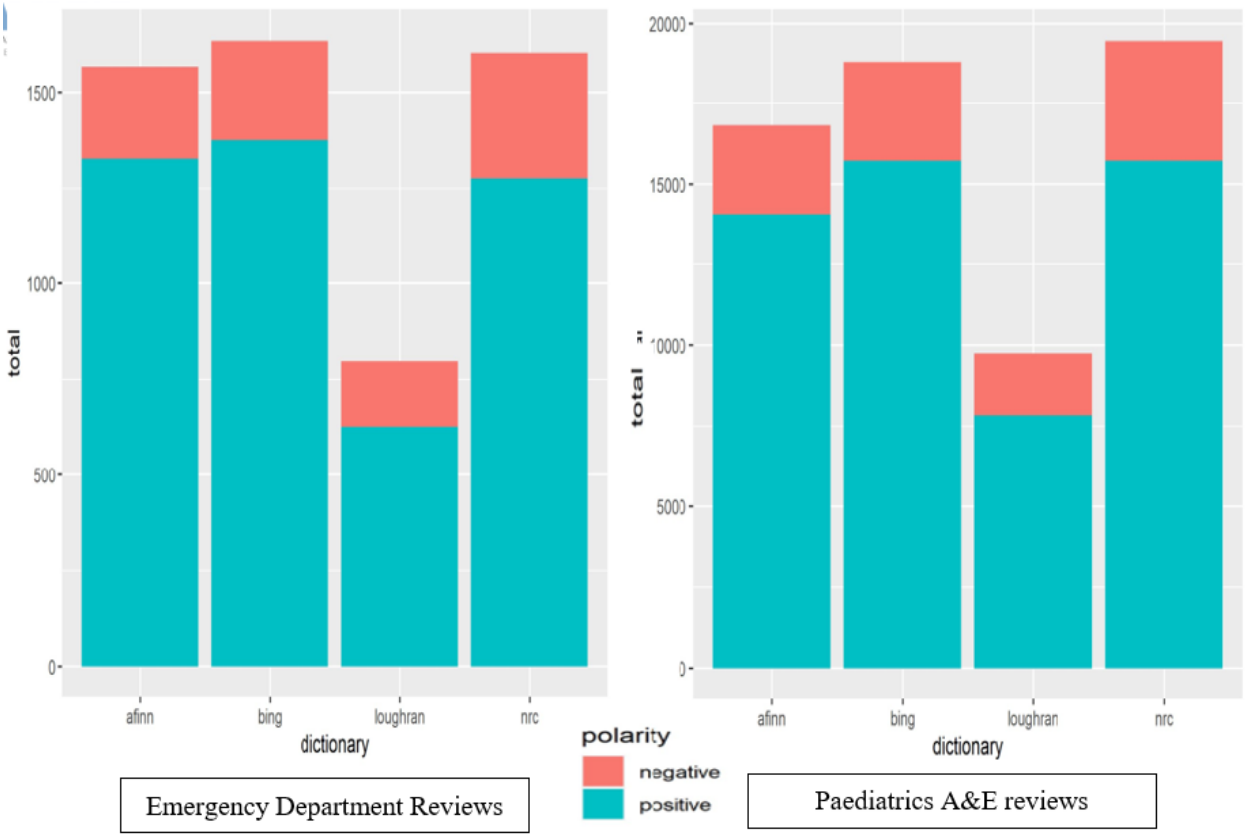

Figure 27. Polarity of Words per Dictionary

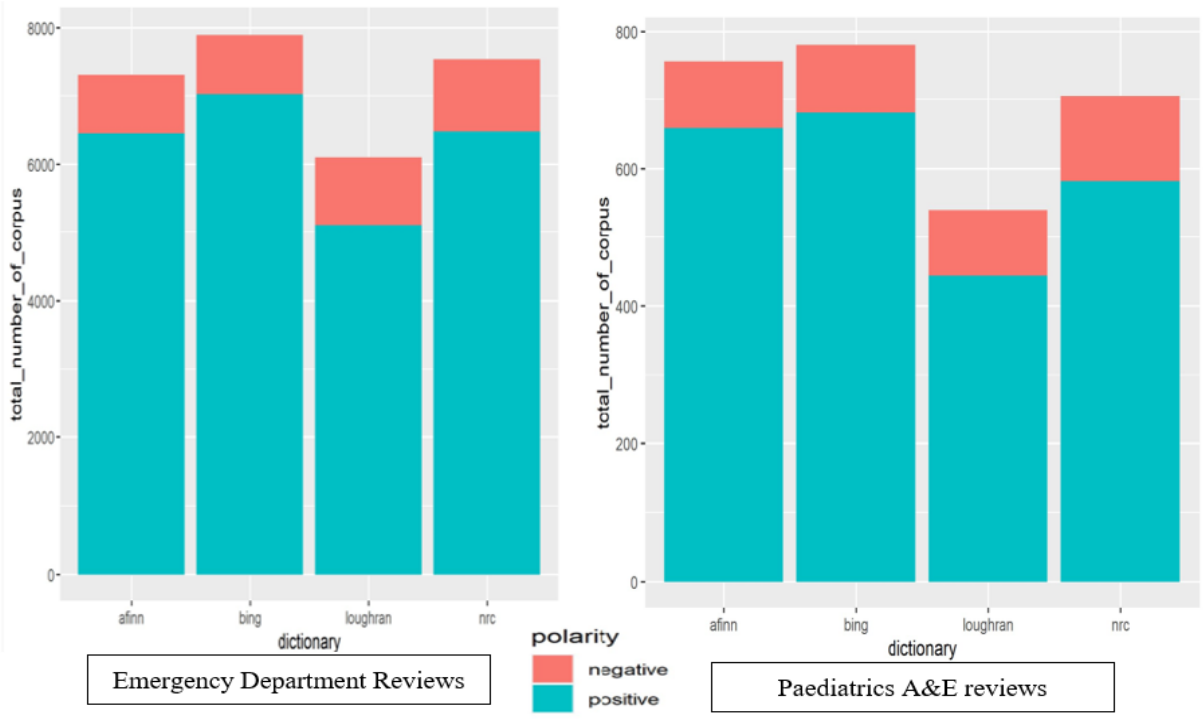

Figure 28. Polarity of Corpuses for Each Dictionary

Sentiment Analysis by Using Bing

Based on the previous results, Bing had the highest coverage of words. This dictionary was the choice for this analysis. Figures 29 and 30 reflect the percentage of negative and positive expressions for A&E and paediatrics, pre-and post-implementation. It informed that there was a slight increase in negative sentiment for both the A&E and Paediatrics. However, most negative words are about illness. Therefore, this concludes that the overall satisfaction is positive.

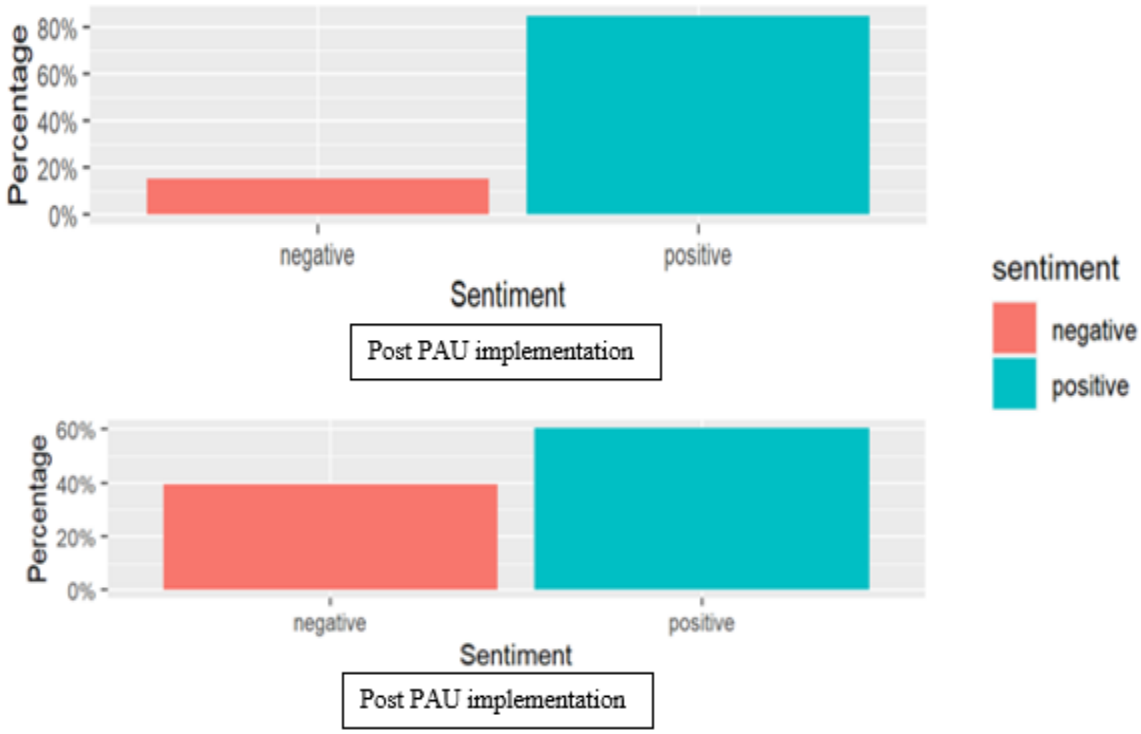

Figure 29.Polarities of Word for Bing Dictionary for A&E

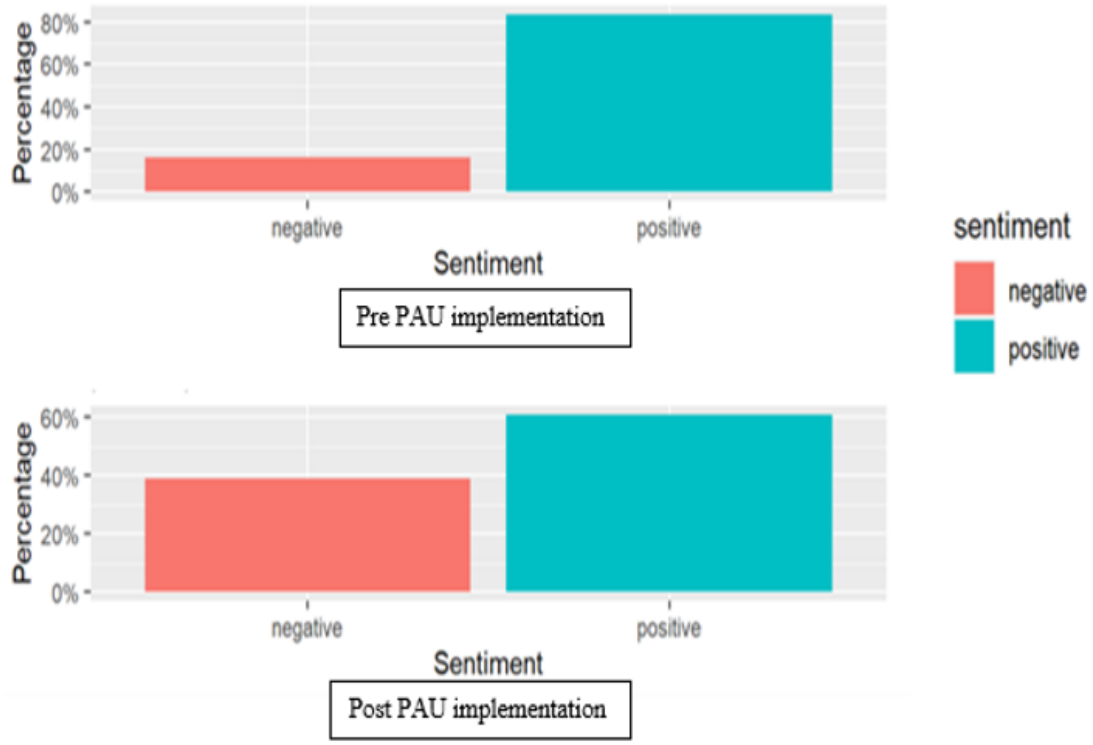

Figure 30. Polarities of Word for Bing Dictionary for Paediatrics

Comparison word cloud for the most negative and positive dominant words

After evaluating the level of sentiment analysis, plotting a Word Cloud containing negative and positive dominant words was next. Figure 31 represents a comparison between the most frequent positive (blue, orange) and negative (black) words. As for the A&E, the most mentioned negative words are delay, complaints, and some negative feelings of stress. However, positive words reflect a friendly, helpful, and improved service, as illustrated in figure 31. On the other hand, for the paediatrics inpatient, there have been concerns about frustration, stress, complaints, and delays, whereas others expressed a friendly, efficient, good, attentive, prompt, and comfortable experience.

Figure 31. Word Cloud Contrast negative and positive

Overall, patients' experience has been satisfactory, as shown by the result from the sentiment analysis. There is a tendency from reviewers to make outstanding positive comments. Therefore, services such as PAU help improve the number of positive patients' experiences.

5. Limitations and future research

During this project, there were two data resources, one that was provided by SWFT team and the other collected through an open-source website. These two have been the backbones for the analysis and conclusions for this dissertation. However, potential limitations and future research alternatives were considered. A compilation of them are as follows:

- It is advisable to carry out this project later, during a post-pandemic period since the data presents biases and is highly affected by these extreme circumstances. COVID affected data collection practices, then the waiting times increased significantly. As explained in the previous sections, the reasons for increased waiting times include the rise in the number of patients visiting the hospital and the diversions put in place as part of COVID-19 measures.

- In the future, more profound research including the staffing, operational capacity and operational performance of the PAU is required to assess the performance of PAU. For example, a study focusing on the impact of having one more nurse rostered would be a more precise approach to make strategic decisions. As described in the literature review, several studies have found this practice effective. These practical approaches make it possible to obtain visible and relevant results for health care services.

- There were additional concerns about potential dubious data. The awareness of what data is available within the department should be considered periodically. The disconnections within the operation area and information system department result in unreliable and delayed data collection.

- Concerns about the data capability were also identified. Since a considerable amount of valuable information is handwritten, it limits the possibility of a short-term study. As a result, manual data collections are needed to maximize data availability. This limits the level of detail reached on the analysis and requires a longer time scope project.

- Lastly, operationally speaking, the evaluation of the PAU is complicated since it admits COVID patients. Patients diagnosed with COVID hold a spectrum that can cause serious health issues due to its nature. In this case, pediatrics patients could have received

treatment in an isolated zone. Operational measures are severely impacted when it comes to extreme circumstances such as COVID symptoms.

6. Conclusion

Since the SWIFT established a PAU, it was necessary to determine the contributions that the PAU made to the A&E department and emergency paediatrics service. As a result, the evaluation of having a PAU was done by performing several approaches to understand, assess and identify relevant insights. Likewise, reviews were collected using sentiment analysis techniques to determine patient's experience regarding the service offered. Having had those, the identification and analysis of results explained the significant role of the PAU for infants and children while trying to cope with increasing waiting times.

Starting with statistical analysis, the mean in waiting times for paediatrics at the A&E did not significantly improve post PAU implementation. It was likely to be due to external factors. However, can be concluded that the PAU:

- Admits around 20% of A&E pediatric patients.
- Assists patients coming from the A&E and GP referrals.
- Focuses on assisting predominantly infants (0-1 year of age) and toddlers (2-4 years old) presenting with high PEWS scores.
- Treats patients who are diagnosed with the most common conditions, respiratory and viral infections.
- Improves patient feedback that has been positive overall.
- Opens when the A&E receives the highest number of visits.
- Is yet to increase the number of staff, therefore extending service availability and discharging patients more rapidly.
- And is a resilient unit that has been dealing with COVID unforeseen consequences due to the COVID pandemic.

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8. Appendix

8.1 Meetings and discussions with staff

(RJC) Research Nurse

- Paediatric units: Ward Macgregor is open 24 hrs (used if children require to stay longer than 24 hours, possess 17 total beds while PAU 5 Beds.
- Children's PAA Assessment Record (Pilot) form keeps prominent level of details about the patients. However, for data handling purposes is tedious no to have it on digital since once a patient is discharged from the PAU the nurse in change scans and uploads this filled form on evolve.
- COVID infection data: Needed for the study from infection prevention team will have local data about prevalence of the infection in Warwick
- Unique Patient ID to assess re-admissions
- Check LOS in PAU:
- Was the LOS higher or short? Were patients being discharged rapidly
- Was the PAU just serving as a bedding facility for higher LOS patients or functioning as an assessment unit
- A&E referrals and admissions If a person is admitted from nursing home – check how that changes the LOS Investigate diagnosis
- Does the LOS vary for similar diagnosis?
- Staffing and bedding capacity in ED/PAU

A&E resources daily

DAY (07:30-19:30)

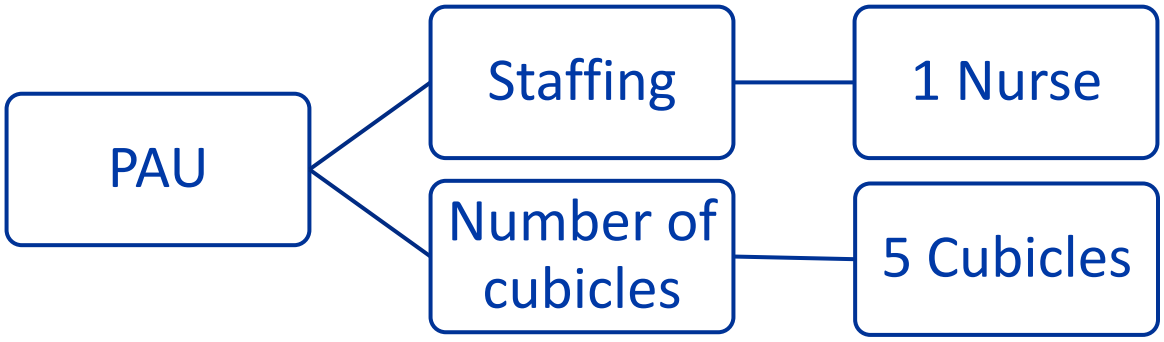
Area	Number of cubicles	Staffing
Triage	2	2 nurses
Ambulance triage	Space for 2 trollies	1 nurse, 1 clinical support worker
Majors	19	4 nurses, 4 clinical support workers
Paeds	4	1 nurse, 1 clinical support worker

Resus	3	1 nurse, 1 CSW
Minors	6	1 GP, ENP (3x morning, 2x afternoon) (08:30-10:00)

NIGHT (19:30-07:30)

Area	**Number of cubicles**	**Staffing**
Triage	1	1 nurse
Ambulance triage	Space for 2 trollies	1 nurse, 1 clinical support worker
Majors	19	4 nurses, 4 clinical support workers
Paeds	4	1 nurse, 1 clinical support worker
Resus	3	1 nurse

PAU Resources:



- PAU: Mental health problems are especially important and can change LOS (in fact it is a huge reason to stay longer), so mental health and safeguarding issues might mean they can't go home soon

- Find a way to explain the KPI are increasing why (give reasons) talk to people why treatment time increase sits with the team and talk to them ... staffing or beds in ED and see if it changed in this time
- What has the SAU (Surgical Assessment Unit) & PAU achieved? What are the gaps? What are the issues (staffing, capacity, opening hours, flow assessment)?
- David to confirm when Solihull hospital stops taking Acute admissions

Reply from (rjc) ward Manager MacGregor Ward Swark-FT 14/07/2022

- Question 1. What are the stages a patient from the PAU or the Ward goes through and what is the estimate time for each of them?

Like Initial triage, first doctor check-up, and/or specialist/senior Paediatrics. Patients are referred from GP or ED. When arrives on PAU will be seen and admitted by nurse within 15-30 minutes and triage. When seen by a dr will depend on how sick the patient is and the workload of doctors.

- Question 2. As far as my understanding is that the PAU admits patients with minor illnesses. May I please know what other roles play the ward apart from receiving patients from the PAU who need to stay overnight?

Ward will accept sicker patients who we have no chance of getting home that same day. They will be on the ward for ongoing treatment CAMHS (Child and Adolescent Mental Health Services) patients will not be admitted to PAU.

- Question 3. If a child tests positive for COVID-19, which unit or ward would he/she be sent?

It depends on if we think we can get the patient home – both ward and PAU accept COVID patients

- Question 4. Could you please confirm if the ward has 17 beds to stay while the PAU has 5? And whether the PAU officially started to operate in 2021 JAN as a bedding unit?

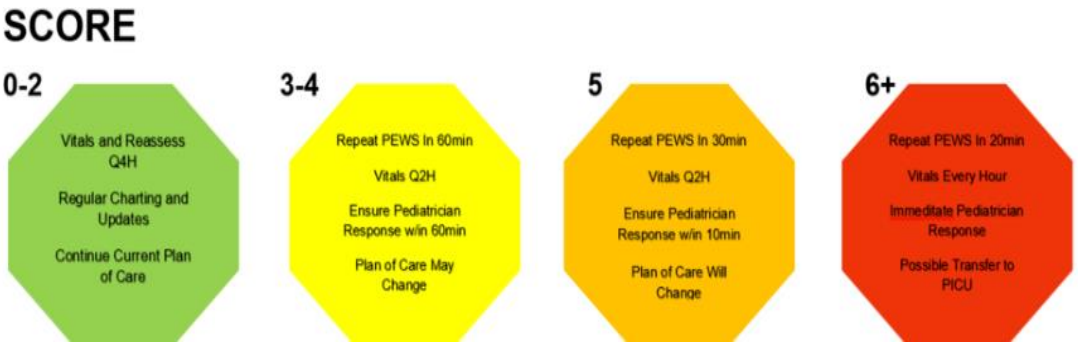
Yes, all correct

- Question 5. Is there any time when the PAU (within its opening hours 10 AM to 10 PM (last admittance 8PM) does not have staff available (staff, Paediatrics)?

If we have staff vacancies / sickness that cannot be covered by agency staff or if the ward staffing is exceptionally low and the pau nurse is needed on the ward.

Discussion with Consultant 18/07/2022 PAU (focus)

Suppose for example you have someone come to hospital with chest infection, if you are not careful a chest infection is a wide spectrum (from being ill to being mild) so what we must do is for example take patients with chest infection, age, severity of symptoms (PEWS SCORE) . Severity include if need oxygen, if blood pressure is low, ask ross if it is possible to check chest infection so all people who came with a chest infection on the PAU , and then I need to compare things that are remarkably similar (similar age group and severity,LOS same units minutes) before the PAU is open/ or the hours when there is no PAU.



