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Substance use and mental diagnoses among adults with and without type 2 diabetes: Results from electronic health records data

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ABSTRACT

Background: Comorbid diabetes and substance use diagnoses (SUD) represent a hazardous combination, both in terms of healthcare cost and morbidity. To date, there is limited information about the association of SUD and related mental disorders with type 2 diabetes mellitus (T2DM).
Methods: We examined the associations between T2DM and multiple psychiatric diagnosis categories, with a focus on SUD and related psychiatric comorbidities among adults with T2DM. We analyzed electronic health record (EHR) data on 170,853 unique adults aged ≥18 years from the EHR warehouse of a large academic healthcare system. Logistic regression analyses were conducted to estimate the strength of an association for comorbidities.
Results: Overall, 9% of adults (n = 16,243) had T2DM. Blacks, Hispanics, Asians, and Native Americans had greater odds of having T2DM than whites. All 10 psychiatric diagnosis categories were more prevalent among adults with T2DM than among those without T2DM. Prevalent diagnoses among adults with T2MD were mood (21.22%), SUD (17.02%: tobacco 13.25%, alcohol 4.00%, drugs 4.22%), and anxiety diagnoses (13.98%). Among adults with T2DM, SUD was positively associated with mood, anxiety, personality, somatic, and schizophrenia diagnoses.
Conclusions: We examined a large diverse sample of individuals and found clinical evidence of SUD and psychiatric comorbidities among adults with T2DM. These results highlight the need to identify feasible collaborative care models for adults with T2DM and SUD related psychiatric comorbidities, particularly in primary care settings, that will improve behavioral health and reduce health risk.

1. Introduction

The prevalence of diagnosed diabetes among United States (U.S.) adults aged ≥18 years increased steadily from 3.5% in 1980 to 9.0% in 2011 (CDC, 2014a). Currently, an estimated 29.1 million Americans have diabetes (ADA, 2015). Type 2 diabetes mellitus (T2DM) accounts for 90–95% of individuals with diabetes (ADA, 2014). In the U.S., individuals with diagnosed diabetes have, on average, medical expenditures 2.3 times higher than those without diabetes (ADA, 2013). The total estimated cost of diagnosed diabetes (type 1 or 2) was $245 billion in 2012 (a 41% increase from a prior estimate in 2007), which included $176 billion in direct medical costs and $69 billion in increased absenteeism and reduced productivity (ADA, 2013). The economic burden is expected to escalate as the prevalence of T2DM continues to rise. Increasing costs will be particularly driven by adults with multiple chronic conditions, including substance use disorders (SUDs; Ashman et al., 2014; Jiang et al., 2014). Having diabetes plus SUD (and/or other psychiatric disorders) represents a hazardous combination, both in terms of healthcare cost and morbidity. SUD and

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mental health comorbidity can compromise patients' adherence to treatment for T2DM, exacerbate existing medical conditions, and heighten the risk for premature mortality among individuals with diabetes (Ducat et al., 2014; Ghitza et al., 2013; Vinogradova et al., 2010). Notably, inpatient care constitutes the major part of medical expenditures for diabetes (ADA, 2013). In the nonelderly Medicaid population (<65 years), individuals with either a diabetes diagnosis with complications, SUD, or a mental disorder (mood, schizophrenia, psychotic) use more inpatient care than patients without such diagnoses (Jiang et al., 2014). Diabetes, SUD, and mental diagnoses also are among the leading medical conditions associated with elevated 30-day hospital readmission rates (Jiang and Wier, 2010).

The fact that some antipsychotics and antidepressants may induce metabolic side effects or significant weight gain is one reason for the co-comorbidity of mood/anxiety disorders and schizophrenia with T2DM (De Hert et al., 2009; Nielsen et al., 2010; Sharma et al., 2014). However, there are limited data about SUD and mental diagnoses other than mood/anxiety and schizophrenia diagnoses among adults with T2DM. Self-reported diabetes data from community sample surveys are limited by a non-specific question about diabetic history, which may not be equivalent to patients in real-world clinical settings who have medical documentation of a diabetic diagnosis. Specifically, cigarette smoking is associated with T2DM in a dose-dependent manner, and it constitutes a risk factor for diabetes-related complications and premature mortality for many diseases (cardiovascular, pulmonary conditions; Ghitza et al., 2013; Willi et al., 2007). Therefore, quantifying the prevalence of nicotine dependence is critical for people with diabetes (Willi et al., 2007). Survey data from the Behavioral Risk Factor Surveillance System estimated that 15.4% of adults aged ≥18 years with self-reported diabetes ("Have you ever been told by a doctor that you have diabetes?") were current cigarette smokers (Fan et al., 2013); however, the extent of tobacco use disorder among adults with T2DM is unclear.

