Real-time Inpatients Risk Profiling in Acute Care: A Comparative Study of Falls and Pressure Injuries Vulnerabilities

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Abstract To effectively manage patients of different vulnerabilities to falls and pressure injury entails understanding the risk drivers and predicting risk profiles in real-time, thus, we determined the core drivers of patients' proneness to these risks while developing a machine learning strategy for their real-time prediction in acute care hospital. By implementing a multivariate logistic analysis, the risk drivers and injury risk probabilities were obtained while establishing a comparative machine learning technique for patients' risk-profiling. We observed Multi sclerosis & motor neuron disease (MSN) and Fall during current admission (FDA) as pronounced risk drivers, and Extra Tree Classifier (ETC) and Random Forest (RF) as the best algorithms with prediction accuracy of 90.6% - 99.8%. With a cost saving of 2.3% - 38.89%, our framework will provide an efficient technique for cost-effective management of inpatients susceptible to falls and pressure injury risks on admission.

Keywords: acute care, cost-effective, fall risk, inpatient, pressure injury risk, risk profiling.

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1 Introduction

Understanding patients' vulnerabilities in acute care hospitalization is vital for efficient management of some underlying risks associated with admission. Thus, early identification of those at high risk of falls or pressure injuries will allow the hospital to mitigate the risks. Falls and pressure injuries are known to be among the most pronounced risks patients face in hospitals with 32%-40% exposed to falls risk (Florence et al. 2018) whereas 2% - 23% are exposed to pressure injury (Gallagher et al. 2008, Moore et al. 2019) annually. Although researchers have released important findings of the factors influencing falls and pressure injury (Gallagher et al. 2008, Moore et al. 2019, Geusens et al. 2003), their focus have revolved around the aged (>65 years) without considering the other age groups, who can be equally susceptible due to health conditions.

Since the knowledge of patients' risk on admission is somewhat limited due to the greater emphasis on the elderly, it is imperative that this study will critically look at the contributing factors to these admission risks for all age groups by exploring the various clinical and psychosocial factors. This information can help to improve care and reduce cost, thus, reducing the slow pace of evaluating falls and pressure injury risks of inpatients. Since biases can be reduced via an autonomous strategy that relies on the routine patients' record for decision support, we can expect improved risk estimation accuracy. Hence, this study will establish the factors responsible for different risk levels of falls, pressure injury, and falls and pressure injury for inpatients on admission using multivariate logistics regression analysis while developing a machine learning model for predicting the risk levels. The cost-saving from using the model will also be developed for various length of stay (LOS) for high-risk patients who are most predisposed to injuries on admission.

2 Background

Pressure and fall injuries are among the danger patients face on admission in acute care hospitals. It has been established that over 70% of hospitalized patients get involved in fall accidents (Coussement et al. 2008) with 2%-15% in acute hospitals (ACSQHC 2018a). Most of these injuries resulted in fracture and intracranial injuries, which affect 4 in 10000 patients in Australia annually (Black et al. 2011). For elderly patients, 30%-50% of falls cause them minor injuries that include bruises, abrasions, and lacerations. However, 10%-16% of these falls cause intracranial injuries and fractures, which significantly result in morbidity and mortality (Ahmad et al. 2012). Numerous studies have linked falls and fall injuries amongst patients to postural instability, blood pressure, dementia, menopause, previous history of falls, orientationally problems, dizziness, mobility problems, and medications (Margolis et al. 2014, O'Neil et al. 2018, Nguyen et al. 2015). Although the effects of numerous disease conditions on the fall rate vary with the severity of the ailments, dementia patients have more than 3 times the risk of falls than other patients. There is an increased risk of falls for patients that use antiepileptic, sedative, hypnotics, antidepressants, and benzodiazepines-based medications (Woolcott et al. 2009, Hartikainen et al. 2007, Neutel et al. 2002). Similarly, the risk of falling increases for patients taking more than 10 medications together than those on high-risk fall inducing medication such as benzodiazepines (Tayyib et al. 2015).