There are patients ill stayed more than a day in the PAU

What trust wants project background info ED, variation on PAU admission, assess the context of the PAU (more detailed) so it means any data that we present we must analyze in the context of what was happening in the ED for all admissions, and for pediatric admissions. The ED is especially important (pediatric admissions) and the situation of the ED with COVID. Has this pau

been effective? Has it (information technology) provided good quality of care??what would happen if we had more resources? What would it be beyond it?
What happens if it becomes fully operational?
How effective it has been (good flow, block of staff??
Would it be worse if we didn't have PAU?

Managerial staff at PAU meeting 21/07/2022

- PAU once admitted the receive medical attention immediately (no waiting times design

Business Information Manager

1. Pandemic buy messy there was no database in such a rush,
2. Quality of data ----dubious data quality
3. Concern about data format
4. Quality and awareness of what data is available
5. Knowledge of the quality of data credible data
6. Disconnection within the operation area and information system department
7. inpatient data exactly waiting times is nor recorded as such detailed because at PAU once is admitted they get seen immediately, there is no waiting times

General Manager Family Health Division 26/07/2022 and Nurse at Paeds A&E

- To be hired and approved business plan Advanced care practitioner (two for PAU and one for A&E paeds) make diagnosis, assess patients work in line with medics
- Fracture lessons or no needed watching out many patients go to MINORS DEPARTMENT

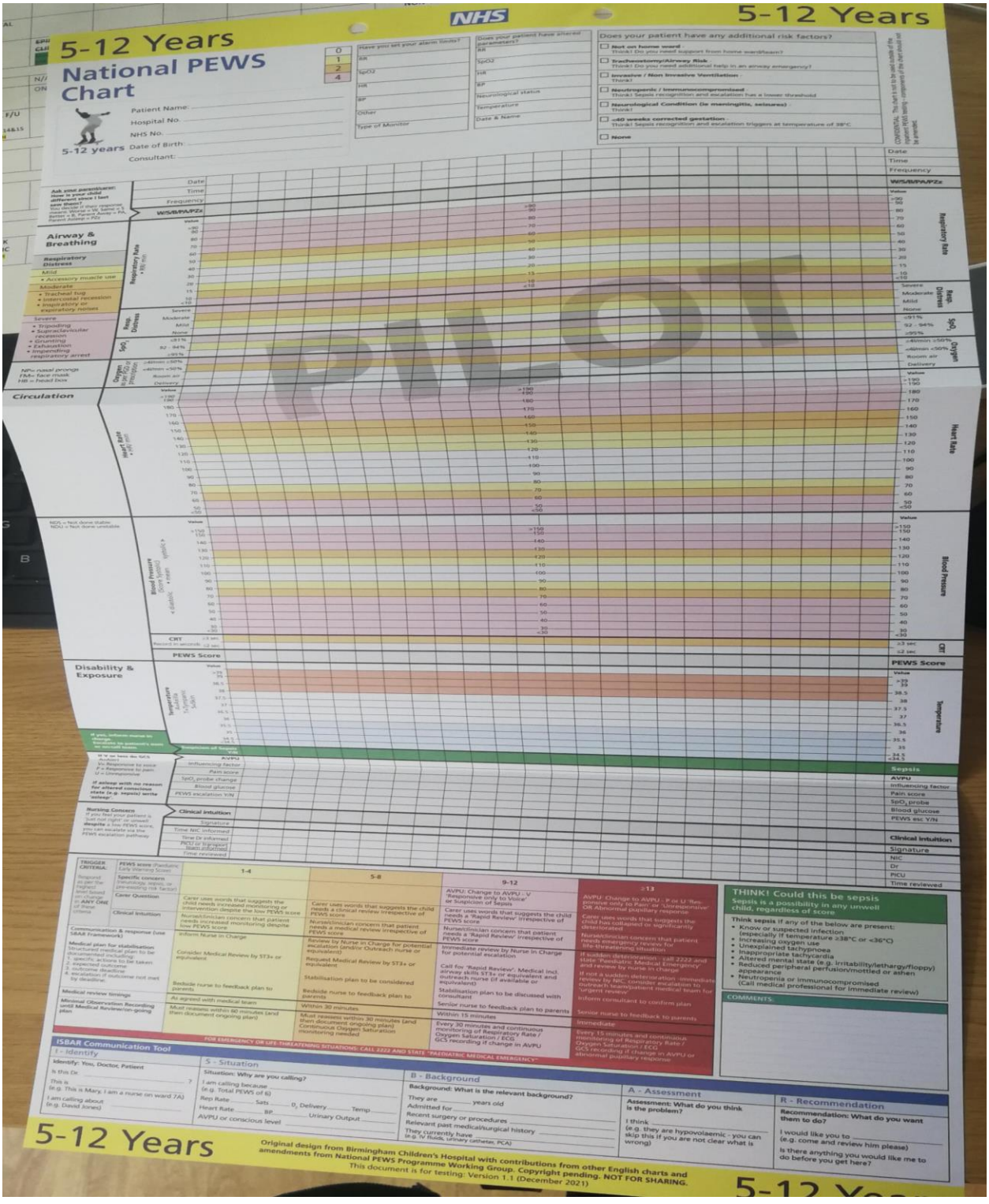
- Unit at Paeds A&E is for patients that need to see a doctor quiet quickly for the doctor and we believe GP are not the best because need long term care be watched

Management Trainee

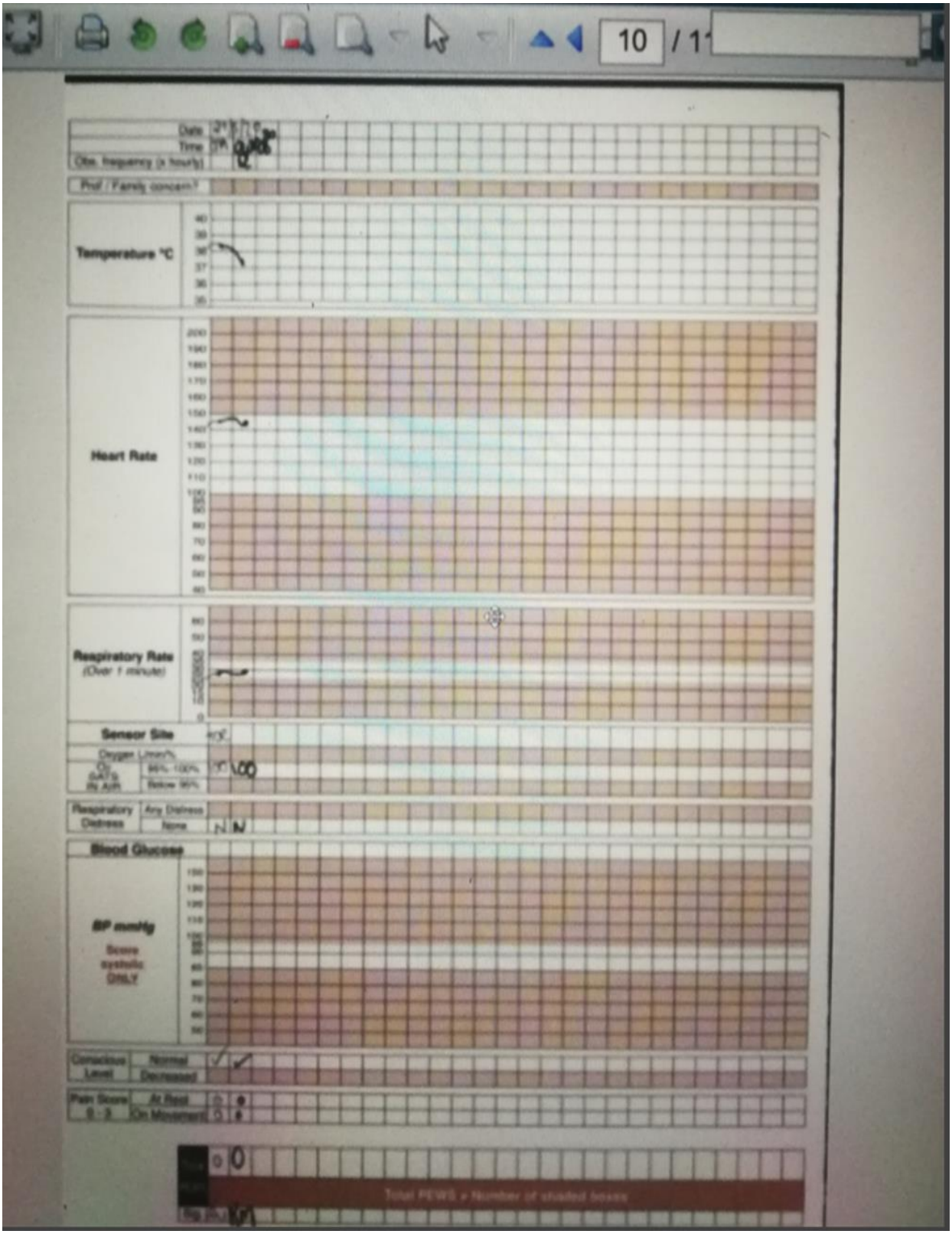
Explanation on variability in the number of patients attending to A&E between JAN 2019 to MARCH 2022: This would probably be due to the pandemic. Each time the UK went into lockdown attendances decreased. Have a look at the dates of the nationwide lockdowns and this will probably coincide with the dips in the graph

8.2 PEWS Score for patients

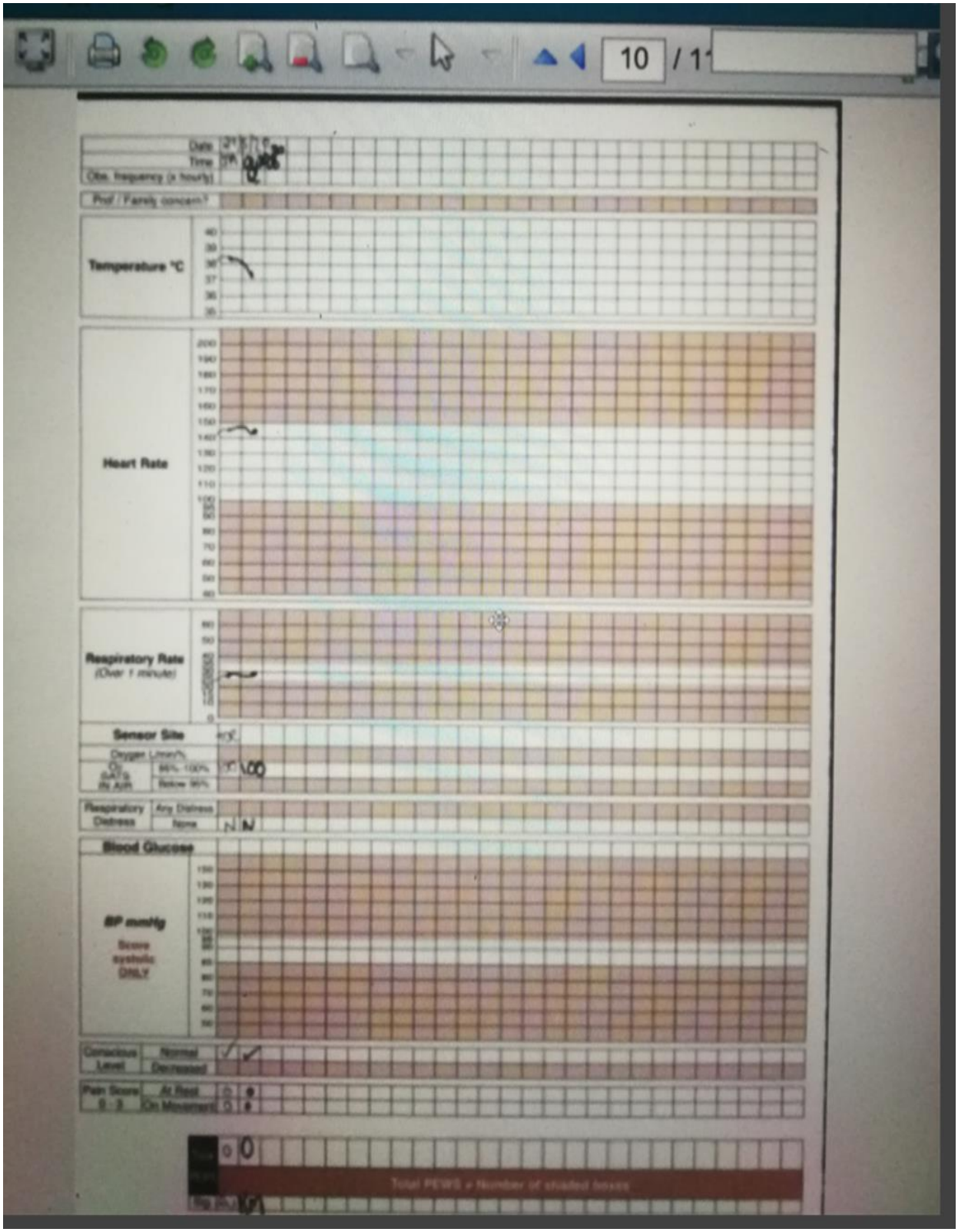
Sample template for PEWS form (Patients 2,5 and 16 did not register filled form on the system)



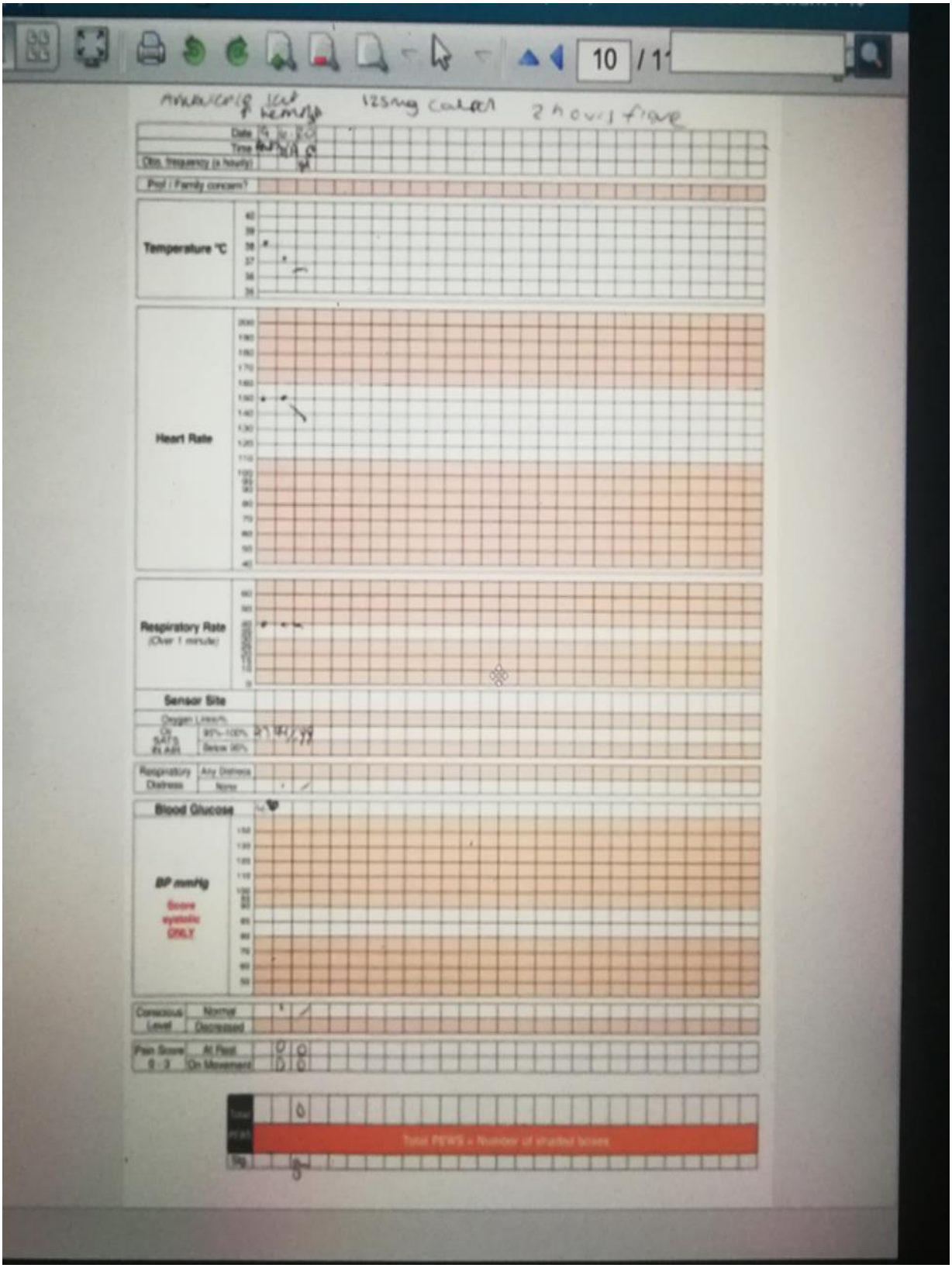
Patient 1


10 / 11
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes

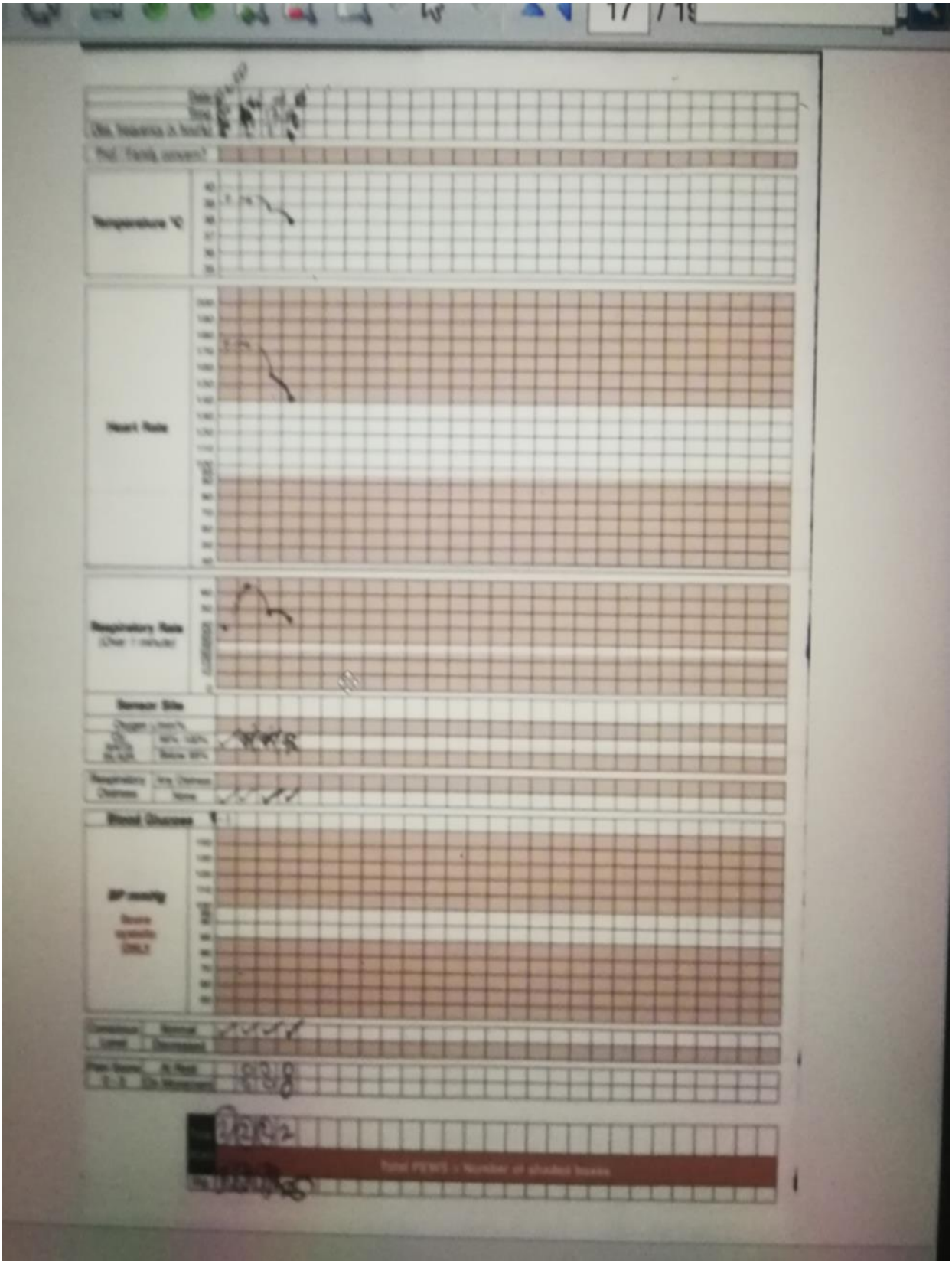
Patient 3


10 / 11
Date
Time
Obs. frequency (4 hourly)
Prof / Family concern?
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Oxygen L/min
O2 Sats
Respiratory Distress
Any Distress
None
Blood Glucose
BP mmHg
Score systolic DIAST
Consious Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes

