Characterizing Outpatient Problem List Completeness and Duplications in the Electronic Health Record

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Scholarly Report Title: Characterizing Outpatient Problem List Completeness and Duplications in the Electronic Health Record

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Purpose: To characterize rates of problem list completeness and duplications in outpatient problem lists and to identify any relationships between problem list completeness and duplications and disease type, demographics, and disease severity.

Methods: We performed a retrospective analysis of electronic health record data from Partners HealthCare. Using a combination of vital sign measurements, lab results, and ICD-10 codes, we identified patients with at least one of eleven chronic diseases: Crohn's disease, ulcerative colitis, depression, schizophrenia, opioid use disorder, hepatitis B, hepatitis C, hypertension, diabetes, asthma, and epilepsy. We then collected additional information regarding the number of disease-related entries on each patient's problem list. We also collected additional information, including vital sign measurements, lab results, medication orders, and hospital admissions, to assess the severity of disease in each patient. Finally, we performed two-proportion z-tests to compare the rates of completeness and duplications by disease type, demographics, and disease severity.

Results: Rates of problem list completeness varied from 35.1% in hepatitis B infection to 92.3% in asthma, whereas rates of problem list duplication varied from 3.4% in hepatitis B to 26.4% in diabetes. Except in certain diseases like hypertension and asthma, there was no consistent relationship between demographic factors and rates of completeness and duplication. There was also no consistent relationship between rates of completeness and disease severity, except in the cases of asthma and epilepsy. However, for eight of the eleven diseases, there was a clear relationship in which increasing disease severity is associated with increased rates of duplication.

Conclusions: Problem list completeness and duplication demonstrated substantial variation across the eleven studied diseases. Rates of completeness and duplication are not consistently affected by demographic factors unless a certain disease is especially prevalent in a certain demographic group. While rates of completeness were also not consistently affected by disease severity, rates of duplication showed a relatively consistent positive correlation with disease severity.

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Glossary of Abbreviations

EHR: electronic health record(s)

EDW: Enterprise Data Warehouse, a database containing electronic health record data at Partners HealthCare

PLE: problem list entry

UC: ulcerative colitis

HBV: hepatitis B virus

HCV: hepatitis C virus

DM: diabetes mellitus

HgbA1c: hemoglobin a1c

HTN: hypertension

Section 1: Introduction

Electronic health records (EHRs) play a central role in modern healthcare systems. They perform a multitude of functions, including storing patient health records, documenting clinical encounters, facilitating communication among healthcare providers, serving as databases for research, and supporting billing. Although EHRs have improved many workflows in medicine, such as the safety of medication orders[7], there remains an immense opportunity for improvement. Common complaints about EHRs include unintuitive and slow interfaces and a lack of interoperability among different EHR vendors[3,4]. These shortcomings of current EHRs have been linked with higher rates of physician burnout, decreased face-to-face time with patients, and lower job satisfaction among physicians[2].

The shortcomings of current EHR implementations can have clinical implications as well. In particular, the clinical documentation of a patient's medical history is often scattered among hundreds, if not thousands, of separate clinical notes – each of which is only subtly different from one another and none of which fully encapsulates a patient's entire medical history. This "atomization" of each patient's medical narrative ultimately leads to a loss of understanding of that whole narrative which is instrumental to medical decision-making[9]. As a result, understanding and reconstructing a patient's complete medical history is often a time-intensive task that requires perusing multiple notes from multiple providers.

Problem lists play a vital role in addressing this problem by identifying and describing each patient's chronic medical problems in a centralized location. This theoretically makes it easier for multiple providers to identify and manage each of those problems over time. Similarly, it also makes it easier for physicians who are taking care of new patients to familiarize themselves with a patient's problems quickly and efficiently. Problem lists are also used for quality measurement, drive clinical decision support, and can be used to identify patients for research. Despite their importance, in practice, problem lists are often incomplete, redundant, or even inaccurate[8,10]. Furthermore, traditional problem lists often fail to document additional semantic information, beyond diagnostic codes, that is often essential to medical decision-making[11]. All of these shortcomings can greatly undermine the clinical utility of the problem list.

Previous studies of problem list utilization have typically focused on the issue of problem list completeness. One study found that problem list completeness for patients with diabetes ranged from as little as 60.2% to 99.4% at ten different healthcare organizations, depending on the presence or absence of "positive deviance" factors for the use of the problem list, such as financial incentives and problem-oriented charting[16]. Such stark differences in problem list completeness may also be related to healthcare providers' diverse attitudes toward issues like problem list ownership and content[6,13,15]. From an interventional perspective, clinical decision support tools, automated alerts, and machine-learning may play a role in improving problem list completeness across a wide range of diseases[1,12,14]. Improving problem list completeness is particularly important to clinical practice because it has the potential to improve clinical outcomes for patients, such as the appropriate prescribing of medication[5].

In addition to the issue of problem list incompleteness, problem list duplications also play a similar role in undermining the effectiveness of problem lists by increasing clutter and distracting providers from the most pertinent information. Compared to problem list completeness, the issue of duplications has not been well-studied in the literature. Characterizing this specific issue will be instrumental to the development of interventions that improve problem list completeness without leading to unnecessary clutter in problem lists.

Section 2: Student Role

With the help of my mentor, Dr. Adam Wright, I developed my own research question which focuses on analyzing how problem list utilization practices, specifically problem list completeness and duplications, vary according to disease type, demographics, and disease severity. After developing my research question, I selected eleven chronic diseases to study and familiarized myself with the Partners HealthCare EHR data inside Enterprise Data Warehouse (EDW). I learned Structured Query Language (SQL) and wrote my own SQL code to query this database for relevant information. I also learned R, a statistical programming language, and wrote my own code to perform statistical analyses of the data. Finally, I created my own figures and tables using Microsoft Excel. Throughout this process, I regularly discussed my findings with Dr. Wright who provided valuable guidance and advice.

Section 3: Methods

We conducted a retrospective analysis of EHR data from Enterprise Data Warehouse (EDW), a database containing EHR data from Partners HealthCare. The database was queried using Structured Query Language (SQL). We focused on eleven chronic diseases: Crohn's disease, ulcerative colitis, depression, opioid use disorder, schizophrenia, hepatitis B infection, hepatitis C infection, diabetes mellitus, hypertension, asthma, and epilepsy. For each of these diseases, a set of criteria was developed, using dates, ICD-10 billing codes, diagnostic tests, and vital signs (see Appendix for complete definitions for each disease). Patients were identified as having a disease if they met the criteria associated with that disease. In total, there were eleven disease populations, one for each disease of interest. Patients can belong to multiple disease populations if they meet multiple sets of criteria.

Eleven separate analyses of problem list completeness and duplications were performed, one for each of the eleven disease populations. For each of these analyses of a single disease population (termed the "target" disease population), a target-specific problem list status was calculated for each patient in the target disease population. Each of the eleven analyses was performed in isolation of one another. In other words, non-target diagnoses and the presence or absence of non-target-related entries have no effect on the analysis of the target disease.

