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Data-driven Decision Support for 30-day Unplanned Readmission Risks of Comorbid Patients with Diabetes – An Action Design Research Paradigm

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Completed Research

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Abstract

Data-driven decision support, which refers to the reliance on knowledge Discovery and Data mining (KDD) via statistical, mathematical, and machine learning algorithms for abstractions has enhanced clinical and non-clinical decisions. Thus, this paper relies on Action Design Research (ADR) for designing, implementing, and understanding Information Technology (IT) artifacts for the risk of 30-days Unplanned Readmission (URA) of comorbid patients of diabetes from diverse cultural backgrounds. The analysis of 17933 patients records at the building, intervention, and evaluation phases of ADR showed a 30-days URA rate of 10.71% for all patients, 10.98% rate for Caucasians (non Black, Indigenous, & people of Colour (BIPOC)), 9.94% for AA-BIPOC – African Americans, and 9.63% for BIPOC- Asians, Hispanics, and other races. This study leads to a better clinical practice via targeted and reflective management of hospitalized comorbid patients of diabetes to forestall early URA.

Keywords

data-driven decision support, comorbid patients with diabetes, Action Design Research, Knowledge Discovery, and data mining, 30-days unplanned readmission, cultural diversity

Abbrev.	Description	Abbrev.	Description
ADM-EMG	admission source (emergency)	GLY-ROS-INS	glyburide-rosiglitazone-insulin
ADM-OTH	admission source (planned)	HbA1C (<7)	HbA1C less than 7%
ADM-REF	admission source (referrals)	HbA1C (>8)	HbA1C >8%
ADM-TRA	admission source (transferred from other facilities)	HbA1C (7-8)	HbA1C 7- 8%
ADR	Action design research	ICD	International classification of diseases
ADT-ELE	admission type (elective)	INS	Insulin
ADT-EMG	admission type (emergency)	IS	information system
ADT-OTH	admission type (planned)	IT	Information technology
ADT-UGT	admission type (urgent)	KDD	Knowledge Discovery and Data Mining
AUC	Area under the curve	MED	medication
BIPOC	Black, Indigenous, and people of colour	MET	Metformin
BSL	Brier score loss	MET-GLI-INS	metformin, glimepiride, and insulin
CMB-CIR	comorbidity (circulatory system)	MET-GLP	metformin and glipizide
CMB-DIA	comorbidity (diabetes)	MET-GLP-INS	metformin, glipizide, and insulin
CMB-DIG	comorbidity (digestive)	MET-INS	metformin, and insulin
CMB-GEN	comorbidity (genitourinary)	MLR	Multivariate Logistic Regression
CMB-INJ	comorbidity (Injury and poisoning)	NDG	number of diagnoses
CMB-MUS	comorbidity (musculoskeletal system and connective tissue)	NEM	number of emergency visits
CMB-NEO	comorbidity (Neoplasms)	NIP	number of inpatient visits
CMB-OTH	comorbidity (others)	NLB	number of labs
CMB-RES	comorbidity (respiratory system)	NMD	number of medications
DSC-FAC	discharge source (care facility)	NOU	number of outpatient visits
DSC-HOME	discharge source (home)	NPR	number of procedures
DSC-HOSP	discharge source (hospital)	NTF	The number of trees in the forest
DSC-OTH	discharge source (others)	PDGN	Primary Diagnosis
GLI	Glimepiride	PIO	Pioglitazone
GLI	glimepiride and insulin	PIO-INS	pioglitazone, and insulin
GLP	Glipizide	ROS-INS	rosiglitazone, and insulin

GLP-INS	glipizide, and insulin	RR	Relative Risk
GLY	Glyburide	SFT	standard deviation of fit time
GLY-INS	glyburide-insulin	STS	standard deviation of test score
GLY-MET	glyburide-metformin	THM	mono therapy
GLY-MET-INS	glyburide-metformin-insulin	TIH	time in hospital
GLY-ROS	glyburide-rosiglitazone	URA	Unplanned readmission

Acronyms

Introduction

To facilitate better judgement in decision making entails the use of data, statistical analysis, and machine learning to guide humans through a systematic approach that identifies hidden insights that will proffer solutions via the identification of trends, visualization, and correlation of events (Sarker 2021, Bohanec et al. 2017). This means that principles, processes, and frameworks that will analyse data through feature engineering, and predictive analytics will be needed to identify the probable solutions to problems (Fayyad et al. 1996), which can only be meaningful to decision-makers after interpretation of results. As a result of this capability, the surge in Information Technology (IT) through the internet of things (IoT) and other smart devices have augmented decision-making in healthcare (Chatterjee et al. 2020) paving ways for improved caregiving that enhances patients' outcomes. To this end, numerous studies on data-driven decision support for healthcare applications have been carried out. Lejarza et al. (2021) used a data-driven technique that hinges on discrete state space for capturing the physiological state of Intensive Care Unit (ICU) patients to recommend the optimal time for their discharge. Todd et al. (2022) used survival analysis to propose applications for managing readmission in public hospitals to identify high-risk patients that may need more attention to forestall URA.

Unfortunately, most of the studies in this area have focused on descriptive and explanatory studies without the consideration and inclusion of the design principles for solving the data-driven problem in a complex healthcare context. As a result, this paper follows a holistic approach to identifying the risk factors by using the Action Design Research (ADR) paradigm to construct and implement IT artifacts for data-driven decision support aimed at identifying the risk factors of 30-days URA for patients of diverse cultural backgrounds. This will help to identify the patients that are at a high risk of 30-days URA and enable a better characterization of comorbid patients with diabetes on admission, hence, giving the clinicians the opportunity of effective and tailored caregiving that will help to forestall the early URA.