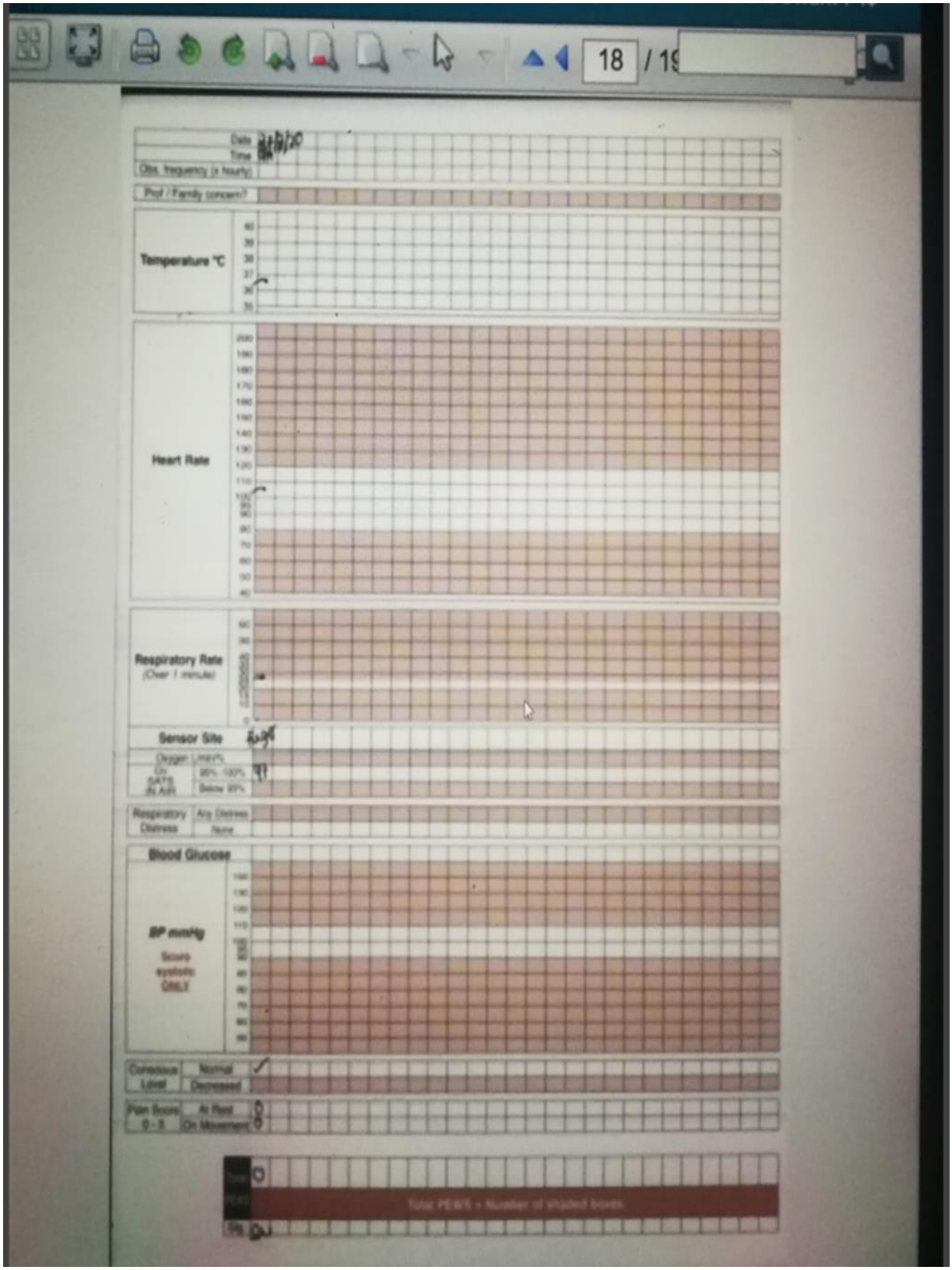
Patient 4


10 / 11
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY

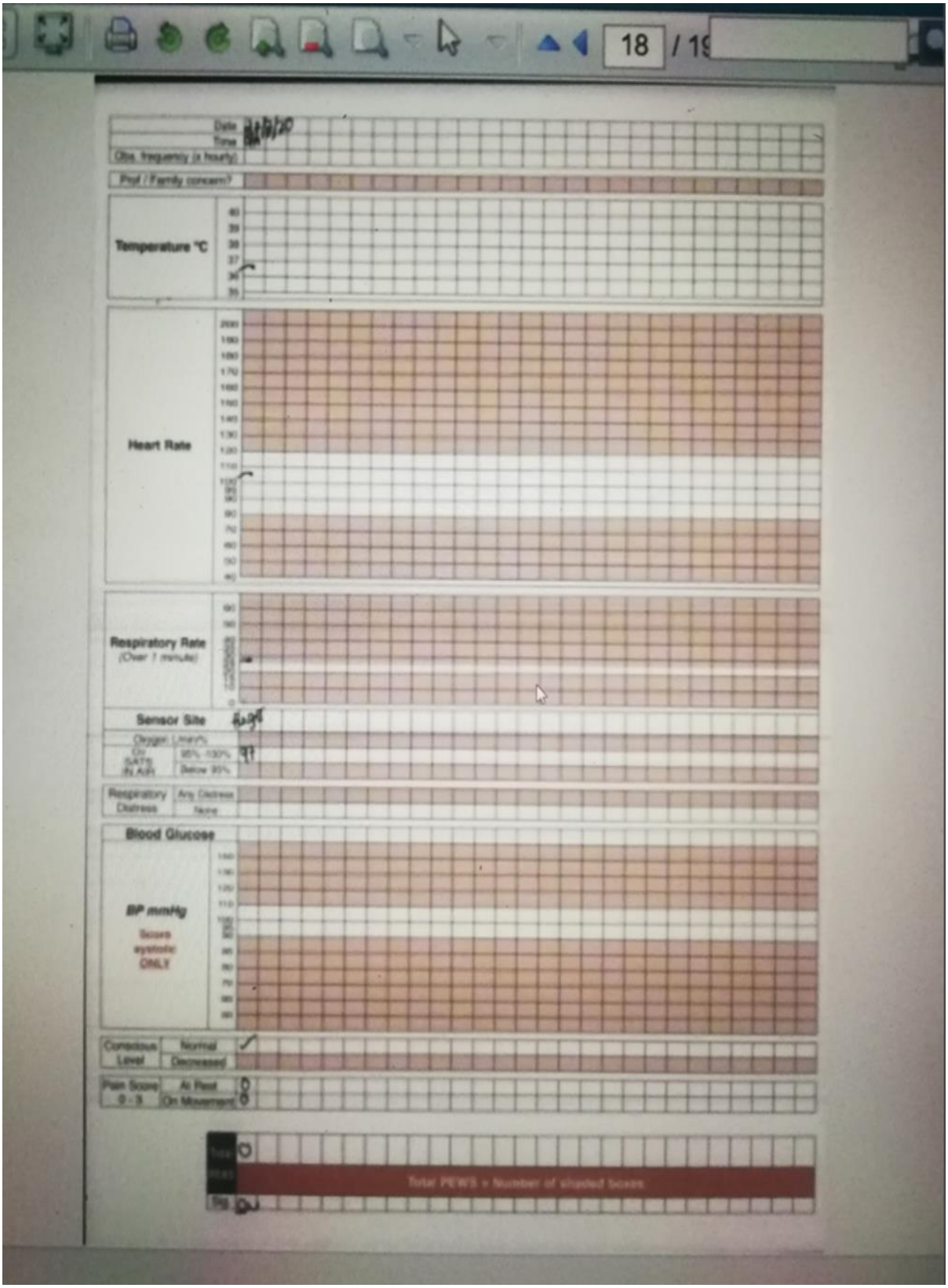
Patient 6


Temperature °C
Heart Rate
Respiratory Rate
Sensor Site
Blood Glucose
BP mmHg

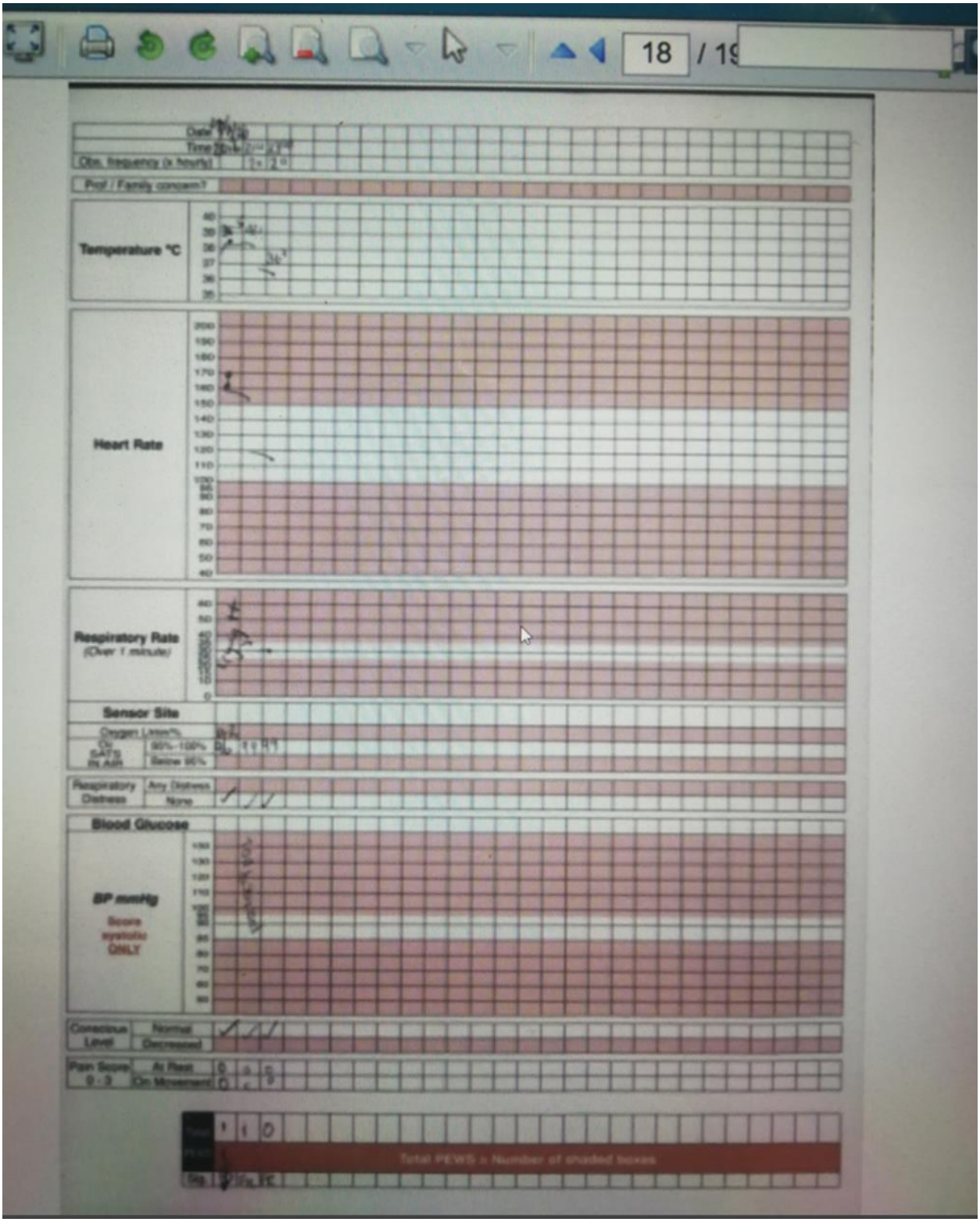
Patient 6


18 / 19
Date
Time
Obs. frequency (x hourly)
Prof / Family concern?
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Oxygen L/min%
O2 SATS IN AIR
95% - 100%
Below 95%
Respiratory Distress
Any Distress
None
Blood Glucose
BP mmHg
Score systolic ONLY
Consious Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes

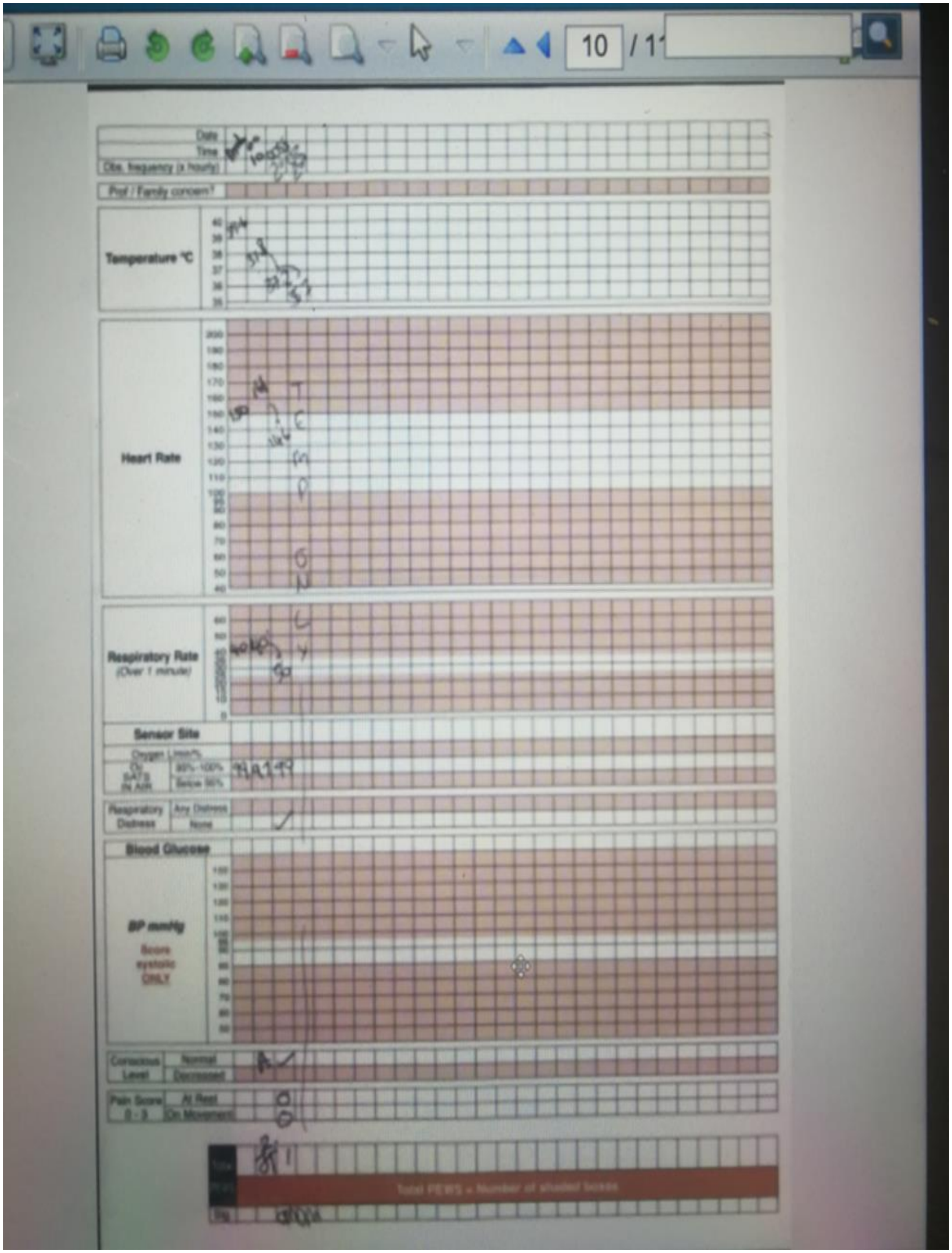
Patient 7


18 / 19
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY
Conscious Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes

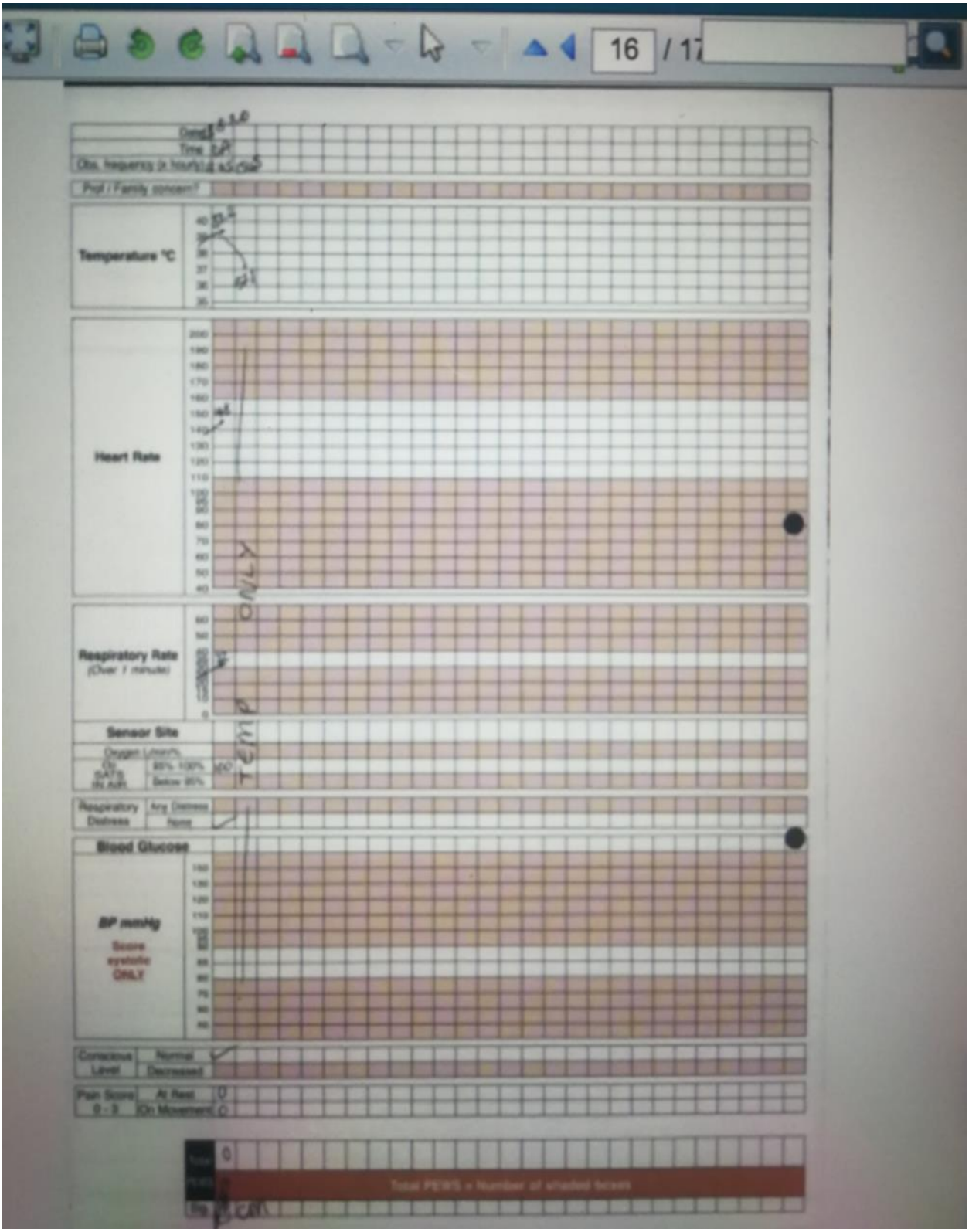
Patient 8


18 / 19
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY
Total PEWS = Number of shaded boxes

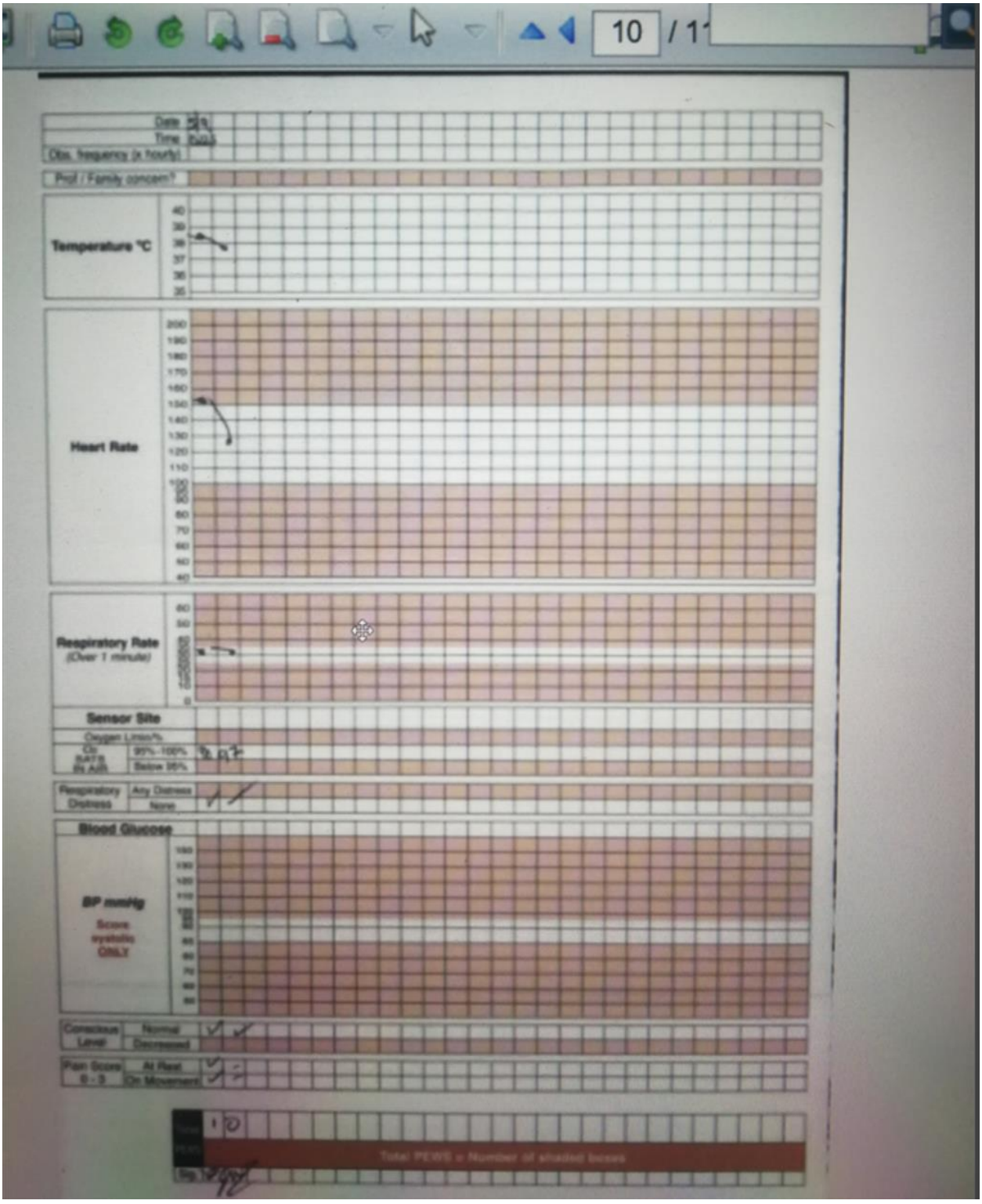
Patient 9


10 / 11
Date
Time
Obs. frequency (x hourly)
Pat / Family concern?
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Oxygen
O2 SATS IN AIR
Respiratory Distress
Any Distress
None
Blood Glucose
BP mmHg
Score systolic ONLY
Conscious Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes

