An Exploratory Analysis of Alzheimer's and Dementia Patient Disposition Following Hospital Admission in Maryland

Daniel Johan Kamyab

Table of Contents

1. Introduction
2. Objective
3. Methods
4. Analysis
    a. Figure 1
        i. Patient Count for Alzheimer’s and Dementia Related Patients
    b. Figure 2
        i. Patient Count Patients by Diagnosis Type
    c. Figure 3
        i. Patient Count by Source Disposition and Discharge Disposition
    d. Figure 4
        i. Percentage breakdown of Source Disposition by Discharge Disposition
    e. Figure 5
        i. Average Count of ICDs Per Patient by Discharge Disposition
    f. Figure 6
        i. Distribution of Patient ICD Count by Discharge Disposition
    g. Figure 7
        i. Percentage Breakdown of Diagnosis Type by Discharge Disposition
    h. Figure 8
        i. Percentage Breakdown of Sex by Discharge Disposition
    i. Figure 9
        i. Percentage Breakdown of Age by Discharge Disposition
    j. Figure 10
        i. Percentage Breakdown of Patient Race by Discharge Disposition
    k. Figure 11
        i. Percentage Breakdown of Marital Status by Discharge Disposition
    l. Figure 12
        i. Average Patient Charlson Index Score by Discharge Disposition
    m. Figure 13
        i. Distribution of Average Patient Charlson Index Score by Discharge Disposition
    n. Figure 14a
        i. Reference Group of Multiple Logistic Regression
    o. Figure 14b
        i. Multiple Logistic Regression
5. Conclusion
6. Learnings & New Competencies
7. Works Cited
8. Acknowledgments

Introduction

Alzheimer's and Dementia are diseases that impact millions of patients across the globe. As much about these diseases remains elusive from a clinical perspective, likewise, much is still not well understood on the various clinical and socioeconomic factors that influence outcomes for these patients. One decision faced by families of patients experiencing Alzheimer's or Dementia, particularly as their condition deteriorates, is to admit the patient to a long-term care facility. Researchers from the National Catholic School of Social Service investigating this decision at the point of hospital discharge found that the condition of the patient was identified as the most influential factor in caregivers' decision making (Cox). Additionally, they found that the second strongest factor was the advice of the patient's physician (Cox). Lastly, they identified the third strongest factor impacting the decision-making process to be the advice of social workers (Cox).

A meta-analysis from Toot et al. approached this decision from a more clinical perspective, compiling factors associated with an increased risk of admission to a nursing home. The meta-analysis noted that poor cognition, behavior, and psychological symptoms of dementia were closely associated with the risk of admission to a nursing home (Toot et al.). They also highlighted that incidence of hip fracture preceding a diagnosis of dementia was also associated with being admitted to a nursing home (Toot et al.).

Objective

While prior literature provides a handful of the factors associated with Alzheimer's and Dementia patients and the outcome of being admitted to a non-home location, many clinical and social factors remain unexplored. In this paper, I seek to conduct an exploratory data analysis of a large publicly available data set to identify additional factors that are associated with whether Alzheimer's and Dementia patients are discharged home or not (disposition), following a hospital admission.

Methods

To answer the question of which factors are differentially associated with Alzheimer's and Dementia patient post-hospital discharge disposition, data from the "Maryland Health Services Cost Review Commission (HSCRC) Non-Confidential Inpatient and Hospital-Based Outpatient Data Set" was used. This data is a de-identified limited data set of hospital discharges from the state of Maryland. Additionally, from this data set, exclusive focus was given to patients with an in-patient hospital admission along with either a Dementia-related or Alzheimer's diagnosis. ICD codes of F01.50, F01.51, F02.80, F02.81, F03.90, F03.91, F04, G13.8, F05, F06.1, F06.8, G31.1, G31.2, G31.01, G31.09, G94, R41.81, or R54 were used to identify patients with dementia-related diagnoses, as per the Centers for Medicare & Medicaid Service's Chronic Condition Warehouse definition (Chronic Conditions Data Warehouse). Additionally, the ICD codes G30.0, G30.1, G30.8, and G30.9 were used to identify patients with Alzheimer's disease (Chronic Conditions Data Warehouse). Moreover, only patients with admissions between the financial year 2017 and 2019 were included, to avoid potential differential patient disposition patterns that may have been caused by the COVID-19 pandemic. The resulting output results in nearly 124,000 patients over the three years, with a roughly similar number of patients for each financial year (Figure 1).