In each analysis, patients were assigned problem list "statuses" according to the number of target-related entries on their problem list. An "incomplete" problem list was defined as any patient having zero target-related entries on their problem list. A "complete" problem list was defined as any patient having one or multiple target-related entries on their problem list. A "duplicated" problem list was defined as any patient having multiple target-related entries on their problem list. The "complete" and "duplicated" problem list statuses were both simultaneously assigned to any patient who had multiple target-related entries.

For example, a patient is identified as having diabetes, hypertension, and Crohn's disease according to our criteria. If the patient has two diabetes entries, one hypertension entry, and zero Crohn's disease entries, then the patient has:

- A complete and duplicated problem list with respect to diabetes

- A complete problem list with respect to hypertension
- An incomplete problem list with respect to Crohn's disease

Additional information, such as age, sex, diagnostic results, vital signs, hospital admissions, and medication orders, were also collected for each patient. These additional parameters were used to assess disease severity for each patient (see Appendix for complete definitions of disease severity for each disease).

Using the R statistical programming language, rates of completeness and duplication were compared according to disease type, patient demographics, and disease severity. Two-proportion z-tests were used to compare how rates of completeness and duplication vary according to patient demographics and disease severity. A p-value of less than 0.05 was considered statistically significant.

Section 4: Results

Overall Population Characteristics

A total of 329,972 unique patients were identified as having at least one of the eleven diseases in this study. The average age and percent female for patients with each disease can be found in Table 1. In total, when looking at the eleven diseases together, there were 376,931 disease-related entries on these patients' problem lists, with an average of 1.14 problem list entries per patient. When evaluating each disease individually, the lowest rate of problem list entries per patient was 0.40 in patients with hepatitis B infection, whereas the highest rate was 1.33 in patients with diabetes. When evaluating only patients with duplicated problem lists, hepatitis C and diabetes had the lowest and highest rates of problem list entries per patient, at 2 and 2.55 entries per patient respectively. The full results can be found in Figure 1.

Overall Rates of Completeness and Duplication by Disease Type

Figure 2 shows the overall rates of incompleteness, completeness, and duplication for each of the eleven diseases. Rates of completeness, defined as having one or multiple disease-related entries in the problem list, typically ranged from 70% to 90%. Asthma had the highest rate of completeness at 92.3%, and hepatitis B infection had the lowest rate of completeness at 35.1%.

Rates of duplication, defined as having two or more disease-related entries in the problem list, ranged from 3.4% in hepatitis B to 26.4% in diabetes. All diseases except for hepatitis B, hepatitis C, and hypertension, had rates of duplication above 10%. The proportion of patients with only one disease-related entry was generally in the 60% to 80% range, except for hepatitis B infection at 31.7%.

Effect of Demographics on Rates of Completeness and Duplication

For some diseases, there was a relationship between age and rates of completeness or duplication. In patients with depression and hypertension, the rate of completeness increased with increasing age. On the other hand, rates of completeness decreased with increasing age in patients with asthma. The results are summarized in Figure 3 (top panel). Rates of duplication also sometimes varied according to changes in age. For patients with hypertension and asthma, the rates of duplication increased with increasing age. In patients with Crohn's disease, the opposite trend was observed. The results are summarized in Figure 3 (bottom panel). For the other diseases, there was no clear relationship between age group and rates of completeness and duplication.

In a similar vein, patient sex was associated with differences in rates of completeness and duplication for only some diseases. Females with asthma, diabetes, or depression had higher rates of completeness compared to their male counterparts ($p < 0.001$). On the other hand, males with hypertension had higher rates of completeness compared to their female counterparts ($p < 0.001$). These findings are shown in Figure 4 (top panel). Finally, females with asthma or hypertension had higher rates of duplication compared to their male counterparts ($p < 0.001$). These findings are summarized in Figure 4 (bottom panel). For the other diseases, there was no clear relationship between sex and rates of completeness and duplication.

Effect of Disease Severity on Rates of Incompleteness, Completeness, and Duplication

In patients with Crohn's disease or ulcerative colitis, patients with an elevated C-reactive protein (CRP) level above 3 μg/mL had higher rates of completeness at 90.7% and 84.5% respectively, compared to 87.7% and 80.9% respectively in patients with normal CRP levels ($p < 0.02$). Similarly, patients with elevated CRP had higher rates of duplication at 25.6% and 16.8%

respectively, compared to 18.1% and 10.4% in their counterparts with normal CRP levels ($p < 0.001$).

In patients with depression or schizophrenia, patients with multiple anti-depressant or anti-psychotic medication orders, respectively, in the past year had higher rates of duplication at 15.9% and 13.8% respectively, compared to 10.9% and 4.9% in patients with zero or one medication order in the past year ($p < 0.001$). For patients with depression, rate of completeness was also higher at 84.9% in those with multiple anti-depressant orders, compared to 84.2% in their counterparts ($p < 0.03$).

For opioid use disorder, patients with a prescription for an opioid reversal agent like naloxone had a higher rate of duplication at 12.1%, compared to 9.8% in patients without a similar prescription ($p < 0.02$). There was no significant difference in rates of completeness between the two groups.

In patients with hepatitis B infection or hepatitis C infection, there were no significant differences in rates of duplication among the lower third, middle third, and upper third percentile groups for HBV and HCV viral loads. Rates of completeness also did not differ for the three groups in hepatitis B infection. However, in the lower third percentile group for patients with hepatitis C, the rate of completeness was 66.4%, which was significantly lower than the rates of completeness in the middle and upper third groups at 83.4% and 81.7% respectively ($p < 0.001$).

For diabetes, patients with HgbA1c scores in the 6.5-7.5% range had the second lowest rate of completeness at 91.5% (Figure 5, top panel). This was significantly lower than the rates of completeness for patients in the 7.5-8.5%, 8.5-9.5%, and 9.5-10.5% ranges ($p < 0.01$). There was no significant difference in rates of completeness among these three groups. Interestingly, patients with HgbA1c scores above 10.5% had the lowest rate of completeness at 90.1%, which was significantly lower than all of the other groups ($p < 0.01$). The results for rates of duplication were similar (Figure 5, bottom panel). Patients with HgbA1c scores in the 6.5-7.5% range had the lowest rate of duplication at 22.9%, which was significantly lower than all other groups ($p < 0.001$). With each percentage point increase in HgbA1c up to 10.5%, the rate of duplication

increased to 28.0%, 31.5%, and 32.7%, respectively. Patients with HgbA1c scores above 10.5% had a rate of duplication of 29.7%, which was significantly lower than the 32.7% duplication rate of the HgbA1c group directly below it ($p < 0.01$).