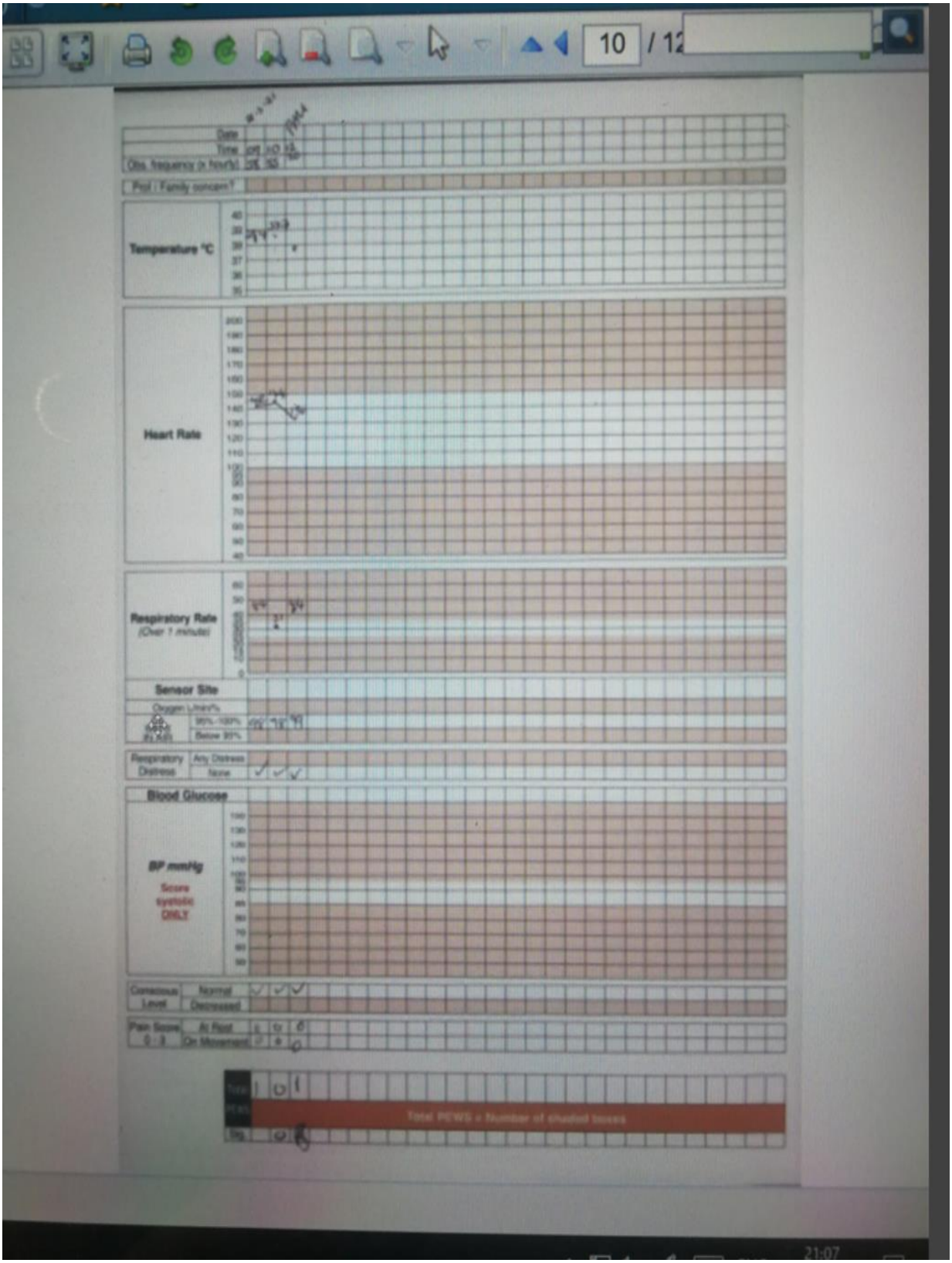
Patient 10


16 / 17
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Oxygen L/min%
On SATS ON AIR
88% -100%
Below 85%
Respiratory Distress
Any Distress
None
Blood Glucose
BP mmHg
Score systolic ONLY
Conscious Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes
ONLY
TEMP

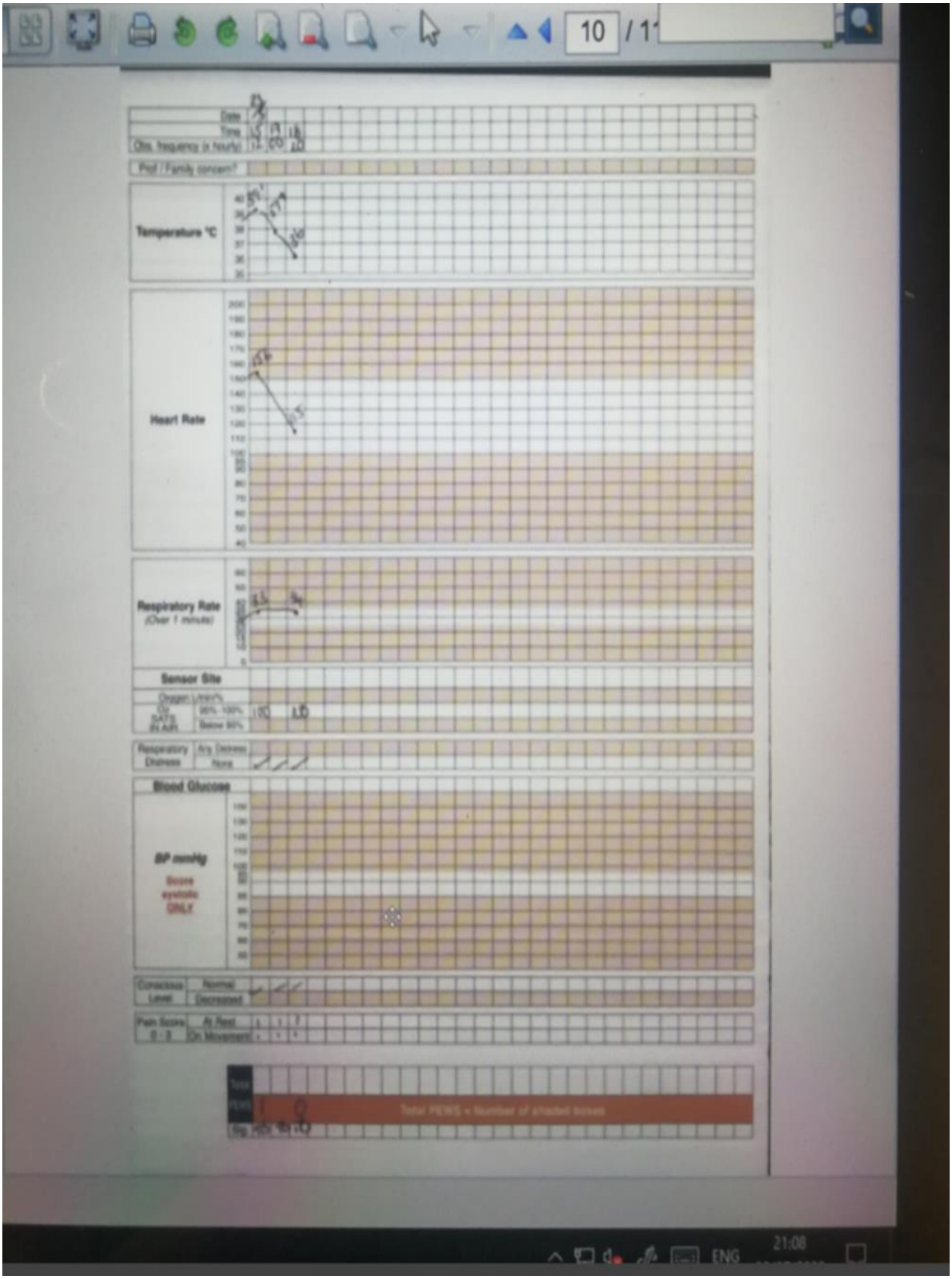
Patient 11


10 / 11
Date
Time
Obs. frequency (x hourly)
Prof / Family concern?
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Oxygen Lmin/%
O2 SATS on Air
95%-100%
Below 95%
Respiratory Distress
Any Distress
None
Blood Glucose
BP mmHg
Score systolic ONLY
Consciousness Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes

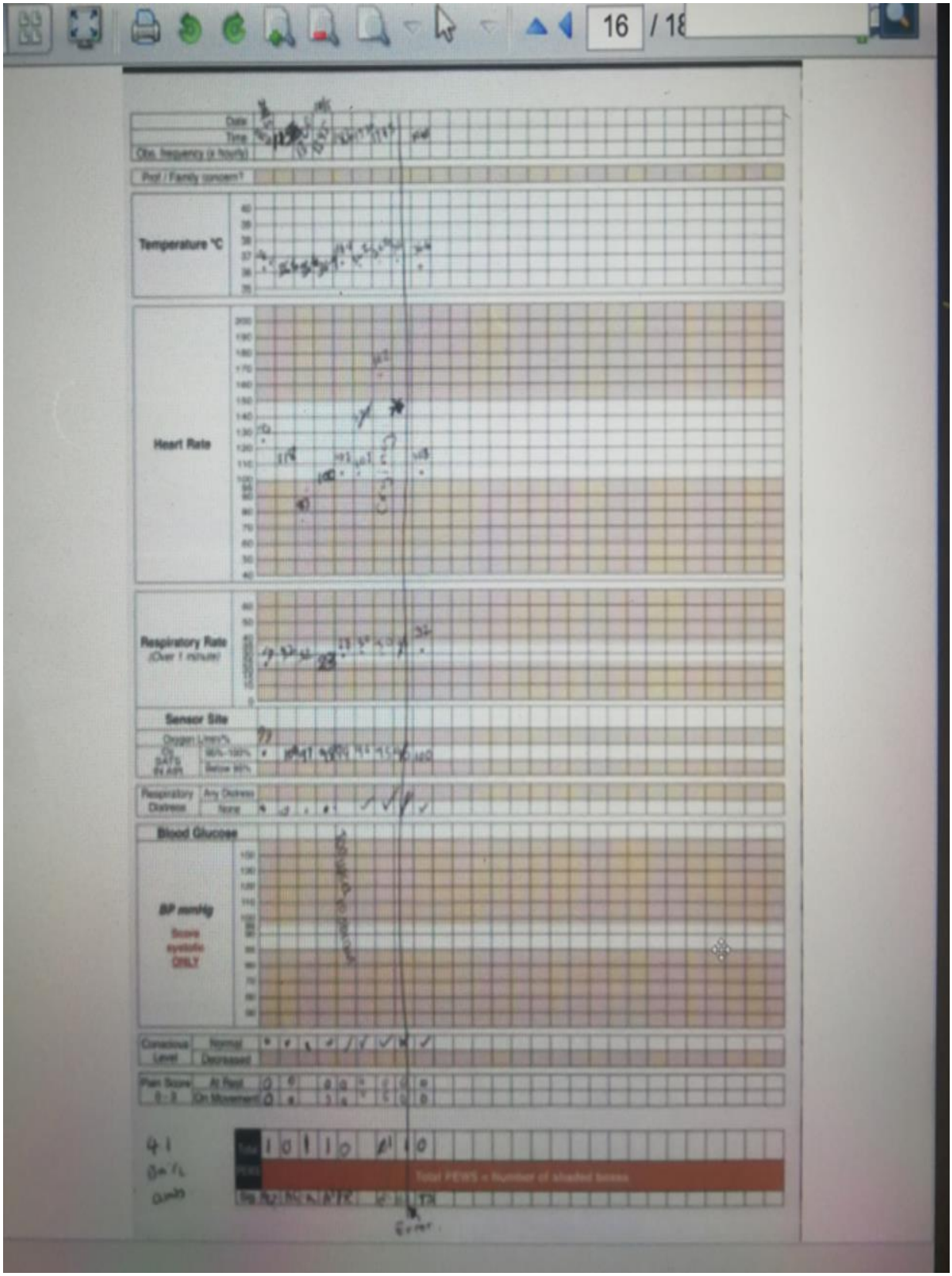
Patient 12


10 / 12
Date
Time
Obs. frequency (x hourly)
Prof / Family concern?
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Oxygen L/min%
Air
95% -100%
Below 95%
Respiratory Distress
Any Distress
None
Blood Glucose
BP mmHg
Score systolic ONLY
Conscious Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes

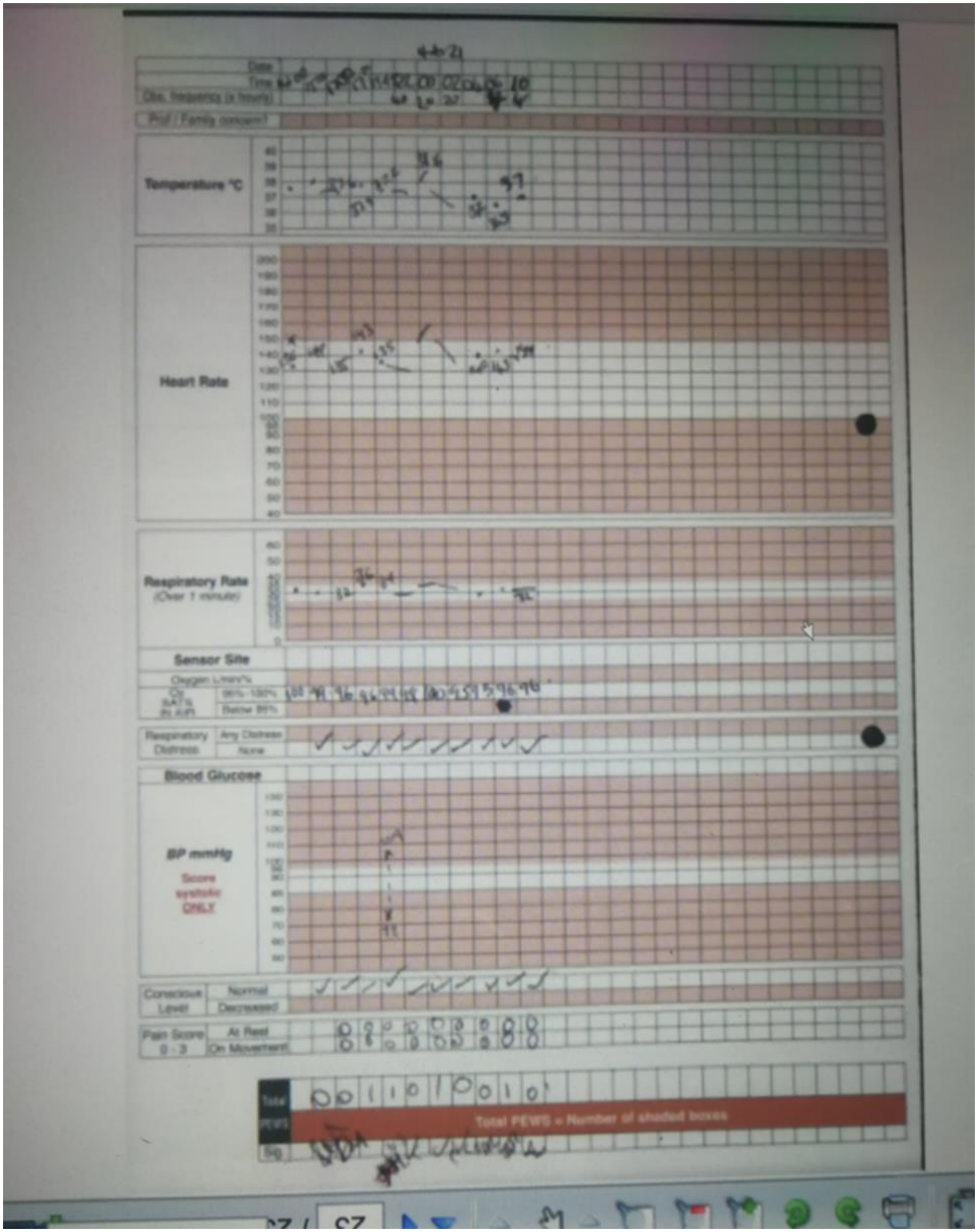
Patient 13


10 / 11
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY
Consciousness Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes
ENG
21:08

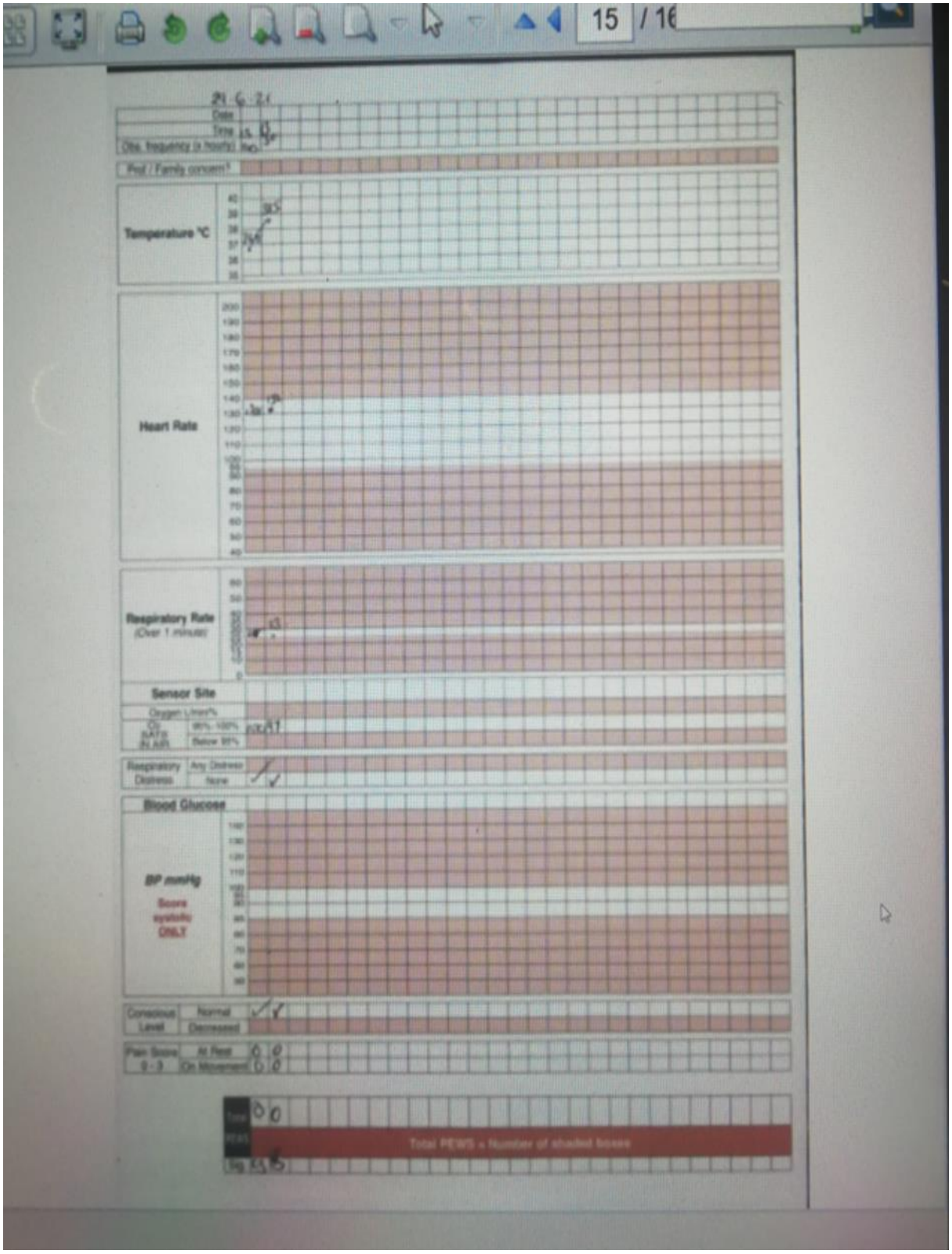
Patient 14


16 / 18
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY
Total PEWS = Number of shaded boxes

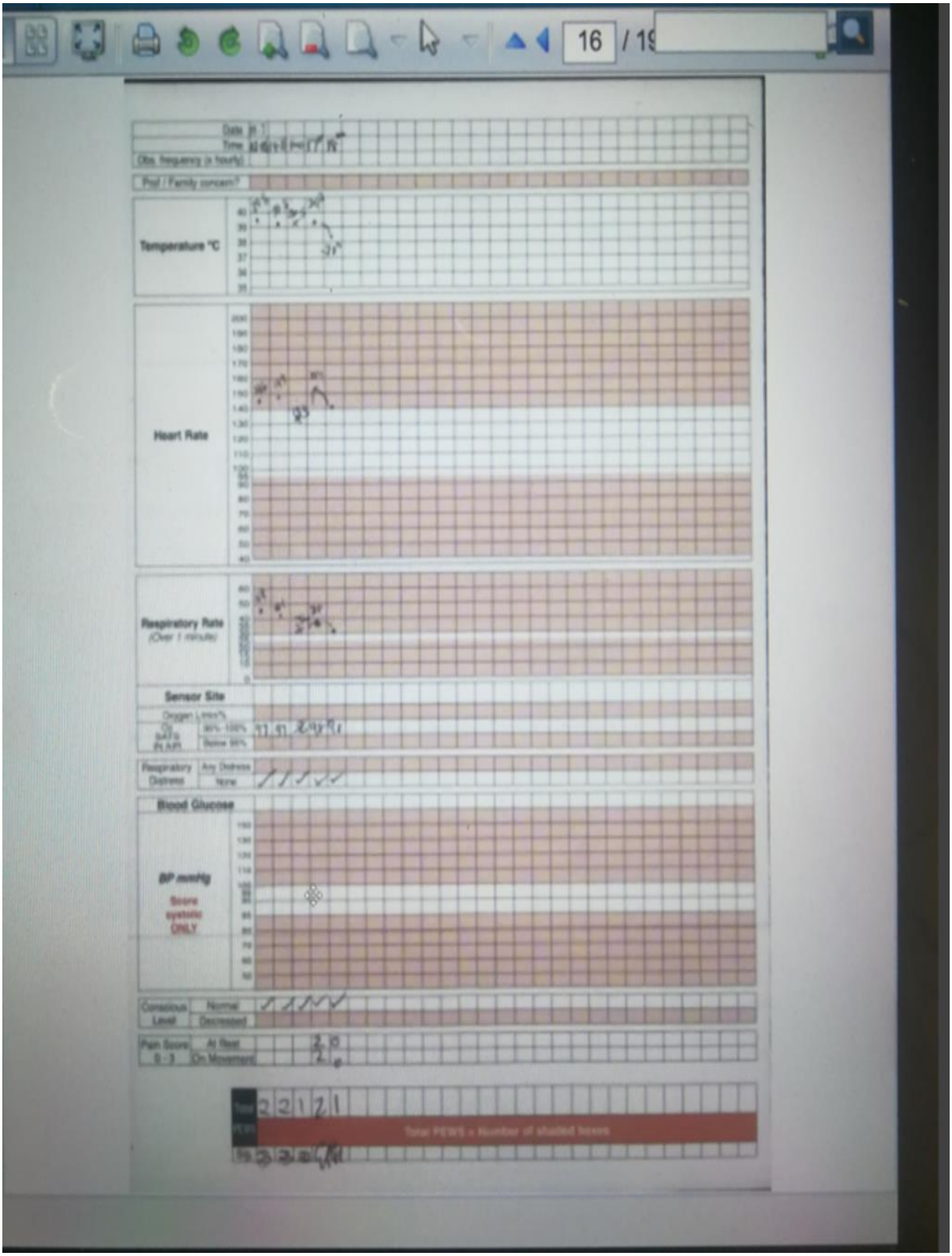
Patient 15


Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY
Total PEWS = Number of shaded boxes