Figure 1
Patient Count for Alzheimer's and Dementia Related Patients Between Financial Year 2017 and 2019

Financial Year	Total Patient Count
2017	41,656
2018	40,885
2019	41,278
Total	123,819

Additionally, when breaking down the total patient pool based on patients with Alzheimer's diagnoses vs Dementia-related diagnoses, it can be seen that year over year, patients with dementia-related diagnoses outnumber patients with Alzheimer's by a factor of roughly 4 to 5 (Figure 2).

Figure 2
Patient Count Patients Between Financial Year 2017 and 2019, Broken Down by Diagnosis Type

Diagnosis Type	Financial Year	Total Patient Count
Alzheimer	2017	7,467
Alzheimer	2018	6,705
Alzheimer	2019	6,209
Dementia	2017	34,189
Dementia	2018	34,180
Dementia	2019	35,069
Total	-	123,819

Lastly, when looking at all the patients across the three years and grouping them based on their "source" of admission and "discharge" disposition, it can be seen that patients who are admitted to the hospital from the "Home" location have a slightly higher propensity of being discharged to a "Non-Home" location (Figure 3). Moreover, patients who start from an outside source and are discharged to an outside location are more common than patients who are discharged home by a factor of more than three, suggesting that a patient's source of admission or the factors impacting a patient's source of admission have an import role to play on a patient's ultimate disposition following discharge.

Figure 3
Patient Count by Source Disposition and Discharge Disposition Between Financial Year 2017 and 2019

	Home (Discharge)	Non-Home (Discharge)
Home (Source)	40,763	53,163
Non-Home (Source)	6,837	23,056
Total	47,600	76,219

To better explore the relationship between the factors associated with a patient's discharge disposition, multiple different clinical and socioeconomic covariates will be investigated. Specifically, these factors are the patient's source of admission, the patient's total count of diagnoses, classification as a patient with Alzheimer's versus Dementia, patient sex, patient age, patient race, patient marital status, and the patient's Charlson score, a co-morbidity index, where a higher score indicates a reduced likelihood of survival (Sundararajan et al.).

Analysis

In this section, this capstone will examine the relationship between each of the covariates mentioned in the section above with respect to patients' discharge disposition. Following the individual examination of each covariate, this capstone will then conduct a multiple logistic regression which will include all of the discussed variables, in order to explore the strength of the relationship of each covariate on the outcome of discharge disposition.

In Figure 4, the distribution of the patient's discharge distribution as a function of their source distribution is presented, similar to the data from Figure 3. From this figure, one can infer that there may be a relationship between having a source of admission of "Non-Home" and also being discharged to a "Non-Home" setting.

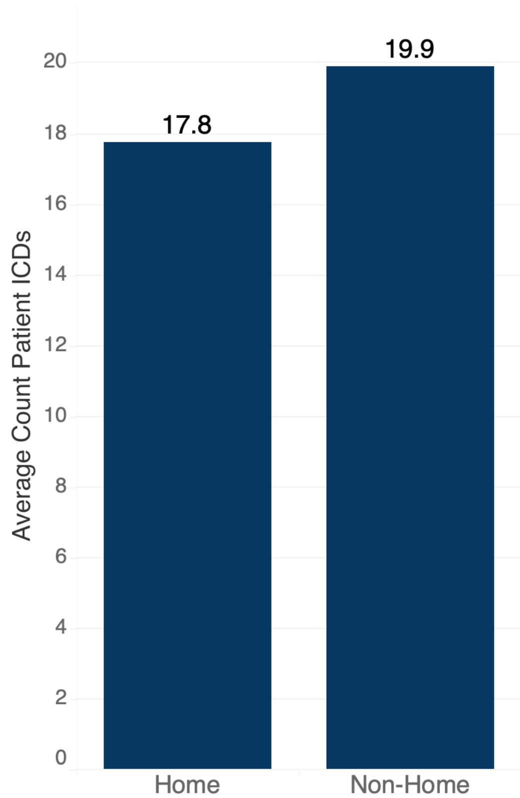
Figure 4
Percentage breakdown of Source Disposition by Discharge Disposition
Between Financial Year 2017 and 2019