Similarly, data is lacking on the prevalence of alcohol and (illicit) drug use disorders in medical settings to inform SUD screening and treatment for adults with T2DM (Ghitza et al., 2013). While low-to-moderate alcohol use is associated with decreased odds of having T2DM, binge or heavy alcohol use increases the risk of T2DM (Baliunas et al., 2009; Pietraszek et al., 2010), demonstrating the need to identify and treat alcohol use diagnoses among individuals with diabetes. A prior study of 65,996 adults with diabetes who received care through Kaiser Permanente Northern California and responded to a survey of alcohol use indicated that 51% of adults with diabetes reported current alcohol use (Ahmed et al., 2006). A greater number of drinks per day were associated with a decreased probability of complying with diabetes care. Another study of male outpatients with diabetes ($n = 3930$) from 7 Veterans Affairs sites suggested that 13% of adults with diabetes had alcohol use problems (Alcohol Use Disorders Identification Test-Consumption [AUDIT-C] score ≥4) and that higher AUDIT-C scores were associated with poorer diabetes self-care (Thomas et al., 2006). Both studies of adults with diabetes in medical settings indicate that problematic or frequent alcohol use can impair diabetes self-care behaviors, yet alcohol use diagnosis data were not available (Ahmed et al., 2006; Thomas et al., 2006). Chronic misuse of illicit or nonmedical psychoactive drugs may also increase psychiatric problems, worsen medical sequelae of diabetes, or complicate diabetes self-care (Brick, 2004; Leung et al., 2011a,b; Volkow et al., 2014). Reliable estimates of drug use disorders by T2DM status are lacking, but are needed to inform targeted screening and interventions.

Taken together, the heavy economic burden associated with diabetes is disproportionally influenced by individuals with comorbid diabetes and SUD disorders, particularly those with both SUD and mental disorders (ADA, 2013; Ghitza et al., 2013; Jiang et al., 2014). Given the lack of information on patterns of comorbidity, we leveraged data from an electronic health record (EHR) warehouse to determine the extent of SUD and related psychiatric comorbidities by T2DM status. Since <1% of young people aged <20 years have diagnosed diabetes (CDC, 2014b), we focused on T2DM in adults. We examined the prevalence of T2DM and determined associations of psychiatric diagnoses (alcohol, tobacco, drug, schizophrenia/psychotic, mood, anxiety, personality, somatic, and disruptive behavioral disorder diagnoses) with T2DM status. Among adults with T2DM, we examined associations of SUD with mental diagnoses, in order to gauge multi-comorbidity. To control for age-related increases in medical problems, we stratified the analyses by age group.

2. Methods

2.1. Data sources

We analyzed the EHR data of unique adults aged ≥18 years from the Duke Medicine Enterprise Data Warehouse (EDW) between January 1, 2007 and December 31, 2011 (i.e., patients were ≥18 years as of January 1, 2007). The primary group of interest was comprised of patients with a T2DM diagnosis ($n = 16,243$); this group was compared with patients without T2DM ($n = 154,610$). Patients aged ≥18 years with type 1 diabetes (ICD-9-CM diagnosis codes) were excluded from the analysis ($n = 2650$), resulting in a sample of 170,853 patients. Briefly, the EHR dataset for this analysis was identified and developed for the Durham Diabetes Coalition project, which leverages EHR data to inform community-based interventions that seek to improve population-level diabetes management, health outcomes, and quality of life for adults living with T2DM in Durham County (Spratt et al., 2015). A geographic health information system was employed to link the EHR and patients' social and environmental data in order to provide a multidimensional understanding of environmental contexts and vulnerabilities for adults living with T2DM in Durham, North Carolina, and to develop tailored community-based interventions. An estimated 80% of Durham County residents received care from a Duke Medicine provider at some point during the interval of 2007–2011. Durham County is located in the Central Piedmont region of North Carolina. Compared with the overall U.S. population, Durham County has a higher proportion of the "Black/African American alone" population (13.2% vs. 38.7%) and lower proportions of the "White alone" (77.7% vs. 53.1%) and "Hispanic/Latino" populations (17.1% vs. 13.5%) (U.S. Census Bureau, 2015).

2.2. Study variables

Demographic variables included age (as of January 1, 2007), sex, patient-identified race (White or Caucasian, American Indian or Alaska Native, Asian, Black or African American, multiracial, Native Hawaiian or Pacific Islander, other, declined, or unavailable), and patient-identified ethnicity (Hispanic or non-Hispanic). Diagnostic variables were based on ICD-9-CM codes (CMS, 2008). Common conditions that tend to be associated with diabetes, including chronic obstructive pulmonary disease (COPD), hypertensive disease, ischemic heart disease, and renal disease (nephritis, nephrotic syndrome, nephrosis), were included as control variables for the analysis of comorbidity (Heron, 2013). We also controlled for the overall number of healthcare encounters (outpatient, inpatient, emergency department) during 2007–2011 to mitigate the confounding effects of healthcare utilization, since those who use healthcare frequently may have an increased diagnostic probability (Jiang and Wier, 2010).

