Effects of LOS on the Probability of Having an AE

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Individual Level Models

- **Model 1:**

$$log\left(\frac{ProbAE_i}{1-ProbAE_i}\right) = \beta_0 + \beta_1 LOS_i + \beta_2 LOS_i \times ShiftBlock_i + \beta_4 Age_i + \beta_5 TotalNumberStaff_i + ShiftBlock_i + CTAS_i + Site_i + Disposition_i + \varepsilon_i$$

{Note that $ShiftBlock_i$, $CTAS_i$, $Site_i$, $Disposition_i$ are the fixed effects considered in Model 1. $TotalNumberStaff_i$ also represents the total number of staff of the shift block that patient i is registered in.}

- "LOS" has significant positive effect on the occurrence of AE.
- Practical significance: Coefficient of LOS is 0.001185, so if we increase LOS by 1 hour, the probability of the occurrence of adverse event approximately increases by % 7 (since AE is a rare event, $(1-p_1)$ and $(1-p_2)$ are close to 1):

$$e^{0.001185*60} = \frac{\frac{p_2}{1-p_2}}{\frac{p_1}{1-p_1}} = 1.07$$

- The probability of the occurrence of AE in shift block 2 is significantly higher than others, but LOS at shift block 2 has lower impact (but still positive) on AE compared to LOS in other shift blocks.
- Older patients have higher rate of AE.
- Site 2 and 7 have lower rate of AE compared to others.
- The probability of having AE for "admitted patients", "the ones who left without being seen", "went to OR and admitted afterwards" is higher than other groups.
- Adding "diagnosis grouping" (adding fixed of $DiagnosisGroup_i$ and term $\beta_3 LOS_i \times DiagnosisGroup_i$ to the above regression model): Group 24 (Hematology) has higher rate of AE compared to others and LOS for group

8 (Mental Health) has lower impact on probability of having AE compared to others.

- **Model 2:**

$$log\left(\frac{ProbAE_i}{1-ProbAE_i}\right)$$
$$= \beta_0 + \beta_1 LOS_i + \beta_2 LOS_i \times CrowdedShift_i + \beta_3 LOS_i \times ShiftBlock_i$$
$$+ \beta_4 CrowdedShift_i + \beta_5 Age_i + \beta_6 TotalNumberStaff_i$$
$$+ ShiftBlock_i + CTAS_i + Site_i + Disposition_i + \varepsilon_i$$

{In addition to the parameters considered in Model 1, binary variable $CrowdedShift_i$ denotes whether patient i is in a crowded shift or not.}

  - For this model, we define a binary variable to show whether patient is in a crowded shift or not. To do so, for each ctas level, we consider a threshold such that if the average LOS for the patients with that ctas level for that shift is above that threshold, we consider that shift as a crowded shift. Estimating this threshold can be one of our contributions. For now, we computed the average LOS for all shifts in the data set within each ctas level, and considered the 60th percentile as a threshold for that ctas level.
  - "LOS of the patient" and "Crowdedness of the shift" have significant impacts on the occurrence of AE.
  - Practical significance: Coefficient of LOS (β_1) is 0.001938, so if we increase LOS by 1 hour, the probability of the occurrence of adverse event approximately increases by %12 (since AE is a rare event, $(1-p_1)$ and $(1-p_2)$ are close to 1):

$$e^{0.001938*60} = \frac{\frac{p_2}{1-p_2}}{\frac{p_1}{1-p_1}} = 1.12$$

  - Coefficient of $CrowdedShift$ (β_4) is 0.5913, so the probability of the occurrence of AE in crowded shifts is approximately %81 higher than a non-crowded shift (Since AE is a rare event, denominators in the following formula is close to 1).

$$e^{0.5913} = \frac{\frac{p_{AE\_crowded}}{1 - p_{AE\_crowded}}}{\frac{p_{AE\_noncrowded}}{1 - p_{AE\_noncrowded}}} = 1.81$$

- LOS in crowded shifts has lower impact on the occurrence of AE compared to the non-crowded ones (coefficient of LOS*crowded shift is negative and significant, but its summation with the main effect of LOS is still positive).
- The rest of the results obtained from Model 1 are valid for this model as well except that we do not have significant difference for groupings and Lwbs anymore. So, the probability of having AE for "admitted patients", and "the ones who went to OR and admitted afterwards" is higher than other groups.

