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Association between DSM-5 and ICD-11 personality dimensional traits in a general medical cohort and readmission and mortality[☆]

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ABSTRACT

Background: Personality has long been studied as a factor associated with health outcomes. Investigations of large, generalizable clinical cohorts are limited by variations in personality diagnostic methodologies and difficulties with long-term follow-up.

Methods: Electronic health records of a cohort of patients admitted to a general hospital were characterized using a previously developed natural language processing tool for extracting DSM-5 and ICD-11 personality domains. We used Cox regression and Fine-Gray competing risk survival to analyze the relationships between these personality estimates, sociodemographic features, and risk of readmission and mortality.

Results: Among 12,274 patients, 2379 deaths occurred in the course of 61,761 patient-years at risk, with 19,985 admissions during follow-up. Detachment was the most common personality feature. Presence of disinhibition was independently associated with a higher mortality risk, while anankastic traits were associated with a lower mortality risk. Increased likelihood of readmission was predicted by detachment, while decreased likelihood of readmission was associated with disinhibition and psychoticism traits.

Conclusions: Personality features can be identified from electronic health records and are associated with readmission and mortality risk. Developing treatment strategies that target patients with higher personality symptom burden in specific dimensions could enable more efficient and focused interventions.

1. Introduction

Personality features are associated with multiple general health outcomes including morbidity, mortality, and service utilization [1]. Nevertheless, the extent to which particular aspects of personality relate to individual health outcomes remains uncertain [2,3], and little is known about the association between personality features and outcomes in medical illnesses [4].

In part, the paucity of data reflects challenges in personality assessment in the medical setting – there are no quick and reliable instruments, and results are difficult to interpret by non-psychiatrists [2]. Moreover, studying outcomes related to personality is complicated by the need for longer-term follow-up [5]. While patient cohorts can be ascertained and studied retrospectively, personality is rarely assessed in this context [6,7]. Characterization of personality features is impacted by factors such as clinical severity, expectation of response to treatment, or familiarity with particular personality diagnosis [8,9]. Therefore, new approaches may be required to investigate the contribution of personality traits to health outcomes at scale [10].

We have previously demonstrated the application of natural language processing (NLP) to electronic health records (EHR) to characterize neuropsychiatric features [11]. This approach allows access to a large corpus of clinical data and clinical observations that may not be reflected in coded diagnoses. In prior work, we applied these methods to characterize personality features in a psychiatric cohort [12]. Here, we use the same approach to study a non-psychiatric population, specifically individuals admitted to a general medical service.

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2. Materials and methods

2.1. Subjects

The cohort included a randomly sampled subset of individuals age 18 or older hospitalized on a general medical service between January 2011 and December 2015 who survived to discharge. Sociodemographic data included age, sex, race/ethnicity, and type of insurance. Discharge documentation was extracted for estimation of personality trait domains by NLP. Overall burden of illness was computed as Charlson Comorbidity Index using the Deyo method and including all diagnoses coded prior to the current admission [13]. Primary outcomes included time to readmission (at either of 2 large academic medical centers) and mortality following discharge. Mortality was identified by querying public death certificate data available from state vital records, complemented by Federal social security data, as in our prior work [14]. These EHR data were managed as an i2b2 datamart [15].

The Partners HealthCare Human Research Committee approved the study protocol. As no participant contact was required in this study based on secondary use of data arising from routine clinical care, the committee waived the requirement for informed consent as detailed by 45 CFR 46.116.

2.2. Generation of personality phenotypes

The personality phenotypes were generated using a previously published methodology to extract personality domains from electronic health records [12]. To briefly recapitulate the previous work, this method uses personality-specific transdiagnostic phenotypes extracted using a specially developed natural language processing (NLP) tool which itself is an extension of early work on transdiagnostic neuropsychiatric phenotyping [11]. The model is based on transfer expertise captured in a curated list of personality domain-specific clinical terms based on DSM-5 (section III) [16] and ICD-11 [2,17] into a lower dimensional representation of the comprehensive clinical lexicon learned through Latent Dirichlet allocation [18].

Both DSM-5 and ICD-11 systems assess personality disorders based on determining levels of functioning/impairment and stylistic traits organized in personality dimensions. These dimensions comprise Negative Affectivity, Detachment, Antagonism, Disinhibition, and Psychoticism in the DSM-5. The ICD-11 includes the same dimensions, except Psychoticism, and adds Anankastia (or obsessive-compulsive features) as a new dimension. DSM-5 and ICD-11 agree in the definition of overlapping dimensions [19]. Trait domain definitions, according to Skodol [20] and Tyrer et al. [2], are provided in Supplemental Table 1 along with examples of personality features that comprise these dimensions.