Background

Despite the chances of reducing 30-days Unplanned Readmission (URA) of patients with diabetes through self-management and reduction of preventable causes (Soh et al. 2020, Fluitman et al. 2016), 14-21% of patients still have URA (Budnitz et al. 2011, Friedman et al. 2012). Many factors such as age, gender, race, cardiovascular conditions, renal disease, chronic kidney disease, cancer, depression, dementia, respiratory illnesses, insulin therapy, and insurance status (Soh et al. 2020, Gould et al. 2020) have been identified as risks of URA of diabetes patients. Png et al. (2018) relied on Electronic Medical Record (EMR) to analyse 30-days URA, which showed illness burden and diabetes medication as risk factors of early URA whereas Rubin and Shah (2021) showed that socioeconomics, comorbidities, Length of hospital Stay (LOS), history of readmission are the determinants of 30-days URA. Even though numerous risk factors of 30-days URA have been identified by researchers, there is still the need to understand how the risk factors influence patients from diverse cultural backgrounds by considering the medication therapies. Other researchers such as Shang et al. (2021), Robbins et al. (2019), Collin et al. (2017), and Rie et al. (2015) have also identified the risk factors of early URA of patients with diabetes to include race, sex, age, admission type, admission location, length of stay, and drug use.

The rest of the paper will include methodology, which describes the Action Design Research (ADR), data acquisition, feature engineering and statistical analysis techniques. The results and the implication of the study is captured in the discussion section while highlighting the limitations and the direction for future research.

Methodology

Action Design Research (ADR)

The need for solving Information System (IS) problems that make both theoretical and practical contributions is vital in research if there will be any abstraction that will benefit practitioners. ADR is an offshoot of the action and design research concept that provides theoretical contributions to IS problems by collecting, analyzing, building, and evaluating IT artifacts in an organizational context to solve these problems (Sein et al. 2011). Thus, helps to solve current and future problems by providing a framework that facilitates quick and better decisions for the numerous IS problems while enabling practitioners to work smarter in a more productive manner. ADR relies on the theoretical knowledge gained about a problem to

develop a design architecture for solving the problem via a stepwise approach that evaluates the IT artifacts following problem formulation, building, intervention, and evaluation, reflection and learning, and formulation of learning. Despite this robust approach used by ADR, some researchers have argued that the effectiveness of ADR rests in the practical translation of problems into solutions that are endorsed by stakeholders. This ensures that the solutions are shaped within practical IT artifacts that will involve end-users of the project early while balancing the political, economic, and societal values of ensuing results of such projects (Keijzer-Broers and de Reuver 2016).

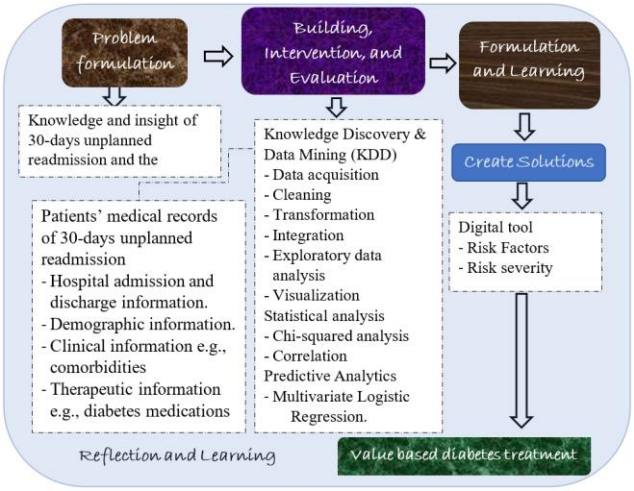

Figure 1: Action Design Research (ADR) architecture for data-driven decision support for 30-days unplanned readmission risk estimation of culturally diverse patients with diabetes.

Problem Formulation

Even though design science research projects can be diverse, the fundamental step in a design project is the identification of a problem that needs solutions, thus allowing researchers to construct IT artifacts for defining the problem before creating specific artifacts for some specific contexts. In this study, the need to understand the risk factors of 30-days URA and their severities for comorbid patients of diabetes from diverse cultural backgrounds treated with numerous medications forms the basis. Since the reliance on theories for designing the IT artifacts cannot be overlooked, the study depends on the data-driven theory of KDD (Fayyad et al. 2011) for crafting the steps for analysing data, obtaining the artifacts, and sub-artifacts for managing 30-days URA following Figure 1. The conceptualization of this project was informed by the challenges posed by the 30-days URA of comorbid patients with diabetes whose experiences after admission are not good due to the diminished quality-of-life after discharge and the subsequent 30-days URA. Furthermore, 30-days URA results in financial penalties on hospitals from health insurance, cast the stigma of poor-quality care services on the hospitals, deprive future patients of the opportunity of bed space, and increase the financial burden on the populace through increased cost of managing healthcare (Clement et al. 2014, AIHW 2017, Considine et al. 2019, Shebeshi et al. 2020).

Building, Intervention and Evaluation

Since 30-days URA of comorbid diabetes patients is not economic and impacts the overall quality-of-life of patients, it becomes imperative to understand the risk factors, their severities, and how they apply to a culturally diverse society. This understanding and the implementation of requisite adjustments for patients affected by the risks will make room for improved caregiving at the hospitals since optimal care engagement can potentially reduce 30-days URA (Bianco et al. 2012, Van der Does et al. 2020, Considine et al. 2020). This stage of ADR involves the implementation of the various steps in KDD through the analysis of patients' medical records to compute the probability, and risk factors (and their severities) using Multivariate Logistic Regression (MLR). There is also data engineering to facilitate high-quality information that will produce a better result following the transformation of some of the predictors of 30-days URA. The implementation of statistical analysis helps to establish the nature of the artifacts (risk factors) at a 95% significant level. The implementation of exploratory data analysis helps to identify the trends and patterns of the 30-days URA rate amongst the various cultural backgrounds and comorbidities. With this systematic implementation of KDD on the historic patients' records, the artifacts, which form the basis for decision support in managing patients are identified. More details about the building, intervention and evaluation steps are discussed in the next 3 sub-sections sections.

Data acquisition

Deidentified data obtained from the Health Facts database (Cerner Corporation, Kansas City, MO), which collects comprehensive clinical records across hospitals in the United States (Strack et al. 2014) is used for the KDD analysis. Over 74 million records from more than 130 hospitals' unique records of patients treated for diabetes and other health conditions provided hospital-specific records such as admission and discharge categories, demographic, and clinical information for this study that relied on information such as emergency, outpatient, and inpatients visits, diagnosed comorbidities following ICD-9-CM codes. From the preliminary analysis, a total of 101,766 records related to comorbid diabetes patients was identified with over 55 features that included medication types and HbA1C levels.