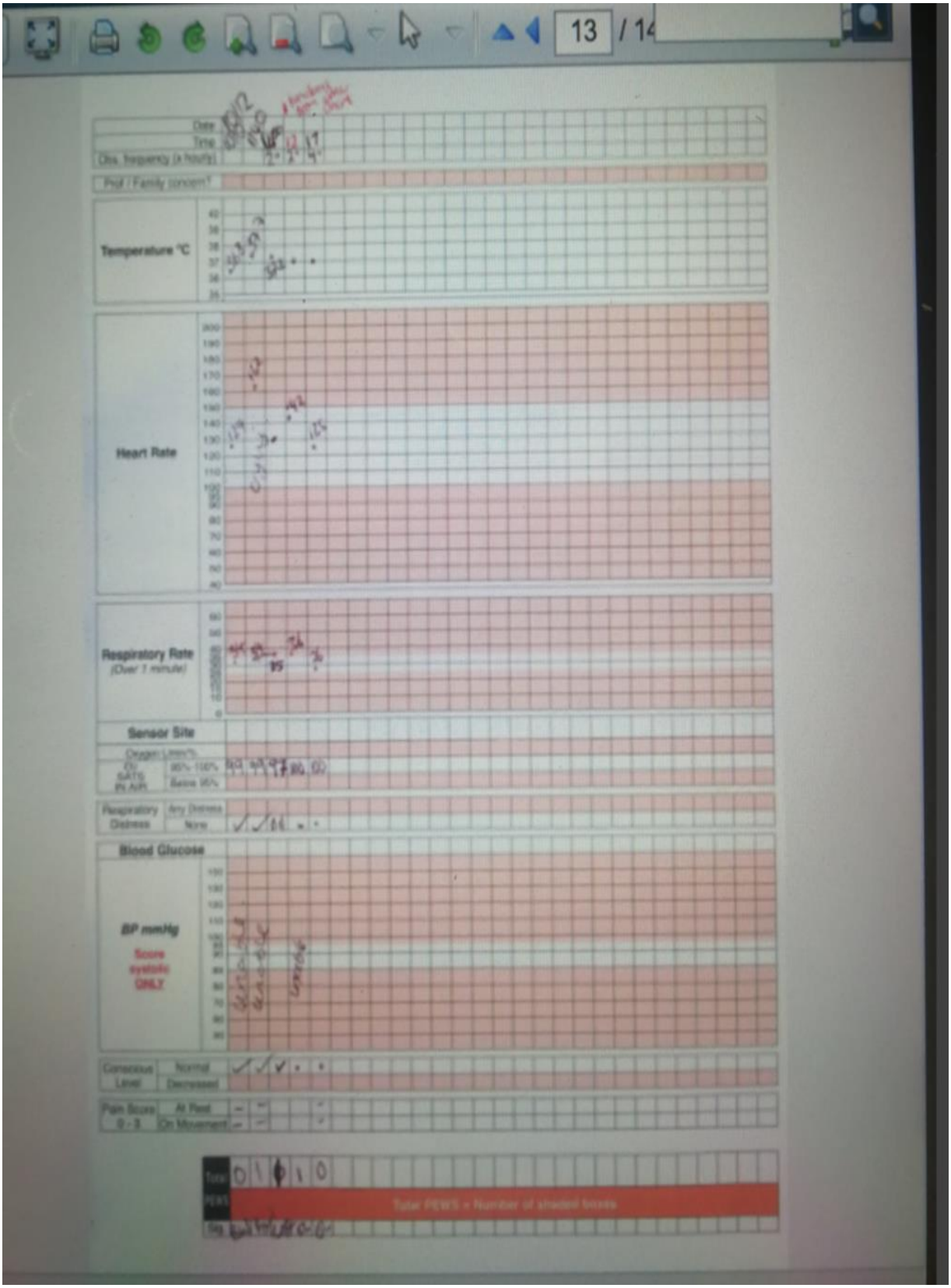
Patient 17


15 / 16
Date
Time
Obs. frequency (x hourly)
Prof / Family concern?
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Oxygen L/min%
O2
SATS
IN AIR
Respiratory
Distress
Any Distress
None
Blood Glucose
BP mmHg
Score
systolic
ONLY
Conscious
Level
Normal
Decreased
Pain Score
0 - 3
At Rest
On Movement
Total PEWS = Number of shaded boxes

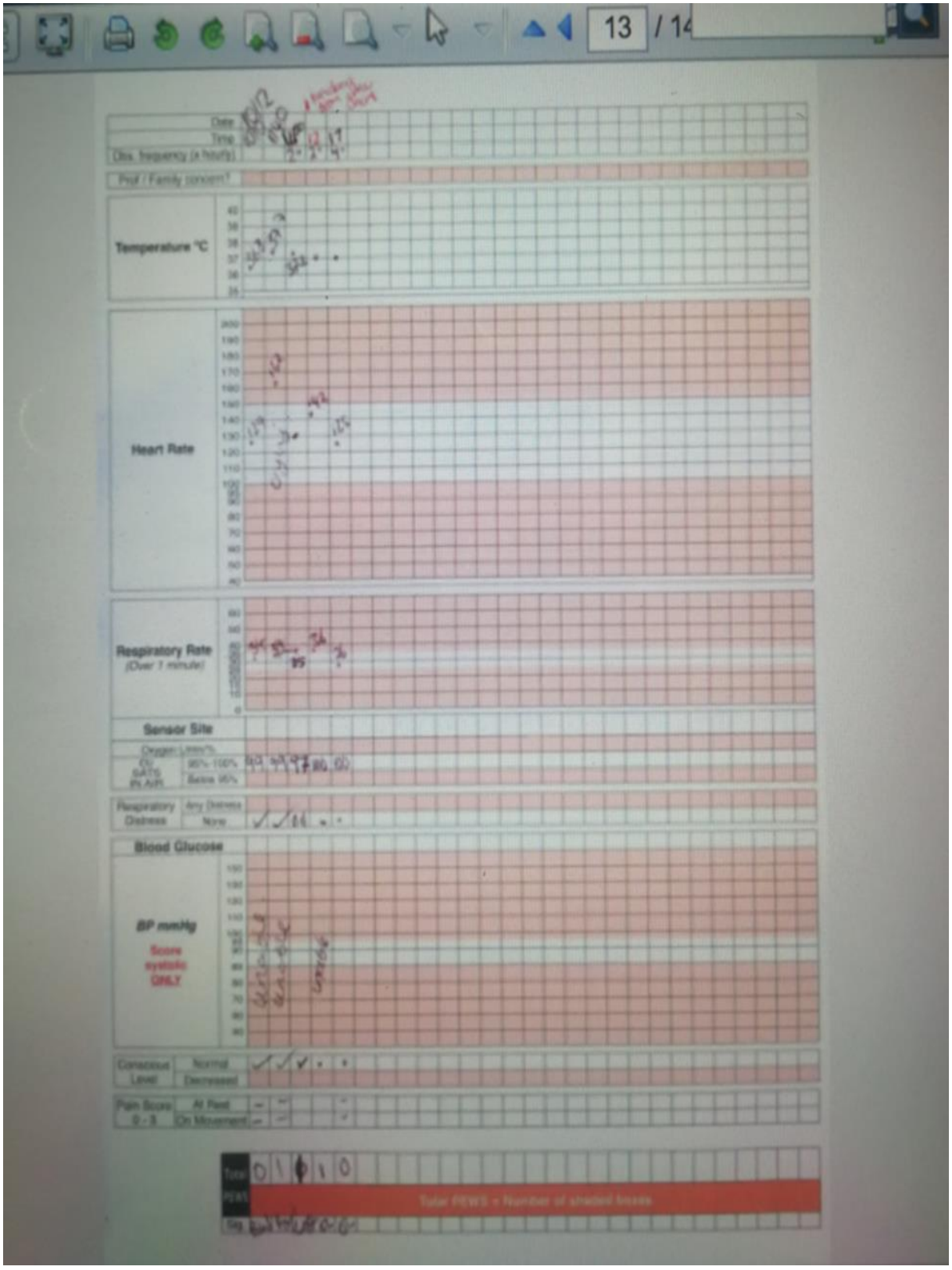
Patient 18


16 / 19
Date
Time
Obs. frequency (x hourly)
Pmt / Family concern?
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Oxygen L/min%
O2
SATs
RA/RR
90% -100%
Below 90%
Respiratory Distress
Any Distress
None
Blood Glucose
BP mmHg
Score systolic ONLY
Consious Level
Normal
Decreased
Pain Score 0 - 3
At Rest
On Movement
Total PEWS
Total PEWS = Number of shaded boxes

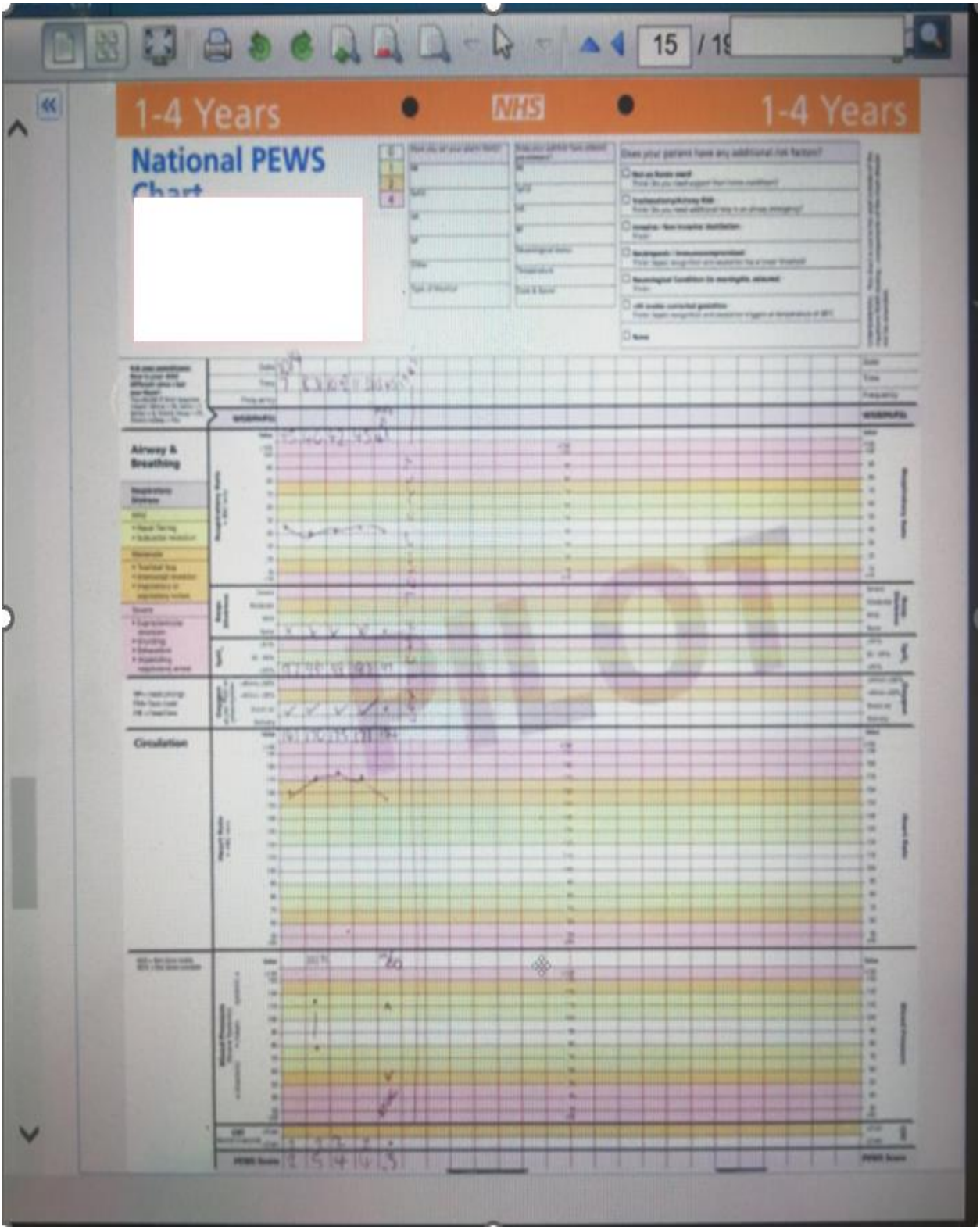
Patient 19

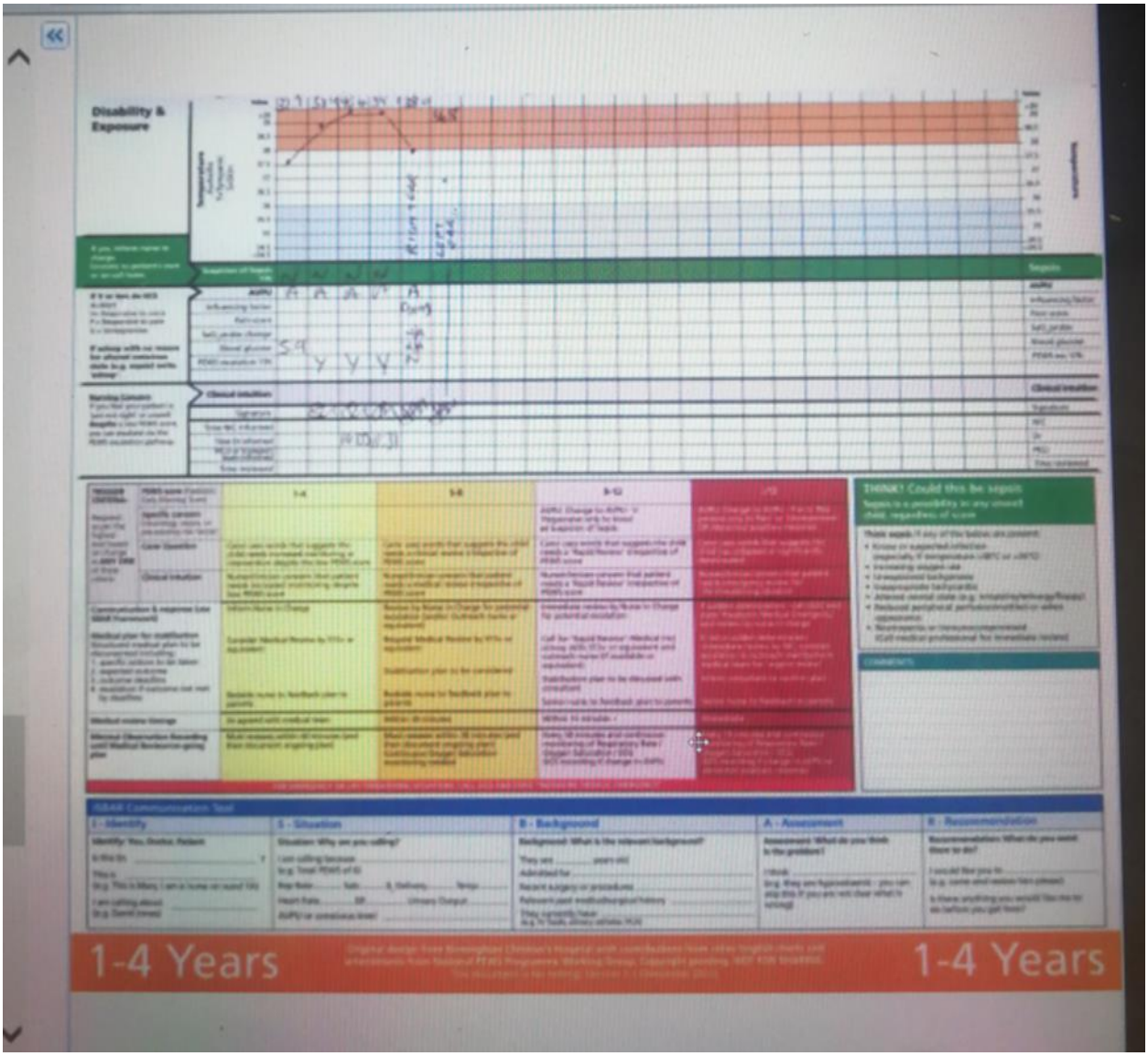

13 / 14
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY

Patient 20

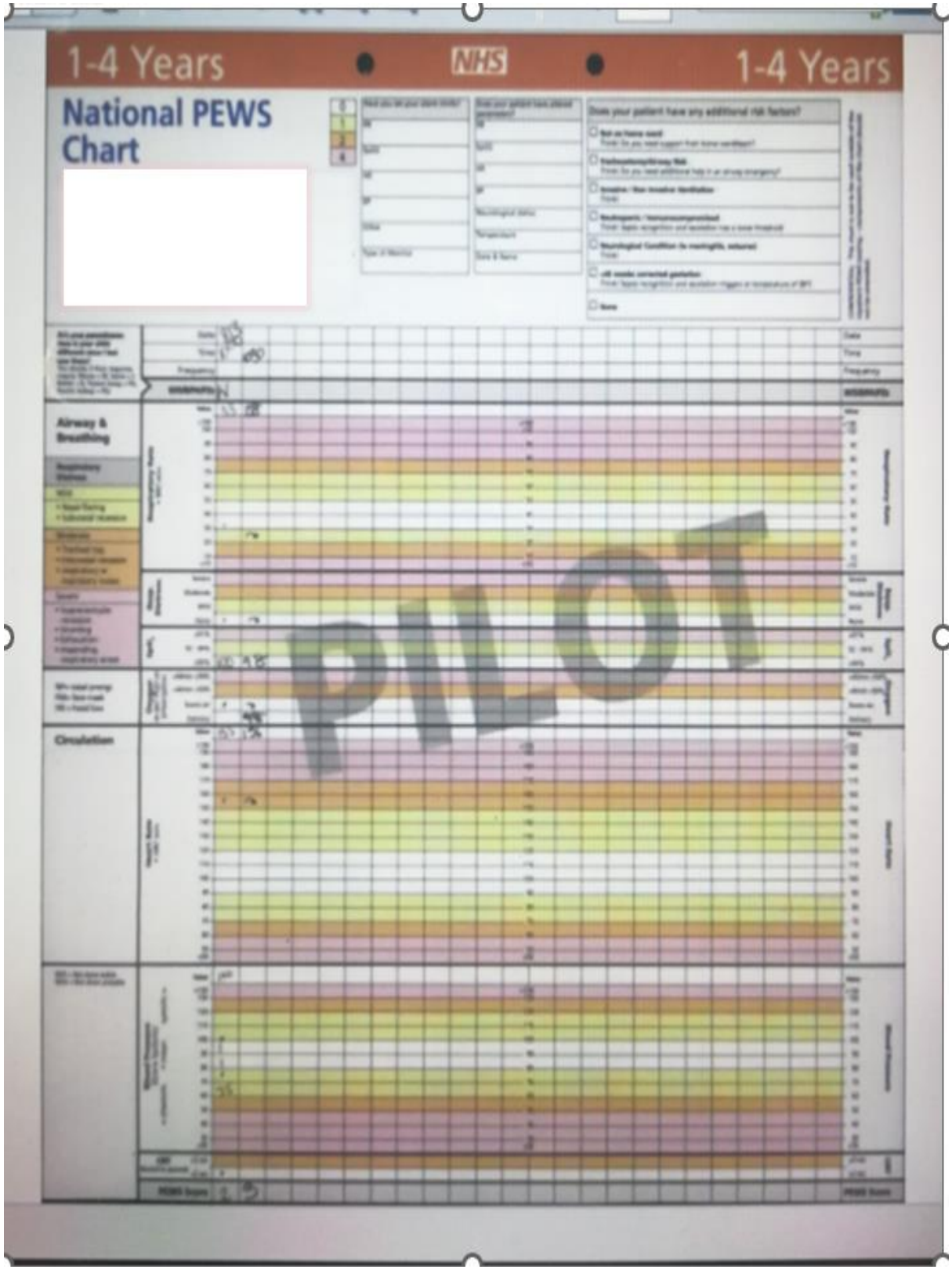

13 / 14
Temperature °C
Heart Rate
Respiratory Rate
(Over 1 minute)
Sensor Site
Blood Glucose
BP mmHg
Score systolic ONLY
Total NEWS = Number of shaded boxes