Pressure injuries such as ulcers occur due to infrequent positioning and age of patients (Tayyib et al. 2015) but enhanced patients management in preoperative settings help to prevent them. Thus, ensuring that patients are not exposed to lengthy pressure during surgery and preventing exposure to frictions during transfers could potentially minimize the risks of pressure injuries (Spruce 2017, Posthauer et al. 2015). Poor hydration and nutrition also play significant roles in the development and exacerbation of pressure injuries (Alderden et al. 2018) especially for the critically ill who may be malnourished during the sickness episode (O'Neil et al. 2018, Nguyen et al. 2015). Not much has been done in predicting falls and pressure injury on admission using machine learning, however, Electronic Medical Records (EMRs) and algorithms such as random forest (RF), Bayesian network, artificial neural network (ANN), and decision trees have been employed by researchers (Alderden et al. 2018, Veredas et al. 2015, Kaewprag et al. 2017, Moon and Lee 2017). These researchers obtained an accuracy measured as the area under the curve (AUC) in the range of 78.7%-89.51%. Other authors have relied on different algorithms for fall detection and classification of videos and signals from wearable devices (Aziz et al. 2017, Ni et al. 2012). Some of the studies have been used to detect fallen residents in aged care facilities or homes whereas others have applied machine learning comparatively with the traditional methods of assessment based solely on scores (Silva et al. 2017). Despite the importance of these studies, there is still a limited focus on real-time profiling of patients' risk levels on admission and the risk level of individuals with proneness to both fall and pressure injury not targeted yet. Thus, the need for this study that highlights the risk factors of both fall and pressure injury separately and collectively, determine the algorithm that will enhance the real-time estimation of risk vulnerabilities and comparatively establish the cost variabilities.

3 Method

This study established the risk profile of patients admitted to a not-for-profit acute care hospital by predicting the fall and pressure injury risks of 1014 patients admitted between December 2016 to July 2018. This sampled population consists of patients aged 1.17 years to 101.25 years with 48 clinical, demographic, and psychosocial characteristics that are closely related to the risks under consideration. The risk levels of the patients that were classified as low, moderate, or high were also obtained from the hospital records. The patients at the risk of fall and pressure injury were extracted from the acquired record by letting high-risk level to supersede either the low or moderate risks for patients susceptible to both risk profiles. Similarly, moderate risk superseded low risk when a patient is exposed to low and moderate risk levels.

Due to the need to establish the factors driving falls, pressure, and the combined falls and pressure injuries of the patients, multivariate logistic analysis of the patients at low, moderate, and high-risk categories were determined and the odds ratios (ORs) established. Different machine learning algorithms that include ANN, gradient boosting model (GBM), RF, Linear discriminant analysis (LDA), K Nearest Neighbour (KNN), Adaboost (ADB), Ridge regression classifier (RCV) and extra tree classifier(ETC) were tested to establish the best algorithm for real-time prediction of the risk profiles. The cost savings from using the real-time estimation was also determined for different LOS.

3.1 Pre-processing of data

The data were cleaned to remove inconsistencies in the entry and parameters with more than 10% of missing values dropped whereas others with less than 10% were filled. Hence, patients at high risk of fall or pressure injury and have a stroke, heart problems, multiple sclerosis, and motor neuron diseases, asthma, breathing problems, fall during current admission, and are passing through chemotherapy and radiation treatment were treated as high-risk patients if they have missing values. The risk classes were later upsized with Synthetic Minority Oversampling Technique

(SMOTE) to ensure a class balanced data while categorical parameters such as the clinical services and gender were characterized dichotomous as "1" for affirmative or "0" if not.

3.2 Factors influencing risk profiles at different levels

The factors influencing the risk categories of fall and pressure injury susceptibility were established at 0.05 significant level following a multivariate logistics model.

