Investigating Trends of Behavioral Healthcare Resource Utilization Burden in Children and Adolescents with Suicidal Symptoms in the United States: An Analysis of Electronic Health Record Data

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BACKGROUND

The prevalence of children/adolescents in the US experiencing mental health disorder and rates of suicide in minors has been increasing over the years.[1] American Academy of Pediatrics, American Academy of Child and Adolescent Psychiatry and Children's Hospital Association published a joint declaration in October 2019 that that children's mental health has become a "national emergency".[2] It is then important to understand how this translate to the burden of mental health care resource utilization.
Aim: We applied natural language processing (NLP) to a large de-identified EHR dataset to investigate trends in the utilization of behavioral health services by minors with suicidal or self-harm symptoms in the United States, and any changes in contributing stressors.

METHOD

- Data from 538,565 patients were obtained from NeuroBlu, a trusted research environment[3] that enables the analysis of de-identified, HIPAA-compliant data from 25 U.S. healthcare providers that employ the MindLinc EHR system.

- Summarize the trend of the percentage of patients <18 years who report suicidality/self-harm symptoms over a 20-year period from 2000-2019; and report the trends of health care utilization and contributing stressors.

- NLP models[4] were used to extract the following Mental Status Examination (MSE) features:
  - **Suicidal ideation**
    Suicidal ideation; suicidal with intent; suicidal with plan; history of ideation; suicidal ideation with means.
  - **Suicidal attempt**
    Suicide attempt; history of attempt.
  - **Self-harm**
    Self-injurious; history of self-injury.

NeuroBlu™ DATABASE

80+ million	925K+	20+ years
rows of patient data	Patients	Longitudinal Data

Structured Data

- Outcome Measures (e.g. CGI-S, GAF)
- Prescription Data
- Emergency department, inpatient, and outpatient data across the same patients in 20 of 25 clinics
- Diagnosis Codes (ICD-9, ICD-10)
- Patient Demographics

Patient volume by psychiatric disorder

| 256k Substance-related Disorders | 135k Bipolar Disorders | 84k Adjustment Disorders | 83k ADHD |
| 252k Major Depressive Disorder | 63k PTSD | 51k Generalized Anxiety Disorder | 57k Personality Disorders / 54k Conduct Disorders / 33k Schizophrenia / 18k Panic Disorder |

Unstructured Data

- **Mental Status Examination (MSE)**
  - Categorized notes on patient function, appearance, and mood at a visit
  - Holmusk developed >30 advanced Neural Network models to predict structured labels from MSE
  - Created >300 psychiatry specific labels in collaboration with clinicians to track disease progression over time
- **External Stressors**
  Social, relational and occupational events that may affect patient mental health

Data Source of US Health Facilities
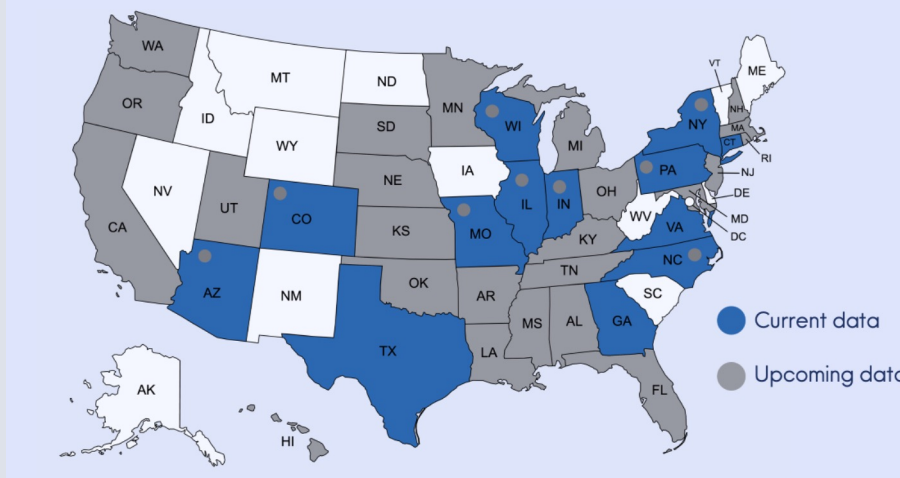

- Current data
- Upcoming data

Figure 1. State-specific data source of NeuroBlu.

De-identified EHR data were obtained from U.S. mental health services that use the MindLinc EHR system. The data were analyzed in NeuroBlu, a secure Trusted Research Environment (TRE) that enables data assembly and analysis using an R/Python code engine.