	Home (Discharge)	Non-Home (Discharge)	Total
Home (Source)	43.4%	56.6%	100% (n = 93,924)
Non-Home (Source)	22.9%	77.1%	100% (n = 29,892)

Next, this capstone looks at the average number of diagnoses per patient across the two discharge disposition groups. It can be observed that a differential of more than 2 diagnoses between the two groups, suggesting that patients that end up at a "Non-Home" location may be on average sicker.

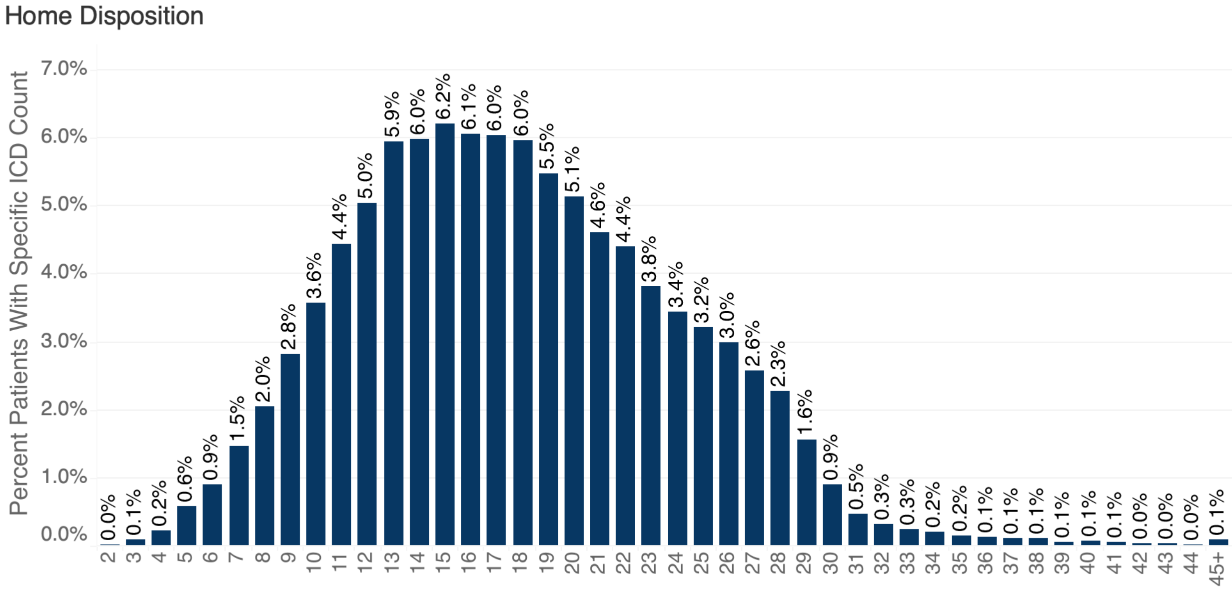
Figure 5

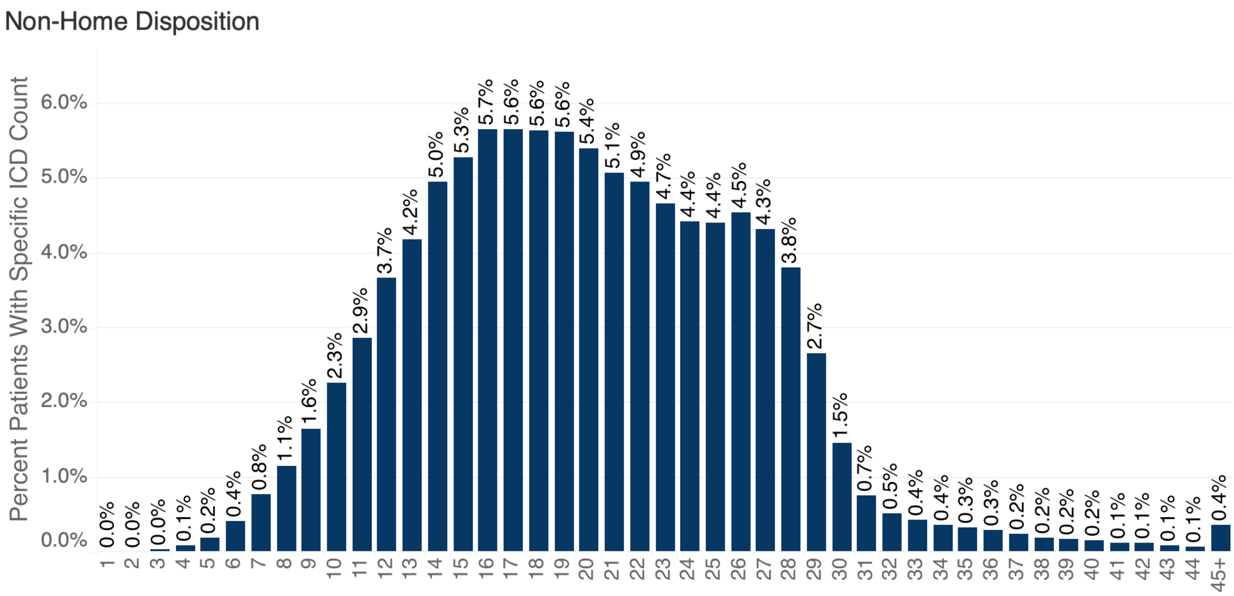
Average Count of ICDs Per Patient by Discharge Disposition
Between Financial Year 2017 and 2019



A further breakdown of the distribution of patients, across ICD Counts on the X-axis illustrates a similar trend, but provides the reader with the insight that both distributions are right-skewed and that the "Non-Home" disposition group has consistently a high proportion of patients with high ICD count values within the right tail.

Figure 6
Distribution of Patient ICD Count by Discharge Disposition
Between Financial Year 2017 and 2019





In Figure 7, this capstone examines the relationship between the diagnoses of Alzheimer's and Dementia on the relative distribution of discharge disposition. Interestingly, while differences certainly exist, the differential between the two groups is relatively small, with a difference of less than two percent. Multiple logistic regression, which will be conducted later in this analysis (Figure 14b), will provide this capstone with insights as to whether this relation is potentially being masked by other covariates.

Figure 7
Percentage Breakdown of Diagnosis Type by Discharge Disposition
Between Financial Year 2017 and 2019

	Home (Discharge)	Non-Home (Discharge)	Total
Alzheimer's	40.0%	60.0%	100% (n = 20,381)
Dementia	38.1%	61.9%	100% (n = 103,435)

In terms of the covariate of sex, it can be seen that a relatively similar percentage of males and females have a "Non-Home" discharge disposition. Again, considering a percentage differential of around one percent, multiple logistic regression will aid this capstone in determining whether or not this differential is statistically significant and separate it from the interactions of other covariates.

Figure 8
Percentage Breakdown of Sex by Discharge Disposition
Between Financial Year 2017 and 2019

	Home (Discharge)	Non-Home (Discharge)	Total
Male	37.8%	62.2%	100% (n = 52,710)

Female	38.9%	61.1%	100% (n = 71,106)

Next, this capstone looks at the relationship between age and discharge disposition. As one would expect, it can be seen that a relatively lower percentage of individuals in the lowest age bracket of 0-49 are being discharged to a “Non-Home” location. This percentage continues to increase until it peaks at 64.4% in the 90-99 bracket.