Feature Engineering

Further analysis of the 10,766 records to identify patients treated with at least one diabetes medication who stayed at least 1 day on hospital admission resulted in 17,933 records used for this study. After dropping the features with more than 10% of missing values and eliminating features that have no direct relevance with 30-days URA, the following features were left for the analysis:- race, gender, age, admission type (ADT), admission source (ADM), discharge disposition (DSC), time in hospital (TIH), number of labs (NLB), number of procedures (NPR), number of medications (NMD), number of outpatient visits (NOU), number of inpatient visits (NIP), primary diagnosis (PDGN), number of diagnoses (NDG), A1C test result (HbA1C), diabetes medications used (MED). The "race" is classified into 3 categories in recognition of the minorities by using the acronym black, Indigenous and people of colour (BIPOC), hence, non-BIPOC are Caucasians, BIPOC is Asians, Hispanic, and other races while AA-BIPOC represents African Americans. Age is grouped into < 40 years, 40-50 years, 50-60 years, 60-70 years, 70-80 years, and >80 years. The sub-classes of the remaining features are ADM: 4, PDGN: 9, DSC: 3, HbA1C: 3, gender: 2, therapy: 2, and MED: 39. The data also identified mono and combo therapies for diabetes medications that include metformin (MET), glipizide (GLP), Insulin (INS), glimepiride (GLI), glyburide (GLY), rosiglitazone (ROS), pioglitazone (PIO) and their combinations.

Statistical analysis

The association between the features used for the analysis was determined with Chi-squared analysis while using Multivariate Logistic Regression (MLR) to compute risk factors and their severities by computing the relative risks (RR) at 95% confidence level. The probability of 30-days URA was determine from the MLR following Eqn. (1). Thus, for the 30-days URA (η) (that has predictor values denoted by $x_1, x_2, \ldots, x_n$) with a dichotomous representation of 1 and 0 (1: 30-days URA, 0: no URA), if the probability of 30-days URA $Pr = Pr(\eta=1)$, and there is an assumption of a linear relationship, then the probability Pr, log-odd l and RR of 30-days URA at $\eta = 1$ is expressed in Eqn. (1).

$$\begin{cases} P_r = \dfrac{1}{1+e^{-l}} \\ l = log_{10}\dfrac{P_r}{1-P_r} = \alpha_0 + \alpha_1 x_1 + \cdots + \alpha_k x_n \\ RR = e^{-l} \end{cases} \quad ------(1)$$

where $\alpha_0, \alpha_1, \ldots, \alpha_n$ are the coefficient of the intercept, and the coefficient of predictors 1, ..., n.

The benchmark described by Ayotollahi et al. [2017] for estimating the risk severities in hospitals as low, moderate, and high was adopted for understanding the trends of 30-days URA risk for the various cultures considered. The computation of the RR based on Eqn. (1) provided information about the influences of the various artifacts and sub-artifacts relating to the risk of 30-days URA. The accuracy, brier score loss, and AUC of the 30-days URA was determined by using the ground truth and predicted 30-days URA status.

Reflection, Learning, and Formalization of Design Principles

The reflection and learning are paralleled stages that are continuous in the entire process of designing and formulating the requisite digital solution for the risk factors and their severities for 30-days URA of patients with diabetes. Hence, minimizing 30-days URA involves understanding the artifacts (contributing risk factors and their severities) to facilitate quick and efficient management of patients to improve their hospitalization experience as well as improve their quality-of-life after discharge. The interaction of the ADR processes in the architecture shown in Figure 1 leads to the building of digital intervention tools that will also provide healthcare practitioners with a medium for both learning and reflective practices to forestall 30-days URA vis-à-vis

providing value-based treatment for comorbid patients with diabetes. Imperatively, the learning and reflective process during problem formulation; building, intervention, and evaluation, and the formulation of learning into a creative solution in the form of a digital tool helped to maximize the benefits of effective digital tool development. The benefit of this reflection and learning is maximized via a cost-effective and practical strategy utilization to facilitate meaningful actions (Anseel et al. 2009) that helps clinicians to minimize 30-days URA. This can result in an improvement in patients' experience of diabetes and comorbid diabetes treatment seeing that therapeutic misconception, healthcare workers' levity, comorbidity burden, and poor diagnosis (Bianco et al. 2012, Van der Does et al. 2020, Considine et al. 2020) can hamper recovery post-discharge and result in 30-days URA.

Results

Overview of 30-days unplanned readmission of comorbid patients with diabetes

Of the 17933 patients identified for this study, 10.71% had 30-days URA with 10.93% females and 10.47% males returning to the hospital after discharge within 30 days. Patients who are described as non-BIPOC have the highest 30-days URA of 10.98% followed by AA-BIPOC with 9.94% while BIPOC patients have the least 30-day URA at 9.63%. The 30-days URA for the age groups varied from 9.28-10.95%, PDGN is from 8.62 – 12.22% with patients in the age group of 60-70 years having the highest rate. For medication therapy and types, those on combo-therapy have 9.44% of 30-days URA, monotherapy treated patients have 11.59% whereas patients treated with GLY-PIO have a 17.31% rate, which is the highest. The remainder of the baseline characteristics of the cohorts is shown in Table 1.