RESULTS

- Of the 107,750 patients who had at least a MSE record in the study period and were aged <18 at the time of measurement, 15,342 reported suicidality; overall mean prevalence of suicidality in the 20-year period was 14.2%. The prevalence of suicidality ranged from 7-21%, lowest in 2011, before increasing year-on-year from 2011 to 2019. (Figure 2)
- The most reported stressors across the years in patients who also report suicidality are shown in Figure 3.
- Utilization of inpatient and emergency department services increased during the years where prevalence of suicidality was trending higher (Figure 4).

Female paediatric patients have consistently higher prevalence of suicidality
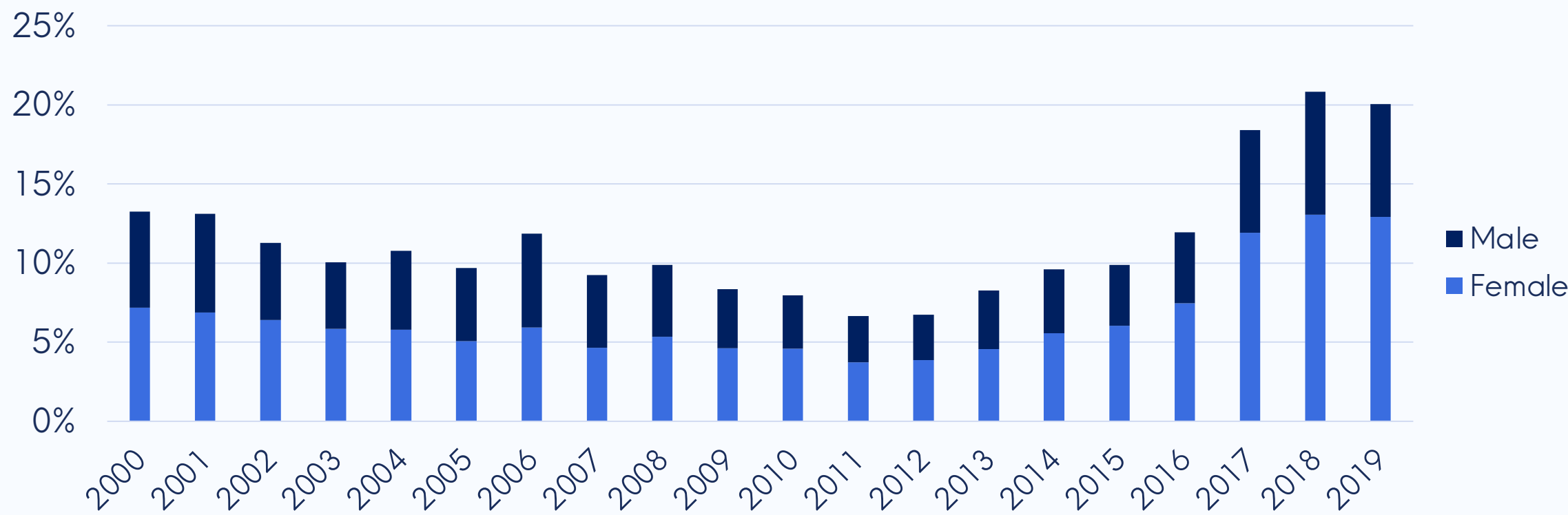

- Male
- Female

Figure 2. Stacked bar plot of the prevalence of pediatric patients with suicidality each year, stratified by gender, amongst patients with MSE measurement in that year in the NeuroBlu database.