In patients with hypertension, the rates of completeness increased with increasing average blood pressure: 100-120 mm Hg at 46.5%, 120-140 mm Hg at 70.6%, 140-160 mm Hg at 78.9%, and 160+ mm Hg at 76.3% (Figure 6, top panel). Similarly, the rates of duplication also increased with increasing average blood pressure: 100-120 mm Hg at 3.1%, 120-140 mm Hg at 4.3%, 140-160 mm Hg at 5.3%, and 160+ mm Hg at 7.3% (Figure 6, bottom panel). The 95% confidence intervals for all four groups did not overlap in both comparisons of completeness and duplications.

For asthma, the rate of completeness for patients with up to one asthma-related hospitalization in the past year was significantly lower at 92.3%, compared to 94.9% for those with multiple hospitalizations in the past year ($p < 0.01$). Similarly, the rate of duplication for patients with up to one asthma-related hospitalization in the past year was 12.6%, which was significantly lower than 38.2% in their counterparts ($p < 0.001$). In patients with epilepsy, the rate of completeness for patients with up to one hospitalization was 83.4%, compared to 95.9% in those with multiple hospitalizations ($p < 0.001$). Likewise, the rate of duplication was lower in patients with up to one hospitalization at 15.2%, compared to 50.1% in patients with multiple hospitalizations ($p < 0.001$). The results are for both asthma and epilepsy are summarized in Figure 7.

Section 5: Discussion, Limitations, Conclusions, and Suggestions for Future Work

Discussion

Overview of Rates of Completeness, Duplication, and Incompleteness

Overall, the rate of completeness hovered in the 70-90% range for all diseases with the exception of hepatitis B infection which had the lowest rate of completeness at 35.1% (Figure 2). This significantly lower result may be explained by the fact that HBV infection was partially defined by laboratory results, specifically positive HBcAb, HBeAg, or HBsAg. While these positive results may be indicative of an acute infection that happened at some point in the past, they do

not necessarily indicate a persistent, chronic infection that warrants inclusion in the problem list from the providers' perspective.

Rates of incompleteness were generally higher than rates of duplication, averaging 21.9% and 12.6% across the diseases, respectively. This shows that the issue of duplications, while smaller on average than its more well-studied counterpart, is not negligible and warrants further study in order to minimize its negative effect on the utility of problem lists.

The proportion of patients with one problem list entry was relatively consistent across all diseases, hovering in the 60-70% range, with the exception of Hepatitis B (31.7%) and asthma (79.1%). In contrast, the proportion of patients with duplicated entries was much more variable, ranging from 3.4% in HBV to 26.4% in diabetes. This suggests that variations in rates of completeness among the different diseases are mostly attributable to variations in rates of duplication specifically, not to variations in the proportion of patients with just one entry. In other words, providers appear to be generally consistent about providing 60-70% of patients with one problem list entry, regardless of the disease type; however, some diseases, such as diabetes and Crohn's disease, are much more prone to having duplicated entries. This may be the case because diabetes has many complications that can be separately identified in the problem list, and Crohn's disease can occur in many different locations within the gastrointestinal tract, each of which can also be separately identified in the problem list.

Effect of Demographics on Rates of Completeness, Duplication, and Incompleteness

Overall, there was no consistent relationship between demographics (age and sex) and rates of completeness or duplication. However, relationships were sometimes observed in diseases that are more prevalent within a certain demographic group. In hypertension, which is more prevalent in older adults, rates of completeness and duplication both increased with increasing age. In contrast, the rate of completeness in patients with asthma appeared to decrease with increasing age, possibly because asthma is more prevalent in children. There were similar findings with regard to sex. Among patients with depression, which has a higher prevalence among females, females had a higher rate of completeness compared to males ($p < 0.001$). On the other hand, for hypertension, which is more prevalent in males for most age ranges, males had a higher rate of completeness compared to females ($p < 0.001$). All of these findings suggest that while there is

no universal relationship between demographics and rates of completeness and duplication, there can be an observed relationship if the disease is more prevalent in a "classic" demographic group. If a patient fits that "classic" presentation, a provider may be more likely to create an entry in the problem list – either because the provider is more primed to recognize and diagnose a specific disease in that specific demographic group, or because the provider is more confident making that diagnosis in a patient who fits the "classic" presentation. On the other hand, a patient who is not in the "classic" demographic group may be less likely to have a problem list entry – either because the provider is not primed to diagnose that disease in an atypical patient, or because there may be more uncertainty associated with diagnosing that disease in an atypical patient. Based on these findings, future EHR interventions that are aimed at improving problem list completeness might focus on providing additional prompts for providers who are treating patients with less typical presentations.

Effect of Disease Severity on Rates of Completeness, Duplication, and Incompleteness

Overall, there was a strong relationship between disease severity and rates of duplication across the diseases. In all diseases except hepatitis B and hepatitis C, rates of duplication increased with increasingly severe disease. This relationship was consistent across these diseases, regardless of the method by which disease severity was assessed (lab values, hospitalizations, medication orders, or vital sign measurements). One notable exception is that patients with HgbA1c scores above 10.5% had lower rates of completeness and duplication than expected (Figure 5). One possible explanation for this finding is that patients whose HgbA1c scores are above 10.5% represent patients with uncontrolled disease who may not have been diagnosed until only recently; hence, there may have been less time for providers to create complete or duplicated problem lists for these patients.

In contrast to the strong relationship between duplications and disease severity, only asthma and epilepsy demonstrated any clear relationship between rates of completeness and disease severity (Figure 7). These findings suggest that for patients with the *same* disease, providers are generally consistent about maintaining complete problem lists at a consistent rate, regardless of disease severity (this should be contrasted against the previous finding that across *different* diseases, providers maintain complete problem lists at different rates).

One possible explanation for the observed relationship between duplications and disease severity is that more severe disease states often lead to more systemic complications that can be separately documented in the problem list. Providers may wish to be more explicit in listing each of these complications so that other providers can be made aware of crucial clinical information. Patients with more severe disease may also have more providers involved in their care, leading to more duplications over time as multiple providers contribute their own individual expertise to the problem list. The problem may then be compounded by providers' unwillingness to have their own problem list entries be edited or deleted by others. Finally, there may be a financial incentive to "up-code" and be more explicit in listing every single complication on the problem list so that providers can receive higher reimbursements for providing more complex care.

Limitations

Our data set was limited to EHR data from Partners HealthCare, which predominantly provides tertiary and quaternary referral care in a metropolitan area. As a result, the patients and providers in this healthcare organization are not necessarily representative of the general population of U.S. patients and providers. Similarly, the database does not capture any clinical documentation, including prescriptions, lab results, and hospitalizations, from outside healthcare organizations. Our study was also limited in scope to eleven chronic diseases.