We used the published crosswalk of Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision (DSM-IV-TR) codes to ICD-9-CM codes from the American Psychological Association (APA) Practice Organization to define psychiatric diagnoses that are consistent with DSM-IV-TR categories (APA, 2002). The crosswalk lists each specific ICD-9-CM diagnosis code corresponding to a DSM-IV-TR diagnosis code. Psychiatric disorder diagnoses included alcohol use, tobacco use, drug use (cannabis, amphetamines, cocaine, hallucinogens, inhalants, opioids, phencyclidine, sedatives, hypnotics, or anxiolytics), schizophrenia or psychotic mood (major depressive, bipolar, manic, manic-depressive), anxiety (panic, generalized anxiety, phobia, obsessive-compulsive, posttraumatic stress), personality (paranoid, affective, chronic hypomanic, chronic depressive, schizoid, introverted, schizotypal, explosive, compulsive, histrionic, dependent, antisocial, narcissistic, avoidant, borderline, passive-aggressive), somatic (somatization, conversion, hypochondriasis, psychogenic pain-site unspecified), and disruptive behavioral disorder (conduct, impulse-control) diagnoses (APA, 2002). A patient was considered to have a given diagnosis if an ICD-9-CM code for that condition was found in the list of discharge or final diagnosis codes for any type of encounter (inpatient, outpatient) at least once during 2007–2011.

Table 1
Characteristics of adults aged 18 or older by T2DM.[a]

Variables	Overall $n = 170,853$	With T2DM $n = 16,243$	Without T2DM $n = 154,610$	Adjusted OR of T2DM (95% CI)
Age (overall)[b]				1.22 (1.20, 1.23)
Mean (SD)	41.6 (17.4)	56.6 (15.6)	40.0 (16.8)	
	%[c]	%[d]	%[d]	
Age groups, years				
18–35	76,297 (44.7%)	1586 (2.1%)	74,711 (97.9%)	1.00
36–50	44,514 (26.1%)	4016 (9.0%)	40,498 (91.0%)	2.24 (2.10, 2.39)
51–64	30,441 (17.8%)	5638 (18.5%)	24,803 (81.5%)	3.41 (3.19, 3.64)
65 and older	19,601 (11.5%)	5003 (25.5%)	14,598 (74.5%)	3.23 (3.01, 3.47)
Sex				
Female	98,178 (57.5%)	9130 (9.3%)	89,048 (90.7%)	1.00
Male	72,591 (42.5%)	7113 (9.8%)	65,478 (90.2%)	1.24 (1.20, 1.29)
Unknown	83 (0.0%)	0 (0.0%)	83 (100.0%)	
Race				
Alaskan Native or American Indian	587 (0.3%)	51 (8.7%)	536 (91.3%)	2.43 (1.75, 3.37)
Asian	6115 (3.6%)	269 (4.4%)	5846 (95.6%)	1.50 (1.31, 1.73)
Black or African American	59,552 (34.9%)	8705 (14.6%)	50,847 (85.4%)	2.07 (1.98, 2.15)
Multiracial	1179 (0.7%)	75 (6.4%)	1104 (93.6%)	2.12 (1.63, 2.76)
Others/unknown	21,553 (12.6%)	870 (4.0%)	20,683 (96.0%)	1.56 (1.41, 1.73)
White or Caucasian	81,867 (47.9%)	6273 (7.7%)	75,594 (92.3%)	1.00
Ethnicity				
Hispanic	11,503 (6.7%)	545 (4.7%)	10,958 (95.3%)	1.62 (1.43, 1.84)
Non-Hispanic	159,350 (93.3%)	15,698 (9.9%)	143,652 (90.1%)	1.00
Medical diagnosis, yes				
COPD	16,120 (9.4%)	3472 (21.5%)	12,648 (78.5%)	1.17 (1.11, 1.22)
Hypertensive disease	46,496 (27.2%)	13,365 (28.7%)	33,131 (71.3%)	6.94 (6.59, 7.31)
Ischemic heart disease	10,108 (5.9%)	3908 (38.7%)	6200 (61.3%)	1.51 (1.43, 1.59)
Renal disease[e]	8657 (5.1%)	3612 (41.7%)	5045 (58.3%)	1.58 (1.50, 1.67)
Log base 10 of the number of encounters[f]				
Median (25th, 75th)	8.0 (3.0, 24.0)	28.0 (11.0, 56.0)	7.0 (2.0, 20.0)	1.86 (1.79, 1.93)

Note. All ORs, with the exception of those for the age group variable, were derived from this logistic model: T2DM as predicted by continuous age, sex, race, ethnicity, individual comorbidities, and log base 10 of the number of patient encounters. A separate model used to calculate ORs for the age group variable was the same as above, with the exception that age group was substituted for continuous age.
Abbreviations: CI, confidence interval; COPD, chronic obstructive pulmonary disease; OR, odds ratio; SD, standard deviation; T2DM, type 2 diabetes mellitus.
[a] Population excludes patients who have type 1 diabetes.
[b] Reference for computation of OR is 10-year increase in age.
[c] Proportions are within the column.
[d] Proportions are across rows.
[e] Renal disease: nephritis, nephrotic syndrome, or nephrosis.
[f] Base 10 log transformation was applied to the number of healthcare encounters due to skewness.