Features	**No (n, %)**	**Yes (n, %)**	**Features**	**No (n, %)**	**Yes (n, %)**
Samples	16013(89.29%)	1920(10.71%)	MED		
Race			GLI	189(90.43%)	20(9.57%)
AA-BIPOC	3370(90.06%)	372(9.94%)	GLI-INS	276(89.9%)	31(10.1%)
BIPOC	713(90.37%)	76(9.63%)	GLI-PIO-INS	53(89.83%)	6(10.17%)
non-BIPOC	11930(89.02%)	1472(10.98%)	GLP	637(87.14%)	94(12.86%)
Gender			GLP-INS	728(89.88%)	82(10.12%)
Female	8275(89.07%)	1015(10.93%)	GLP-PIO	76(95%)	4(5%)
Male	7738(89.53%)	905(10.47%)	GLP-PIO-INS	81(89.01%)	10(10.99%)
Age			GLP-ROS	67(93.06%)	5(6.94%)
40-50 years	1917(89.2%)	232(10.8%)	GLP-ROS-INS	80(87.91%)	11(12.09%)
50-60 years	3006(90.41%)	319(9.59%)	GLY	570(90.19%)	62(9.81%)
60-70 years	3269(89.05%)	402(10.95%)	GLY-INS	483(91.13%)	47(8.87%)
70-80 years	3579(88.11%)	483(11.89%)	GLY-PIO	43(82.69%)	9(17.31%)
<40 years	1584(90.72%)	162(9.28%)	GLY-PIO-INS	58(90.63%)	6(9.38%)
>80 years	2658(89.19%)	322(10.81%)	GLY-ROS	47(94%)	3(6%)
HbA1C			GLY-ROS-INS	65(90.28%)	7(9.72%)
<7	4775(89.12%)	583(10.88%)	INS	6761(88.34%)	892(11.66%)
7-8	3761(89.04%)	463(10.96%)	MET	770(88.4%)	101(11.6%)
>8	7477(89.53%)	874(10.47%)	MET-GLI	71(95.95%)	3(4.05%)
PDGN			MET-GLI-INS	159(89.33%)	19(10.67%)
CIR	4663(87.93%)	640(12.07%)	MET-GLP	226(89.68%)	26(10.32%)
DIA	2561(89.99%)	285(10.01%)	MET-GLP-INS	372(93%)	28(7%)
DIG	1073(87.95%)	147(12.05%)	MET-GLP-PIO-INS	52(92.86%)	4(7.14%)
GEN	672(88.42%)	88(11.58%)	MET-GLP-ROS	105(88.24%)	14(11.76%)
INJ	403(91.38%)	38(8.62%)	MET-GLY	306(92.45%)	25(7.55%)
MUS	489(90.22%)	53(9.78%)	MET-GLY-INS	290(92.95%)	22(7.05%)
NEO	309(87.78%)	43(12.22%)	MET-GLY-ROS	51(92.73%)	4(7.27%)
OTH	3272(89.45%)	386(10.55%)	MET-GLY-ROS-INS	52(88.14%)	7(11.86%)
RES	2571(91.46%)	240(8.54%)	MET-INS	980(91.33%)	93(8.67%)
Therapy			MET-PIO	65(97.01%)	2(2.99%)
combo	6686(90.56%)	697(9.44%)	MET-PIO-INS	136(90.07%)	15(9.93%)
mono	9327(88.41%)	1223(11.59%)	MET-ROS	81(84.38%)	15(15.63%)
ADM			MET-ROS-INS	135(88.24%)	18(11.76%)
EMG	8879(89.33%)	1061(10.67%)	OTH	831(91.12%)	81(8.88%)
OTH	3113(88.11%)	420(11.89%)	PIO	182(87.08%)	27(12.92%)
REF	3229(89.77%)	368(10.23%)	PIO-INS	327(86.74%)	50(13.26%)
TRA	792(91.77%)	71(8.23%)	REP	44(88%)	6(12%)
ADT			REP-INS	129(88.36%)	17(11.64%)
ELE	1522(90.76%)	155(9.24%)	ROS	149(88.17%)	20(11.83%)
EMG	8180(89.65%)	944(10.35%)	ROS-INS	286(89.38%)	34(10.63%)
OTH	3719(87.63%)	525(12.37%)	NDG*	7.31(±2.03)	7.62(±1.82)
UGT	2592(89.75%)	296(10.25%)	NEM*	0.2(±0.75)	0.42(±1.38)
DSC			NIP*	0.47(±1.04)	1.02(±1.96)
FAC	4783(86.74%)	731(13.26%)	NLB*	48.59(±20.09)	48.47(±20.61)
HOME	9409(91.15%)	913(8.85%)	NMD*	16.77(±8.27)	17.8(±8.37)
HOSP	411(86.16%)	66(13.84%)	NOU*	0.39(±1.33)	0.43(±1.15)
OTH	1410(87.04%)	210(12.96%)	NPR*	1.18(±1.69)	1.24(±1.7)
			TIH*	4.81(±3.09)	5.17(±3.11)

Table 1: Baseline characteristics of the study population showing the cohorts that have 30-days unplanned readmission (NB: * mean ± std).

Table 2 shows the cumulative rate of 30-days URA for the various cultural backgrounds and primary comorbidity diagnosis of the patients treated with the various diabetes medications. Patients diagnosed with circulatory system conditions (CIR) are most prone to 30-days URA with non- BIPOC patients having the most likelihood at 3.69% compared to the BIPOC and AA-BIPOC that have 3.18% and 3.3% respectively. Apart from those who were diagnosed with DIA, RES, and OTH disease conditions as their primary diagnosis, the 30-days URA rates of the remaining comorbidities are < 1%.

Features	**All Patients** (n=1920,10.71%)	**Non-BIPOC** (n=1472, (10.98%)	**AA-BIPOC** (n=372, 9.94%)	**BIPOC** (n=76, 9.63%)
CIR	640(3.57%)	495(3.69%)	119(3.18%)	26(3.3%)
DIA	285(1.59%)	203(1.51%)	70(1.87%)	12(1.52%)
DIG	147(0.82%)	115(0.86%)	25(0.67%)	7(0.89%)
GEN	88(0.49%)	69(0.51%)	17(0.45%)	2(0.25%)
INJ	38(0.21%)	30(0.22%)	6(0.16%)	2(0.25%)
MUS	53(0.3%)	41(0.31%)	11(0.29%)	1(0.13%)
NEO	43(0.24%)	31(0.23%)	9(0.24%)	3(0.38%)
OTH	386(2.15%)	288(2.15%)	83(2.22%)	15(1.9%)
RES	240(1.34%)	200(1.49%)	32(0.86%)	8(1.01%)

Table 2: Cumulative rate of 30-days unplanned readmission for different cultural diversities and patients' primary diagnosis

According to Figure 2, the patients at high risk of 30-days URA are <1% of the population prone to URA despite their cultural group while BIPOC patients have the highest rate of patients at low risk of 30-days URA followed by AA-BIPOC, but non-BIPOC patients constituted the most moderate risk-prone patients. The number of BIPOC patients exposed to high risk of 30-days URA is 238%, 177%, and 780% respectively more than all the patients, non-BIPOC, and AA-BIPOC patients at high risk.

