Nurse Task Frequency Uniformity Analysis And its Impact on Nurse Burnout and Resource Allocation

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Abstract

The Electronic Medical Record (EMR) system allows medical personnel to store and access patient medical information on a computerized system. To find tasks with the greatest impact on the ICU nurses, we analyzed the three timernames (tasks) from EMR log data, that comprised greater than 5% of the total frequency. The independent variables in our experiment were the nurses. The dependent variables in our experiment were the frequencies of the timernames. The log data we analyzed was the average frequency per day each nurse visited a specific timername over a period of two weeks. In other words, we found the long-run expected frequency of each timername. In a Chi-Square goodness of fit test, the null hypothesis is that the data fits with the long-run expected frequency. The alternative hypothesis is that at least one independent variable in the data does not fit with the long-run expected frequency. Our results showed that for all three timernames, the null hypothesis was rejected. This leads to the conclusion that the overall data does not conform to the uniform distribution. Therefore, there is a difference between expected and observed frequency values among nurses for the specific timernames. From this analysis, we can conclude that a nurse or group of nurses interacts with the EMR system differently relative to the other nurses. A fair distribution of work between nurses is a sign of good workload management. Equal workload management also decreases the peak stress on the overcompensating nurses. By decreasing stress, patient care is increased, and burnout is decreased. Because some nurses interact with the EMR more on average it might be beneficial to afford these nurses improved infrastructure to facilitate their documentation. From this information, it may be possible to tailor the allocation of resources to specific nurses that have a higher usage rate of the EMR system relative to other nurses.

Keywords: EMR, ICU, Nurse Workload, Resource Allocation, Nurse Task, RTMS, Log Data, Nurse Workflow, Workload Management

(1) Project Motivation

Before the computerization of patient medical information, hospitals and clinics held vast paper records containing patient data. Since the computer age, however, the entire method of collecting and accessing patient data has been altered. Instead of storing the information physically, the information is stored in a database in the form of Electronic Medical Records (EMR). Studies have mixed results about the perception of the EMR. On one hand, Nurses perceived an enhancement of patient safety during the EMRs implementation (Top & Gider, 2011). While on the other hand nurses report that the EMR has no positive impact on patient care and takes time away from treating the patient. Either way, in both studies the EMR has increased communication, increased the visibility of patient medical information, and facilitated the nursing experience. In recent years, nurses are experiencing high rates of burnout (Shah et al., 2021). One of the main causes of this burnout epidemic is workload (Greenglass et al., 2001). Through the study of workload trends and the application of workload management techniques, we hope to decrease nurse burnout.

While the EMR system has drastically improved the patient care process, it may be worth considering if we should analyze EMR data on a nurse-to-nurse basis. Do all ICU nurses have a similar EMR workload? If nurses have a similar EMR workload, then they all use the EMR system uniformly, which means they should all have the same infrastructure regarding their EMR workstations. If they are different, however, it may be beneficial to vary the infrastructure for the nurse's EMR workstation based upon their usage rates. We want to know if all ICU nurses have EMR usage uniformity. A nurse's position might require them to be around the EMR more or fewer times than others, and this difference can be measured. A reasonable conclusion to finding such a nurse would be to increase infrastructure around a high EMR usage nurse to facilitate EMR documentation. This can be done by improving this nurse's computer, internet connection, or work environment when interacting with the EMR.

For nurse task frequency, the uniform distribution is the expected distribution. In our research, we are testing the current distribution of work between nurses. To see what, if any, steps need to be taken to achieve uniformity. Uniformity is the desired distribution because of workload management. "Good workload management will also help keep employees healthy, as a high workload is a predictor for burnout" (Oetelaar et al., 2016). Oetelaar states "We aim for a fair and sensible distribution of nursing staff over the wards, resulting in an equally distributed and manageable workload for all nursing staff" (Oetelaar et al., 2016). Just like Oetelaar, we are aiming for a fair distribution of work between nurses, regardless of nurse-specific job resources that can counter the job demand workload. In the context of this research, our research objective is to use task frequency uniformity to determine the fairness of nurse workload.

Nurse workload increases emotional exhaustion. Emotional exhaustion leads to cynicism which in turn can negatively impact a nurse's professional efficacy (Greenglass et al., 2001). By having an ICU where all nurses uniformly take the burden of work, the peak stress placed on an individual worker is diminished. Nurse workload predicts nurse mental well-being, decreased job satisfaction, and increased risk of burnout (Greenglass et al., 2001).

(2) Methods
2.0 Participants and RTMS Data:
The Real-Time Measurement System (RTMS) dataset was collected by recording nurse-EMR interaction. The RTMS is necessary to prove the hypothesis because it was required to pull the data from the nurses. However, a risk factor is that it does not record everything a nurse does. The RTMS data only recorded actions within the EMR and does not record nurse-patient interaction. The data is comprised of a long list of rows. Each row corresponds to a timername and a large list of other variables relating to when, where, and how the timername was used. In our research, we focus on only the timername category and find how many times each timername is recorded.