2.3. Statistical analysis

We examined frequencies for study variables by T2DM status and used logistic regression analyses to determine associations of demographics, medical variables, number of healthcare encounters, and inpatient treatment with T2DM status. We then examined the prevalence of psychiatric diagnoses by T2DM status. To control for age difference in health status, we stratified the analysis by age group. We conducted logistic regression analyses to determine associations of each psychiatric diagnosis with T2DM, adjusting for age, sex, race, ethnicity, and number of healthcare encounters. Finally, among patients with T2DM, we conducted logistic regression analyses to determine the association of SUD with psychiatric diagnoses, adjusting for age, sex, race, ethnicity, COPD, hypertensive disease, ischemic heart disease, renal disease, and number of healthcare encounters. We report 95% confidence intervals (CIs) for prevalence and adjusted odds ratio (OR) estimates. All analyses were performed using SAS® software, version 9.2 (SAS Institute, Inc., Cary, NC).

3. Results

3.1. Demographics

Of 170,853 adults aged 18–90 years, 57.5% were female, 11.5% were older (aged 65–90 years), 34.9% were black, and 6.7% were Hispanic.

3.2. Factors associated with T2DM (Table 1)

Overall, 9% ($n = 16,243$) of the sample had T2DM. Prevalence of T2DM increased with age strata (18.5%, aged 51–64; 25.5%, aged 65–90 years), was higher in men (9.8% vs. 9.3% in women) and black adults (14.6% vs. 7.7% in whites), and was elevated among adults with COPD (21.5%), hypertensive disease (28.7%), ischemic heart disease (38.7%), and renal disease (41.7%).

In the adjusted logistic regression model—which included age, sex, race, ethnicity, COPD, hypertensive disease, ischemic heart disease, renal disease, and number of encounters—all nonwhite groups had greater odds than whites of having T2DM; each medical diagnosis and number of encounters were associated with increased odds of having T2DM.

3.3. Prevalence of psychiatric diagnoses by T2DM (Table 2)

In the overall sample ($n = 170,853$), all of the psychiatric diagnosis categories examined were more prevalent among adults with T2DM than among those without (Fig. 1). Overall, 37.36% of adults with T2DM had a psychiatric diagnosis compared with 18.93%

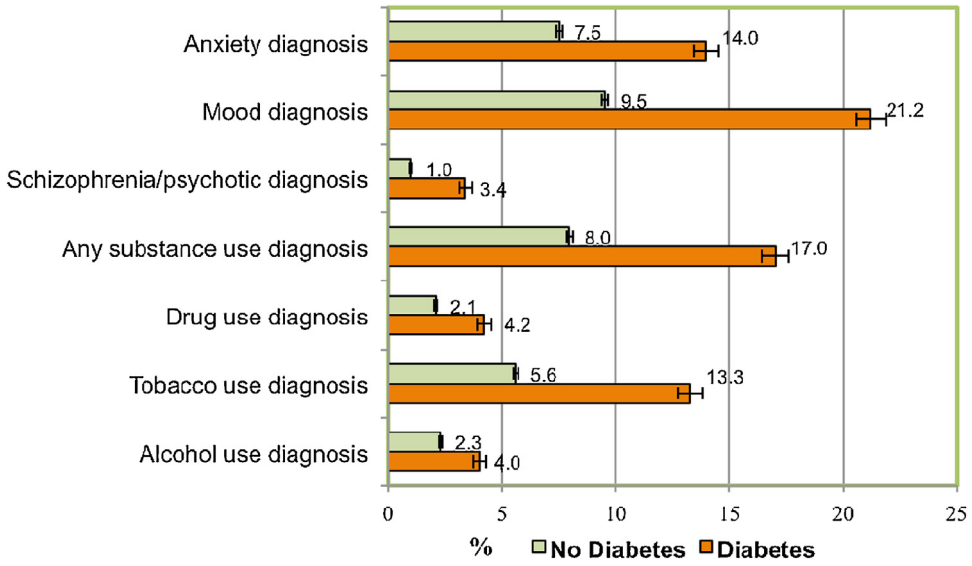

Fig. 1. Prevalence of psychiatric conditions. This figure displays the prevalence of psychiatric conditions among adults aged 18 or older, by T2DM (percent and 95% CI). *Abbreviations*: CI, confidence interval; T2DM, type 2 diabetes.

of adults without T2DM. Prevalent diagnoses among adults with T2DM were mood (21.22%), SUD (any SUD 17.02%: tobacco 13.25%, alcohol 4.00%, illicit drugs 4.22%), and anxiety diagnoses (13.98%), followed by schizophrenia/psychotic (3.38%) and other psychiatric diagnoses (<1%).

3.4. Adjusted OR of psychiatric diagnoses by T2DM (Table 3)

We conducted an adjusted logistic regression analysis to determine the strength of the association between T2DM and each psychiatric diagnosis, while controlling for age, sex, race, ethnicity, and number of encounters. Except for alcohol use and somatic diagnoses, T2DM was associated with elevated odds of having each of the other psychiatric categories in the overall sample (n = 170,853). We also stratified the analysis by age, and a similar pattern was observed across age groups. Additionally, T2DM was associated with elevated odds of having alcohol use disorder in the 18–35 age group.

3.5. Adjusted OR of comorbid SUD and psychiatric diagnoses among adults with T2DM (Table 4)

Finally, we conducted adjusted logistic regression analyses of adults with T2DM (n = 16,243) to determine the strength of

Table 2
Prevalence of psychiatric conditions by T2DM (percent and 95% CI).