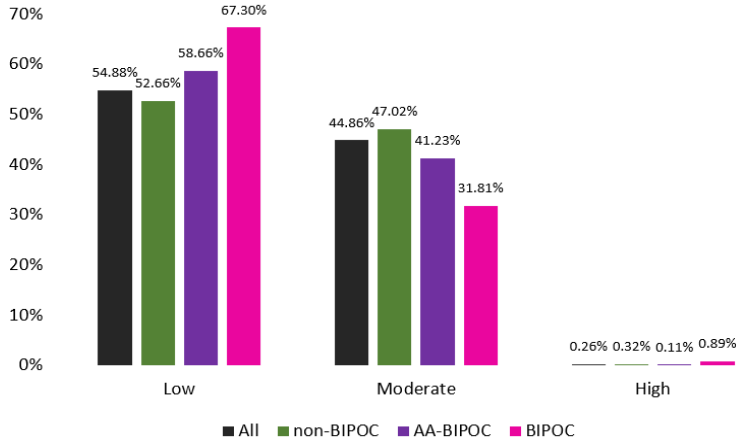

Figure 2: 30 days unplanned readmission risk of the patients arranged according to risk severity and cultural diversity

Risk factors of 30-days unplanned readmission

The risk factors for 30-days URA and their severities measured as the *RR* for all the patients and the various cultural groups are shown in Table 3. At 95% significant level, the risk factors are as follows: - all patients {ADM(TRF), ADT (ELE, UGT, EMG), ages, PDGN (DIG, INJ, MUS, OTH, RES), DSC (FAC, HOSP, OTH), HbA1C (7-8, >8), MED (GLY), NDG, NEM, NIP, NOU, NLB, race (AA-BIPOC)}. So, compared to non-BIPOC patients, AA-BIPOC patients are prone to 30-days URA after discharge, but not BIPOC patients. The most pronounced risk factors for all the patients are: - DSC (FAC)- 1.41(1.25-1.59), P: <0.0001; DSC(HOSP) - 1.41(1.06-1.86), P: 0.0165; DSC(OTH) - 1.27(1.08-1.51), P: 0.0047 and NIP - 1.23(1.19-1.28), P: <0.0001. Table 3 highlights the 30-days URA risk factors for culturally diverse patients and shows that DSC (FAC, HOSP, OTH) are the only risk factor for 30-days URA for non-BIPOC patients. For AA-BIPOC patients, NIP - 1.23(1.12-1.36), P: <0.0001; NEM -1.15(1.04-1.28), P: 0.0087 and NPR- 1.09(1.01-1.17), P: 0.0338 are risk factors of concern whereas NIP - 1.31(1.03-1.65), P: 0.0251 remains the risk factor of concern for BIPOC patients.