Figure 9
Percentage Breakdown of Age by Discharge Disposition
Between Financial Year 2017 and 2019

Age (Years)	Home (Discharge)	Non-Home (Discharge)	Total
0-49	60.3%	39.7%	100% (n = 2,163)
50-59	48.1%	51.9%	100% (n = 4,287)
60-69	40.5%	59.5%	100% (n = 12,912)
70-79	39.0%	61.0%	100% (n = 30,816)
80-89	37.1%	62.9%	100% (n = 48,682)
90-99	35.6%	64.4%	100% (n = 24,168)
100+	38.2%	61.8%	100% (n = 788)

In Figure 10, this capstone examines the relationship between race and discharge disposition. While “Decline to Answer”, “Unknown”, and “Hawaiian or Pacific Islander” have a relatively high percentage of patients with a “Non-Home” discharge disposition, this capstone will later show in Figure 14b that, due to a small number of individuals in these categories, the results are statistically insignificant. Separately, it can be seen that the categories of “White” and “Black or African-American” have a high percentage of “Non-Home” discharge disposition as compared to other groups. The upcoming multiple logistic regression analysis will serve as a powerful tool to unmask the interactions of the multiple covariates that have been discussed thus far and give this capstone a clear picture of the strength of the relationship between the different categories of race.

Figure 10

Percentage Breakdown of Patient Race Versus Discharge Disposition
Between Financial Year 2017 and 2019

Race	Home (Discharge)	Non-Home (Discharge)	Total
White	37.7%	62.3%	100% (n = 77,383)
Black or African-American	39.0%	61.0%	100% (n = 39,474)
Asian	43.7%	56.3%	100% (n = 2,442)
American Indian or Alaskan Native	47.8%	52.2%	100% (n = 268)
Hawaiian or Pacific Islander	38.4%	61.6%	100% (n = 112)
Other	46.5%	53.5%	100% (n = 2,855)
Declined to Answer	33.5%	66.5%	100% (n = 528)
Unknown	34.3%	65.7%	100% (n = 522)
Multiracial	42.7%	57.3%	100% (n = 232)

In terms of the covariate of marital status, an interesting and intuitive insight from the "Non-Home" discharge disposition can be seen. Specifically, the "Married" category has the lowest percentage of "Non-Home" discharges. One can posit that this stands to reason, as living with a spouse may reduce the need for professional caretaking services and thus reduce the likelihood of admission to an outside healthcare institution.

Figure 11

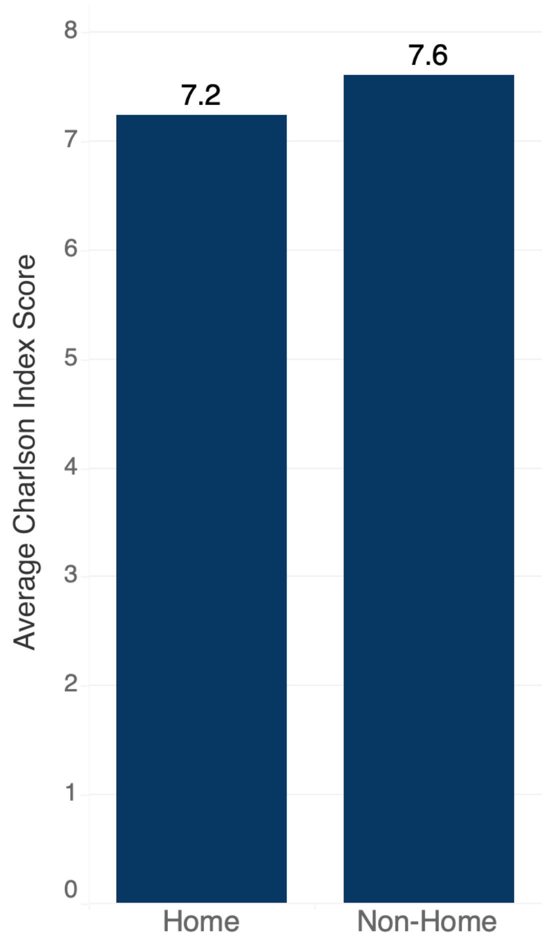
Percentage Breakdown of Marital Status by Discharge Disposition
Between Financial Year 2017 and 2019

Marital Status	Home (Discharge)	Non-Home (Discharge)	Total
Single	36.3%	63.7%	100% (n = 24,086)
Married	42.2%	57.8%	100% (n = 41,725)
Widow/Widower	37.0%	63.0%	100% (n = 43,950)
Divorced	35.5%	64.5%	100% (n = 10,341)
Separated	40.0%	60.0%	100% (n = 1,356)
Unknown	32.1%	67.9%	100% (n = 2,358)

Next, this capstone looks at the average patient Charlson Index Score across the two discharge dispositions. The Charlson Index Score is a weighted score of various comorbidity diagnoses & age and is designed to predict the risk of death of patients. A higher Charlson Index Score is indicative of a higher risk of death (Sundararajan et al.). In Figure 12, it can be seen that a slightly higher Charlson Index Score is associated with the "Non-Home" discharge disposition.