3.3 Real-time estimation of patients' risk profiles

It is important to establish the machine learning algorithms that will result in a better prediction of the risk classes by testing numerous algorithms. They include Ridge Regression (RCV, Linear Discriminant Analysis (LDA), Gradient boosting machine (GBM), Random Forest (RF), Artificial neural network (ANN), K Nearest Neighbour (KNN), Adaboost (ADB), Support Vector Machine (SVM) and Extra Tree classifier (ETC). The performance of the real-time risk profiling model, sensitivity (recall), specificity(precision) and accuracy were determined using the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

3.4 Cost optimization with real-time risk profiling

To estimate the cost-savings associated with the patients LOS on admission when real-time risk profiling is carried out, it was assumed that $\$\eta$ is spent per day of hospitalization. If φ patients were treated for ψ days, the total expenditure (E_{tot}) can be represented by Eqn. (1).

$$E_{tot} = \eta\varphi\psi \qquad (1)$$

If Υ number of falls or pressure injuries results in λ increase in the LOS of the patients following the findings from previous researchers (Worsley et al. 2016, Morello et al. 2015, ACSQHC 2018b), the cost of managing the patients in consideration of those that have fall or pressure injury (E_{inj}) will increase following the additional days spent by the injured patients per Eqn. (2).

$$E_{inj} = (1-\Upsilon)E_{tot} + \Upsilon\eta\varphi(\lambda+\psi) \qquad (2)$$

Since real-time risk profiling results in the prediction of the inherent risk of falls and pressure injuries to an accuracy of β, the extra cost incurred by treating the injured patients will be reduced by (1-β) times of the cost of managing injured patients {ϒη(λ+ψ)} because of the expected fewer casualties. Thus, the cost of managing the patients when real-time risk profiling is carried out (E_{rsk}) can be represented by Eqn. (3).

$$E_{rsk} = (1 - \Upsilon)E_{tot} + E_{tot}(1 - \beta)(\lambda + \psi) \quad (3)$$

The cost-saving expected from using real-time risk profiling (E_{sav}) is obtained as the difference between Eqn. (2) and Eqn. (3) and the percentage of savings can be computed with Eqn. (4).

$$E_{sav} = \left(1 - \frac{(1 - \Upsilon)\psi + \Upsilon(1 - \beta)(\lambda + \psi)}{(1 - \Upsilon)\psi + \Upsilon(\lambda + \psi)}\right) * 100\% \quad (4)$$

3.5 Injury probability on admission

The injury probability of the high-risk patients is determined by computing the mean risk index following the expressions shown in Eqn. (5) – Eqn. (6).

By using a logistic regression model with binary dependent variable y_i representing patients of high-risk susceptibility P (y_i = 1), the probability of injury proneness can be written as Eqn. (5).

$$p(y_i = 1) = \frac{e^{(\beta_0 + \sum_{i=1}^{m} \beta_i x_i + \varepsilon)}}{1 + e^{(\beta_0 + \sum_{i=1}^{m} \beta_i x_i + \varepsilon)}} \quad (5)$$

Here, β_0, β_i, m, and ε is the intercept, coefficient of a given patient characteristics (clinical and psychosocial) x, number of explanatory variables in consideration and random error. The mean values of the patient characteristics x are used alongside the coefficient estimated with Eqn. (5) to compute the mean risk index (MRI) in Eqn. (6).

$$MRI = \frac{\sum p(y_i = 1)}{\sum AGE} \quad (6)$$

4 Results

The summary of the clinical and psychosocial characteristics of the patients shown in Table 1 has 59.3% females and 40.7% males, and the proportion of the patients admissioned for various disease conditions.

Table 1: Summary of the clinical and psychosocial conditions used for modelling fall risk on admission and the proportion of patients associated with the studied conditions.