To perform this experiment our research used several software tools. We employed the software language R to read and write csv files and count the frequency of timernames over two weeks. R was also used to create the frequency pie chart. Minitab was used to conduct statistical analysis and run a Chi-Square goodness of fit test. Excel helped in data checking when manually inspecting data for corruption.

The RTMS dataset we received for analysis consists of 160 CSV files recorded over a period of just over two months and by 7 nurses. These nurses worked within the ICU at the University of Missouri. For each day that data was recorded, a folder was created (see Appendix 1.1). Within that folder are several CSV files associated with each of the nurses. In some folders, an individual nurse's data is split between several CSV files. An example of this is shown in the figure. The name of the folders relating to a particular day is the day's date written in the format year-month-day with no spaces. The name of the CSV file pertaining to date and nurse is written as date_nurse. CSV an example of this formatting is shown in Appendix 1.2.

The primary way that we are reducing the size of the dataset is by filtering out unnecessary variables. This greatly reduces the size of the data. Currently, we are working on a derivative dataset that contains only 1 of the original 76 columns. The column we chose to analyze is timername (task).

2.1 Data Wrangling:
The first step before analysis can be done is data wrangling. In our research, the data wrangling task is separated into two parts. Part one, receive RTMS_2021 folder. Part two set a working directory within R.

Acquiring the RTMS dataset presents a few problems. The first problem is finding a copy of the RTMS_2021 folder. In our research, this folder was provided by Professor Seo. The second problem pertains to the movement of the dataset. As the dataset is large it cannot be easily transmitted through the internet. To avoid this issue our research relied on physical hard drives to move the data.

Once we have the data stored on a hard drive it can be copied over onto a desktop. The address of the RTMS_2021 folder should be noted for future use. To let our programming language, know where to look for the data we set a working directory within R. We use the address of the RTMS_2021 so R has an easy time reading and writing files into a designated location. From now on R is linked to the RTMS data.

2.2 Compilation:
The second step of our methods is compilation. Compilation means putting together individual CSV files from the RTMS_2021 data. The way this is done is through the rbind function. In short, this function has a list of filenames as an input and has a concatenated CSV file as an output.

Before we can start reading files, we need to tell the computer what files to read in. This is done by inputting a starting date and an ending date and a name. The first filter by date. In our research, we chose 20210211 and 20210225, a two-week period. From the date input, the program will subset the RTMS_2021 data into only files written between these two dates. This is done by creating all possible days between the start date and the end date and comparing that vector with the list of file addresses. We find the intersection of those two lists, and it returns a vector of dates this is shown in Figure 2.21. If a file sees a match between its address and the date range, then the address of the file is stored to be read later. If there is no match between the date range input and the files within the RTMS_2021 the intersection will be zero.

The second filter is by name. This filter must come second because it receives an output from the first filter. We already have a list of file names from the first filter. Now we must filter out all files that do not contain the name of the nurse we are trying to investigate. From this filter, we can single out nurses and separate them from their peers. All of this is done within the date restriction.

Once the filtering is complete, we are left with a list of file addresses that reside within the date range and that are authored by a single nurse. A list of these files is shown in figure 2.22. The process now comes down to reading and storing each of the CSV files into a data frame. This is done by going down the list

```
> intersection
[1] "20210211" "20210212" "20210218" "20210219" "20210222" "20210224" "20210225"
```

Figure 2.21

```
> list_0_files_names
[1] "C:/Users/joshj/OneDrive/Documents/Fellowship/RTMS_2021/20210211/20210211/20210211_arneyd.csv"
[2] "C:/Users/joshj/OneDrive/Documents/Fellowship/RTMS_2021/20210218/20210218/20210218_arneyd_part1.csv"
[3] "C:/Users/joshj/OneDrive/Documents/Fellowship/RTMS_2021/20210218/20210218/20210218_arneyd_part2.csv"
[4] "C:/Users/joshj/OneDrive/Documents/Fellowship/RTMS_2021/20210218/20210218/20210218_arneyd_part3.csv"
[5] "C:/Users/joshj/OneDrive/Documents/Fellowship/RTMS_2021/20210218/20210218/20210218_arneyd_part4.csv"
[6] "C:/Users/joshj/OneDrive/Documents/Fellowship/RTMS_2021/20210224/20210224/20210224_arneyd.csv"
```

Figure 2.22

of addresses and reading in and binding the active data frame to the building data frame. An important step that occurs during this time pertains to data size regulation. The size of the data frame is reduced through the reduction of columns. Each active data frame is reduced from 76 columns to 1 column, this column is timername. The binding process stores each of the active data frames directly below the previous data frame. At the end of the process, all CSV files have been filtered and bonded together into a list that shows every task the nurse has performed within those two weeks. Table 2.23 is a table containing information about the compilation process.