The DSM-5 and ICD-11 terms were expanded using the Personality Inventory for DSM-5 items [21], other personality trait studies [19,22–24], and a thesaurus [25] as previously described [12]. In parallel, we used Latent Dirichlet Allocation (LDA) to train a probabilistic topic model of clinical documentation [12]. LDA is a form of unsupervised machine learning which has proven useful in a range of clinical applications including transdiagnostic neuropsychiatric phenotyping [11,26,27]. LDA models documents as a probabilistic mixture of topics which are themselves probability distributions over the full clinical vocabulary [28]. Here, the expert-curated knowledge, in the form of seed words, is transferred into the learned topic model by matching a personality domain to the topic distribution under which the seed terms are, cumulatively, most probable [11,12]. For topic modeling, we used the R interface to a Gibbs sampler implementation of LDA (*topicmodels* v0.2), one of many widely used open source implementations of LDA licensed under free software licenses [29].

2.3. Study design and analysis

Recognizing that personality features might be less prevalent among a non-psychiatric population, we first examined distribution of scores. For all but the 'detached' dimension, as only a small proportion of individuals had nonzero scores, the personality scores were transformed into a binary indicator (i.e., presence/absence of at least one feature). As distribution of the 'detached' personality dimension approximated normality, it was not transformed.

All regression models were computed with adjustment for age, sex, race/ethnicity (coded as white/non-white), private vs. public/no insurance, age-adjusted Charlson Comorbidity Index, and ICD-9 diagnosis category coded by Healthcare Cost and Utilization Project (HCUP) level 1 category. ICD-9 was the clinical diagnostic system in use when care was administered and thus is relevant for patient level analysis, whereas ICD-11 has a more robust representation of personality traits and was therefore used for development of the seed lists.

Primary analysis examined all available admissions during the study period, allowing multiple admissions per patient, with results clustered by patient. For primary analysis of time to death following discharge, we utilized Cox regression. For analysis of time to hospital readmission, we utilized Fine-Gray competing risk survival [30–32] as a way to account for the competing risk of mortality with results censored at loss to follow-up or event. A sensitivity analysis paralleled the primary analysis, but the sample was limited to the index (i.e., first observed) admission for each individual. Sensitivity analysis also examined the effect of incorporating length of stay and calendar year of admission in survival models. Analyses utilized the *stcox* and *stcrreg* packages in Stata/SE 13.1 (Statacorp, College Station, TX).

3. Results

Characteristics of the full sample of 12,274 subjects are displayed in Table 1. A total of 2379 deaths occurred in the course of 61,761.13 patient-years at risk. All the subjects included in the cohort had a total of 19,985 admissions during follow-up.

Distribution of personality trait domains in the 5 most common clinical diagnostic categories is shown in Fig. 1; Supplemental Table 2 reports association between personality symptoms and sociodemographic and clinical features. Overall, detachment was the most common personality feature identified, followed by obsessive-compulsive features.

3.1. Personality and mortality risk

Mortality was greatest among individuals who were older, white

Table 1
Cohort characteristics at index admission.

Variables	N = 12,274
Age at admission (years, mean (SD))	61.33 (18.75)
Charlson Comorbidity Index (mean (SD))	5.19 (5.11)
Length of stay (mean (SD))	5.87 (6.96)
Sex (male, n (%))	6764 (55.11)
Private insurance (n (%))	4035 (32.87)
Race/ethnicity (n (%))	
White	9966 (81.20)
Black	844 (6.88)
Asian	236 (1.92)
Other/unknown	1228 (10.00)
Diagnosis at admission (n (%))	
Cardiovascular disease	1948 (15.87)
Respiratory disease	1723 (14.04)
Gastro-intestinal disease	1580 (12.87)
Substance use	1278 (10.41)
Injury/poisoning	1154 (9.40)
Other	4591 (37.41)

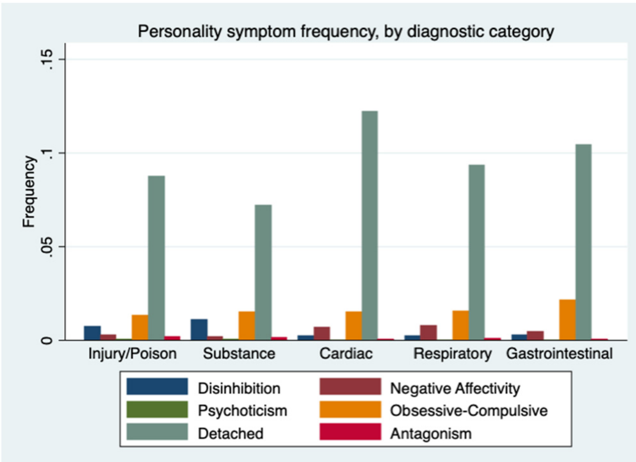

Fig. 1. Personality dimensional traits by the 5 most common medical diagnostic categories.
Detachment was the most common personality feature identified.