Parameters	All Patients	non-BIPOC	AA-BIPOC	BIPOC
	RR (95% CI), P-value	RR (95% CI), P-value	RR (95% CI), P-value	RR (95% CI), P-value
ADM				
OTH	ref	ref	ref	ref
EMG	0.97(0.8-1.17), P: 0.7163	0.99(0.8-1.23), P: 0.9338	0.69(0.42-1.13), P: 0.1423	1.04(0.4-2.75), P: 0.9316
REF	0.9(0.73-1.1), P: 0.3136	0.79(0.62-1), P: 0.0495^	1.08(0.64-1.83), P: 0.7709	1.72(0.65-4.57), P: 0.274
TRA	0.68(0.5-0.93), P: 0.0146^	0.49(0.33-0.73), P: 0.0004^	0.86(0.46-1.62), P: 0.6454	2.11(0.5-8.86), P: 0.3088
ADT				
OTH	ref	ref	ref	ref
ELE	0.7(0.55-0.88), P: 0.0028^	0.94(0.72-1.22), P: 0.6216	0.26(0.13-0.49), P: <0.0001^	0.18(0.05-0.7), P: 0.0134^
EMG	0.77(0.66-0.9), P: 0.0011^	0.79(0.66-0.94), P: 0.007^	0.79(0.51-1.2), P: 0.264	0.5(0.23-1.08), P: 0.0777
UGT	0.76(0.64-0.91), P: 0.0034^	0.85(0.69-1.04), P: 0.1121	0.49(0.3-0.79), P: 0.0039^	0.72(0.32-1.61), P: 0.4198
AGE				
<40 years	ref	ref	ref	ref
>80 years	0.53(0.43-0.65), P: <0.0001^	0.49(0.39-0.62), P: <0.0001^	0.67(0.4-1.13), P: 0.1347	0.78(0.24-2.51), P: 0.6718
40-50 years	0.67(0.55-0.81), P: <0.0001^	0.57(0.45-0.73), P: <0.0001^	0.85(0.58-1.22), P: 0.3723	1.32(0.48-3.67), P: 0.5919
50-60 years	0.59(0.49-0.71), P: <0.0001^	0.55(0.44-0.7), P: <0.0001^	0.68(0.47-0.99), P: 0.0433^	0.46(0.15-1.4), P: 0.1699
60-70 years	0.67(0.56-0.81), P: <0.0001^	0.62(0.5-0.78), P: <0.0001^	0.78(0.53-1.15), P: 0.2063	0.92(0.33-2.57), P: 0.871
70-80 years	0.64(0.53-0.78), P: <0.0001^	0.58(0.46-0.72), P: <0.0001^	0.86(0.57-1.28), P: 0.4506	1.21(0.43-3.43), P: 0.7165
PDGN				
DIA	ref	ref	ref	ref
CIR	0.91(0.78-1.06), P: 0.2185	0.88(0.73-1.05), P: 0.1632	1.07(0.77-1.5), P: 0.6877	0.62(0.27-1.43), P: 0.2615
DIG	0.7(0.57-0.87), P: 0.0012^	0.7(0.55-0.9), P: 0.0053^	0.76(0.47-1.24), P: 0.2791	0.37(0.13-1.04), P: 0.0597
GEN	0.79(0.61-1.02), P: 0.0725	0.77(0.57-1.03), P: 0.0765	1.13(0.63-2.01), P: 0.6866	0.25(0.05-1.29), P: 0.0978
INJ	0.53(0.37-0.76), P: 0.0005^	0.47(0.31-0.71), P: 0.0003^	1.09(0.43-2.76), P: 0.8567	0.23(0.04-1.31), P: 0.0983
MUS	0.57(0.41-0.78), P: 0.0005^	0.5(0.35-0.72), P: 0.0002^	1.33(0.65-2.75), P: 0.4335	0.13(0.01-1.23), P: 0.0753
NEO	0.85(0.6-1.21), P: 0.374	0.75(0.5-1.14), P: 0.1778	1.34(0.6-2.97), P: 0.4748	0.91(0.18-4.7), P: 0.911
OTH	0.65(0.55-0.76), P: <0.0001^	0.6(0.5-0.72), P: <0.0001^	0.89(0.64-1.24), P: 0.5022	0.3(0.13-0.69), P: 0.0042^
RES	0.54(0.45-0.65), P: <0.0001^	0.56(0.46-0.69), P: <0.0001^	0.52(0.33-0.8), P: 0.0034^	0.23(0.08-0.65), P: 0.0051^
DSC				
HOME	ref	ref	ref	ref
FAC	1.41(1.25-1.59), P: <0.0001^	1.48(1.29-1.7), P: <0.0001^	1.12(0.84-1.5), P: 0.4488	1.86(0.97-3.57), P: 0.0627
HOSP	1.41(1.06-1.86), P: 0.0165^	1.47(1.08-2), P: 0.0132^	1.31(0.59-2.9), P: 0.51	1.46(0.3-7.1), P: 0.6383
OTH	1.27(1.08-1.51), P: 0.0047^	1.36(1.12-1.65), P: 0.002^	1.16(0.8-1.7), P: 0.4273	1.27(0.39-4.11), P: 0.6896
Gender				
Female	ref	ref	ref	ref
Male	0.83(0.75-0.91), P: <0.0001^	0.82(0.73-0.91), P: 0.0003^	0.85(0.69-1.06), P: 0.1506	1.18(0.69-1.99), P: 0.5467
HbA1C				
<7	ref	ref	ref	ref
7-8	0.78(0.69-0.88), P: <0.0001^	0.73(0.63-0.84), P: <0.0001^	1.03(0.76-1.4), P: 0.8319	1.01(0.51-2.02), P: 0.9695
>8	0.67(0.6-0.75), P: <0.0001^	0.69(0.6-0.78), P: <0.0001^	0.69(0.54-0.87), P: 0.002^	0.42(0.22-0.8), P: 0.0081^
MED				
INS	ref	ref	ref	ref
GLI	0.8(0.5-1.29), P: 0.3615	0.84(0.49-1.43), P: 0.5185	0.63(0.19-2.14), P: 0.4635	0.57(0.06-5.23), P: 0.6215
GLI-INS	0.35(0.05-2.78), P: 0.3238	0.47(0.06-3.86), P: 0.4833	-	0(0-0), P: 0.9998
GLI-PIO-INS	0.41(0.05-3.67), P: 0.4241	0.7(0.07-6.74), P: 0.7599	-	0(0-0), P: 0.9997
GLP	0.96(0.76-1.22), P: 0.7599	1.01(0.78-1.32), P: 0.9224	0.78(0.43-1.43), P: 0.423	0.75(0.23-2.47), P: 0.6304
GLP-INS	0.32(0.04-2.47), P: 0.2755	0.53(0.07-4.2), P: 0.547	-	-
GLP-PIO	0.12(0.01-1.18), P: 0.0694	0.11(0.01-1.37), P: 0.0864	-	-
GLP-PIO-INS	0.37(0.04-3.14), P: 0.3651	0.65(0.07-5.67), P: 0.6933	-	-
GLP-ROS	0.19(0.02-1.79), P: 0.1486	0.39(0.04-3.69), P: 0.4096	-	-
GLP-ROS-INS	0.35(0.04-2.95), P: 0.3373	0.61(0.07-5.32), P: 0.6556	-	-
GLY	0.73(0.55-0.96), P: 0.027^	0.76(0.56-1.04), P: 0.0849	0.71(0.36-1.43), P: 0.3434	0.5(0.06-4.48), P: 0.5365
GLY-INS	0.27(0.03-2.06), P: 0.2055	0.43(0.05-3.43), P: 0.4236	-	-
GLY-PIO	0.52(0.06-4.5), P: 0.5527	0.92(0.1-8.21), P: 0.9397	-	-
GLY-PIO-INS	0.34(0.04-3.03), P: 0.3313	0.62(0.07-5.72), P: 0.6705	-	-
GLY-ROS	0.19(0.02-2.01), P: 0.1694	0.25(0.02-3.11), P: 0.2834	-	-
GLY-ROS-INS	0.33(0.04-2.89), P: 0.3163	0.37(0.04-3.65), P: 0.3928	-	-
MET	0.9(0.72-1.13), P: 0.3551	0.96(0.74-1.24), P: 0.7429	0.67(0.39-1.16), P: 0.1526	1.31(0.44-3.95), P: 0.6256
MET-GLI	0.14(0.01-1.41), P: 0.0941	0.28(0.03-2.97), P: 0.2905	-	-
MET-GLI-INS	0.41(0.05-3.3), P: 0.4038	0.61(0.07-5.11), P: 0.6463	-	-
MET-GLP	0.33(0.04-2.57), P: 0.2877	0.56(0.07-4.6), P: 0.5905	-	-
MET-GLP-INS	0.23(0.03-1.8), P: 0.1617	0.38(0.05-3.15), P: 0.372	-	-
MET-GLP-PIO-INS	0.24(0.02-2.32), P: 0.2168	0.23(0.02-2.81), P: 0.249	-	-
MET-GLP-ROS	0.48(0.06-3.93), P: 0.4952	0.88(0.1-7.53), P: 0.9082	-	-
MET-GLY	0.23(0.03-1.78), P: 0.1571	0.37(0.05-3.07), P: 0.3599	-	-
MET-GLY-INS	0.22(0.03-1.76), P: 0.154	0.43(0.05-3.55), P: 0.4335	-	-
MET-GLY-ROS	0.2(0.02-1.96), P: 0.1675	0.3(0.03-3.21), P: 0.3201	-	-
MET-GLY-ROS-INS	0.41(0.05-3.59), P: 0.4193	0.77(0.08-7.21), P: 0.8212	-	-
MET-INS	0.27(0.04-2.09), P: 0.2122	0.4(0.05-3.14), P: 0.3811	-	-
MET-PIO	0.09(0.01-1.09), P: 0.0585	0.19(0.02-2.33), P: 0.1947	-	-
MET-PIO-INS	0.36(0.04-2.88), P: 0.3328	0.61(0.07-5.24), P: 0.6528	-	-
MET-ROS	0.46(0.06-3.78), P: 0.4721	0.97(0.11-8.22), P: 0.9791	-	-
MET-ROS-INS	0.42(0.05-3.36), P: 0.4121	0.64(0.08-5.43), P: 0.683	-	-
OTH	0.32(0.04-2.4), P: 0.2682	0.5(0.07-3.85), P: 0.5067	-	-
PIO	1.02(0.67-1.55), P: 0.9371	0.94(0.57-1.57), P: 0.8251	1.02(0.43-2.42), P: 0.9704	1.23(0.16-9.2), P: 0.8393
PIO-INS	0.4(0.05-3.06), P: 0.3748	0.61(0.08-4.88), P: 0.6383	-	-
REP	0.99(0.41-2.38), P: 0.986	0.81(0.28-2.33), P: 0.6941	0.86(0.1-7.23), P: 0.8879	6.66(0.52-85.05), P: 0.1445
REP-INS	0.4(0.05-3.2), P: 0.3859	0.6(0.07-5.1), P: 0.6435	-	-
ROS	0.93(0.58-1.5), P: 0.7674	1.13(0.67-1.92), P: 0.648	0.48(0.14-1.67), P: 0.2487	-
ROS-INS	0.31(0.04-2.45), P: 0.2693	0.47(0.06-3.81), P: 0.4781	-	-
NDG	0.91(0.89-0.94), P: <0.0001^	0.91(0.89-0.94), P: <0.0001^	0.92(0.87-0.97), P: 0.0021^	0.92(0.8-1.06), P: 0.2383
NEM	1.09(1.04-1.14), P: 0.0006^	1.07(1.02-1.13), P: 0.0102^	1.15(1.04-1.28), P: 0.0087^	1.05(0.76-1.45), P: 0.7672
NIP	1.23(1.19-1.28), P: <0.0001^	1.23(1.19-1.28), P: <0.0001^	1.23(1.12-1.36), P: <0.0001^	1.31(1.03-1.65), P: 0.0251^
NLB	0.99(0.99-1), P: 0.0002^	1(0.99-1), P: 0.0138^	0.99(0.98-1), P: 0.0012^	0.99(0.97-1), P: 0.0942