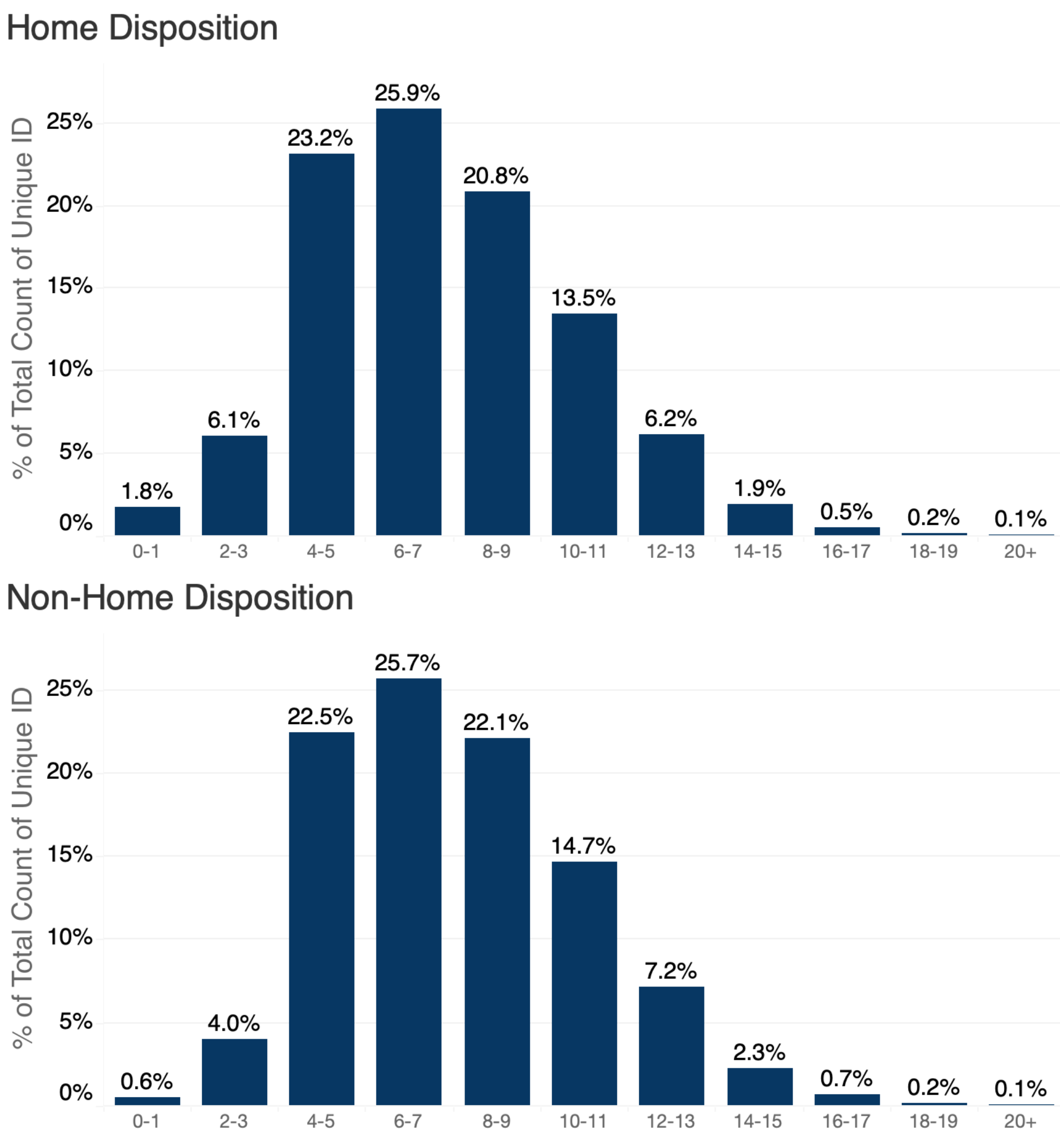
Figure 12

Average Patient Charlson Index Score by Discharge Disposition
Between Financial Year 2017 and 2019