Psychiatric diagnosis, prevalence	T2DM	% (95% CI)				
		Overall	Aged 18–35	Aged 36–50	Aged 51–64	Aged 65 and older
Alcohol	Yes	4.00 (3.70–4.31)	3.66 (2.79–4.70)	5.85 (5.15–6.62)	4.35 (3.83–4.91)	2.22 (1.83–2.67)
	No	2.27 (2.20–2.35)	1.57 (1.48–1.66)	3.18 (3.01–3.36)	3.18 (2.96–3.40)	1.83 (1.62–2.06)
Tobacco	Yes	13.25 (12.74–13.79)	11.35 (9.83–13.01)	17.43 (16.27–18.64)	15.36 (14.43–16.33)	8.14 (7.39–8.93)
	No	5.58 (5.47–5.70)	3.21 (3.08–3.34)	7.67 (7.41–7.93)	8.97 (8.62–9.33)	6.19 (5.81–6.60)
Drugs	Yes	4.22 (3.91–4.54)	5.93 (4.82–7.20)	6.60 (5.85–7.41)	3.57 (3.10–4.08)	2.50 (2.08–2.97)
	No	2.07 (2.00–2.14)	1.80 (1.71–1.90)	2.98 (2.81–3.15)	1.73 (1.57–1.90)	1.47 (1.28–1.68)
Any substance	Yes	17.02 (16.44–17.60)	16.14 (14.36–18.05)	21.74 (20.47–23.05)	18.84 (17.82–19.88)	11.45 (10.58–12.37)
	No	7.96 (7.83–8.10)	5.41 (5.25–5.58)	10.53 (10.24–10.84)	11.19 (10.80–11.59)	8.38 (7.93–8.84)
Schizophrenia or psychotic	Yes	3.38 (3.11–3.67)	3.97 (3.07–5.05)	3.49 (2.94–4.10)	2.66 (2.26–3.11)	3.92 (3.40–4.49)
	No	0.98 (0.93–1.03)	0.65 (0.59–0.71)	0.97 (0.87–1.07)	1.15 (1.02–1.29)	2.44 (2.19–2.70)
Mood	Yes	21.22 (20.59–21.86)	19.67 (17.74–21.72)	22.61 (21.32–23.94)	22.24 (21.16–23.35)	19.45 (18.36–20.57)
	No	9.55 (9.40–9.69)	6.41 (6.24–6.59)	11.29 (10.98–11.60)	12.93 (12.51–13.35)	15.00 (14.43–15.59)
Anxiety	Yes	13.98 (13.45–14.52)	11.79 (10.24–13.48)	14.64 (13.56–15.77)	14.37 (13.46–15.31)	13.71 (12.77–14.70)
	No	7.53 (7.39–7.66)	5.64 (5.47–5.81)	8.44 (8.17–8.71)	9.74 (9.38–10.12)	10.88 (10.38–11.39)
Personality	Yes	0.91 (0.77–1.07)	1.70 (1.12–2.47)	1.54 (1.19–1.97)	0.71 (0.51–0.96)	0.38 (0.23–0.59)
	No	0.36 (0.33–0.39)	0.34 (0.30–0.38)	0.47 (0.41–0.55)	0.30 (0.23–0.37)	0.27 (0.19–0.37)
Somatic	Yes	0.44 (0.34–0.55)	0.76 (0.39–1.32)	0.72 (0.48–1.04)	0.39 (0.24–0.59)	0.16 (0.07–0.31)
	No	0.18 (0.16–0.20)	0.11 (0.09–0.14)	0.23 (0.19–0.29)	0.24 (0.18–0.31)	0.21 (0.14–0.30)
Disruptive behavioral	Yes	0.16 (0.10–0.23)	0.50 (0.22–0.99)	0.27 (0.14–0.49)	0.11 (0.04–0.23)	0.02 (0.00–0.11)
	No	0.06 (0.05–0.07)	0.07 (0.05–0.09)	0.07 (0.05–0.11)	0.04 (0.02–0.07)	0
None of the above	Yes	62.64 (61.89–63.38)	66.08 (63.69–68.41)	60.13 (58.60–61.65)	60.77 (59.48–62.04)	65.66 (64.33–66.98)
	No	81.07 (80.88–81.27)	86.57 (86.32–86.81)	77.80 (77.39–78.20)	74.75 (74.20–75.29)	72.79 (72.06–73.51)

Note. Due to small patient counts in several cells, all reported confidence intervals are exact.
All abbreviations can be found in Table 1.

Table 3
Adjusted logistic regression analysis of psychiatric diagnosis in relation to T2DM.