Demographic information		
Parameter	Mean ± SD	
Age(years)	48.59±22.08	
Weight, WGT(Kg)	79.81±25.56	
Height, HGT(cm)	168.46±12.98	
Body Mass Index (BMI)	27.96±8.03	
Length of stay, LOS (days)	6.53±11.89	
Psychosocial and clinical conditions		
Condition	**Acronym**	**Total**
Arthritis	ARS	16%
Asthma	ASM	19%
Bowel bleeding, constipation & diarrhoea	BBC	18%
Blood clotting problems	BCP	6%
Bladder problems & incontinence	BPI	10%
Breathing problems	BRP	18%
Cough & cold in the last 2 weeks	CCL	13%
Cancer	CNR	22%
Chemotherapy & radiation treatment	CRT	15%
Current wounds & skin breaks	CWB	12%
Dentures	DEN	14%
Dementia	DMA	1%
Diabetes	DTS	8%
Epilepsy & seizures	EPS	3%
Fall during the current admission	FDA	3%
Fallen in the last 6 months	FIL	13%
High and low blood pressure	HBP	28%
Hospitalisation in the last 12 months	HIL	47%
History of multi residual bacteria	HMB	2%
Home oxygen	HOX	4%
Heart problems	HTP	13%
Infectious diseases	IFD	1%

Indigestion & reflux	IRF	21%
Impaired vision & hearing	IVH	26%
Kidney disease	KDS	5%
Lives alone	LAL	10%
Limited jaw movement	LJM	2%
Migraines & motion sickness	MMS	17%
Multi sclerosis & motor neuron	MSN	2%
Neck & back problems	NBP	25%
Pregnant & breastfeeding	PBF	1%
Physical disability & mobility problems	PMP	16%
Prostate problems	PRP	6%
Psychiatric problems	PSP	20%
Short term memory loss	SML	5%
Speech & swallowing difficulties	SSP	4%
Stroke	STK	5%
Vaccination for chickenpox	VCP	25%

4.1 Combined falls and pressure injuries risks

The conditions that influenced the risk of injuries for patients that are susceptible to both falls and pressure injuries risks are summarized in Table 2. The influence of MSN, which carries the highest risk for patients at high risk is quite pronounced with 59% - 811% more likelihood of causing injuries than the other influencing variables. FDA poses lesser risk than MSN but has between 194% - 473% more chances of triggering falls and pressure related injuries on admission than the HGT, AGE, VCP, and FIL.

Table 2: Summary of features influencing combined fall and pressure injury of high risks susceptible patients on acute hospital admission

Parameters	P values	2.50%	97.50%	OR
HGT	0.00002	0.97	0.99	0.98
AGE	0.00318	1.01	1.04	1.0251
FDA	0.00379	1.75	18.04	5.6117
MSN	0.01857	1.44	55.24	8.9266
VCP	0.02117	1.09	2.85	1.7616
FIL	0.03756	1.04	3.50	1.9059

The summary of the various algorithms used for the real-time estimation of falls and pressure injuries risk is shown in Table 3.

Table 3: Summary of training and testing results of the combined fall risk and pressure injury risks;fld:fold; ALG: algorithm; PRC: precision; RCL: recall; ACC: accuracy of test data, bold indicates the best.

ALG	fld1	fld2	fld3	fld4	fld5	mean	Std.	PRC	RCL	ACC
RCV	0.66	0.58	0.63	0.60	0.59	0.61	0.03	0.64	0.62	0.62
LDA	0.68	0.60	0.64	0.62	0.63	0.64	0.03	0.65	0.63	0.63
GBM	0.89	0.88	0.89	0.85	0.89	0.88	0.02	0.90	0.90	0.90
RF	0.88	0.86	0.88	0.85	0.88	0.87	0.01	0.91	0.90	0.90
ANN	0.85	0.89	0.90	0.79	0.86	0.86	0.04	0.89	0.89	0.89
KNN	0.75	0.75	0.79	0.73	0.76	0.76	0.02	0.83	0.80	0.79
ADB	0.75	0.77	0.73	0.72	0.71	0.74	0.02	0.74	0.74	0.73
SVM	0.64	0.60	0.62	0.62	0.65	0.63	0.02	0.65	0.62	0.62
ETC	0.87	0.90	0.90	0.86	0.89	**0.88**	0.02	0.91	0.91	**0.91**

The mean values of the 5-fold cross-validation of the training dataset indicate that ETC (in bold) as the algorithm that produced the best result with a mean accuracy of 88.4% of the cross-validation and 90.9% accuracy of the test data.