In Figure 13, this capstone continues on the analysis from Figure 12 but looks at the percentage distributions across the various Charlson Index Scores on the X-axis. Firstly, it can be seen that the distributions of Charlson Index Scores are relatively normal across the two groups. Additionally, it can be seen that the bottom "Non-Home" discharge disposition chart consistently has a higher percentage of patients in the higher Charlson Index Scores.

Figure 13
Distribution of Average Patient Charlson Index Score by Discharge Disposition Between Financial Year 2017 and 2019



The purpose of Figure 14a is to provide context as to the odds ratios provided in the multiple logistic regression in Figure 14b. Thus, one can think of the reference group as white males, with a "single" marital status, who experience Dementia, and who lived at home prior to being admitted to the hospital. Additionally, as the reference group for the Y-variable is discharge disposition of “Home”, an odds ratio above a value of 1.0 indicates an increased risk of the patient being discharged to a “Non-Home” location.

Figure 14a
Reference Group of Multiple Logistic Regression

Covariates	Reference Value
Y Covariate	
Discharge Disposition	Home
X Covariates	
Source of Admission	Home
Diagnosis	Dementia
Sex	Male
Race	White
Marital Status	Single

Lastly, the multiple logistic regression in Figure 14b provides this capstone with some of this works most meaningful insights. In addition to the benefit of controlling for the influence of the various covariates of interest and determining whether each covariate is statistically significant, one can also infer the degree to which each covariate is associated with the odds of a patient being discharged to a “Non-Home” location.

To provide a frame of context for the following odds ratios, the odds of having a “Non-Home” discharge is 1.63 for the reference group described above, across all Ages, Charlson Index Scores, and ICD counts. In Figure 14b, it can specifically be seen that most of the covariates chosen are statistically significant, except for certain categories of Race and Marital status. Of note, it can be seen that the strongest increase in the odds of being discharged to a “Non-Home” location is associated with whether the patient was admitted from a “Non-Home” location. Moreover, it can be seen that each additional ICD diagnosis a patient accumulates increases the odds of being discharged to a “Non-Home” location by 5.8%. Additionally, it can also be seen that each year of age also increases the odds of this outcome by 3.6%.

Interestingly, it can be seen that patients experiencing Alzheimer's see a reduction of 8.2% in the odds of being discharged to a “Non-Home” location as compared to Dementia patients. Moreover, despite the relatively similar distributions in discharge for “Sex” in Figure 8, multiple logistic regression uncovers a nearly 10% reduction in the odds of being discharged to a “Non-Home” location for females as compared to males. Moreover, it can be seen that patients who are married see more than a 30% reduction in the odds of being discharged to a “Non-Home” location as compared to single patients.

Interaction terms were added to the regression model, due to concerns of colinearity between the Charlson Index Score and the covariates of “Age” and “Count of ICD”. In fact, the Charlson Index Score is calculated using both Age and specific ICD codes, with both high age and an accumulation of certain ICD codes leading to a higher Charlson Index Score. Prior to the addition of interaction terms, the regression model indicated an unintuitive <1 odds ratio with an increasing Charlson Index Score. Following the addition of these two interaction terms, it can now be seen that a single point increase in the Charlson Index Score is associated with an increase of 14.9% in the odds of being discharged to a “Non-Home” location.