There are also inherent limitations to using EHR data. Many patient records had incomplete data, such as missing blood pressure measurements and lab values. For the purpose of calculations and statistical tests, these patients with missing values were censored, which likely introduces some bias. Furthermore, the definitions for each of our diseases were limited by the types of data in EHRs and therefore did not incorporate clinical input from healthcare professionals. As a result, our method of identifying patients with disease may have failed to capture patients with well-controlled disease and patients without the requisite lab values. We also relied on ICD-10 codes to determine which entries belonged to which disease. Without manual review of each chart, this method fails to capture any entries that were created manually (as opposed to entries that are automatically created and suggested by the EHR itself).

Finally, the sample sizes for hepatitis B, hepatitis C, and opioid use disorder were all small, making point estimates for these three diseases much more susceptible to random variation. For the rest of the eight studied diseases, there were also small sample sizes within the pediatric populations, similarly leading to much more susceptibility to random variation.

Suggestions for Future Work

Because our findings focus on characterizing rates of completeness and duplication strictly at the disease-level, future studies should assess how rates of completeness and duplication vary by provider and/or healthcare setting. It is possible that individual provider usage habits and/or healthcare organization policies play a large role in shaping the overall patterns of problem list utilization. Similarly, software design may affect the way problem lists are utilized, so repeating this study with another EHR vendor can potentially yield different results. Our study also does not evaluate the unstructured content of the problem lists, namely their comments sections. Future studies into the unstructured content of problem lists are warranted and may yield helpful information regarding the types of unstructured information that providers often input into problem lists.

While our findings are helpful in characterizing the current shortcomings in problem list utilization patterns, they do not provide any insight into why these shortcomings occur. Future studies should qualitatively analyze provider behaviors, usage patterns, and opinions with regard to problem list utilization, completeness, duplication, and maintenance. This information will be instrumental to the future development of EHR interventions that can address the current shortcomings of problem list utilization. In particular, future interventions should focus on minimizing duplications or at least allowing duplications to be organized in a more logical and orderly fashion. Future investigations might even explore the development of automated tools or machine learning algorithms that constantly maintain or "prune" problem lists to prevent them from becoming overpopulated.

Conclusions

Our study analyzed problem list utilization across eleven chronic diseases, focusing on how problem list completeness and duplications vary according to disease type, demographics, and disease severity. Overall, rates of problem list completeness and duplication varied widely across

the different diseases. Demographic factors like age and sex did not consistently affect problem list completeness and duplication, except in certain cases where demographics are essential to the medical conception of the disease. In contrast, increasing disease severity is often associated with higher rates of duplication in problem lists. These findings demonstrate the shortcomings of current problem list utilization habits and highlight the need for further research into this vital function of the EHR.

Section 6: Acknowledgements

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Tables and Figures

Table 1: Patient demographics (n = 329,972)

	Average Age (years)	**% Female**

Crohn's Disease	44.1	52.1
Ulcerative Colitis	48.1	54.6
Opioid Use Disorder	44.5	38.3
Depression	51.8	67.2
Schizophrenia	48.0	34.4
HBV	56.1	44.4
HCV	51.6	38.0
Diabetes	63.8	45.5
HTN	65.9	52.6
Asthma	51.5	62.1
Epilepsy	47.2	50.7

Figure 1: Number of Problem List Entries Per Patient

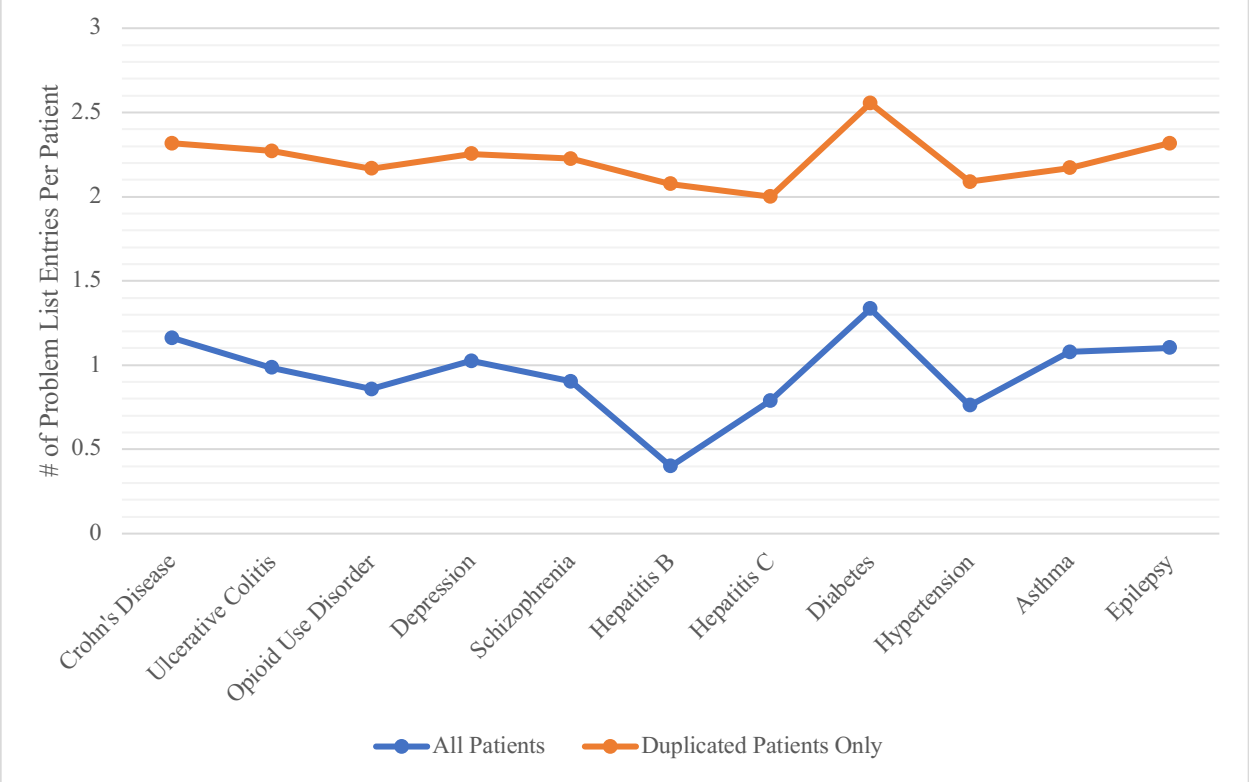


Figure 2: Overall Rates of Problem List Incompleteness, Completeness, and Duplication by Disease Type