Table 2.23

Dataset info

When:	from 2021-02-11 to 2021-02-25 year-month-day	
How many:	7 datasets	
Nurse names:	number of csv files read:	length of dataset(observations):
arneyd	6	140496
krsrh5	4	649135
beache	1	473013
wetterp	2	2197873
cairera	4	961891
robertsonsn	3	803400
arechigaa	8	1015005

2.3 Simple Statistics:

After all the data has been compiled, we are left with 7 large CSV files that contain information on all the actions performed by each nurse. Next, we look at one of these CSV files at a time and construct the frequency for each of the timernames. The first thing that we must do is group the data frame by timername. This means that we need to go down the large CSV file and collect each instance of a particular task and group them all together so they can be analyzed. Once the timernames are grouped we can find the length of the grouping, this is the frequency. This was done for all seven nurses and each of the files was saved. This information is stored in a data frame that contains timernames and frequency. Table 2.3 shows how the statistic table looks. This table only represents the frequencies gathered from one nurse.

Table 2.3

	X	timernames	frequency
59	59	USR:IPV.SHOW IMAGE	31
44	44	USR:CARECOMPASS.LOADTIMELINECOLLAPSED	756
2	2	CAP:CARECOMPASS.RESULTSFACEUP	260
24	24	USR: CLINICAL NOTES: LOAD NOTE	520
1	1	CAP:CARECOMPASS.POBLANO	229

2.4 Aggregate Statistics:

Up until now, we have only focused on each nurse individually. We already have a simple statistic for each nurse so we will use the simple statistic data frames to construct the aggregate statistic data frame. We need to merge all 7 statistical data frames into one place so it can be easily worked. Each of these 7 statistical data frames contains 2 columns (timername, frequency). However, we need to align the other columns based on timername so the timername column does not need to be repeated. This means that the total number of columns of the aggregate statistical table is 1 for timername plus 1 for each nurse. An additional column was computed by summing frequency across nurses. We will refer to the sum of frequencies across nurses as the aggregate frequency. The aggregate frequency gives us the number of times the timername

was recorded within the two weeks. This brings the final column total up to 9. A portion of the combined data is shown in Table 2.4.1. All the nurses do not share all the timernames with each other. So, in creating this aggregate table we need to decide what to do with NA cells. In this circumstance, the fix is simple as a frequency of zero means the event never happened. In our research, we simply replaced all NA cells with zero.

Table 2.4

	X	timername	freq.arechigaa	freq.arneyd	freq.beache	freq.cairera	freq.krsrk5	freq.wetterp	freq.robertsonsn	t.frequency
106	106	USR:ICU-IVIEW-CREATE CHARTED VALUE	275540	41891	94233	234681	109155	261950	470489	1487939
204	204	USR:PWR-SWITCHFRAME	146455	22089	73121	145494	93452	122525	341720	944856
41	41	CKPT: DOC STOP PN BAND	64093	4476	28433	46443	16469	55900	100409	316223
197	197	USR:PWR-CREATE VIEW	41930	5002	24337	47827	26427	15275	62902	223700
203	203	USR:PWR-SHOW VIEW	44326	4919	25587	36579	26527	10725	51698	200361
43	43	CKPT:WINDOWSSESSIONMONITOR-ALERT	13777	0	0	0	48258	34775	95630	192440
103	103	USR:ICU-IVIEW-ADDING A RESULT	24559	2446	6918	9453	7660	19175	96580	166791
57	57	USR: PDOC NAVIGATOR DOC SET CLICK	0	1932	854	3288	3064	3900	151726	164764
48	48	ICU: DIALOG TWO STATE GENERIC TIMER	19767	2318	11169	15207	12256	36725	58556	155998

2.5 Compare:

To identify timernames worthy of investigation, we sorted the data by total frequency. We re-ordered the rows so that the timername with the highest aggregate frequencies was at the top. By doing this, we were able to find timernames that occurred the most frequently across all the nurses. We then selected the top three most frequently used. We chose three timernames because only three timernames had above 5% of the total frequency. In Figure 2.5, the frequency of each of these timernames is shown relative to the entire number of frequencies recorded as a pie chart. The timernames selected were the following: "USR:ICU-IVIEW-CREATE CHARTED VALUE", "USR:PWR-SWITCHFRAME", "CKPT: DOC STOP PN BAND". The percentage associated with the three timernames are 23.8%, 15.1%, 5.0% respectively. These timernames account for 43.9% of all the frequencies for timernames used. Additionally, timernames below our cutoff point of 5% were used much less frequently with the fourth timername only occupying 3.5%.
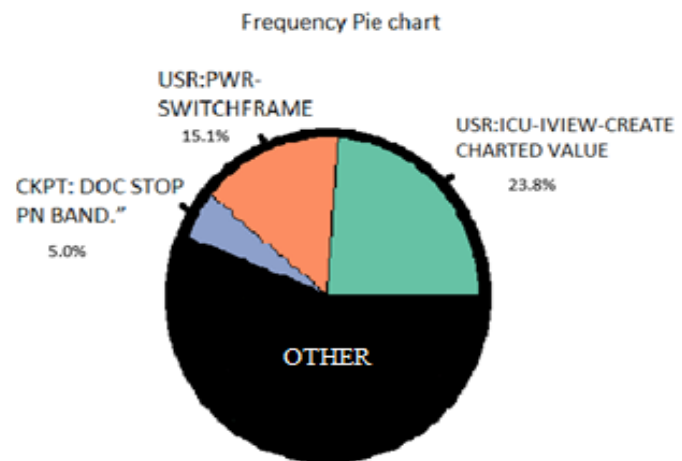