Table 2
Regression model of personality trait domains and mortality (n = 19,985 admissions)[a].

Variables	Model with personality trait domains	
	Hazard ratio (95% CI)	p-Value
Personality domain		
Disinhibition (binary)	1.217 (1.064–1.390)	**0.004**
Psychoticism (binary)	0.967 (0.562–1.664)	0.904
Negative Affectivity (binary)	1.017 (0.922–1.122)	0.735
Antagonism/ (binary)	0.903 (0.658–1.239)	0.528
Obsessive-compulsive (binary)	0.859 (0.802–0.920)	< **0.001**
Detachment (dimensional)	0.682 (0.202–1.536)	0.356
Sociodemographic features		
Age at admission	1.022 (1.019–1.026)	< **0.001**
Sex, male	1.091 (0.982–1.232)	0.104
Race, white	1.329 (1.133–1.558)	< **0.001**
Private insurance	0.996 (0.900–1.102)	0.943
Charlson Comorbidity Index	1.116 (1.107–1.126)	< **0.001**

[a] Analysis using index admit only yielded similar results.

(vs. non-white), and who had a greater Charlson index (Table 2). Personality effect on mortality, adjusted for sociodemographic variables and other personality trait domains, are reported in Table 2. Presence of disinhibition was associated with a 21.7% increase in hazard for mortality, and obsessive-compulsive features with a 14.1% decrease in hazard for mortality. Sensitivity analysis considering only index admission, or incorporating length of stay and year of admission, yielded similar results.

3.2. Personality and risk of readmission

All-cause readmission risk was greatest among individuals who were older, did not have private insurance, and had greater overall medical comorbidity as indicated by Charlson index (Table 3). The presence of detachment predicted a higher likelihood of readmission (Table 3). For every 10% increase in the detachment topic score, hazard of readmission increased by 21%. On the other hand, presence of at least one feature of disinhibition and psychoticism predicted a 9% and 23.6% decreased likelihood of readmission, respectively. As with mortality, sensitivity analyses with additional covariates did not yield meaningfully different results.

Table 3
Competing risk regression model of personality trait domains and all readmissions (n = 19,985 admissions)[a].

Variables	Model with personality trait domains	
	SHR	p-Value
Personality domain		
Disinhibition (binary)	0.908 (0.851–0.968)	**0.003**
Psychoticism (binary)	0.764 (0.594–0.981)	**0.035**
Negative affectivity (binary)	0.989 (0.941–1.038)	0.642
Antagonism (binary)	1.004 (0.907–1.111)	0.937
Obsessive-compulsive (binary)	1.028 (0.994–1.063)	0.105
Detachment (dimensional)	1.209 (1.168–1.253)	< **0.001**
Sociodemographic features		
Age at admission	0.991 (0.990–0.993)	< **0.001**
Sex, male	1.012 (0.969–1.056)	0.590
Race, white	1.012 (0.958–1.068)	0.680
Private insurance	0.834 (0.799–0.871)	< **0.001**
Charlson Comorbidity Index	1.044 (1.040–1.048)	< **0.001**

[a] All medical diagnosis categories included in the model but not shown.

4. Discussion

In aggregate, our results demonstrate that individual personality features can be identified in narrative clinical notes drawn from non-psychiatric cohorts, and that such features associate with outcomes including mortality and readmission. In general, however, such features were uncommon, such that personality as a dimensional feature could only be estimated for detachment. Most notably, we found that disinhibition was associated with an increased risk of mortality. We could identify no similar studies with which to directly compare our results, as ours appears to be the first study to apply DSM-V/ICD-11 personality trait domains to study mortality. However, in a prior study, disinhibition was inversely correlated with conscientiousness (r = −0.69) [33]. Low conscientiousness is an equivalent to disinhibition and involves impulsivity, low persistence, poor self-control, distractibility, irresponsibility and lack of long-term planning [19,23]. In this sense, our results are in line with those of a Jokela et al. meta-analysis, which found that low conscientiousness was associated with a 37% increase in mortality risk (hazard ratio = 1.37, 95% confidence interval: 1.18, 1.58), compared with individuals in the top 2 tertiles of this dimension [3]. Conversely, other studies have shown that high conscientiousness traits consistently predict an increased lifespan across cultures and age groups [34].