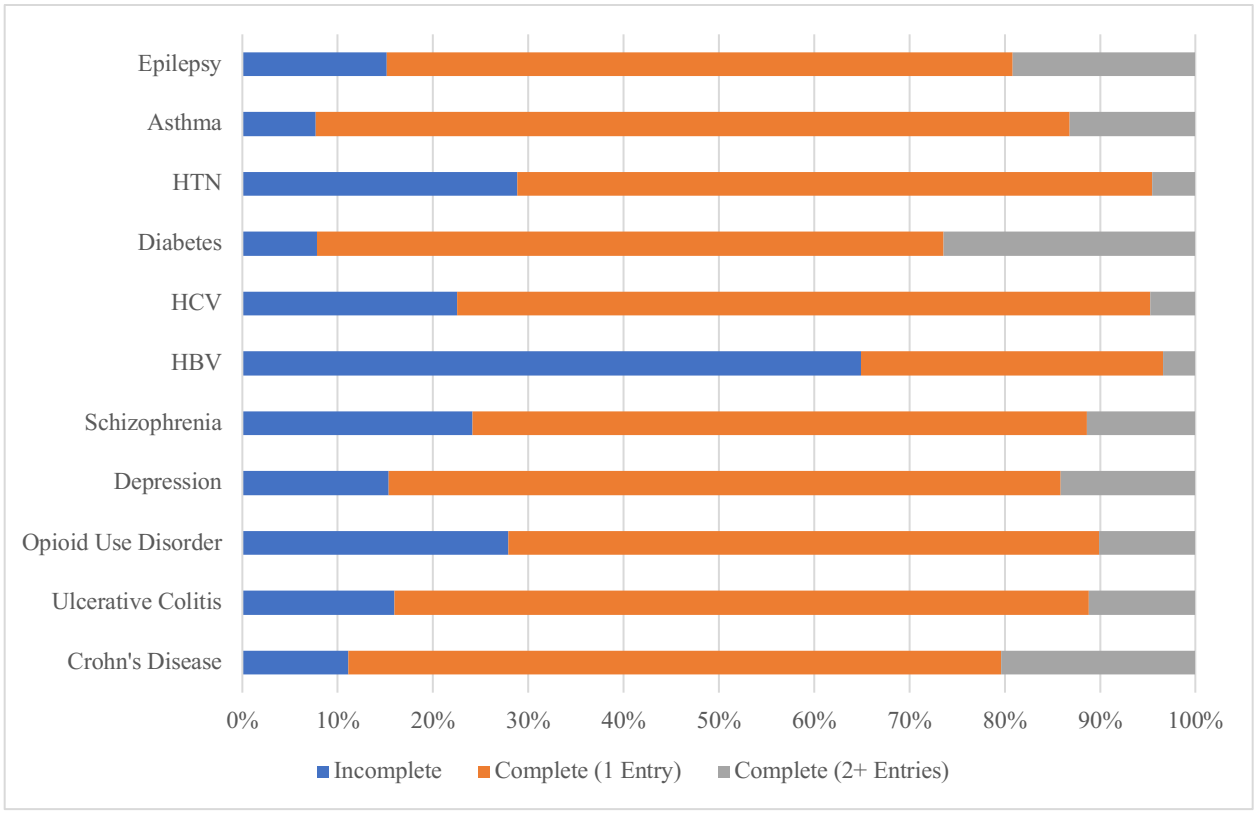
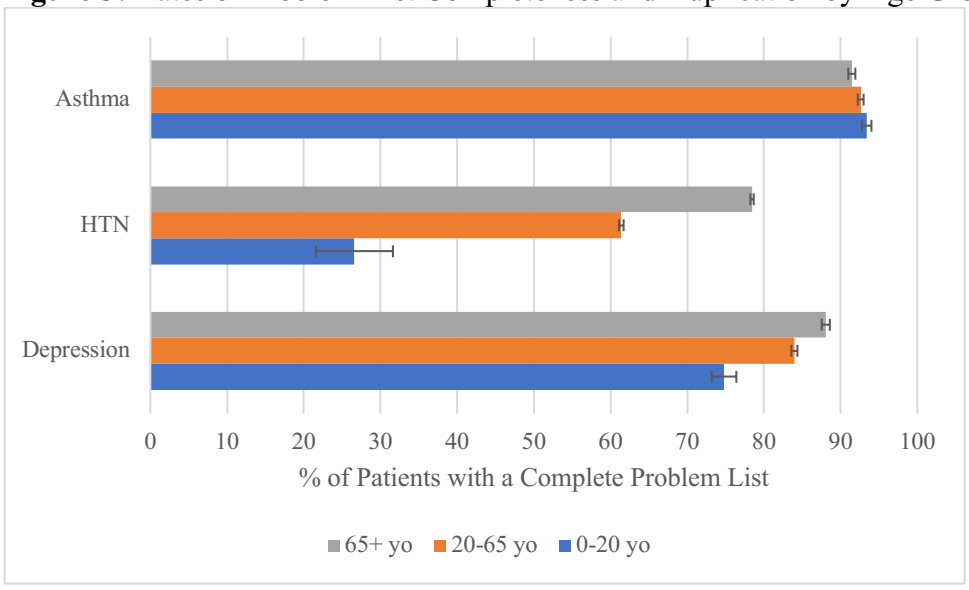