4.2 Falls risks

According to Table 4, the high risk of falls on admission is mostly influenced by MSN, which predisposes patients to falls injuries 538% more than the FDA, which is the second most influencing factor.

Table 4: Summary of the features influencing fall risks on the admission of high risks susceptible patients

Parameters	P values	2.50%	97.50%	OR
AGE	0.0008	1.01	1.05	1.0308
HGT	0.0017	0.97	0.99	0.9842
MSN	0.0026	2.89	153.38	21.0706
PMP	0.0328	1.06	4.00	2.061
DEN	0.0372	1.04	3.55	1.9211
FDA	0.0457	1.02	10.72	3.3119

The real-time estimation of falls risks can be predicted with RF per Table 5.

Table 5: Summary of training and testing performance of falls risks, fld:fold; ALG: algorithm; PRC: precision; RCL: recall; ACC: accuracy of test data, bold indicates the best

ALG	fld1	fld2	fld3	fld4	fld5	mean	Std.	PRC	RCL	ACC
RCV	0.68	0.67	0.72	0.65	0.67	0.68	0.02	0.67	0.67	0.67
LDA	0.69	0.68	0.71	0.64	0.69	0.68	0.02	0.67	0.66	0.66
GBM	0.91	0.88	0.93	0.89	0.91	0.90	0.02	0.90	0.90	0.90
RF	0.91	0.90	0.92	0.889	0.89	0.90	0.01	0.91	0.91	**0.91**
ANN	0.89	0.90	0.90	0.86	0.89	0.89	0.02	0.90	0.90	0.90
KNN	0.80	0.81	0.81	0.75	0.79	0.79	0.02	0.82	0.80	0.79
ADB	0.78	0.73	0.79	0.75	0.77	0.75	0.03	0.78	0.78	0.78
SVM	0.65	0.68	0.72	0.65	0.67	0.67	0.03	0.67	0.66	0.66
ETC	0.94	0.89	0.91	0.91	0.89	**0.91**	0.02	0.90	0.90	0.90

4.3 Pressure injury risks

According to Table 6, pressure injury risks are caused by some of the parameters that influence the other risks discussed in the previous except for some new parameters that include CWB, LJM, and BMI.

Table 6: Summary of the features influencing pressure injury risks on the admission of high risks susceptible patients

Parameters	**P values**	**2.50%**	**97.50%**	**OR**
HGT	0.0002	0.88	0.96	0.92
FDA	0.003	5.07	2732.30	118.00
MSN	0.03	1.59	9228.94	121.21
CWB	0.0381	1.10	32.98	6.03
BMI	0.04	0.78	0.99	0.88
LJM	0.042	0.00	0.82	0.00

Table 7 also indicates that ETC predicted the test data to an accuracy of 99.8% compared to RF and GBM that estimated them at 99.4% and 98.6% respectively while other algorithms have lower estimates.

Table 7: Summary of training and testing performance of pressure injury risk,fld: fold; ALG: algorithm; PRC: precision; RCL: recall; ACC: accuracy of test data

ALG	fld1	fld2	fld3	fld4	fld5	mean	Std.	PRC	RCL	ACC
RCV	0.89	0.86	0.90	0.90	0.88	0.89	0.02	0.88	0.88	0.878
LDA	0.88	0.83	0.87	0.90	0.87	0.87	0.02	0.87	0.87	0.864
GBM	0.99	0.99	0.98	0.99	0.97	0.98	0.01	0.99	0.99	0.986
RF	0.99	0.98	0.98	0.99	0.97	0.98	0.01	0.99	0.99	0.994
ANN	0.97	0.97	0.97	0.97	0.99	0.97	0.01	0.98	0.98	0.979
KNN	0.90	0.86	0.88	0.86	0.87	0.88	0.02	0.91	0.89	0.884
ADB	0.91	0.92	0.90	0.92	0.90	0.91	0.01	0.89	0.89	0.890
SVM	0.83	0.85	0.86	0.86	0.85	0.85	0.01	0.86	0.86	0.856
ETC	0.988	0.985	0.985	0.99	0.985	0.989	0.00	0.998	0.998	**0.998**