Figure 14b
Multiple Logistic Regression
* Bolded Covariates Signify Statistically Significance (p-value < 0.05)

Covariate	Odds Ratio	P-value
Source of Admission Non-Home	**2.550**	**<0.001**
Count of ICD	**1.058**	**<0.001**
Age	**1.036**	**<0.001**
Alzheimer	**0.918**	**<0.001**
Female	**0.896**	**<0.001**
Patient Race (American Indian or Alaskan Native)	**0.687**	**0.003**
Patient Race (Asian)	**0.871**	**<0.001**
Patient Race (Black or African-American)	1.000	0.996
Patient Race (Declined)	1.132	0.198
Patient Race (Hawaiian or Pacific Islander)	1.134	0.532
Patient Race (Multi-racial)	0.778	0.072
Patient Race (Other)	**0.775**	**<0.001**
Patient Race (Unknown)	0.918	0.380
Marital Status (Married)	**0.685**	**<0.001**
Marital Status (Separated)	**0.828**	**0.002**
Marital Status (Divorced)	**0.924**	**0.002**
Marital Status (Widow/Widower)	**0.790**	**<0.001**
Marital Status (Unknown)	1.079	0.119
Charlson Index Score	**1.149**	**<0.001**
Interaction Term 1 (Count of ICD * Charlson Index Score)	**1.000**	**0.042**
Interaction Term 2 (Age * Charlson Index Score)	**0.998**	**<0.001**

Conclusion

Thanks to the large sample size of over 120,000 patients, the findings of this exploratory analysis suggest that besides patient source of admission, “Age”, “ICD Count”, and “Charlson Index Score” are positively associated with “Non-Home” disposition following hospital discharge. Moreover, on the flip side, the results also suggest that “Marriage” has a rather large negative association with “Non-Home” disposition following hospital discharge. With regards to ICD count, one area of future interest would be to learn more about how certain ICDs impact post-hospitalization discharge differentially. This could be of clinical significance, providing an understanding as to which diseases are most associated with non-home post-hospital dispositions and lead to public health interventions that intervene to prevent and mitigate these diagnoses. Additionally, another avenue for further investigation is the association between hospital length of stay and post-discharge disposition. Lastly, elaborating on the socioeconomic factors examined in this capstone, further work would allow for the investigation of whether patients' zip code of residence is associated with post-hospital discharge disposition.

Learnings & New Competencies

1. Data Prepping
    a. ICD Coding Crosswalk
    b. Charlson Index Calculation
    c. Working with Large Datasets
2. Data Analysis
    a. Microsoft Access
        i. SQL
        ii. Subqueries
        iii. Joins

        iv. Group Bys
    b. R
        i. Filtering Data
        ii. Casting Covariates Datatypes
        iii. Logistic Regression
            1. Reordering reference groups
        iv. Recoding Covariates
        v. Scatterplots
        vi. Object-Oriented Programing
    c. Tableau
        i. Custom visuals
3. Conceptual
    a. Working with Discharge Data
    b. Charlson Index & Quantifying Comorbiditiy Severity
    c. Alzheimer’s and Dementia familiarity
    d. Formulating a finite problem out of a vast dataset

Works Cited

1. Chronic Conditions Data Warehouse. (n.d.). Retrieved April 21, 2022, from https://www2.ccwdata.org/web/guest/condition-categories-chronic

2. Cox, C. B. (1996). Discharge planning for dementia patients: Factors influencing caregiver decisions and satisfaction. *Health & Social Work*, *21*(2), 97–104. https://doi.org/10.1093/hsw/21.2.97

3. Sundararajan, V., Henderson, T., Perry, C., Muggivan, A., Quan, H., & Ghali, W. A. (2004). New ICD-10 version of the Charlson Comorbidity Index predicted in-hospital mortality. *Journal of Clinical Epidemiology*, *57*(12), 1288–1294. https://doi.org/10.1016/j.jclinepi.2004.03.012

4. Toot, S., Swinson, T., Devine, M., Challis, D., & Orrell, M. (2016). Causes of nursing home placement for older people with dementia: A systematic review and meta-analysis. *International Psychogeriatrics*, *29*(2), 195–208. https://doi.org/10.1017/s1041610216001654

Acknowledgments

I would like to sincerely thank Dr. Conan Dickson for his support throughout the development of this work. His prior analysis using this same data set served as the inspiration behind this capstone project and he generously spent many hours brainstorming new questions to pursue. Moreover, I was the beneficiary of much work to structure the underlying data inside a relational database, which without a doubt, saved me countless hours.