Figure 3: Rates of Problem List Completeness and Duplication by Age Group



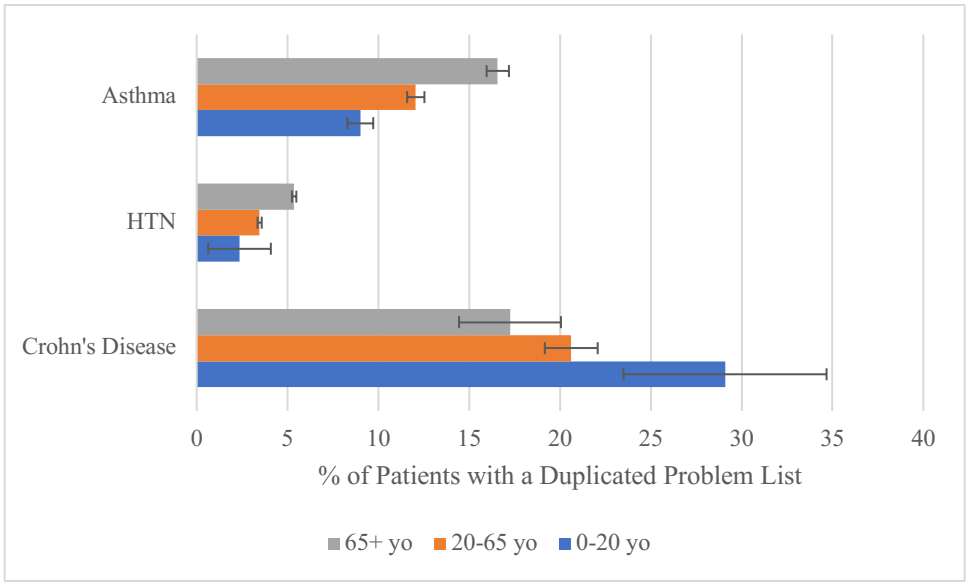
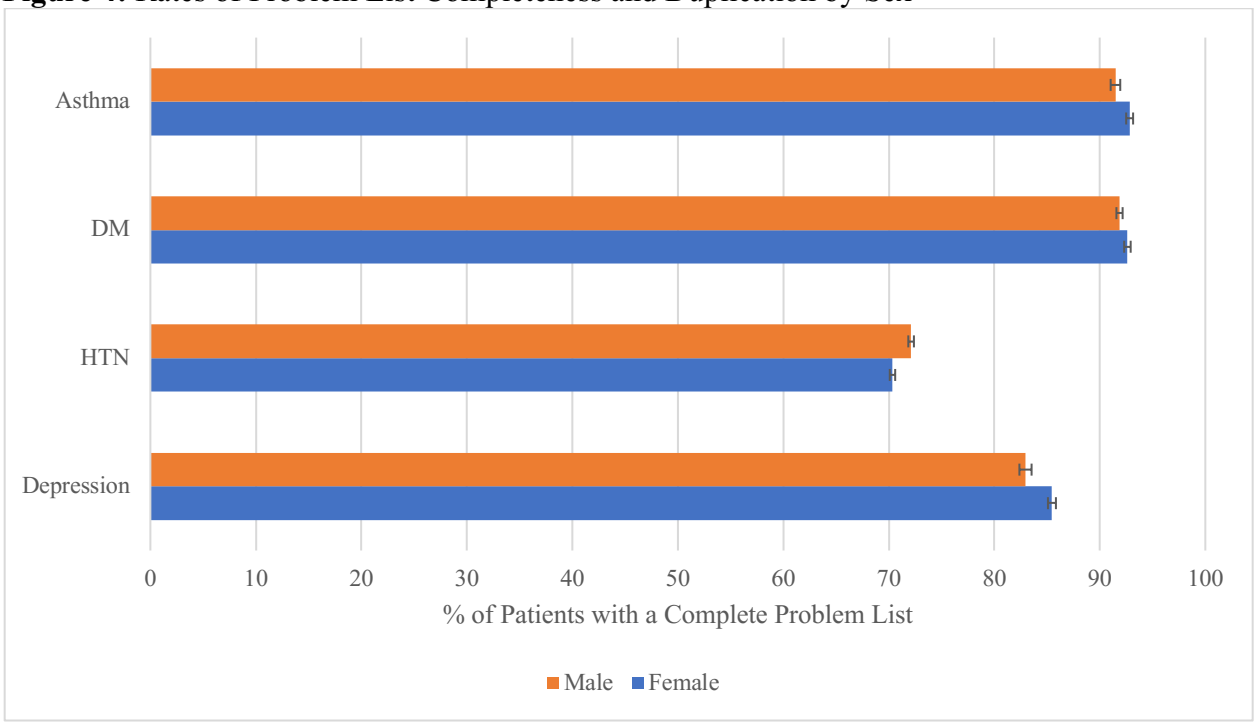


Figure 4: Rates of Problem List Completeness and Duplication by Sex



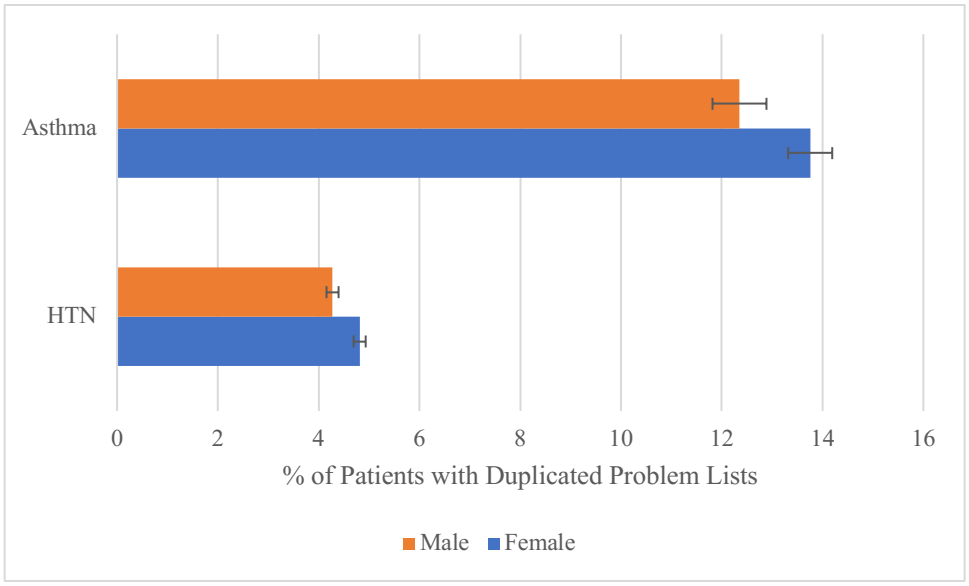
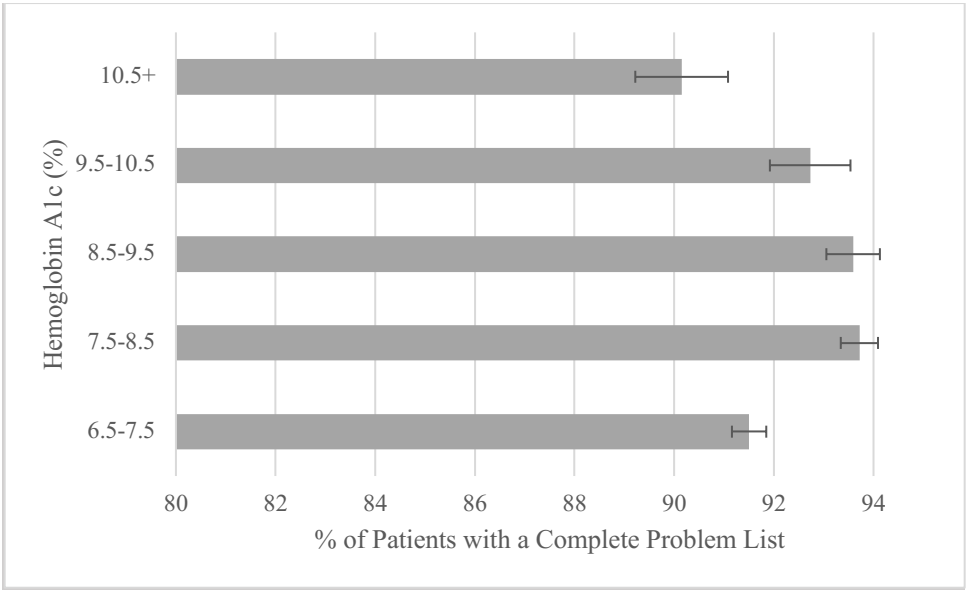


Figure 5: Rates of Problem List Completeness and Duplication by Disease Severity in Patients with Diabetes