4.4 Injury probability on admission for high-risk patients

The MRI of the patients considered in this study is 3.69E-03 yr^{-1}, 4.04E-03 yr^{-1}, and 9.59E-11 yr^{-1} respectively for those with combined falls and pressure injury risk, fall injury risk, and pressure injury risk. The risk for those prone to the combined falls and pressure injury risk is lower than those that are only prone to falls injuries. But the MRI of pressure injury-prone patients is relatively very small, which may be an indication of the limited occurrence of such injuries due to the proper management strategy. The injury risks increase with the age of the patients (Coussement et al. 2008), thus, making an 80 years old patient 23% more prone to falls injury than a 65-year-old. The elderly can be prone to atrophy of joint muscles, which could cause instability because of limited activities, and sometimes vitamin D deficiency may help to enhance poor gait functionality, muscle weakness, and osteoporosis (Vassallo et al. 2009). These conditions can be responsible for the increased frailty of the elderly and susceptibility to higher falls injury probability per Figure 1.

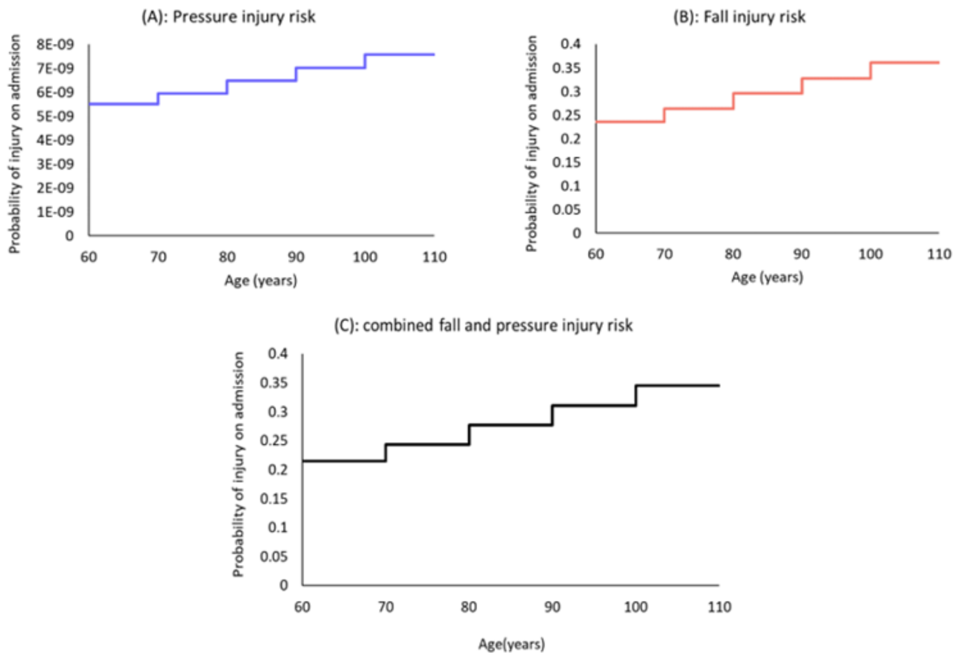

Figure 1: Probability of injury on admission for the patient that are 60 years and over – (A) pressure injury risk, (B) falls injury risk, (C) combined falls and pressure injury risk

4.5 Cost savings with real-time risk profiling

The real-time risk profiling using different algorithms showed that ETC and RF are the most efficient algorithms for predicting accurately the risk class of patients. This gives room for better patients' management that will forestall falls or pressure injuries on admission since the status of most patients can be known early enough. We have assumed that 2% and 3% of falls injuries and pressure injuries respectively are experienced on admission following information from the hospital. Since falls injuries can increase LOS significantly between 5.9 days – 23.6 days (Worsley et al. 2016, ACSQHC 2018b) and those with pressure injuries can stay more 8 days - 18.8 days (Black et al. 2011, Morello et al. 2015), the cost savings with different LOS has been computed with 90% accuracy of the real-time risk profiling (Figure 2).