Frequency Pie chart

Figure 2.5

To define the timernames we used, we referred to a timer dictionary. For the timername "USR:PWR-SWITCHFRAME," the definition is defined as a "user timer." The timer begins when the organizer or chart window gets the focus or loaded for the first time. The timer stops immediately after focus is restored. For the other two timernames, however, the timernames are not in the timer dictionary. This is likely due to the timername dictionary being out of date. It was written in 2017, while our nurse EMR data was collected in Spring 2021. However, after contacting Prof. Kim, he had this to say about the other timernames: "I think "USR:ICU-IVIEW-CREATE CHARTED VALUE" is related to opening the patient assessment page in IView section to add and sign the assessment results. However, I am not sure what "CKPT: DOC STOP PN BAND" means. Timers under CKPT category are usually related to 'Order.'" There is some ambiguity about the description of many timernames in our collected EMR data. However, our research is unaffected by this since it focuses on the frequency of timernames, rather than the contents of the timernames.

2.6 Chi-Square Goodness of Fit Test:

The Chi-Square goodness of fit test evaluates whether the given data fits within a distribution. Put simply, it shows if the sample data collected truly represents the population data. The test evaluates a null and alternative hypothesis. The null hypothesis contains the assumption that there is no significant difference between the observed and expected values of an independent variable's dataset. This means the nurse's EMR workload is the same. The alternative hypothesis is that there is a significant difference between the observed and expected values of at least one independent variable's dataset. To evaluate the hypothesis, the Chi-Square goodness of fit test evaluates the difference of each independent variable's observed and expected value. It then takes this difference, squares it, and divides it by the expected value. Lastly, the resulting values for each independent variable are summed together. This value represents the Chi-Square calculated value. This value is compared to a Chi-Square distribution table, which determines the Chi-Square value. If the calculated value is greater than the critical value, then the null hypothesis is rejected. If the calculated value is less than the critical value, fail to reject null. Finally, this is used to evaluate if the observed values from the independent variables are representative of the true values of the population.

To run statistical analysis on the three timernames chosen, we used the Chi-Square goodness of fit test. First, we determined how many days each nurse worked during our time period. Next, we divided the total frequency the nurse encountered the timername by the number of days they worked. This gives us the average frequency per day the nurse accessed the specific timername. After completing this procedure for all nurses, we entered the nurses and their respective average frequency per day into Minitab. From there, we ran a Chi-Square goodness of fit test on the data. We conducted the following hypothesis test for each of the three timernames:

- **H_o: The data are consistent with a uniform distribution.**
- **H_a: The data are *not* consistent with a uniform distribution.**

A uniform distribution of frequencies across nurses means that the nurses have statistically similar usage rates of specific timername compared to the other nurses. While a non-uniform distribution of frequencies across nurses would mean that nurses have different usage rates of specific timernames.

(3) Results

Observations

Category	USR.ICU-IVIEW-CREATE CHARTED VALUE	USR:PWR-SWITCHFRAME	CKPT: DOC STOP PN BAND
arechigaa	137770	73228	32046.5
arney	13964	7363	1492.0
beache	94233	73121	28433.0
cairera	117341	72747	23221.5
krsrk5	109155	93452	16469.0
wettero	261950	122525	55900.0
robertsons	156830	113907	33469.7

Table 3.1

In Table 3.1, the top three timernames are listed. The total frequency for the two-week period of each nurse on each timername is also listed. From this information, we performed the Chi-Square goodness of fit test. From this statistical analysis, we found that there is a significant difference between the nurses' observed and expected values for all the timernames. This is because their respective p-values are less

than 0.05 (95% confidence). Therefore, we reject the null hypothesis. Figure 3.2 contains several values related to the Chi-Square goodness of fit test including, the total observed frequencies for each timername, degrees of freedom, Chi-Square value, and the P-value. In Figure 3.3, the chart for observed and expected values are listed, along with the timername descriptions. Orange bars refer to expected values and the blue bars refer to the observed values. Notice the difference between the expected and observed values. A closer look at the individual graphs from 3.3 can be found in the appendix.

Chi-Square Test

USR.ICU-IVIEW-CREATE CHARTED VALUE

N	DF	Chi-Sq	P-Value
891242	6	262953	0.000

USR.PWR-SWITCHFRAME

N	DF	Chi-Sq	P-Value
556342	6	107691	0.000

CKPT.DOC STOP PN BAND

N	DF	Chi-Sq	P-Value
191032	6	61554.4	0.000

Figure 3.2

USR.ICU-IVIEW-CREATE CHARTED VALUE (top left):The timer begins when the organizer or chart window gets the focus or loaded for the first time. The timer stops immediately after focus is restored.

USR:PWR-SWITCHFRAME(bottom left):related to Opening the patient assessment page in IView section to add and sign the assessment results.