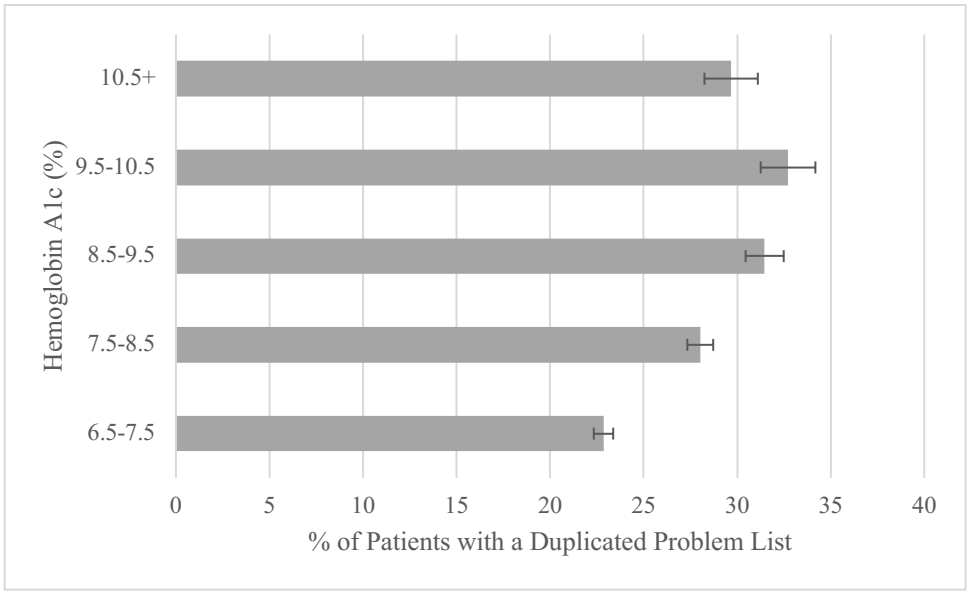
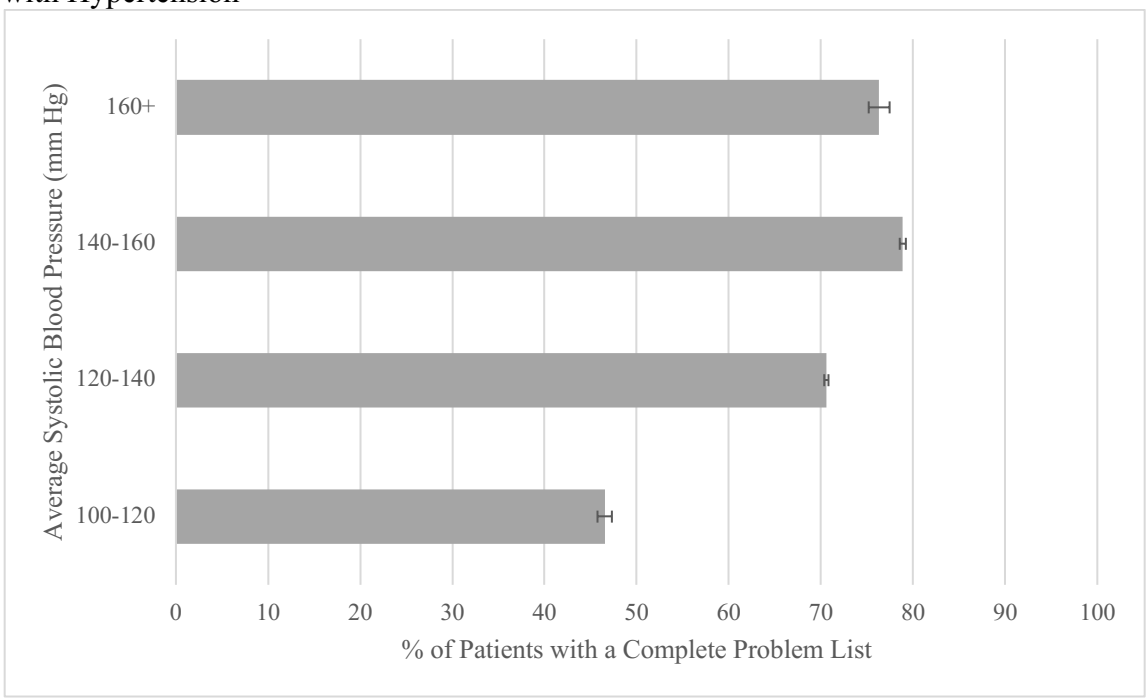


Figure 6: Rates of Problem List Completeness and Duplication by Disease Severity in Patients with Hypertension