Psychiatric diagnosis	Adjusted OR (95% CI)				
	Overall $n = 170,853$	Aged 18–35 $n = 76,297$	Aged 36–50 $n = 44,514$	Aged 51–64 $n = 30,441$	Aged 65 and older $n = 19,601$
Alcohol	1.041 (0.950–1.143)	**1.488 (1.124–1.970)**	1.110 (0.954–1.292)	0.923 (0.791–1.078)	0.906 (0.718–1.143)
Tobacco	**1.226 (1.160–1.296)**	**1.425 (1.199–1.694)**	**1.413 (1.283–1.555)**	**1.170 (1.069–1.280)**	1.041 (0.916–1.182)
Drugs	**1.217 (1.109–1.335)**	**1.375 (1.095–1.728)**	1.156 (0.999–1.338)	**1.272 (1.062–1.523)**	**1.445 (1.147–1.820)**
Any substance (alcohol, tobacco, or drugs)	**1.236 (1.176–1.299)**	**1.488 (1.284–1.724)**	**1.349 (1.236–1.472)**	**1.195 (1.099–1.298)**	**1.124 (1.007–1.254)**
Schizophrenia or psychotic	**1.673 (1.500–1.866)**	**2.731 (2.051–3.638)**	**1.993 (1.619–2.454)**	**1.603 (1.297–1.980)**	**1.498 (1.246–1.802)**
Mood	**1.364 (1.301–1.429)**	**1.607 (1.397–1.848)**	**1.465 (1.339–1.603)**	**1.429 (1.317–1.549)**	**1.238 (1.133–1.354)**
Anxiety	**1.127 (1.068–1.190)**	1.094 (0.925–1.293)	**1.186 (1.069–1.316)**	1.087 (0.990–1.194)	**1.126 (1.016–1.248)**
Personality	**1.780 (1.455–2.176)**	**2.057 (1.345–3.145)**	**1.838 (1.353–2.496)**	**1.959 (1.303–2.943)**	1.439 (0.815–2.540)
Somatic	1.070 (0.807–1.417)	1.827 (0.961–3.476)	1.280 (0.827–1.983)	0.885 (0.529–1.478)	0.607 (0.273–1.350)
Disruptive behavioral	**1.771 (1.094–2.869)**	**2.615 (1.170–5.845)**	1.465 (0.713–3.010)	1.449 (0.500–4.199)	–

Note. For all age category columns, the following model was used to calculate ORs and CIs: psychiatric condition as predicted by T2DM, continuous age, sex, race, ethnicity, and log base 10 of the number of patient encounters. The race variable in the model consists of these collapsed values: black, white, and other. For the overall column, the same model as above was used to calculate ORs and CIs, with the addition of stratification by age category. Bold face: $P < 0.05$
All abbreviations can be found in Table 1.

Table 4
Adjusted logistic regression model of psychiatric disorder in relation to substance use disorder diagnosis among adults with a T2DM[a] diagnosis.

Psychiatric diagnosis	Adjusted OR (95% CI)				
	Overall $n = 16,243$	Aged 18–35 $n = 1586$	Aged 36–50 $n = 4016$	Aged 51–64 $n = 5638$	Aged 65 and older $n = 5003$
Schizophrenia or psychotic	**2.975 (2.454–3.607)**	**3.774 (2.160–6.597)**	**2.735 (1.904–3.928)**	**4.496 (3.141–6.437)**	**1.993 (1.345–2.953)**
Mood	**2.229 (2.016–2.465)**	**2.546 (1.814–3.573)**	**3.052 (2.522–3.694)**	**2.084 (1.767–2.458)**	**1.638 (1.324–2.026)**
Anxiety	**1.857 (1.656–2.081)**	**1.977 (1.324–2.952)**	**1.960 (1.583–2.428)**	**1.638 (1.357–1.978)**	**1.974 (1.565–2.490)**
Personality	**3.649 (2.559–5.203)**	**7.836 (3.046–20.158)**	**3.726 (2.144–6.475)**	**2.571 (1.291–5.118)**	2.031 (0.707–5.835)
Somatic	**2.831 (1.707–4.694)**	**6.675 (1.666–26.750)**	**2.474 (1.134–5.400)**	2.141 (0.864–5.306)	2.542 (0.529–12.212)
Disruptive behavioral	**4.682 (2.033–10.782)**	3.915 (0.803–19.075)	**8.286 (2.097–32.739)**	2.888 (0.505–16.512)	–

Note. For all age category columns, the following model was used to calculate ORs and CIs: psychiatric condition as predicted by any substance use diagnosis, continuous age, sex, race, ethnicity, COPD, hypertensive disease, ischemic heart disease, renal disease, and log base 10 of the number of patient encounters. The race variable in the model consists of these collapsed values: black, white, and other. For the overall column, the same model as above was used to calculate ORs and CIs, with the addition of stratification by age category. All reported ORs are for the variable "any substance use diagnosis" (alcohol, tobacco, or drug use). Bold face: $P < 0.05$
All abbreviations can be found in Table 1.
[a] Analysis sample: patients had a T2DM diagnosis.

the association between SUD and each of the mental diagnoses, respectively, while controlling for age, sex, race, ethnicity, COPD, hypertensive disease, ischemic heart disease, renal disease, and number of encounters. An SUD diagnosis was positively associated with having schizophrenia/psychotic, mood, anxiety, personality, somatic, and disruptive behavioral diagnoses, respectively. A similar pattern was found when the analysis was stratified by age group.