CKPT.DOC STOP PN BAND(top right): Application related to PN band. Exact definition unknown.
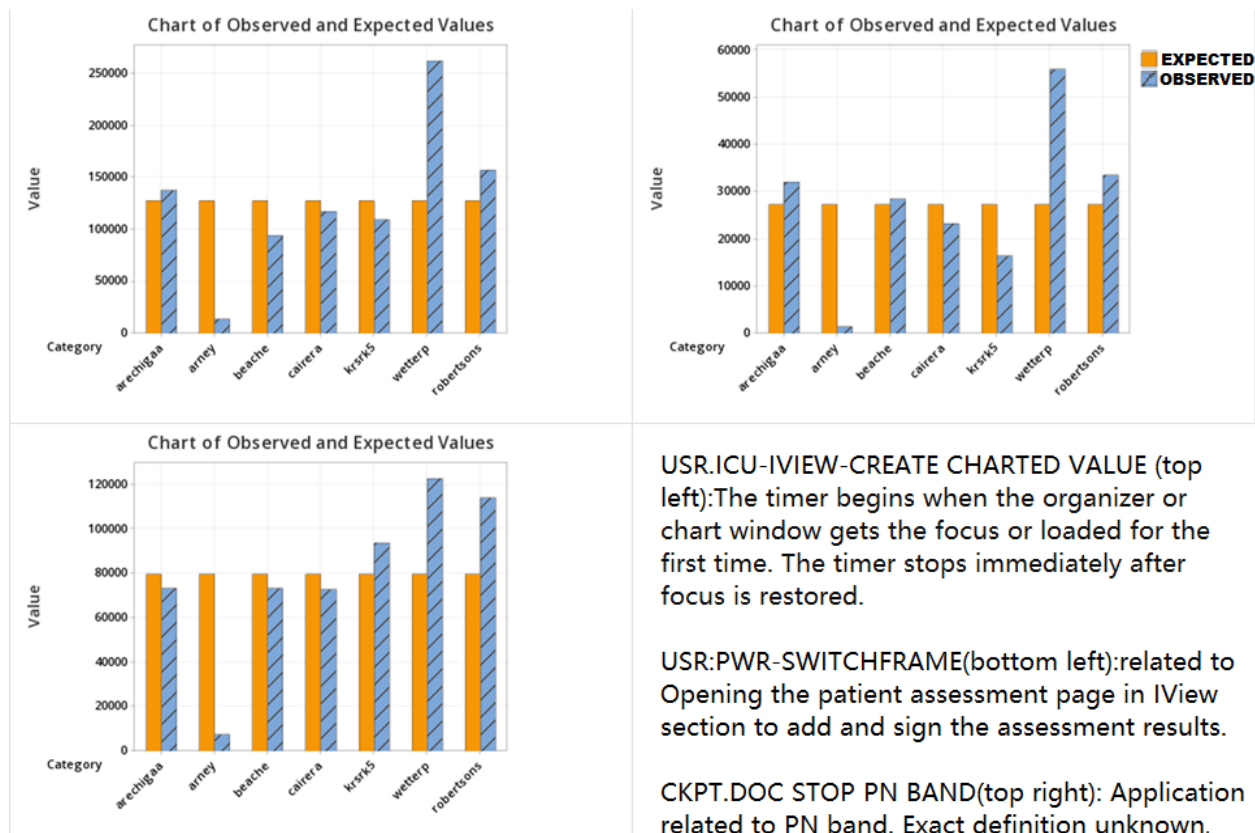
Figure 3.3

For the timername "USR.ICU-IVIEW-CREATE CHARTED VALUE", both arney and wetterp show the greatest difference between expected and observed values relative to other nurses. For the timername "USR:PWR-SWITCHFRAME," arney, wetterp, and robertsonsn show the greatest difference between expected and observed values relative to other nurses. For the timername "CKPT.DOC STOP PN BAND", wetterp and arney show the greatest difference between expected and observed values relative to other nurses. From visual inspection, we see wetterp's observed frequency is consistently higher than the expected value. It can also be seen that arney's observed frequency is consistently lower than the expected frequency.

(4) Discussion

Our focus was between nurses to see if the nursing workload changed per nurse. We used RTMS data to determine whether some nurses had increased EMR activity compared to other nurses and investigated the average frequency of timernames of nurses in the ICU. The results of the research show that for all three timernames the nurses do not exhibit uniform workflow patterns. In the following section, we will identify several studies and draw connections between their work and ours.

4.0 Workload Management:

Our result relates to nurse burnout. Nurse workload increases emotional exhaustion. Emotional exhaustion leads to cynicism which in turn negatively impacts a nurse's professional efficacy (Greenglass et al., 2001). By having an ICU where all nurses uniformly take the burden of work the peak stress placed on an individual worker is diminished. Nurse workload predicts nurse mental well-being, decreased job satisfaction, and increased risk of burnout (Greenglass et al., 2001). Firstly, we recommend workload management methods such as the RAFAELA be applied to this system so there is a fair distribution of workload. Secondly, it was not known for certain how much nurse EMR workload deviated between nurses. However, our research concluded that nurse EMR workload cannot be thought of as uniform, and each nurse has different EMR usage rates. This conclusion can guide future research in the field to study nurses on an individual level.