Prior work suggests that the association between disinhibition and mortality may be explained by a combination of factors at three levels. First, disinhibition is related to impulsivity, sensation seeking, and externalizing behaviors. These may predispose to risky behavior such as substance use, violence, accidents, and suicidality [35–38], and more generally with greater interpersonal difficulties impacting relationships with healthcare professionals [2]. All of these are associated with increased mortality rates [39]. Secondly, disinhibition has been related to varying degrees of dysfunction in cognitive domains (i.e., altered executive function, intelligence) [40,41] that may affect compliance with medical prescriptions and monitoring. Finally, disinhibition may contribute to inability to avoid more hazardous or unsafe environments [35] which has generally been related to more unhealthy lifestyles [2,4]. Alternatively, comorbidity may underlie the association between increased mortality and disinhibition, such as sleep dysfunction or obesity [34,42]. Regardless of mechanism, our results support the assertion that disinhibition/low-conscientiousness is linked to poor health outcomes [43–45].

Conversely, the presence of anankastic traits was associated with lower likelihood of mortality. This may be related to traits like harm avoidance, risk and loss aversion, and future-oriented thought – all of which are frequent in patients with high anankastic traits [4,46]. Patients with these personality features may be more likely to engage in health-oriented behaviors such as participating in prevention programs, scheduling medical follow-ups, adhering to medication prescriptions, and seeking consultation earlier about worrisome symptoms [46]. Obsessive-compulsive features are correlated with high conscientiousness (r = 0.62) [23], which is itself related to decreased mortality [3].

Beyond mortality, disinhibition and psychoticism were both associated with a lower likelihood of hospital readmission, while detachment was associated with a higher likelihood of this outcome. Prior studies using personality disorder categories found that patients with personality disorders in general have an increased risk of admission and readmission [1,47–49]. Studies on personality disorders or behavioral problems where either disinhibition or psychoticism is common (i.e., borderline personality disorder, substance use disorders, cluster A personality disorder) [19] also found increased readmission rates [50–52] and medical service overuse [53,54].

Our results suggest greater complexity in the relationship between personality and health services use. For example, it is possible that patients with disinhibition and psychoticism may access other available health interventions associated with lower readmission rates [55], or that health professionals are less willing to readmit these patients because expert and guideline recommendations advise against hospitalization unless there is a high risk for suicide or serious self-harm [56,57]. Notably, lower readmission rates do not preclude increased mortality [58].

On the other hand, detachment was associated with increased likelihood of readmission, which may reflect the increased somatization and greater psychological distress that may impact these patients in the context of medical illness [59,60]. The latter two factors are significant predictors of hospital readmission [61,62]. Another possibility may be that patients are simply more willing to accept hospitalization, since detachment is a personality trait that helps to see things more objectively [63]. Finally, detachment may represent a consequence of chronic disease. Further study will be required to distinguish among these hypotheses.

In aggregate, our results add to a growing literature indicating the utility of narrative notes in identifying predictors of clinical outcomes [11,14]. The approach we describe is simple and portable enough to facilitate identification of personality features in a range of settings. Moreover, while personality features are not systematically assessed in medical settings, and appear to be poorly documented, they may represent an opportunity to better understand differential outcomes among individuals hospitalized for non-psychiatric illness.

An important limitation of our approach is the potential lack of sensitivity and specificity of our personality features. That is, this strategy cannot replace comprehensive assessment of personality using standard measures and risks including terms that do not represent personality dimensions reliably. However, a majority of trait domain descriptive features are not used in routine general medicine language except to describe a patient's characteristics or behavior; those that are used more broadly (i.e., abnormal, rigid) should otherwise be approximately equally distributed across patients. Moreover, relying directly on narrative notes allowed us to address some of the difficulties related to personality assessment, specifically regarding the lack of consistent personality assessment and diagnosis in the general medical setting. Additional limitations of those of electronic health records-based studies in general, including inability to exclude admissions to out-of-network hospitals and lack of quantitative measures of disease-specific severity.

5. Conclusions

Integrating personality dysfunction as a risk factor for long-term medical outcomes requires novel assessment strategies, particularly in non-psychiatric settings such as medical inpatient units. The present study is among the first to use natural language processing to address the relationship between DSM-5/ICD-11 personality trait domains and relevant health outcomes in this context. Such high-throughput phenotyping, while coarse, may allow identification of individuals with relevant personality features and development of targeted strategies to improve their medical outcomes.

CRediT author statement

Sergio Barroilhet: Conceptualization; Roles/Writing – original draft; Writing – review & editing.

Alexandra Bieling: Roles/Writing – original draft; Writing – review & editing.

Thomas McCoy: Data curation; Formal analysis; Writing – review & editing.

Roy Perlis: Conceptualization; Formal analysis; Supervision; Roles/Writing – original draft; Writing – review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.genhosppsych.2020.01.003.

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