4. Discussion

This analysis of EHR data from 170,853 adult patients provides important clinical evidence of the high prevalence of SUD and other psychiatric comorbidities in adults with T2DM. First, all non-white groups had higher odds of T2DM than whites. Second, all psychiatric diagnosis categories that we examined were found to be more prevalent among adults with T2DM than among those without T2DM; a similar pattern (except for somatic diagnosis) was identified by adjusted logistic regression analyses. Third, among adults with T2DM, SUD was positively associated with schizophrenia, mood, anxiety, personality, somatic, and disruptive behavioral disorders, respectively, indicating multi-comorbidity. These findings increase our understanding of the prevalence of SUD and related psychiatric comorbidities by T2DM status, and have implications for SUD, psychiatric screening, and the development of collaborative care models to improve health outcomes.

4.1. What this study adds to our knowledge

Prior research on mental health conditions in patients with diabetes has mainly focused on depression or anxiety, and used self-reported psychiatric and medical status derived from survey questions answered by the sampled participants (Roy and Lloyd, 2012; Smith et al., 2013). SUDs are among the leading conditions contributing to high rates of hospital readmissions (Jiang and Wier, 2010), but little is known about SUD prevalence and SUD-related comorbidity in adults with T2DM. Due to health care reform (e.g., the 2010 Affordable Care Act and the Mental Health Parity and Addiction Equity Act of 2008), SUD treatment services are considered an essential health benefit, and the development of integrated behavioral (especially SUDs) and physical care models to improve behavioral health care in primary care has become a priority (Tai and Volkow, 2013). The use of patients' medical records data from EHRs to aide data collection and monitor clinical outcomes is recognized as a fundamental element in practical clinical research for developing learning healthcare systems (IOM, 2010). The Health Information Technology for Economic and Clinical Health (HITECH) Act also promotes national adoption of the EHR in clinical care. Consequently, the EHR is a pivotal tool for facilitating the implementation of integrated SUD care and tracking clinical outcomes for both clinical and research purposes (Tai et al., 2012). The EHR captures a wide range of psychiatric diagnoses from a large and broad patient population. Our study analyzed EHR data from a large sample, in hopes of providing much-needed SUD and related psychiatric comorbidity data on patients in real-life medical settings to inform EHR-enabled research and clinical efforts related to screening and integrated care. The results of our study add new and comprehensive psychiatric profiles (e.g., SUDs, schizophrenia, personality, somatic diagnoses) for adults with and without T2DM in medical settings, which may not be captured by community surveys.

One critical finding concerns the high prevalence of any SUD (17.02%) among adults with T2DM compared with adults without T2DM (7.96%); there is a pervasive pattern in comorbid SUD with mental diagnoses. National survey data estimate that 12.9–13.6% of adults aged ≥18 had current nicotine dependence, and that 7.0% and 2.5% of adults had an alcohol and drug use disorder in the past year, respectively (SAMHSA, 2014). We found that 13.25%, 4.00%, and 4.22%, had a documented tobacco, alcohol, and drug use disorder diagnosis, respectively. Moreover, among adults with T2DM, more than 1 in 3 (37.36%) had a documented psychiatric diagnosis in their EHRs, and SUD was positively associated with each of the 6 mental diagnosis categories examined, highlighting a need to increase SUD research in individuals with T2DM and to improve their SUD care. The co-occurrences of SUD with mental disorders may be influenced by multiple pathways (e.g., self-medication, common risk factors, diathesis-stress) (Conway et al., 2006; Green, 2005; Ingram and Luxton, 2005). Importantly, our study adds new estimates by revealing a particularly burdensome SUD and psychiatric multi-comorbidity among adults with T2DM in medical settings, which may also be related to treatment factors, including selection bias (severity increasing treatment use and diagnoses; De Hert et al., 2009; Vinogradova et al., 2010).

Integrated healthcare models aimed at improving SUD care among adults with T2DM should also consider other psychiatric conditions, especially mood and anxiety diagnoses. Consistent with EHR data from individuals seeking care in behavioral healthcare clinics (Wu et al., 2013a,b), we found that mood (21.22%), SUD (17.02%), and anxiety (13.98%) diagnoses are the most common disorders in the sample. National survey data estimate that 19.54% of adults aged ≥18 have a mood disorder and 16.16% have an anxiety disorder in their lifetime (Kessler et al., 2005). Additionally, depression was nearly twice as common among adults with T2DM (19.1%, range 6.5–33%) compared with those without T2DM (10.7%, range 3.8–19.4%) (Roy and Lloyd, 2012). Another review found that 14% of adults with diabetes had a current anxiety disorder (Grigsby et al., 2002). The association between T2DM and mood/anxiety have been suggested to be multifactorial in nature, including lifestyle and treatment factors that are associated with depression or obesity (e.g., physical inactivity, use of some antidepressants or antipsychotics; Faith et al., 2011; Grundy et al., 2014; Patten et al., 2011; Ramaswamy et al., 2006) as well as diabetes-related stress (De Hert et al., 2009; Ducat et al., 2014). This study adds newer clinical evidence that reveals a high prevalence of SUDs and a pervasive pattern of SUD-psychiatric comorbidity among adults with T2DM. These results demonstrate a critical need to address the potential impact of mood/anxiety diagnosis on severity and treatment compliance for adults living with both T2DM and SUD (Ducat et al., 2014; Najt et al., 2011).