4.1 Nurse-EMR Infrastructure:

A major factor not specifically addressed in our research is the current nurse-EMR infrastructure. The current nurse-EMR infrastructure at the MU hospital ICU is unknown. We do not have data on both the quality of the infrastructure and the type of infrastructure. The several types of infrastructure that need to be delineated are the following: mobile, patient-side desktop, office desktop, and laptop. We should consider the type of infrastructure as it may be a major factor of nurse-EMR interaction (Kim, 2015). Further analysis should be carried out to ensure that our results are not a byproduct of differing EMR input devices. Pollack and Amaravadi write about resource allocation pertaining to the treatment of patients and resource allocation pertaining to nurses, respectively. Our research addresses gaps in the research literature because we are addressing the resource allocation of nurse-computer infrastructure. Debergh explains why there is a gap in the literature by saying, "Particularly in the Intensive Care Unit (ICU), the cost of the nursing workforce is substantial, largely outnumbering the investment in technology and equipment" (Debergh, 2012). Our conclusions can be used by other papers and hospitals when they are deciding how to update the ICU. It is reasonable that a hospital that is experiencing financial difficulties might ask themselves if all workstations are equally important to upgrade. The conclusion that EMR usage is not consistent between nurses may be helpful in their decisions

4.2 Limitations and Future Works:

Several limitations of this research include timeframe, ICU capacity, patient care versus EMR demand, and environmental controls. The list above could have an impact on the results of our study and were not accounted for in our experimental design. In the following paragraphs, we will explain each one individually.

The primary way our study could be improved is to increase the amount of data read into the frequency tables. The ICU environment is chaotic and day-to-day fluctuations are expected. By increasing the timeframe of the study, we remove the daily fluctuations and find the true average timername frequency. Care was taken in our method to make it very easy to replicate this experiment on a much larger scale. Bluntly speaking data taken from 6 nurses over two weeks is not enough to draw meaningful conclusions.

Many factors could impact timername frequency. Two factors that we want to highlight include ICU capacity and patient care demand versus EMR demand. The ICU capacity directly influences the frequency of tasks because a nurse is more likely to be idle when the ICU is empty. A nurse who is idle when the ICU is empty does not input into the EMR. A nurses' workload can be split into two groups. The first group is patient demand, and the second group is EMR demand. Patient demand is the workload associated with the many kinds of treatment and data collection. EMR demand includes all actions that update or load the EMR. EMR demand is related to login in, loading patient medical data, and inputting patient medical data. A nurse who is working a shift that experiences above-average patient demand might exhibit fewer timername frequencies. This is because the nurses had been engaged in other duties. RTMS data can only give us insight into EMR demand and thus cannot make assumptions about patient demand.

Another factor that could impact timername frequencies is outside interference. This would include any activity that is not directly related to the job. For future works, it may be prevalent to add a few controls. For example, these controls could be related to ergonomic environmental conditions. This would include maintaining optimal temperature, lighting, sound, etc. Controlling and managing technological factors such as internet speed, computer performance would make sure each nurse is in an optimal environment. If these steps are taken we can be certain that outside interference from working conditions is minimized.

Additional analysis needs to be performed regarding the relationship between ICU nurse workstations and workflow. If this analysis concludes that ICU nurse deteriorated workstations do not inhibit workflow, resources should not be spent to upgrade workstations. On the other hand, if the analysis concluded that optimal workstations do offer improvements to workflow our research could make a direct impact on the cost-effectiveness of those infrastructure improvements.

Our research objective was to use task frequency uniformity to determine the fairness of nurse workload. From our statistical analysis, it is clear that nurses use the EMR system differently. We showed this by utilizing the Chi-Square statistical analysis. Based on these findings, our research objective has been answered. Therefore, the nurse's infrastructure regarding the EMR system could be tailored to their usage rate of the EMR system. This might improve the working conditions of the high EMR usage rate nurses while being more cost-effective than improving EMR infrastructure uniformly.