Patient 21

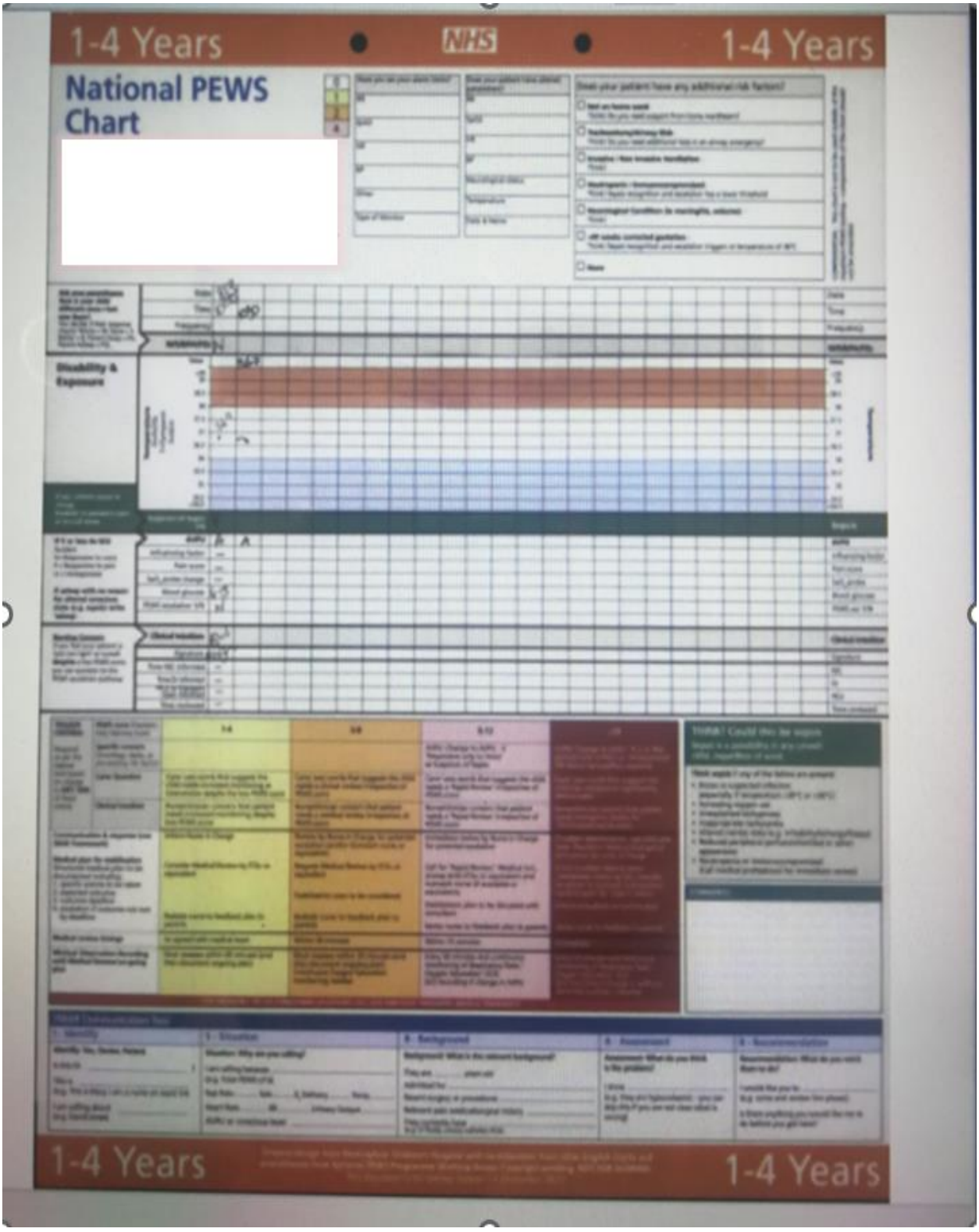

15 / 19
1-4 Years
NHS
1-4 Years
National PEWS Chart
Airway & Breathing
Circulation


Disability & Exposure
1-4
5-9
9-12
>12
THINK! Could this be sepsis
1-4 Years
1-4 Years

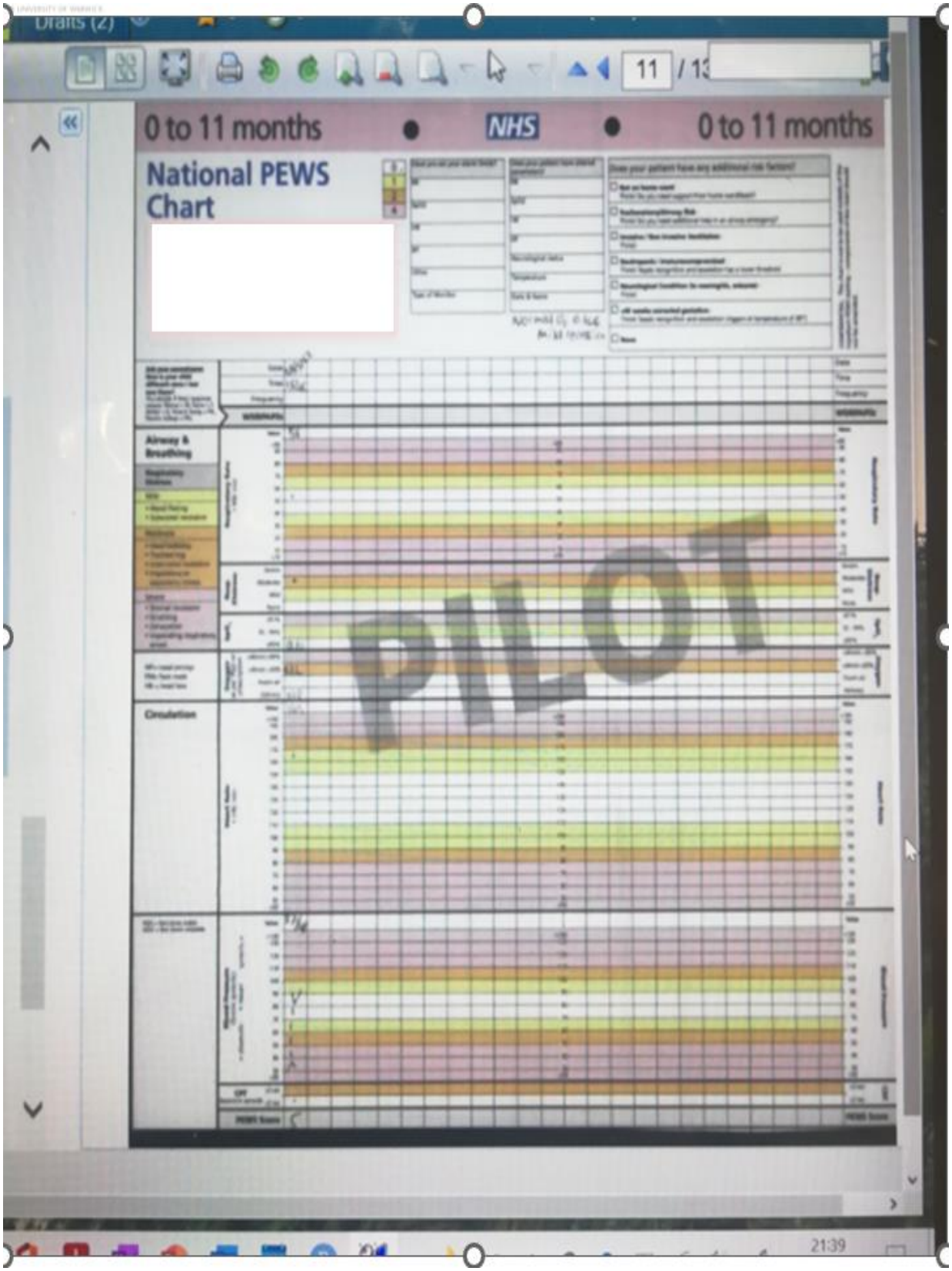
Patient 22

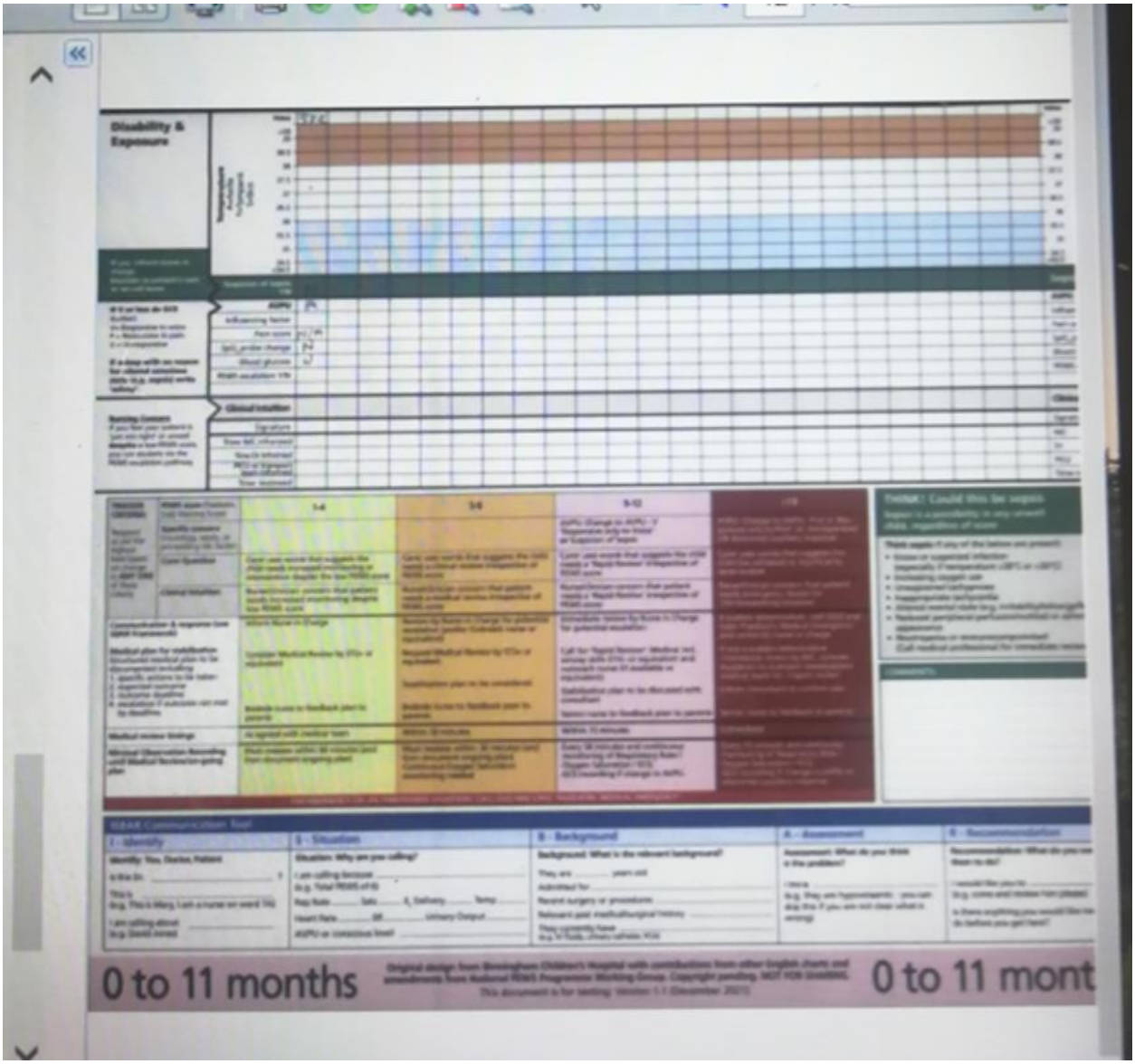

1-4 Years
NHS
1-4 Years
National PEWS Chart
Airway & Breathing
Circulation
PILOT

Patient 23

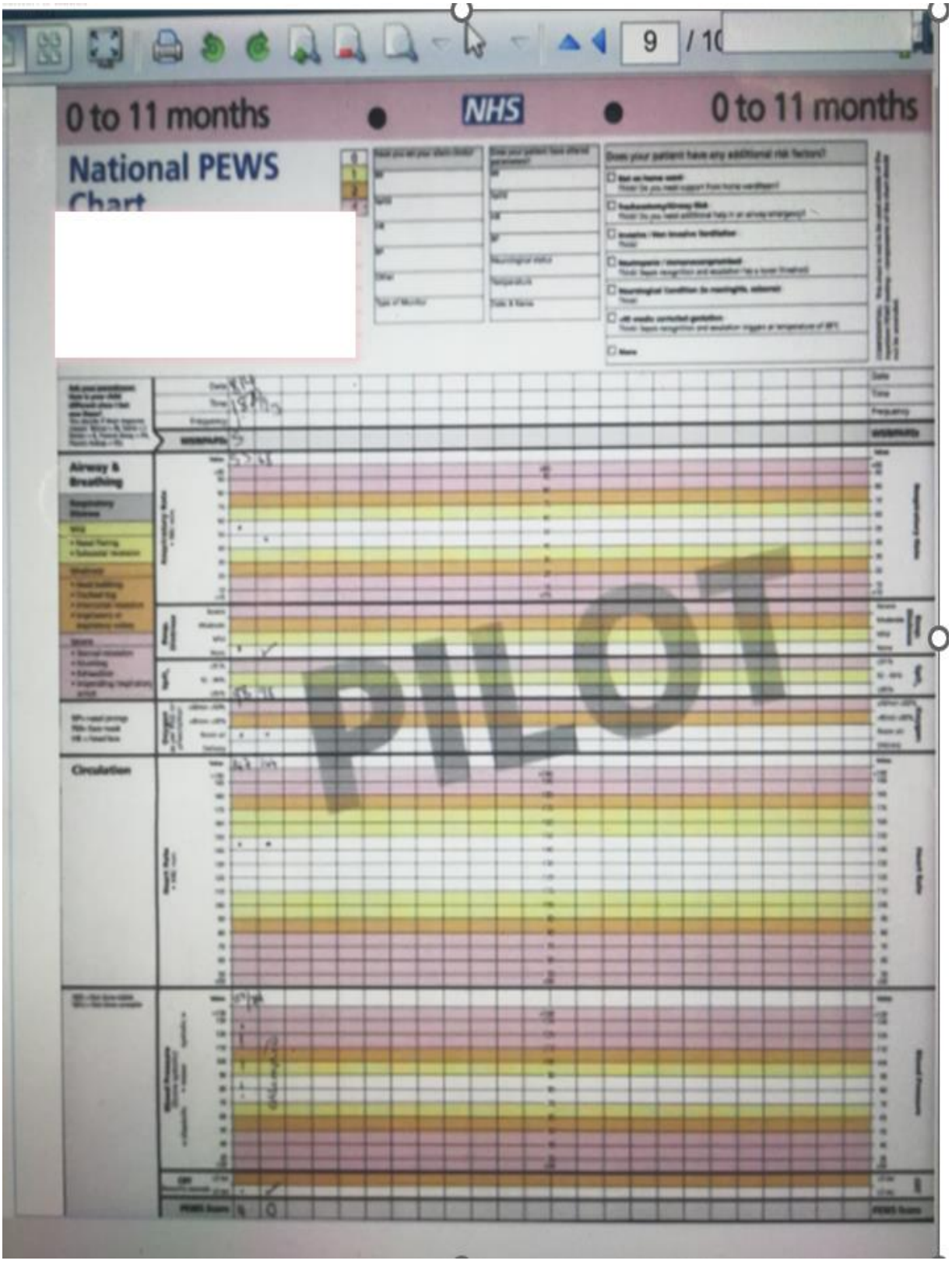

1-4 Years
NHS
1-4 Years
National PEWS Chart
Disability & Exposure
1-4 Years
1-4 Years

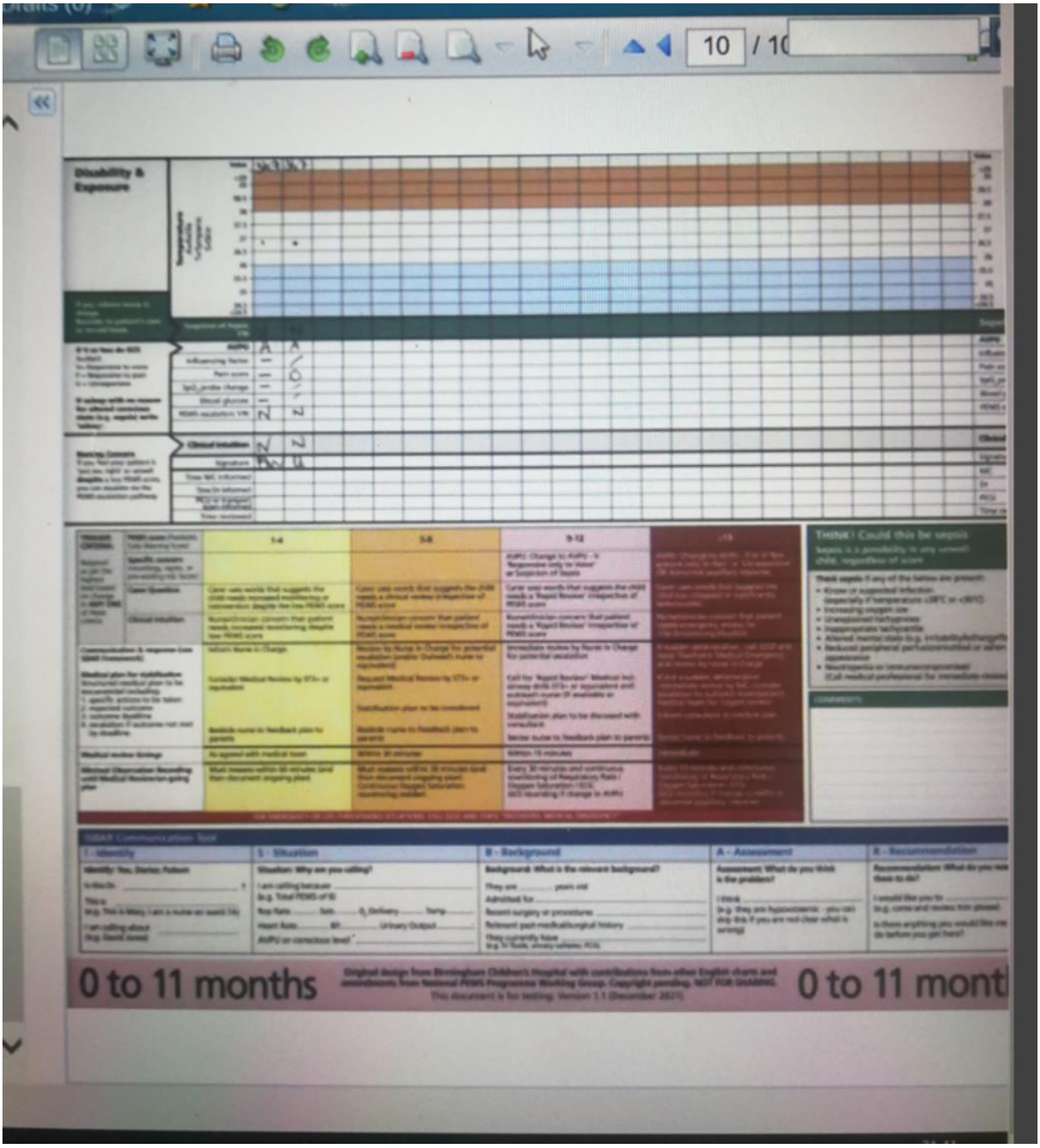
Patient 24


Drafts (2)
11 / 13
0 to 11 months
NHS
0 to 11 months
National PEWS Chart
Airway & Breathing
Circulation
PILOT
21:39