NMD	1(0.99-1.01), P: 0.7948	1(0.99-1.01), P: 0.7067	1.01(0.99-1.03), P: 0.57	1.01(0.96-1.06), P: 0.7926
NOU	0.94(0.9-0.98), P: 0.0075^	0.95(0.91-1), P: 0.0323^	0.89(0.77-1.04), P: 0.1491	0.9(0.68-1.21), P: 0.4959
NPR	1.03(0.99-1.06), P: 0.1047	1.01(0.97-1.05), P: 0.6192	1.09(1.01-1.17), P: 0.0338^	1.21(1-1.46), P: 0.0554
TIH	1.01(0.99-1.03), P: 0.5364	1.01(0.98-1.03), P: 0.5545	1(0.96-1.04), P: 0.9309	0.98(0.88-1.1), P: 0.7457
Therapy				
mono	ref	ref		
combo	2.63(0.35-19.84), P: 0.3488	1.73(0.22-13.49), P: 0.6002	-	-
RACE				
non-BIPOC	ref			-
AA-BIPOC	0.78(0.69-0.89), P: 0.0001^	-	-	-
BIPOC	0.78(0.61-1), P: 0.0507	-	-	-

Table 3: Predictors of 30-days unplanned readmission for patients of different cultural backgrounds (^: significant at 95% confidence level, CI: confidence interval)

The accuracy of prediction of the probability of the 30-days URA for the various cultural groups has been captured in Figure 3 which showed patients with BIPOC backgrounds were predicted with the highest accuracy {acc: 90.75%, AUC: 76%, BSL: 7.57%} while non-BIPOC patients have the least accuracy {acc: 89.07%, AUC: 64%, BSL: 9.47%}.

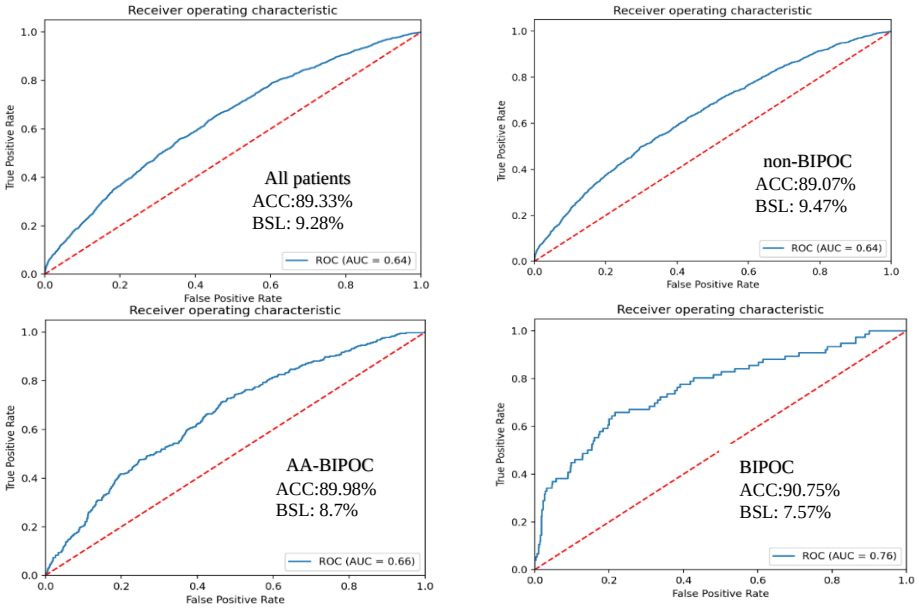

Figure 3: Prediction accuracy of multivariate Logistic regression model used for predicting the risk factors of 30-days unplanned readmission, BSL: brier score loss, acc: accuracy, AUC: area under the curve