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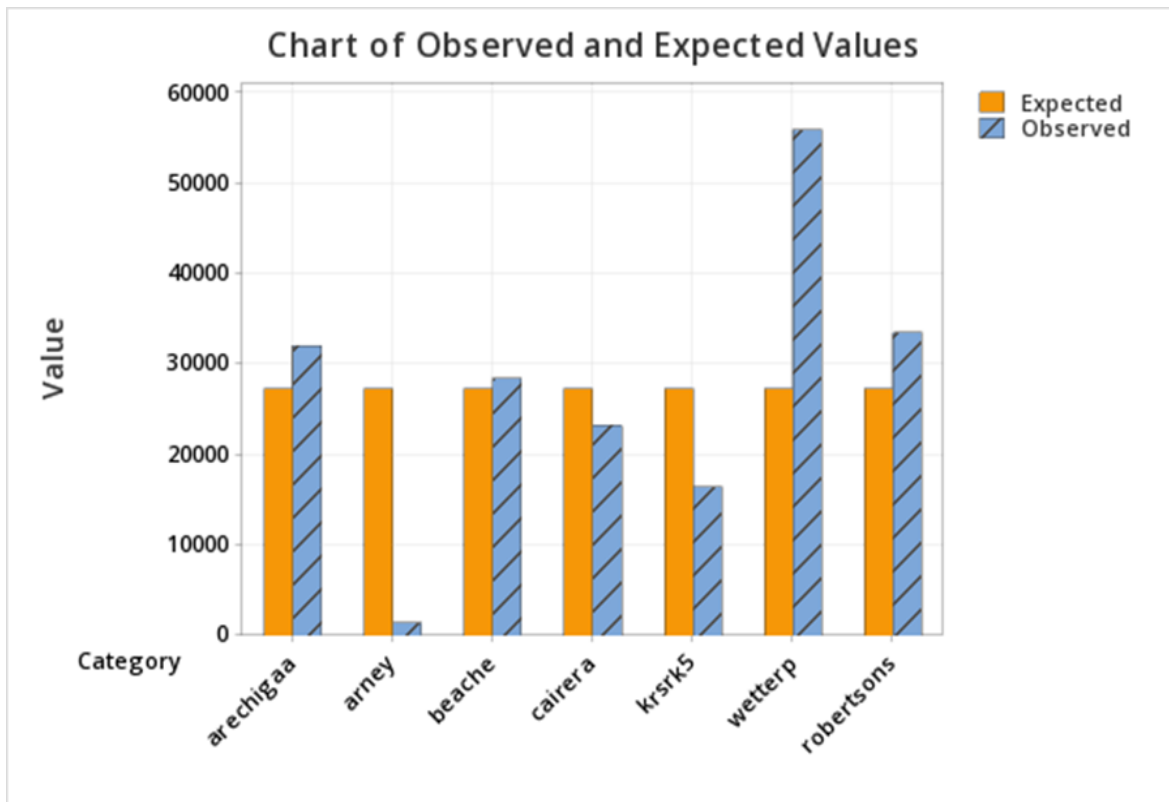
Appendix

A link to the data is here:
https://mailmissouri-my.sharepoint.com/personal/mjsrkq_umsystem_edu/Documents/Documents/Frequency_table.csv

Appendix 1.1

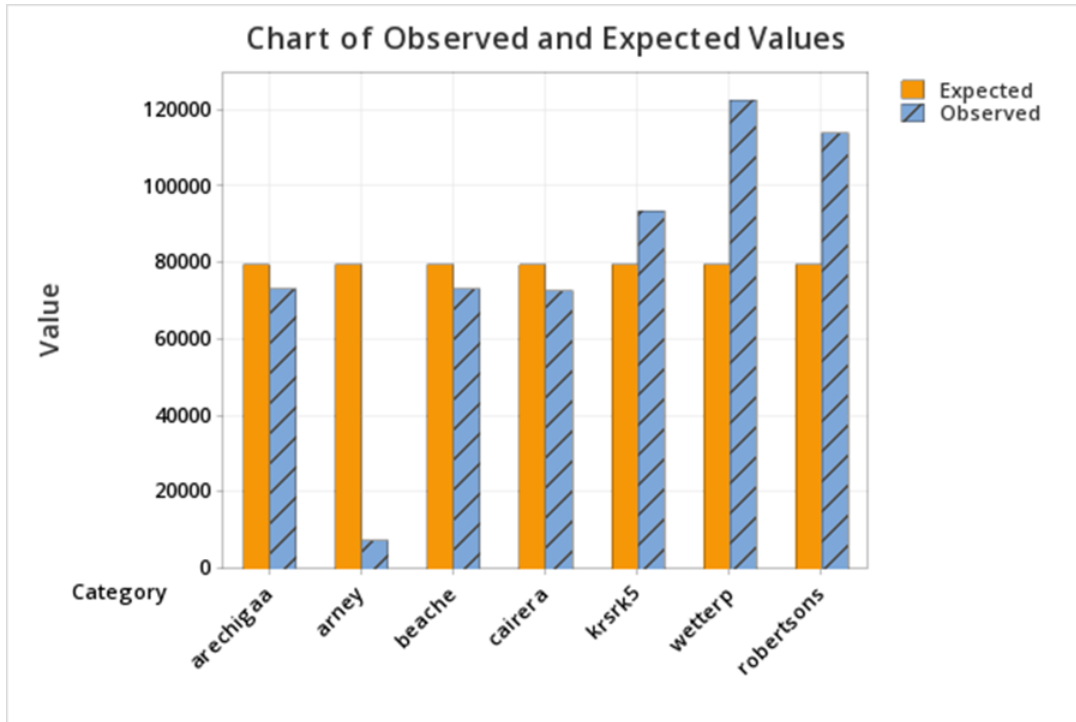|		
20210211	9/2/2021 9:18 PM	File folder
20210212	9/2/2021 9:19 PM	File folder
20210218	9/2/2021 9:19 PM	File folder
20210219	9/2/2021 9:19 PM	File folder
20210222	9/2/2021 9:19 PM	File folder
20210224	9/2/2021 9:20 PM	File folder
20210225	9/2/2021 9:20 PM	File folder