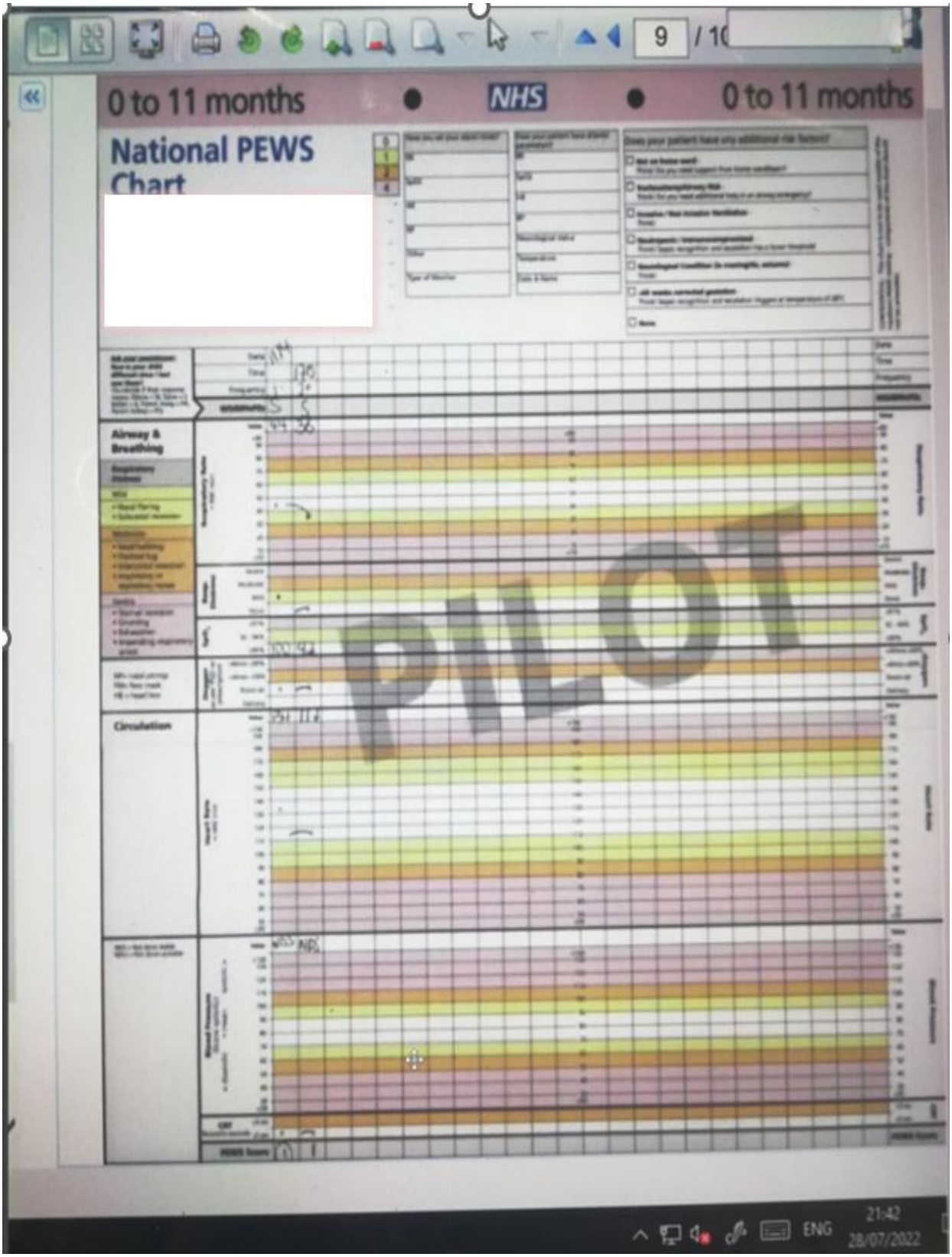

Disability & Exposure
0 to 11 months
0 to 11 mont

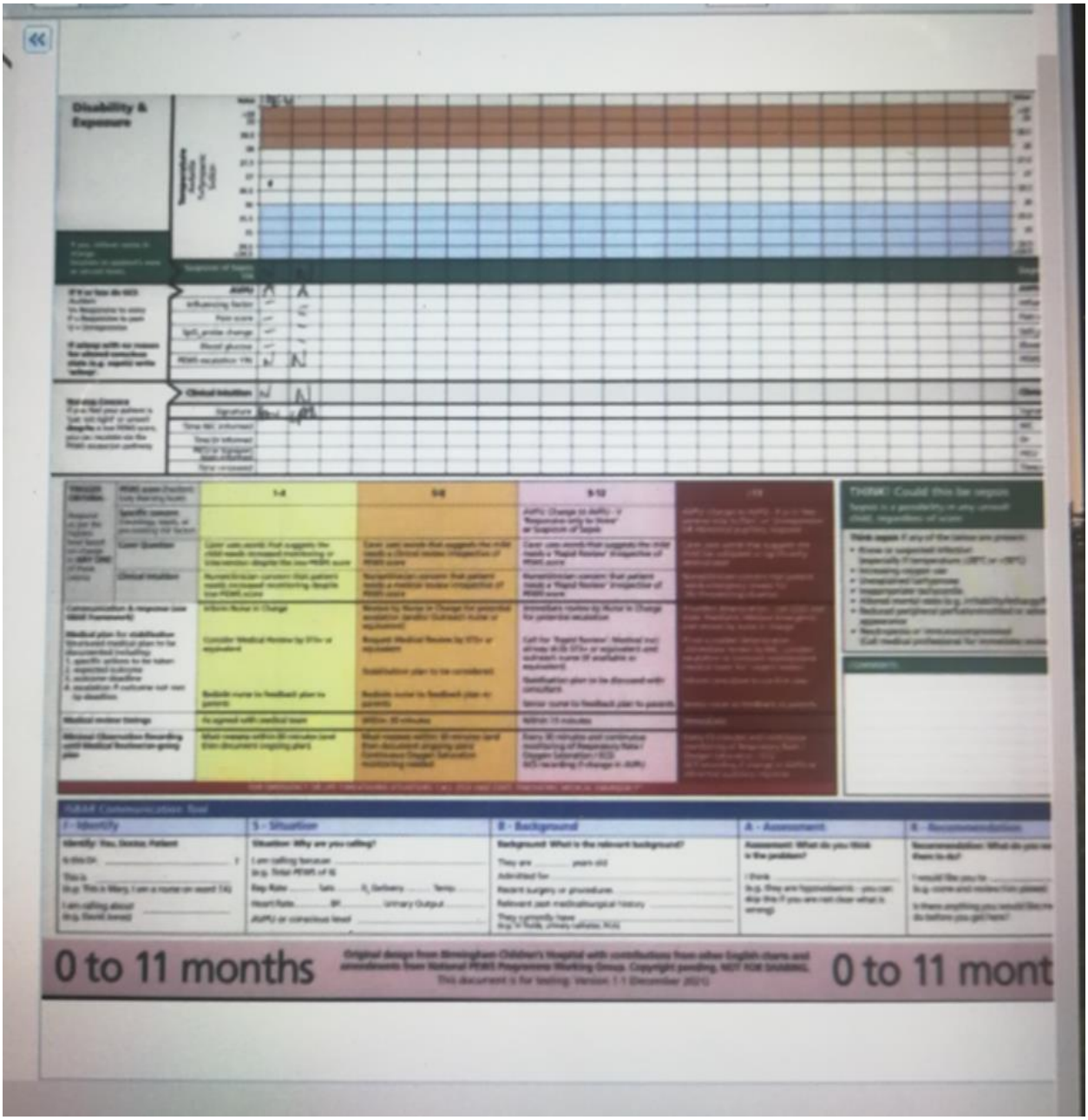
Patient 25


9 / 10
0 to 11 months
NHS
0 to 11 months
National PEWS Chart
Does your patient have any additional risk factors?
Airway & Breathing
Circulation
PILOT

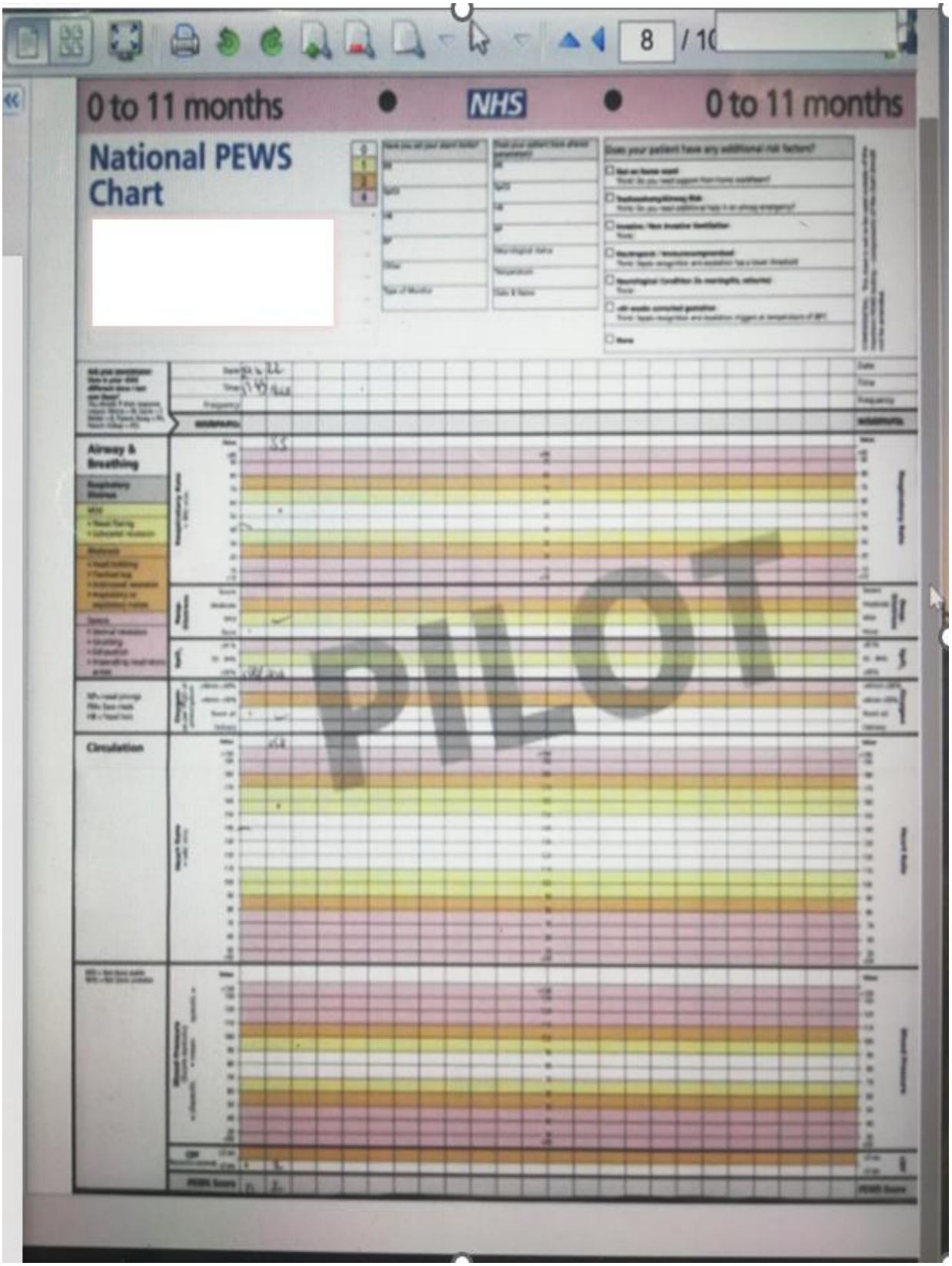

10 / 10
Disability & Exposure
0 to 11 months
0 to 11 mont

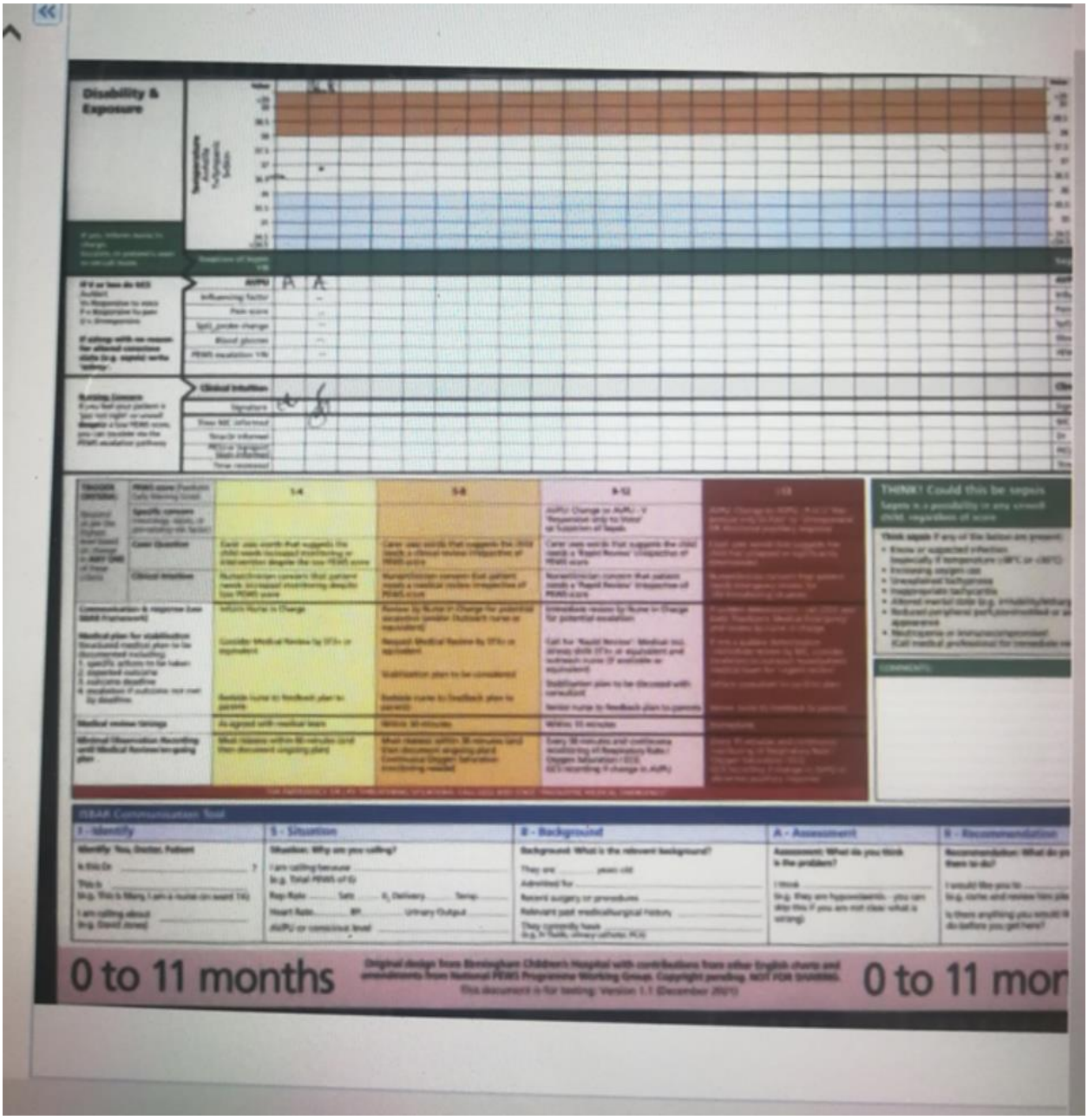
Patient 26


9 / 10
0 to 11 months
NHS
0 to 11 months
National PEWS Chart
Airway & Breathing
Circulation
PILOT
ENG
21:42
28/07/2022

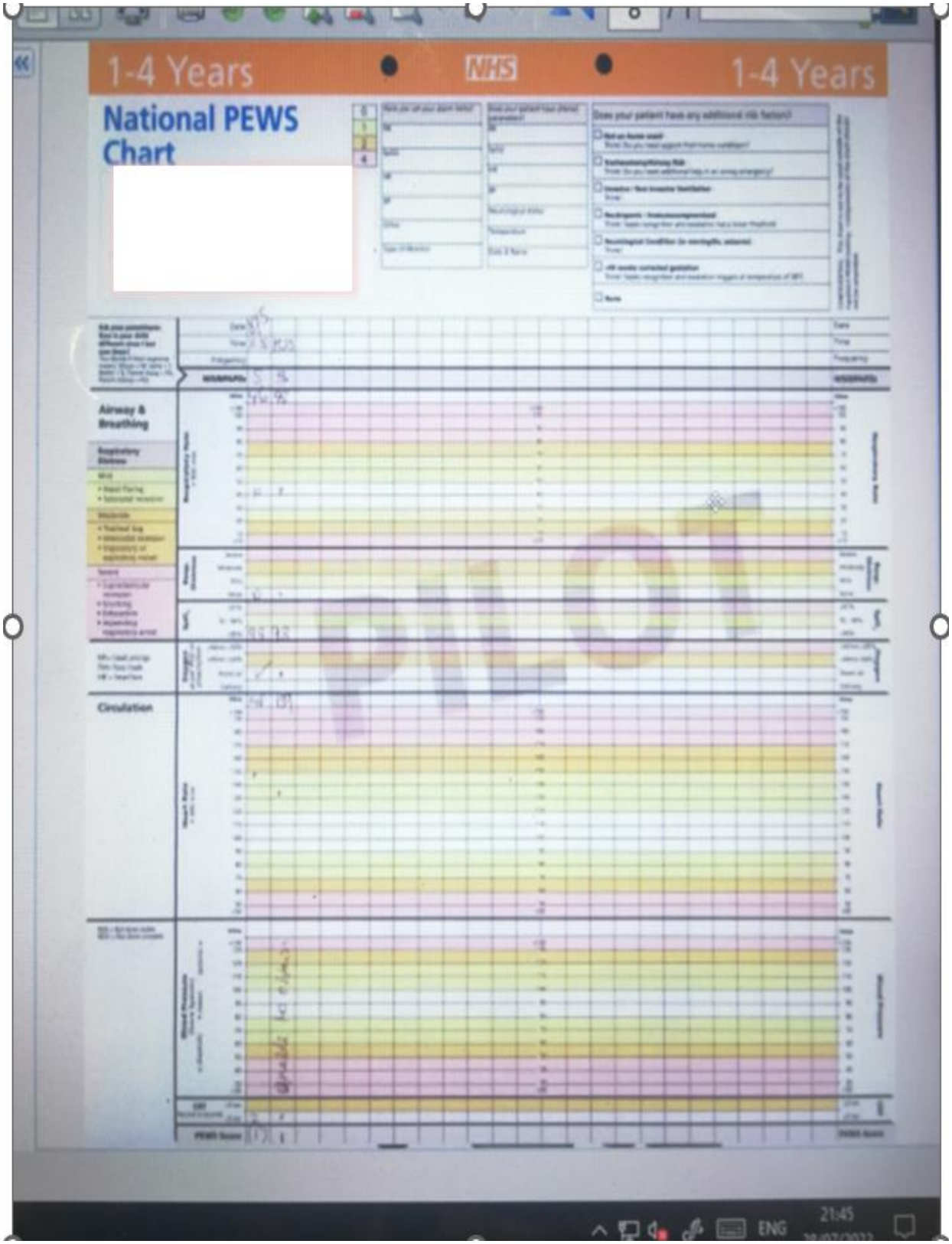

Disability & Exposure
0 to 11 months
0 to 11 mont

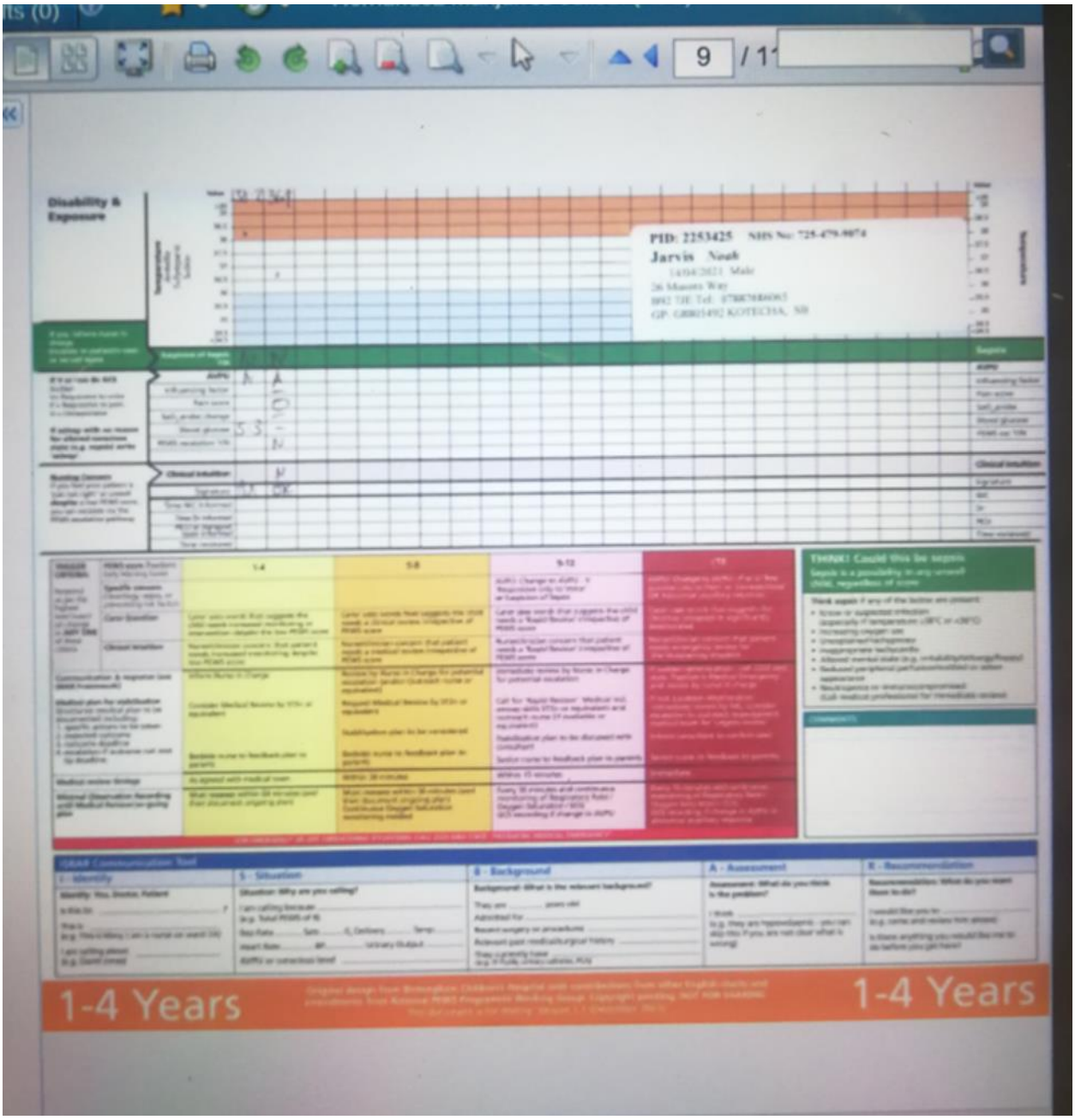
Patient 27


8 / 10
0 to 11 months
NHS
0 to 11 months
National PEWS Chart
Does your patient have any additional risk factors?
Airway & Breathing
Circulation
PILOT