Discussions

This study relies on the ADR paradigm to identify the artifacts that relate to 30-days URA of comorbid patients with diabetes treated with either mono or combo therapy that includes INS, MET, GLY, GLI, GLP, ROS, ROS, PIO, MET-GLY, and the combinations of the various medications. By gaining insights from the secondary data of patients from different cultural backgrounds treated for primary diagnosis based on ICD-9 coding using KDD, the risk factors and their severities were identified. The risk factors such as age, comorbidities (DIG, INJ, MUS, NEO), DSC, HbA1C, race (AA-BIPOC) are similar to some of the findings by previous researchers (Robbins et al. 2019, Collin et al. 2017, Rie et al. 2015). However, medications (except GLY- 0.73(0.55-0.96), P: 0.027) are not risk factors at 95% confidence level since the p-values are >0.05. Even at this, other researchers such as Png et al. (2017) attributed diabetes-related medication adherence to late URA, which occurs between 31 and 180 days.

The significance of this study on diabetes management cannot be overemphasized seeing that the knowledge of the risk factors has a far-reaching implication for effective clinical practice, which can reduce the practice variation that is inherent across many healthcare settings (Atsma et al. 2020). Even though the ability of clinicians to draw inference from previous experiences and that of others in managing health conditions is vital for reflective practice (Mantzourani et al. 2019), the combination of this approach with the pre-knowledge of the risk factors will enhance patients' outcomes.

The patients who have African American background are shown to be at risk of 30-days URA. Unfortunately, African Americans also have a very high rate of diabetes-related morbidity (Cunningham et al. 2018), which is one of the risk attributes of patients who have 30-days URA (Bianco et al. 2012, Van der Does et al. 2020). Again, the HbA1C of patients with a reading of <7% is not very different from those whose readings are 7-8% and >8%.

Previous studies have also linked increased mortality of patients with diabetes to the increasing levels of HbA1C (Forbes et al. 2018). HbA1C abnormality is also linked to comorbidities such as microvascular diseases, peripheral arterial disease, cardiovascular diseases, and chronic kidney disease (Li et al. 2020, Kang et al. 2015, Yang et al. 2020, Muntner et al. 2005, Saba et al. 2013). Thus, despite the low-risk level (as indicated by the RR) of HbA1C for all the patients {7-8%: 0.78(0.69-0.88), P: <0.0001; >8%: 0.67(0.6-0.75), P: <0.0001}, it is important that intensive glycaemic normalization and glucose variability controls are targeted in diabetes treatment to ensure optimal clinical outcome (Yang et al. 2020) that will forestall 30-days URA.

Some of the limitations of this study are the small populations of some of the sub-classes of the predictors used. This caused the MLR not to have results for the risk severity of some of the predictors because of the infinite values obtained following the few or no 30-days URA associated with such features. This calls for bigger data that will be able to capture the 30-days URA status of patients in a reasonable size for the various classes of predictors considered. It may also be necessary to reduce some of the sub-classes to a more manageable size to make it easier to interpret the results obtained from the analysis, an approach that may be suitable for the medications considered in this study. The need for considering late URA for patients who were readmitted after 30 days of discharge would have complimented this study seeing that understanding the risk factors of long-term URA will help to reduce the cost of healthcare despite the cogent need for minimizing early URA before 30 days of discharge. Finally, lumping the comorbidities in broader classes such as CIR conditions makes it difficult to figure out the real impacts of most comorbidities on 30-days URA. This makes it imperative to narrow the study down to unique comorbidities such as stroke, hypertension, heart failure, dementia, etc.

Conclusions

This study relied on ADR to develop a strategy for identifying the artifacts associated with the risk of 30-days URA for comorbid patients of diabetes treated with mono and combo therapies that include INS, MET, GLY, GLI, GLP, ROS, ROS, PIO, MET-GLY, MET-PIO-INS, and their combinations. Hence, the formulation of a strategy that hinged on the KDD for identifying the risk factors and their severities for patients from diverse cultural backgrounds such as non-BIPOC, BIPOC, and AA-BIPOC to understand how the various predictors considered in the study contribute to an early URA 30 days after hospital discharge. Following the reflection and learning obtained from the problem formulation stage of the ADR, and the building, intervention, and evaluation of the secondary data from patients' records, it was possible to formulate a creative solution that identified the risk factors and their severities for all the patients and those from the Caucasian background (non-BIPOC), African American race (AA-BIPOC) and other races that are neither Caucasians nor African Americans (BIPOC).

It was found that patients from AA-BIPOC backgrounds are most prone to 30-days URA when compared to other cultural backgrounds even though the rate of 30-days URA for all races is within a 2% difference from 9.63 – 10.98%. The risk of 30-days URA for all the patients is highest with patients who are discharged to other facilities (DSC- FAC) and hospitals (DSC-HOSP). For non-BIPOC patients, the highest risk factor is associated with DSC-FAC while NIP is the highest risk factor for patients of AA-BIPOC and BIPOC backgrounds. The risk associated with HbA1C levels are low (RR of <1), however, the potentials of uncontrollable blood sugar levels triggering a major health crisis for patients with diabetes cannot be overemphasized, thus the need for intensive glycaemic normalization and glucose variability controls to ensure optimal clinical outcomes for comorbid patients with diabetes.

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