Percentage of patients with stressor type reported in those with suicidality
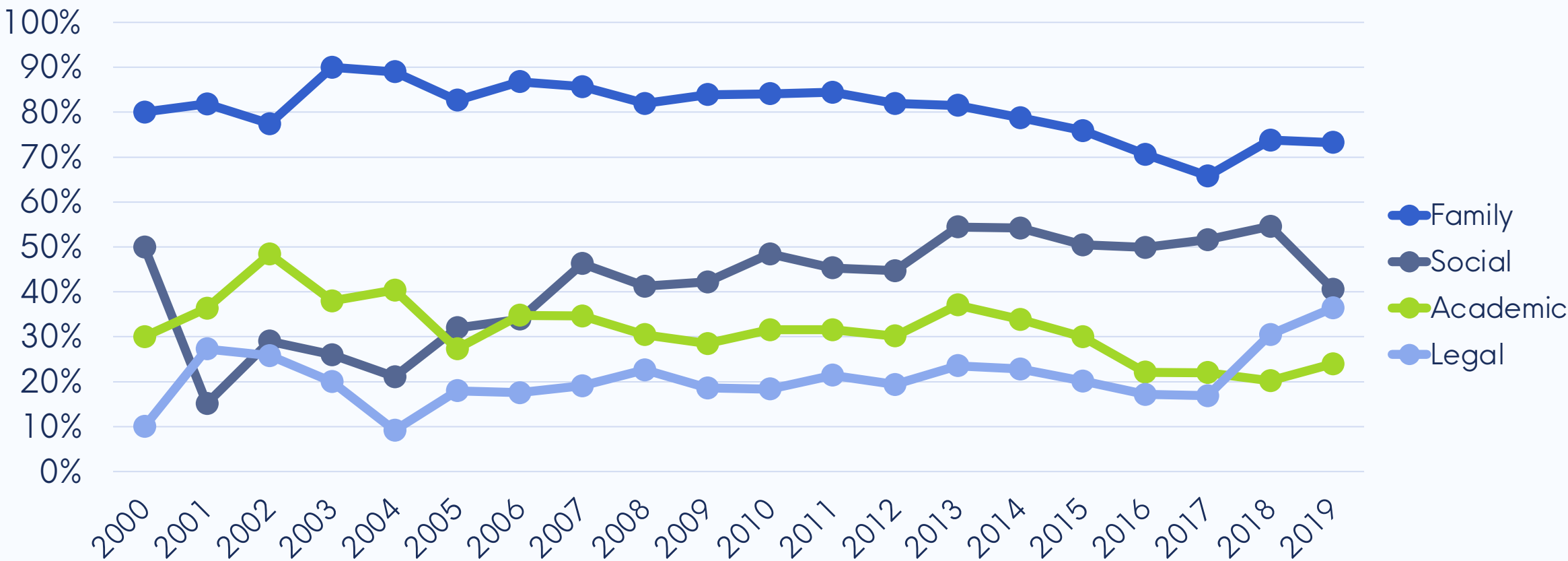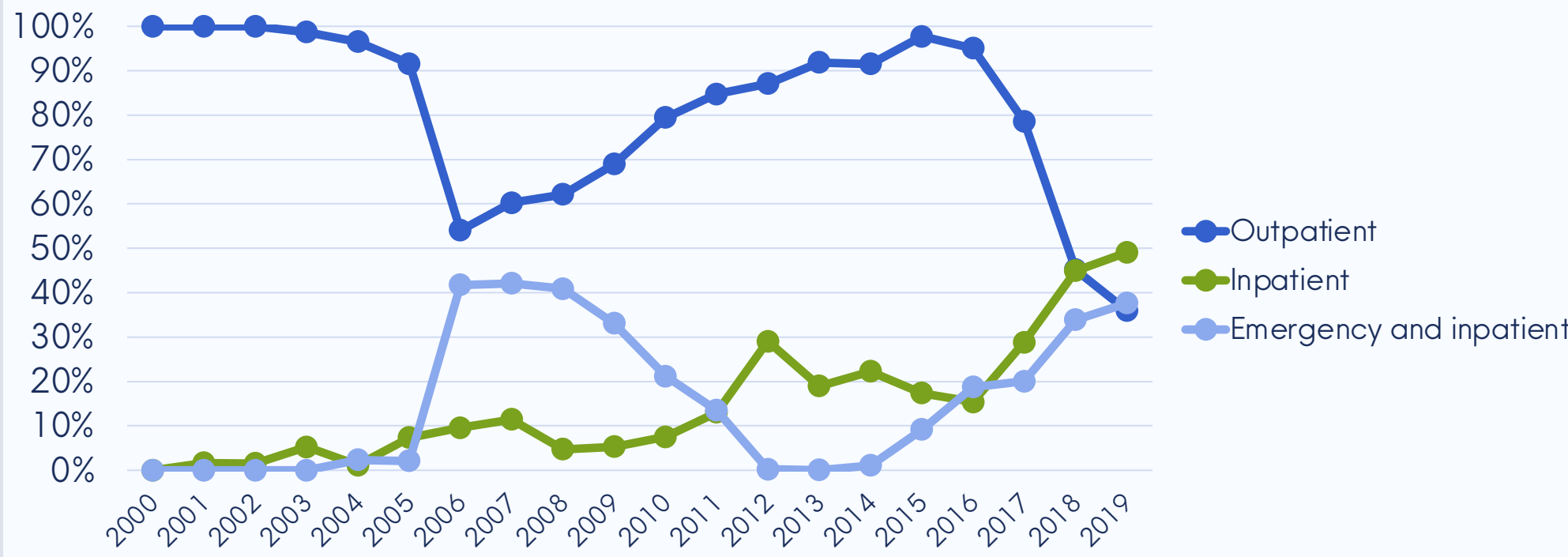

- Family
- Social
- Academic
- Legal

Figure 3. Percentage of pediatric patients reporting the top 4 stressor type in each year.