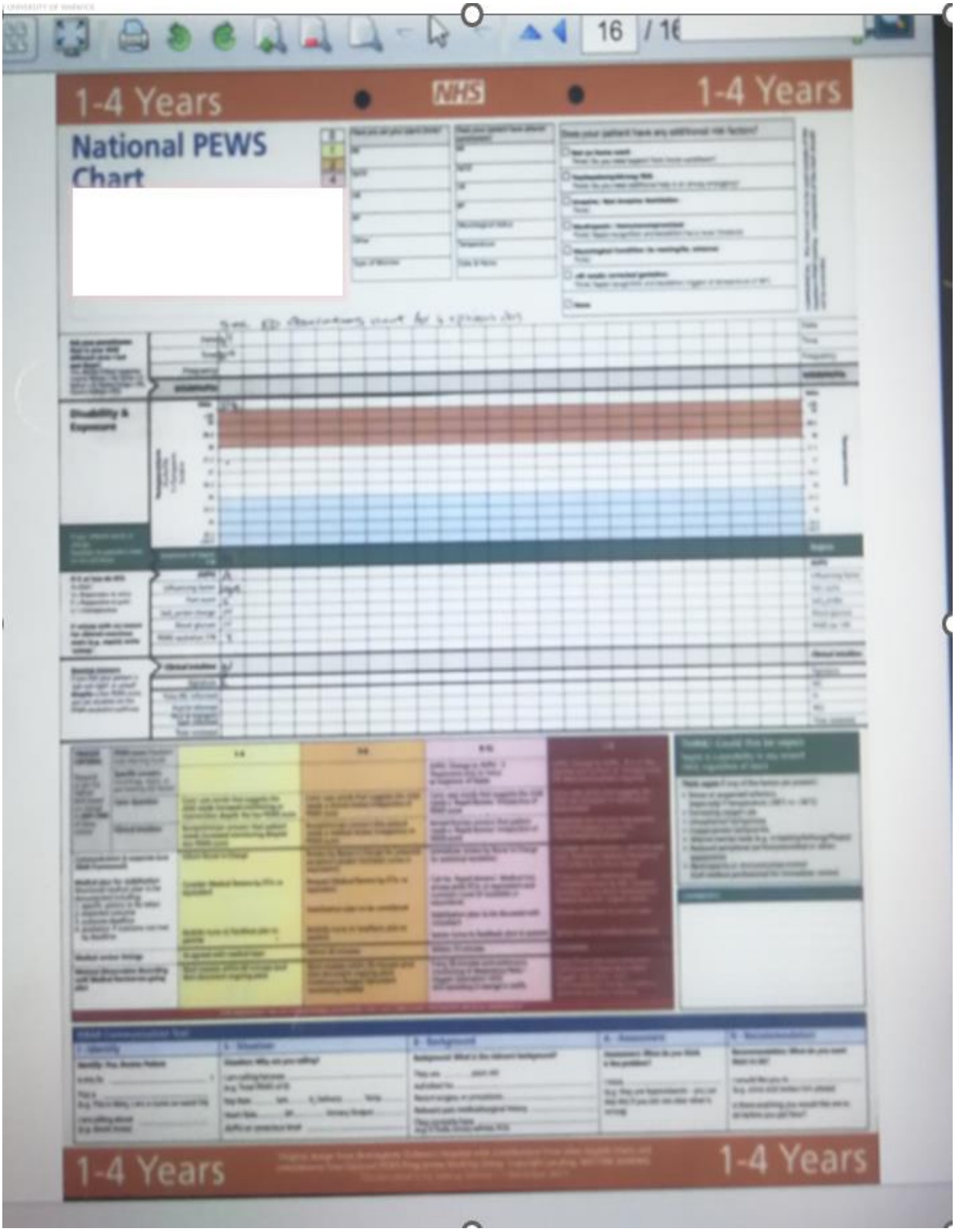

Disability & Exposure
ISBAR Communication Tool
I - Identify
S - Situation
B - Background
A - Assessment
R - Recommendation
0 to 11 months
0 to 11 mor

Patient 28

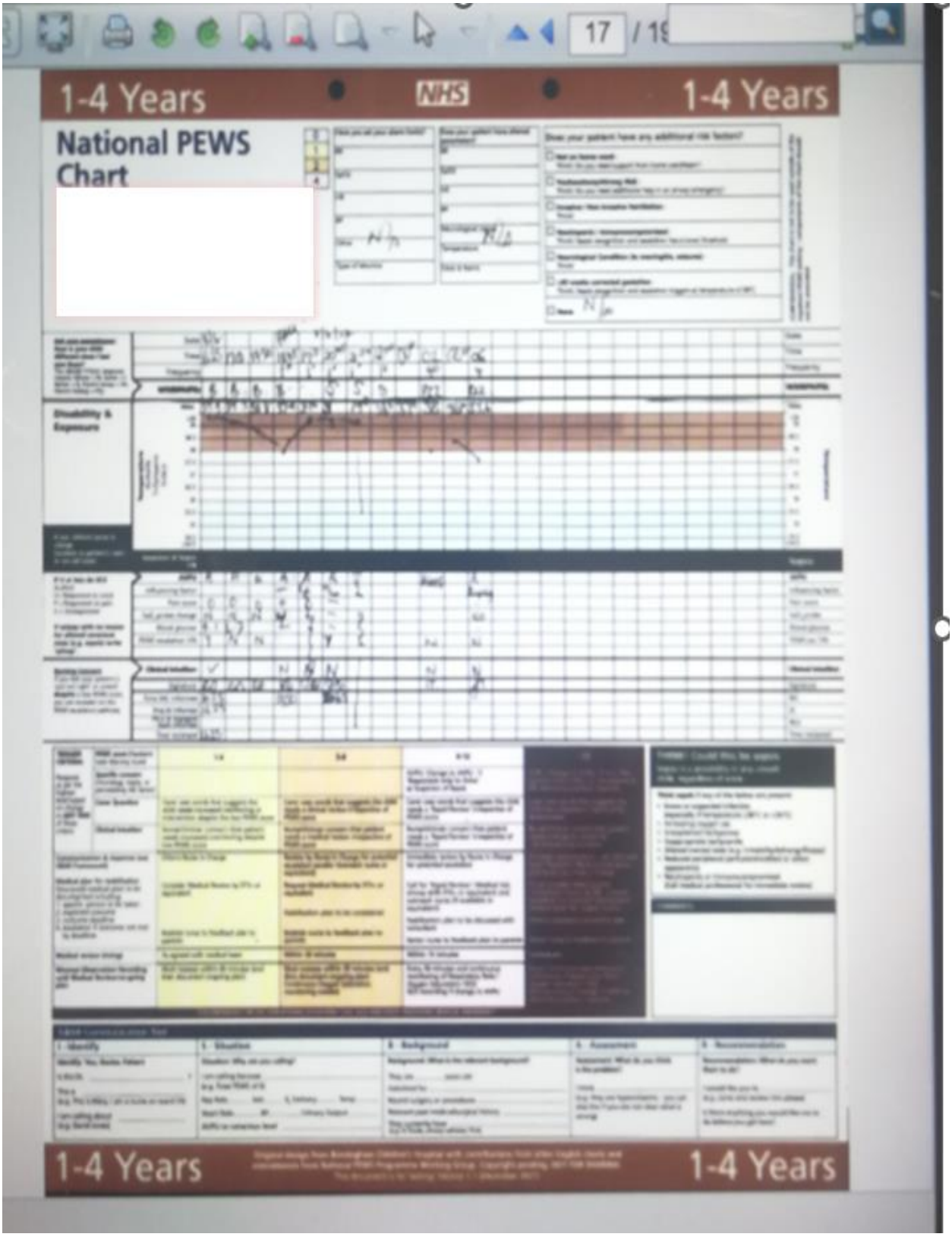

1-4 Years
NHS
1-4 Years
National PEWS Chart
Airway & Breathing
Circulation
ENG
21:45


9 / 11
Disability & Exposure
PID: 2253425
Jarvis Noah
1-4 Years
1-4 Years

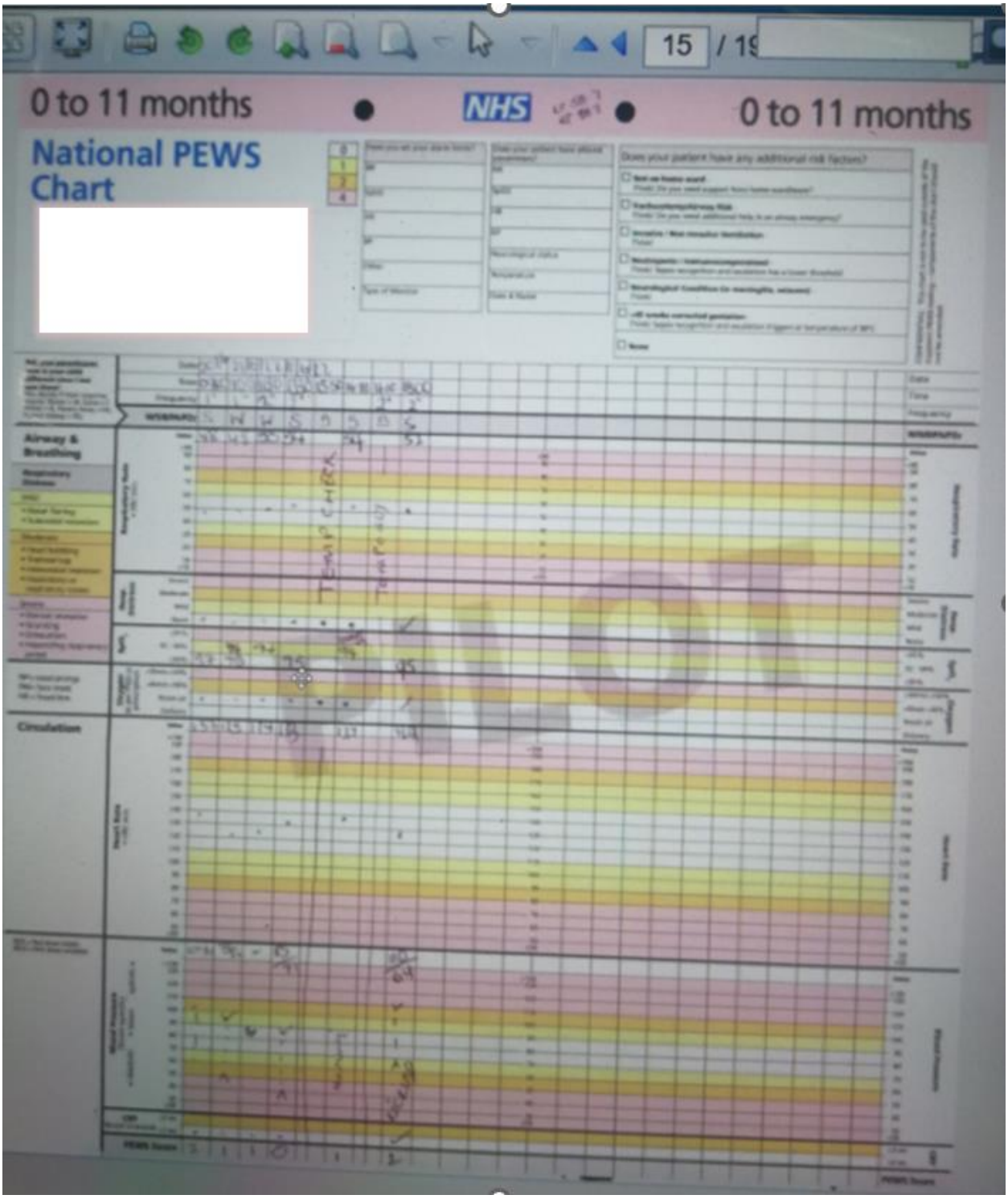
Patient 29


1-4 Years
NHS
1-4 Years
National PEWS Chart
Disability & Exposure
1-4 Years
1-4 Years

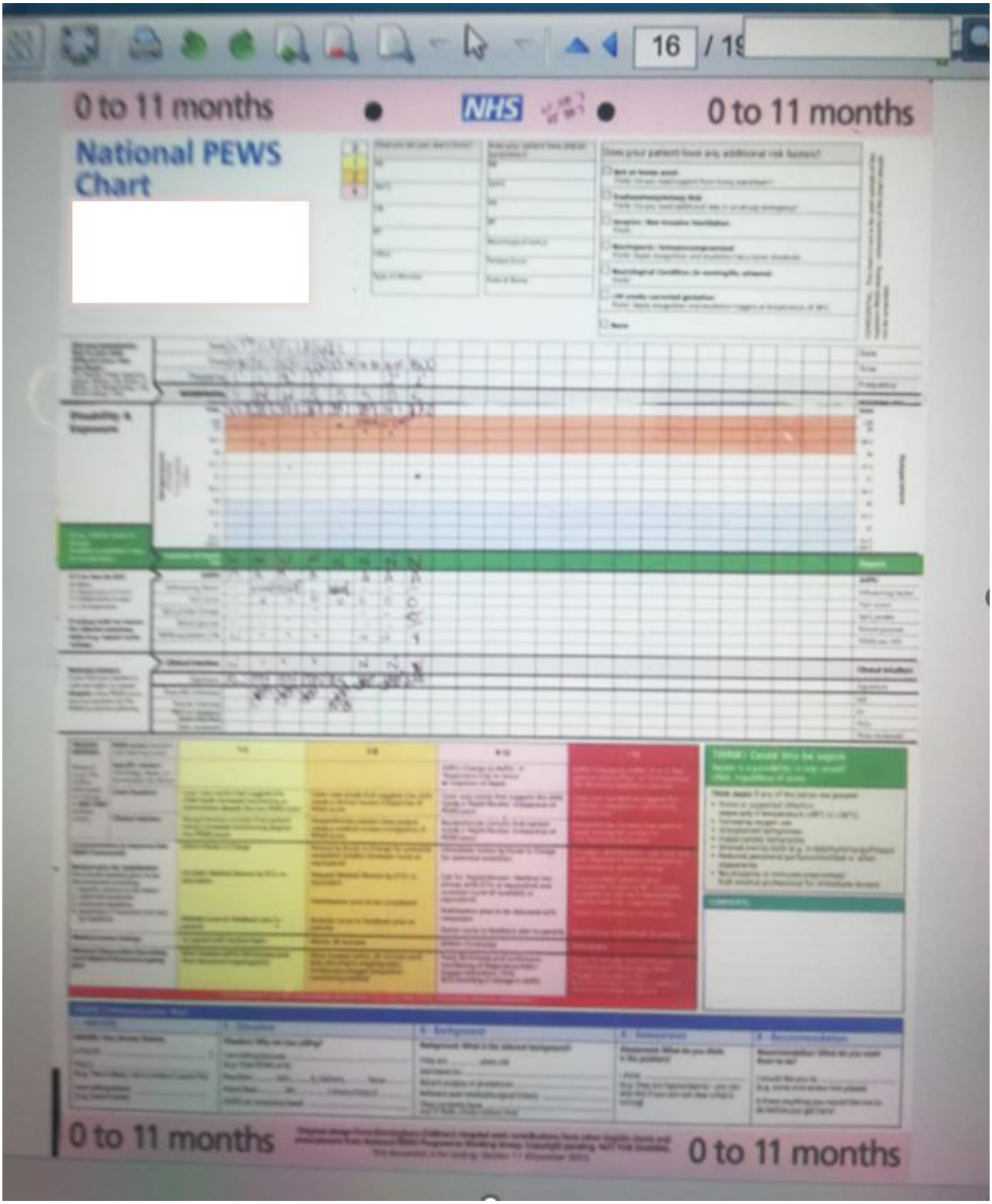
Patient 30


17
1-4 Years
NHS
1-4 Years
National PEWS Chart
Disability & Exposure
1-4 Years
1-4 Years

Patient 31


15 / 19
0 to 11 months
NHS
0 to 11 months
National PEWS Chart
Does your patient have any additional risk factors?
Airway & Breathing
Circulation

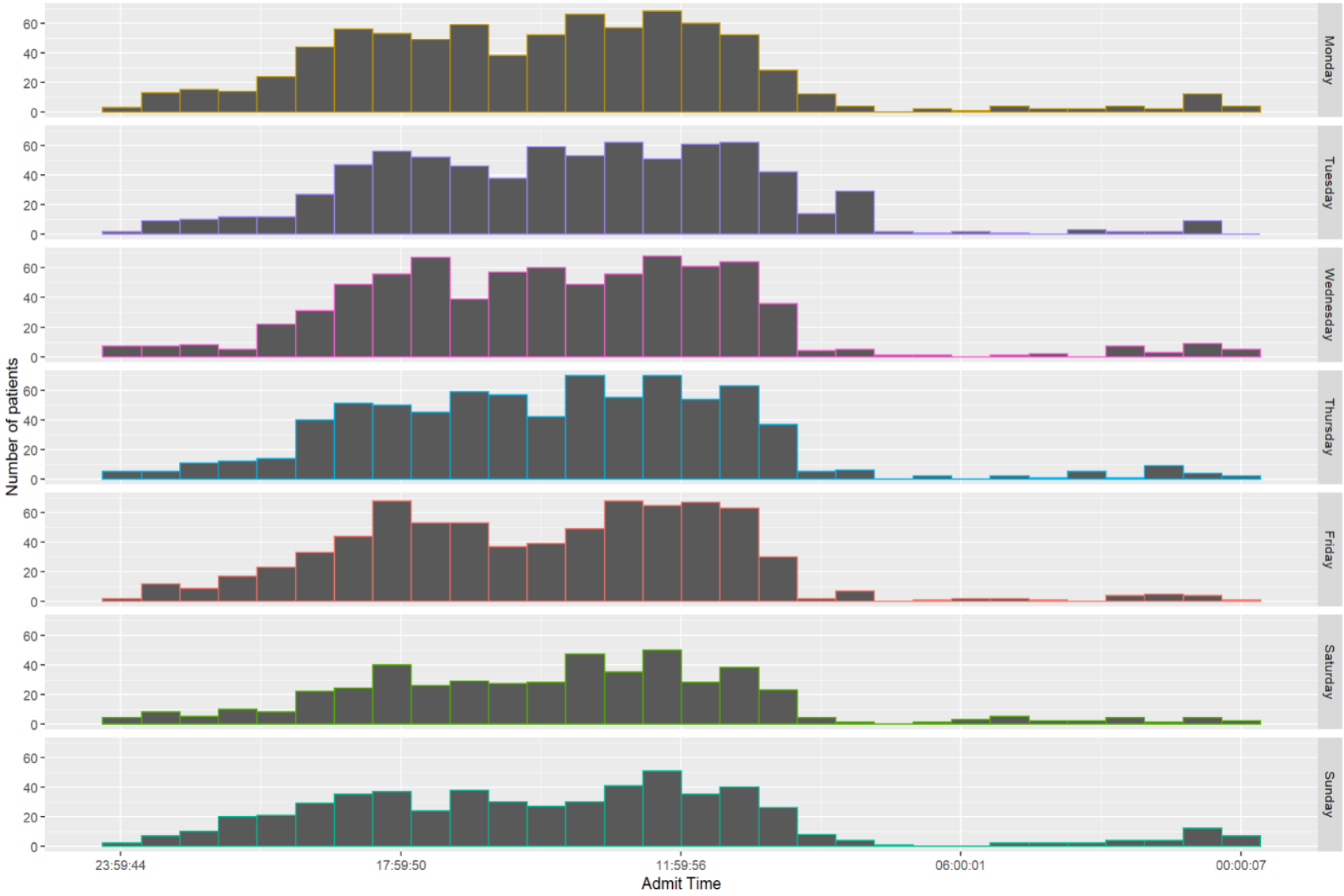
Patient 32


16 / 19
0 to 11 months
NHS
0 to 11 months
National PEWS Chart
0 to 11 months
0 to 11 months

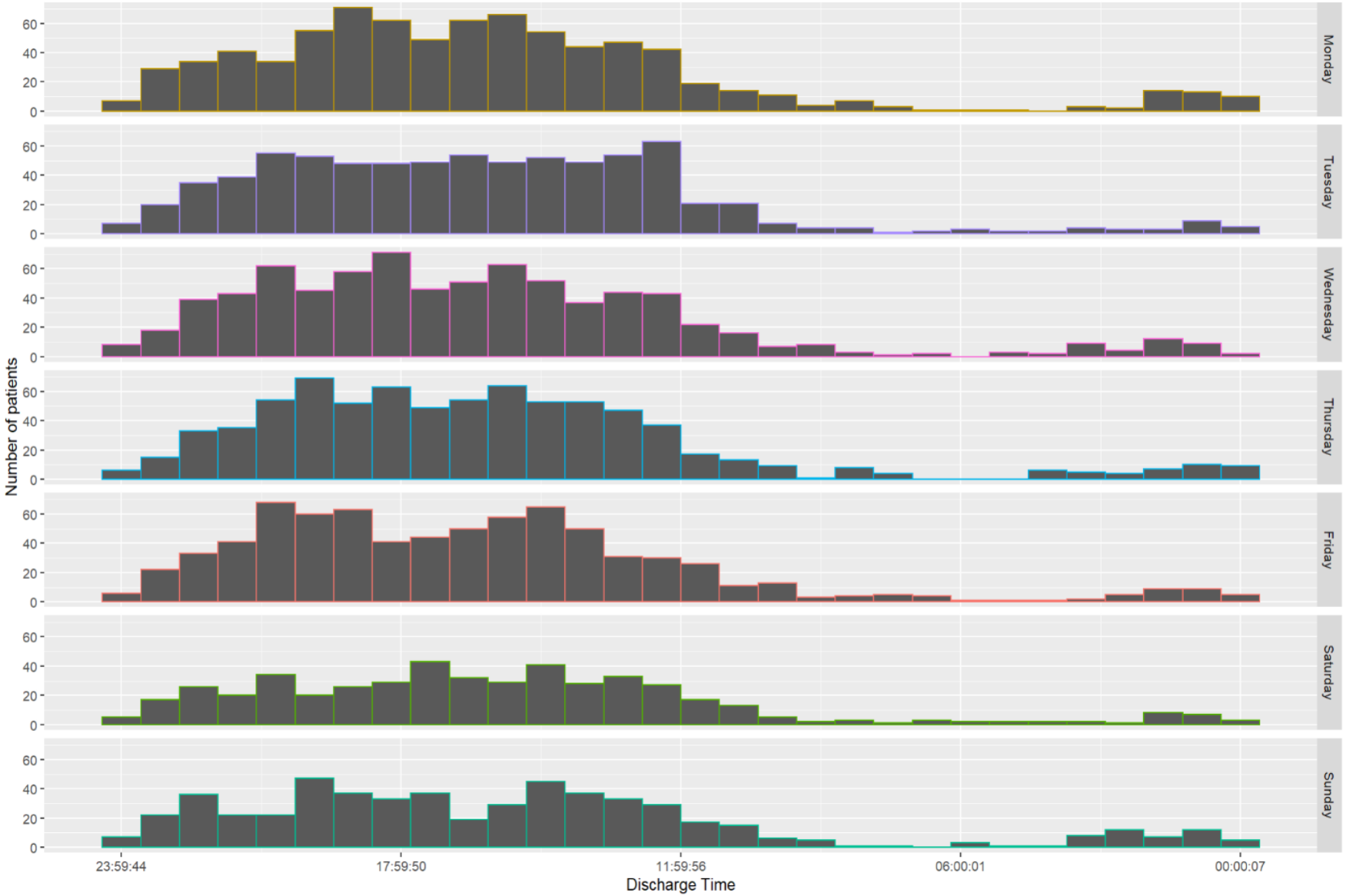
8.3 Extra graphs

Several admission at the PAU is stable over the months and across days. Weekdays are expected to be the busiest time.

Number of patients from 2020 to 2022 at PAU by wee



Distribution of the number of patients at each Arrival Time by weekday for PAU



Distribution of the number of patients at each Discharge Time by weekday for PAU