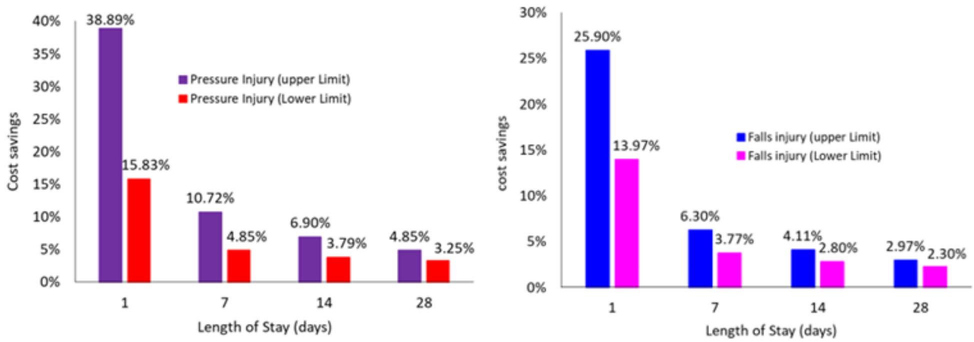

Figure 2: Expected cost savings using the risk-time risk profiling of patients in an acute hospital for different length of hospital admissions for – (A) pressure injury, (B) falls injury

5 Discussion

The core drivers of falls and pressure injuries have been identified to include HGT, FIL, VCP, CRT, DEN, LOS, AGE, SSP, FDA, DMA, MSN, PMP, BMI, ASM, LJM, HOX, SSP, BCP and CWB. Some of these conditions are among those identified previously by researchers however, they only influenced low and moderate risk patients and may not be of utmost concern like the ones influencing high-risk patients. Mobility problems and fall history, which were equally attributed to falls injuries in previous research were identified as among the conditions responsible for high-risk patients' susceptibility to fall injuries.

This study has linked patients diagnosed with high susceptibility to the falls and pressure injuries to MSN, FDA, FIL, VCP, AGE, LJM, BMI, CWB, AGE, and HGT but the strong influences of MSN and FDA make it imperative that patients who have these attributes will be given more attention. Although not so much is known about MSN, the pathological characteristics of death upper and lower motor neurons and the presence of numerous protein inclusions in the remaining motor neurons resulting in impaired transactive responses (Neumann et al. 2006,Wright et al. 2016) culminates in problems that can lead to poor gait and memory loss (Olivier et al. 2016). Thus, the strong influence of MSN on falls and pressure injures may be explained by the association between poor gait functionality and memory loss.

The probability of pressure injuries on admission is relatively low compared to fall injuries. This may be because of the healthcare strategy of the hospital which prioritise pressure injuries vulnerabilities. However, the probability of getting falls or pressure injuries increase with the age of the patients, the number and types of comorbidities (Rondinelli et al. 2018).

6 Conclusions

This study has affirmed the importance of real-time risk profiling in the efficient management of patients that are susceptible to falls and pressure injuries on admission by showing the cost-saving associated with the implementation of the technique. The core drivers of the risks were also established for patients with the various levels of predispositions to injuries while establishing the high-risk drivers that include MSN, FDA FIL, VCP, AGE, LJM, BMI, CWB, AGE, and HGT. The cost savings expected for real-time risk profiling ranges from 3.25% - 38.89% for pressure injury risks and 2.3% - 25.90% for fall risk injury when a 1 to 28 days LOS is considered. ETC and RF with enhanced accuracy of 10% - 11% were identified as the most efficient algorithms for predicting the patients' risk categories using the clinical and psychosocial conditions. Comparatively, patients prone to pressure injury risk have a very small likelihood of becoming injured on admission than those susceptible to falls risk and combined fall and pressure risks on admission. This could attest to the proper pressure injury management practices in the hospital and the need for improving fall mitigation strategies.

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