Appendix 1.2

20210414_arechigaa.csv	6/3/2021 2:38 PM	Microsoft Excel C...	423,562 KB
20210414_arneyd_part1.csv	6/3/2021 2:41 PM	Microsoft Excel C...	524,363 KB
20210414_arneyd_part2.csv	6/3/2021 2:45 PM	Microsoft Excel C...	520,910 KB

CKPT.DOC STOP PN BAND

Chart of Observed and Expected Values

USR:PWR-SWITCHFRAME

Chart of Observed and Expected Values
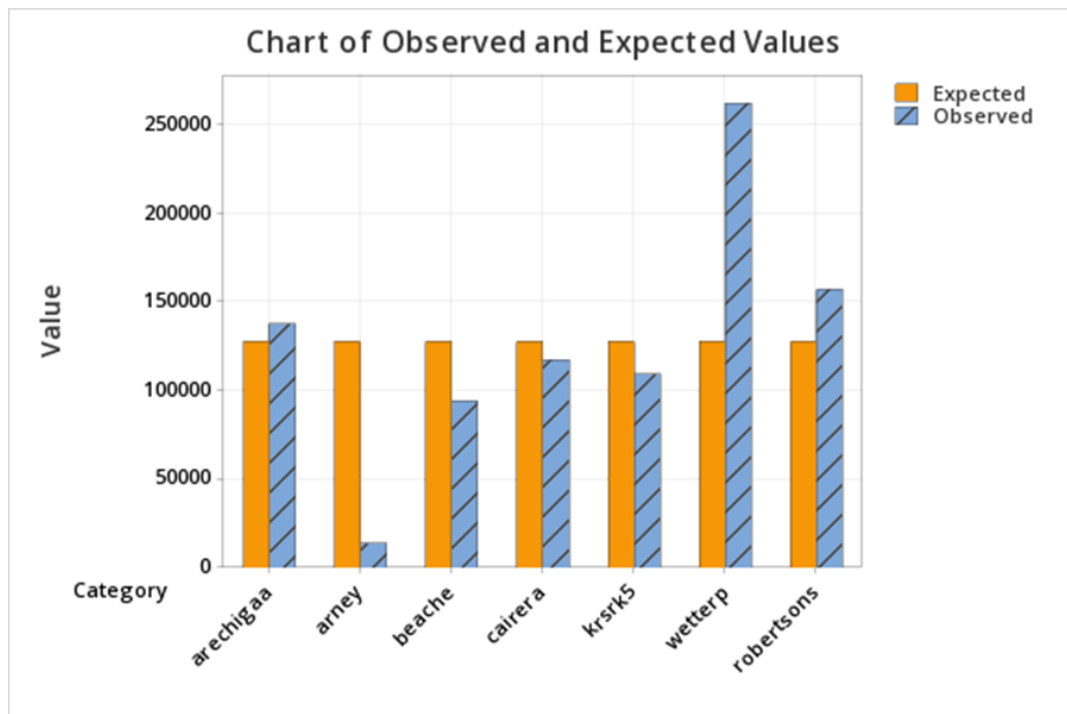
USR.ICU-IVIEW-CREATE CHARTED VALUE

USR.ICU-IVIEW-CREATE CHARTED VALUE

Figure 3.1.1
Chi-Square Test

N	DF	Chi-Sq	P-Value
891242	6	262953	0.000

Category	Observed	Test Proportion	Expected	Contribution to Chi-Square
arechigaa	137770	0.142857	127320	858
arney	13964	0.142857	127320	100924
beache	94233	0.142857	127320	8599
cairera	117341	0.142857	127320	782
krsrk5	109155	0.142857	127320	2592
wettero	261950	0.142857	127320	142359
robertsons	156830	0.142857	127320	6839

USR.PWR-SWITCHFRAME

Chi-Square Test

N	DF	Chi-Sq	P-Value
556342	6	107691	0.000

Category	Observed	Test Proportion	Expected	Contribution to Chi-Square
arechigaa	73228	0.142857	79477.5	491.5
arney	7363	0.142857	79477.5	65433.6
beache	73121	0.142857	79477.5	508.4
cairera	72747	0.142857	79477.5	570.0
krsrk5	93452	0.142857	79477.5	2457.1
wettero	122525	0.142857	79477.5	23315.9
robertsons	113907	0.142857	79477.5	14914.6

Figure 3.1.1

CKPT.DOC STOP PN BAND

Chi-Square Test

N	DF	Chi-Sq	P-Value
191032	6	61554.4	0.000

Category	Observed	Test Proportion	Expected	Contribution to Chi-Square
arechigaa	32046.5	0.142857	27290.2	828.9
arney	1492.0	0.142857	27290.2	24387.8
beache	28433.0	0.142857	27290.2	47.9
cairera	23221.5	0.142857	27290.2	606.6
krsrk5	16469.0	0.142857	27290.2	4290.9
wettero	55900.0	0.142857	27290.2	29993.1
robertsons	33469.7	0.142857	27290.2	1399.2