A. Healthcare resource utilization of patients with suicidality

- Outpatient
- Inpatient
- Emergency and inpatient

B. Healthcare resource utilization of patients without suicidality
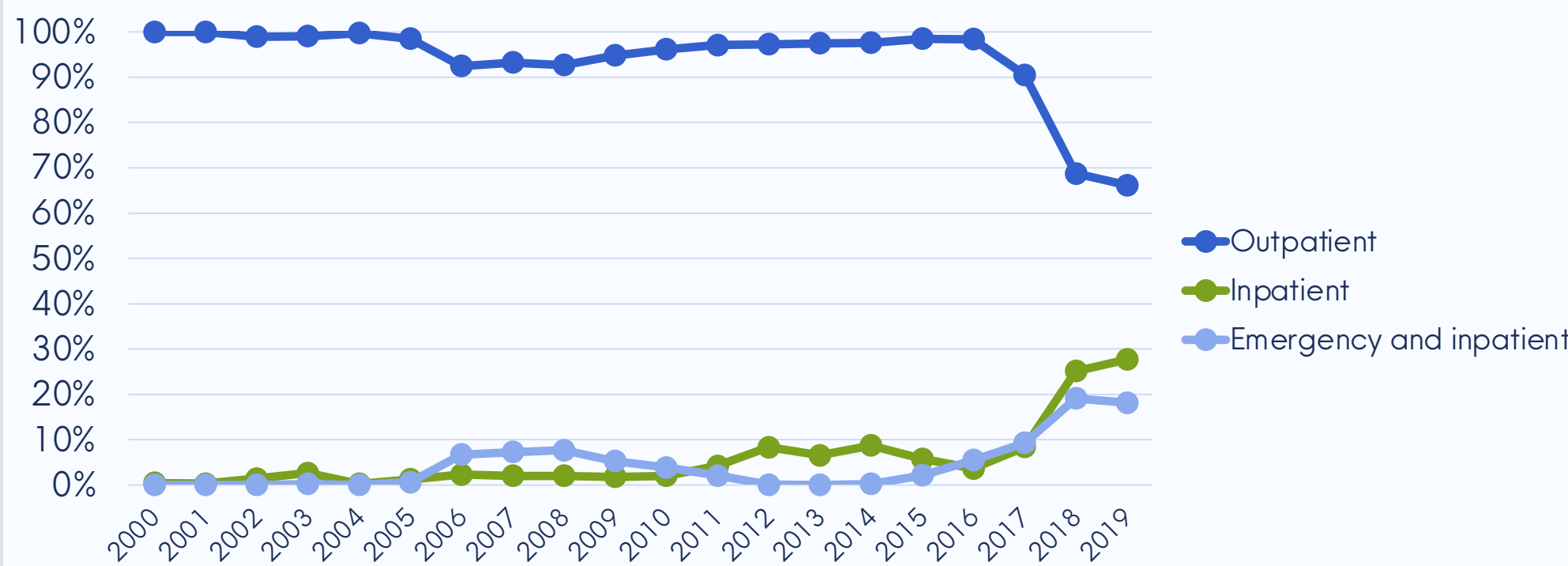

- Outpatient
- Inpatient
- Emergency and inpatient

Figure 4. Percentage of pediatric patients that had an inpatient (green), outpatient (dark blue), or emergency and inpatient visit (light blue) who also (A) reported suicidality or (B) who did not report suicidality in that year.

CONCLUSION

Findings from this study illustrate the steady rise in childhood mental health concerns and suicide over the recent years, which in turn translate to a burden to the healthcare systems reflected by the increased healthcare resource utilization. Potential stressors were also identified, that could support strategies to improve mental health promotion, prevention, and treatment in pediatric patients facing these challenges. Through this study, we also demonstrate the potential for NLP-derived measures enrich EHR data.

References:
1. Polanczyk GV, Salum GA, Sugaya LS, et.al. Annual research review: a meta-analysis of the worldwide prevalence of mental disorders in children and adolescents. J Child Psychol Psychiatry. 2015;56:345–65.
2. American Academy of Pediatrics. AAP-AACAP-CHA Declaration of a National Emergency in Child and Adolescent Mental Health. https://www.aap.org/en/advocacy/child-and-adolescent-healthy-mental-development/aap-aacap-cha-declaration-of-a-national-emergency-in-child-and-adolescent-mental-health/
3. Patel R, Wee SN, Ramaswamy R, et al NeuroBlu, an electronic health record (EHR) trusted research environment (TRE) to support mental healthcare analytics with real-world data. BMJ Open, 2022;12:e057227. doi: 10.1136/bmjopen-2021-057227
4. Mukherjee SS, Yu J, Won Y, et al. Natural Language Processing-Based Quantification of the Mental State of Psychiatric Patients. Comput Psychiatry 2020;4:76

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