4.2. Limitations and strengths

Our study results should be interpreted within the following limitations. This analysis focuses on understanding the prevalence of SUD and mental diagnoses among patient with T2DM, and results reflect associations, not causality. Results are based on patients who accessed healthcare at one of the clinics/practices of a large academic healthcare system. Although the EHR data that we studied included diverse racial/ethnic groups in the communities, results are not completely generalizable to patients in different regions. The EHRs may tend to include severe or frequent treatment-seeking people, so those with T2DM, but without manifested medical conditions, might not be diagnosed. Nonetheless, disorders with objective diagnostic features like diabetes have a high level of EHR coding accuracy (Jordan et al., 2004; Pringle et al., 1995).

Similar to other medical conditions, underdiagnoses or misclassification of SUD and psychiatric diagnoses are possible (Banta and Montgomery, 2007; Menchetti et al., 2009; Rockett et al., 2003). Diagnoses in EHRs are based on actual treatment as part of usual care settings, which are determined by using the available information from medical histories and evaluations, patient reports, and interactions among providers, patients, and family members. Since it is not feasible to assess all diagnoses systematically, people with mild forms of a disorder or those who did not disclose symptoms might not be recognized. Detection of SUD and psychiatric disorders may be influenced by patient demographics, presentation of symptoms, treatment-seeking frequency, and clinicians' specialties (Docherty, 1997; Garland et al., 2005; Herran et al., 1999; Menchetti et al., 2009). Nevertheless, having a longstanding provider-patient relationship, using criteria for diagnoses, and using EHRs systematically (allowing reevaluation and monitoring of the problems) are important factors for improving diagnostic accuracy (Pringle et al., 1995; van Weel-Baumgarten et al., 2000; van Weel-Baumgarten and Lucassen, 2009). Overall, our results should be considered conservative estimates, particularly for SUDs, which may be underestimated due to perceived stigma and a lack of systematic screening in general medical settings (Tai et al., 2012).

Our examination of EHR data also has important strengths. Results reflect clinical patterns among patients in real-world general medical settings in the Southeastern United States. To our knowledge, our study includes the largest sample of patients ever examined for SUD and related psychiatric comorbidity by T2DM status in the United States. This large sample size allowed stratified analyses by age group to inform reliability of estimates. The Duke University Health System is among the pioneers developing EHRs for its clinics/practices. In 1968, Duke investigators began developing a working prototype of a general purpose electronic medical record (EMR) that eventually evolved into one of the first EMRs in the United States (Duke University, 2010). The long-term use of an EMR to enhance healthcare and the longitudinally captured EHRs may improve completeness of diagnostic and treatment data (Horvath et al., 2014; Pringle et al., 1995; Silfen, 2006; Silow-Carroll et al., 2012; Weiner et al., 2007).

4.3. Conclusion and clinical implications

The prevalence of T2DM in this study is consistent with the national estimate (ADA, 2015). We found that more than 1 in 3 adults with T2DM had a documented psychiatric diagnosis. Individuals that have diabetes with complications, SUD, or chronic mental diagnoses use more costly inpatient care than those without such diagnoses (Jiang and Wier, 2010; Jiang et al., 2014); these co-existences further aggravate morbidity and increase healthcare expenditures (Ducat et al., 2014; Vinogradova et al., 2010). The most costly 10% of the patient population in the United States accounted for 66% of total healthcare expenditures (Cohen, 2014). Therefore, the identified SUD-psychiatric comorbidities among adults with T2DM highlight a critical need to apply preventive services (e.g., screening, intervention) in primary care in order to enhance early detection and intervention for SUD and associated psychiatric problems. There is a tremendous demand for coordinated care models aimed at improving behavioral health and reducing avoidable hospitalizations for patients with multi-comorbidities (Katon et al., 2012). Research efforts are needed to identify effective approaches for screening substance misuse/SUD, implementing interventions, and coordinating referrals to SUD treatment and follow-ups for individuals with diabetes (Ghitza et al., 2013). There are limited data available to inform smoking cessation in people with diabetes. Given that tobacco use disorder was the most prevalent SUD in our sample, this finding reaffirms the need for clinical research to test tailored smoking cessation interventions for people with diabetes (Nagrebetsky et al., 2014). Collaborative care models have been

found to improve health outcomes for individuals with depression and diabetes, and this line of efforts should be expanded to also address SUD and related psychiatric comorbidity for people with diabetes (Huang et al., 2013).

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Contributors

Li-Tzy Wu originated research questions and wrote the drafts of the paper; Michael J. Pencina, Leoncio Flavio Rojas, Benjamin A. Goldstein, and Tony Schibler conducted data analyses; all authors contributed to designs, critical revisions, and interpretations of the findings to result in the final manuscript.

Conflicts of interest

The authors have no conflicts of interest to disclose.

Institutional review board approval

This work has been approved by the Duke University Health System Institutional Review Board.

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