- **Model 3: (Similar to Model 2, but with Preventable AE)**

$$\begin{aligned} log\left(\frac{ProbPreventableAE_i}{1 - ProbPreventableAE_i}\right) &= \beta_0 + \beta_1 LOS_i + \beta_2 LOS_i \times CrowdedShift_i + \beta_3 LOS_i \times ShiftBlock_i \\ &+ \beta_4 CrowdedShift_i + \beta_5 Age_i + \beta_6 TotalNumberStaff_i \\ &+ ShiftBlock_i + CTAS_i + Site_i + Disposition_i + \varepsilon_i \end{aligned}$$

- For this model, we again computed the average LOS for all shifts in the data set within each ctas level, but considered the 70th percentile as a threshold for that ctas level.
- "LOS of the patient" and "Crowdedness of the shift" have significant impacts on the occurrence of preventable AEs.
- Practical significance: Coefficient of LOS (β_1) is 0.00159, so if we increase LOS by 1 hour, the probability of the occurrence of preventable adverse event approximately increases by %10 (since AE is a rare event, $(1 - p_1)$ and $(1 - p_2)$ are close to 1):

$$e^{0.00159*60} = \frac{\frac{p_2}{1 - p_2}}{\frac{p_1}{1 - p_1}} = 1.10$$

- Coefficient of $CrowdedShift$ (β_4) is 0.6224, so the probability of the occurrence of preventable AE in a crowded shift is approximately %86 higher than a non-crowded shift (Since AE is a rare event, denominators in the following formula is close to 1).

$$e^{0.6224} = \frac{\frac{p_{PreventableAE\_crowded}}{1 - p_{PreventableAE\_crowded}}}{\frac{p_{PreventableAE\_noncrowded}}{1 - p_{PreventableAE\_noncrowded}}} = 1.86$$

- The probability of having preventable AE for “the patients who left without being seen” is higher than others.
- The probability of the occurrence of preventable AE in shift block 2 is significantly higher than the other blocks.
- Older patients have higher rate of preventable AE.
- Site 2 has lower rate of preventable AE compared to others.

Shift Level Models

- **Model 4:**

$$log(NumberAEShift_{ijtk}) = \beta_0 + \beta_1 AvgLOS_{ijtk} + \beta_2 AvgNumberStaff_{jtk} + \beta_3 NumberLwbs_{jtk} + \beta_4 NumberDischarged_{jtk} + \beta_5 Numberadmitted_{jtk} + ShiftBlock_j + CTAS_i + Site_k + \varepsilon_{ijtk}$$

{Note that $NumberAEShift_{ijtk}$ denoted the total number of adverse events for CTAS level i, shift block j, shift date t within site k. Also, $AvgLOS_{ijtk}$ represents the average LOS for the patients with i within shift block j, shift date t and site k. $AvgNumberStaff_{jtk}$, $NumberLwbs_{jtk}$, $NumberDischarged_{jtk}$, and $Numberadmitted_{jtk}$ show the average number of staff, total number of patients who left without being seen, who discharged or admitted within shift block j, shift date t for site k.}

- We do the aggregated level analysis here. If we combine disposition and diagnosis groups, we can consider other aggregation levels as well. We can even change the time window.
- “$AvgLOS$” has significant impacts on the number of AEs within that shift.
- Practical significance: Coefficient of average $AvgLOS$ is 0.001479, so if we increase average LOS of the shift by 1 hour, number of adverse events within that shift approximately will increase by 9.3%.

$$\log\left(\frac{NumberAEShift_2}{NumberAEShift_1}\right) = 0.001479 * 60$$

- Number of discharged and admitted patients within the shift have significant effect on the number of AE of that shift.

- **Model 5: (Similar to 4, but with preventable AEs)**
  - We get similar results to model 4, just the coefficient of $AvgLOS$ and consequently its effect on the number of preventable AEs within that shift drop to 0.0012027 and %7.5 respectively.

Summary of the Models:

Colored cells show the variables and fixed effects included in each model.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	$ProbAE_i$	$ProbAE_i$	$ProbPreventableAE_i$	$NumberAEShift_{ijtk}$	$NumberPreventableAEShift_{ijtk}$
LOS_i	(*)	(*)	(.)		
Age_i	(**)	(**)	(***)		
$LOS_i \times ShiftBlock_i$	(.)	(.)			
$TotalNumberStaff_i$					
$CrowdedShift_i$		(**)	(*)		
$LOS_i \times CrowdedShift_i$		(.)			
$AvgLOS_{ijtk}$				(**)	(.)
$AvgNumberStaff_{jtk}$					
$NumberLwbs_{jtk}$					
$NumberDischarged_{jtk}$				(**)	(***)
$Numberadmitted_{jtk}$				(***)	(**)
Fixed Effects					
$CTAS$					
$Site$					
$ShiftBlock$					
$Disposition$					

'*' p<0.001, '**' p<0.01, '*' p<0.05, '.' p<0.1**

Questions:

- Combining diagnosis groups to have lower number and more general categories

- What factors can affect LOS and AE at the same time that we do not have the related data? (Trying to find out the source of endogeneity)
- Combining disposition groups: for instance, can we consider “admitted”, “direct to OR and admitted afterwards” as one group? For direct to OR, are the booking times the same as the time that they leave ED? Leaving time for other categories: we just have it for dispositions 0,1,4,8.
- Update on the analysis of the other statistical team to avoid repetition
- Was there any variation for resources (number of beds or equipment)? For instance, was there any major changes in hospital policies or resources during the data collection period in any of the sites?
- Is estimating the threshold for LOS that we discussed above interesting to your audience?
- Discussing about other possible interesting questions that we can answer using this dataset
- Discussing about non-preventable adverse events