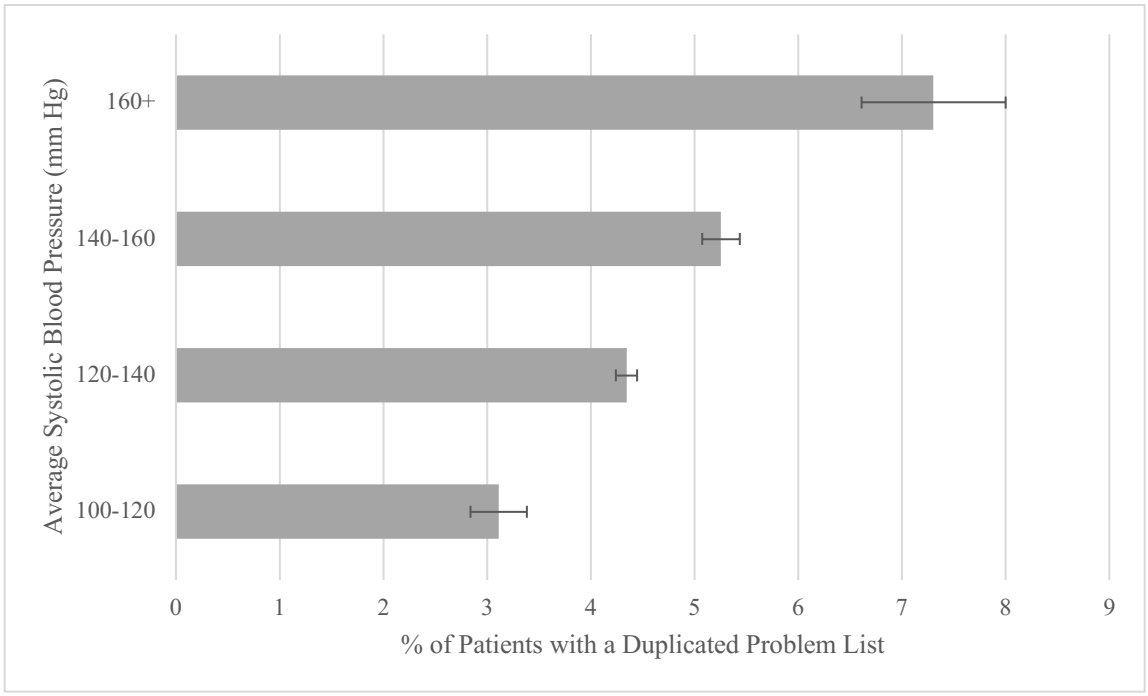
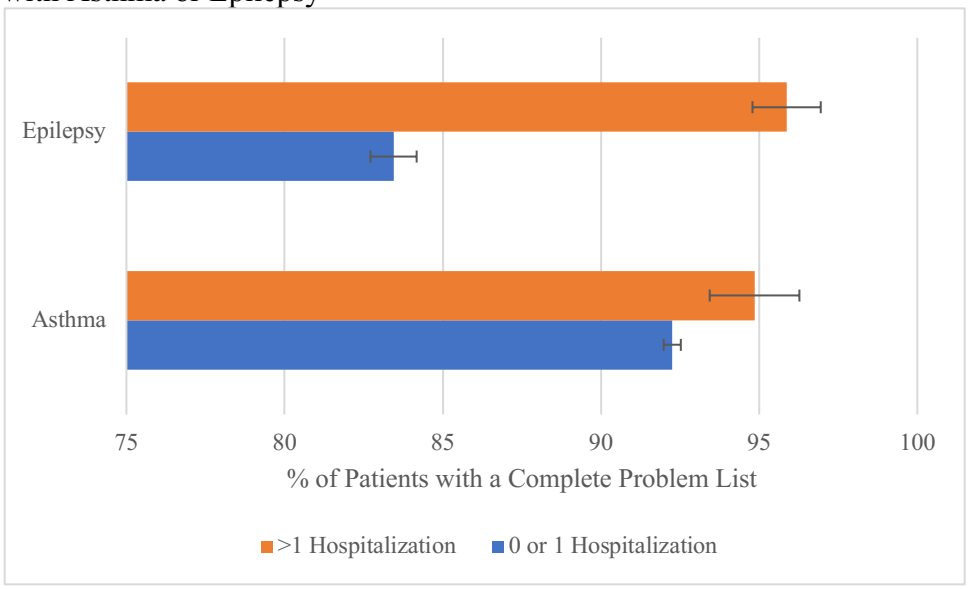
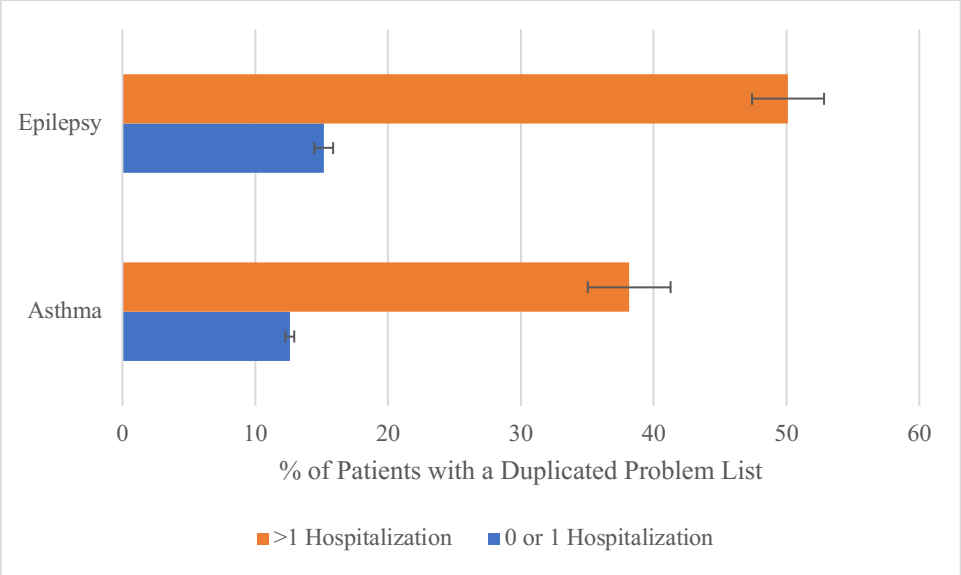


Figure 7: Rates of Problem List Completeness and Duplication by Disease Severity in Patients with Asthma or Epilepsy





Appendix

Disease Definitions

Disease	**Criteria** • *"Time frame" refers to 1/1/2018 to 7/31/2019*
Crohn's Disease	Both: • At least 3 healthcare encounters within the time frame billed with an ICD-10 code starting with K50 • At least 1 prescription for an immunomodulator medication within the time frame
Ulcerative Colitis	Both: • At least 3 healthcare encounters within the time frame billed with an ICD-10 code starting with K51 • At least 1 prescription for an immunomodulator medication within the time frame
Depression	Both: • At least 3 healthcare encounters within the time frame billed with an ICD-10 code starting with F31-34 or F39 • At least 1 prescription for an anti-depressant medication within the time frame
Opioid Use Disorder	Both: • At least 3 healthcare encounters within the time frame billed with an ICD-10 code starting with F11 • At least 1 prescription for buprenorphine or methadone within the time frame
Schizophrenia	Both: • At least 3 healthcare encounters within the time frame billed with an ICD-10 code starting with F20

	• At least 1 prescription for an anti-psychotic medication within the time frame
Hepatitis B infection	Any of the following: • Positive HBcAb, HBeAg/HBeAb, or HBsAg within the time frame • Non-zero HBV viral load within the time frame
Hepatitis C infection	Both: • Non-zero HCV viral load or positive HCV antibody within the time frame • At least 1 prescription for an HCV anti-viral medication within the time frame
Diabetes mellitus	Both: • At least 1 Hemoglobin A1c greater than 6.5% within the time frame • At least 1 prescription for an anti-hyperglycemic medication within the time frame
Hypertension	Both: • At least 3 healthcare encounters with systolic blood pressure greater than 130 mm Hg or diastolic blood pressure greater than 80 mm Hg during the time frame • At least 1 prescription for a cardiovascular-related medication within the time frame
Asthma	Both: • At least 3 healthcare encounters within the time frame billed with an ICD-10 code of J44.9 or starting with J45 • At least 1 prescription for an anti-asthmatic medication within the time frame
Epilepsy	Both: • At least 3 healthcare encounters within the time frame billed with an ICD-10 code of P90, G83.84, G93.81, R56.1, R56.9, or starting with G40 • At least 1 prescription for an anti-convulsant medication within the time frame

Disease Severity Definitions

Disease	**Disease Severity Definition** • *"Time frame" refers to 1/1/2018 to 7/31/2019*
Crohn's disease	Average C-Reactive Protein level in the time frame (µg/mL)
Ulcerative Colitis	Average C-Reactive Protein level in the time frame (µg/mL)
Depression	Number of anti-depressant medication orders in the time frame
Schizophrenia	Number of anti-psychotic medication orders in the time frame
Opioid use disorder	Presence of an opioid reversal agent prescription within the time frame
Hepatitis B	Average Hepatitis B viral load in the time frame (copies, by percentile group)

Hepatitis C	Average Hepatitis C viral load in the time frame (copies, by percentile group)
Diabetes	Average Hemoglobin A1c in the time frame (%)
Hypertension	Average systolic blood pressure in the time frame (mm Hg)
Asthma	Number of asthma-related hospital admissions in the time frame
Epilepsy	Number of epilepsy-related hospital admissions in the time frame