Mental Health Effects on Decision Making for Medical Care

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Abstract

This paper examines how mental health conditions shape timeliness in health-related decision making. Using National Health Interview Survey micro data (30,000 adults), we estimate logistic models for three outcomes: (i) delays in cost-related decisions, (ii) delays in seeking medical care, and (iii) delays in accessing mental health care. Depression and anxiety-related symptoms are the key predictors, with demographic and socioeconomic controls. Across specifications, ongoing treatment and some lower-intensity symptoms (e.g., frequent but managed worrying) are associated with fewer delays, whereas severe symptomatology (e.g., high depression severity, uncontrolled worry, fatigue, low self-esteem, sleep disturbance) predicts substantially greater delay. These results suggest that when thinking feels hard and emotions are unsettled, people procrastinate more and are less likely to follow through on medical care. The findings highlight the importance of integrating mental health support into pathways for medical care to mitigate avoidable delays and improve outcomes.

Keywords: mental health, decision making, medical care

I Introduction

Decision-making is essential in daily life and particularly crucial in healthcare, where stress and uncertainty complicate choices. Mental health conditions like anxiety and depression significantly affect cognitive and emotional processes, influencing decision-making. This paper focuses on how mental health impacts medical care decisions, emphasizing delays caused by psychological and financial barriers.

Prior research shows that mental health disorders often result in impaired cognitive control, increased impulsivity, and altered risk perception. Slade (2017) emphasizes the importance of shared decision-making (SDM) in empowering individuals with severe mental illnesses to participate in treatment planning, bridging the gap between reduced decision-making capacity and autonomy. Similarly, Cáceda et al. (2014) find that severe mental illnesses (e.g., schizophrenia and mood disorders) affect reward sensitivity and long-term decision-making, complicating everyday choices.

Beyond clinical settings, mental health directly and indirectly influences financial decision-making. Gärling et al. (2009) highlight the role of financial stress and cognitive biases—often exacerbated by mental health conditions—in limiting individuals' access to healthcare. These pressures can lead to delays or avoidance in seeking necessary care, underscoring the interplay between mental health, financial stability, and healthcare.

From an economic perspective, Knapp and Wong (2020) underscore the far-reaching consequences of mental health disorders on productivity and healthcare costs. Targeted interventions that address symptoms can reduce economic burdens and enhance individuals' capacity for optimal decision-making.

Evidence (e.g., Robinson et al., 2015) indicates that under stress, people with lower anxiety tend to avoid risk, whereas higher anxiety is associated with stress-induced risk-seeking. These patterns illustrate nuanced interactions between mental health and cognitive-emotional regulation, highlighting the complexity of decision-making under psychological distress.

Consequences of impaired decision-making are particularly severe in healthcare. Mental health disorders can delay care-seeking, exacerbating conditions and increasing system burdens. Supported/shared decision-making models (Slade, 2017; Simmons and Gooding, 2017; Jeste et al., 2018) aim to address these challenges by providing structured support that improves timely, collaborative choices.

Building on this literature, we examine how specific symptoms—fatigue, concentration difficulties, and diminished self-esteem—affect healthcare decision-making. We use logistic regression on National Health Interview Survey (NHIS) microdata (about 30,000 observations), which include mental-health indicators (frequency/severity of depression and anxiety) and demographics/socioeconomics (age, income, job status, education). We study delays in seeking medical care and delays in cost-related decisions. Overall, we find that ongoing treatment and mild depressive symptoms support timely decisions, whereas severe symptoms create important barriers.

II Model Setup

We estimate a binary-response model via logistic regression. Let $Y \in \{0, 1\}$ denote the event of interest and $X = (X_1, \ldots, X_k)$ predictors. The conditional probability is:

$$\Pr(Y = 1 \mid X) = \frac{\exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k)}{1 + \exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k)}. \tag{1}$$

Equivalently, the log-odds satisfy

$$\log\left(\frac{\Pr(Y = 1)}{1 - \Pr(Y = 1)}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k. \tag{2}$$

To classify observations, a threshold t is applied to $\widehat{p}_i = \Pr(Y_i = 1 \mid X_i)$:

$$\widehat{Y}_i = \begin{cases} 1 & \text{if } \widehat{p}_i \geq t, \\ 0 & \text{if } \widehat{p}_i < t. \end{cases}$$

In the baseline implementation, we set t to the sample mean of predicted probabilities (other thresholds or ROC-based cutoffs can be used in robustness checks).

Data preparation excludes missing values and codes outcomes as binary indicators. Predictors are chosen based on theoretical and practical relevance. Estimated coefficients and marginal effects inform the direction and strength of relationships.

III Method for Accuracy Evaluation

For each observation i, we compute the predicted probability

$$\widehat{p}_i = \frac{\exp(\widehat{\beta}_0 + \sum_k \widehat{\beta}_k X_{ik})}{1 + \exp(\widehat{\beta}_0 + \sum_k \widehat{\beta}_k X_{ik})}.$$

Let $\bar{p} = \frac{1}{n} \sum_{i=1}^{n} \widehat{p}_i$ denote the average predicted probability. Define:

$$\widehat{Y}_i = \begin{cases} 1 & \text{if } \widehat{p}_i \geq \bar{p}, \\ 0 & \text{if } \widehat{p}_i < \bar{p}. \end{cases}$$

We then tabulate $\widehat{Y}$ against Y to assess agreement. Additional diagnostics (e.g., ROC/AUC, calibration plots) can complement this mean-threshold rule.

IV Estimation and Findings

We estimate six survey–weighted logistic models in parallel: three use depression–related predictors and three use anxiety–related predictors, each mapped to a distinct delay outcome:(i) cost–related decisions, (ii) seeking medical care, and (iii) accessing mental health care. All six specifications use an identical covariate set for comparability: basic demographics (age, sex), socioeconomic controls, a monotone log transformation of income to address right–skew, and class–of–worker indicators with a clearly stated reference group. Mental health measures enter as dummy or ordered indicators, allowing effects to be interpreted relative to symptom absence/low intensity.

Tables 1–6 report logit coefficients, standard errors, z–statistics, p–values, and 95% confidence intervals. Interpretation is based on coefficient signs and statistical significance; higher symptom burden is associated with greater delays.

Depression (Tables 1–3) Across outcomes, indicators tied to treatment and symptom management are linked to timelier action, whereas indicators of greater symptom burden are linked to postponement. In particular, taking medication for depression (`DEPRX`) is consistently associated with fewer delays, suggesting that active engagement with care eases follow-through. By contrast, higher depression severity (`DEPFEELVL`) and core PHQ components—sleep problems (`PHQSLEEP`), low energy (`PHQENGY`), poor appetite/overeating (`PHQEAT`), low self-worth (`PHQBAD`), difficulty concentrating (`PHQCONC`), and psychomotor changes (`PHQMOVE`)—are each associated with more delays, consistent with cognitive load and diminished capacity to plan, initiate, and sustain care-seeking.

The frequency measure (`DEPFREQ`) is negative in multiple specifications. This pattern is compatible with two, nonexclusive mechanisms: respondents who experience depression more often may (i) have stronger motivation to seek help and thus encounter fewer bottlenecks, or (ii) be more connected to services (screening, counseling, routine visits) that lower frictions once symptoms arise. Importantly, this relationship coexists with the positive associations for severity and PHQ components, underscoring that *management status and symptom burden capture different facets* of depression.

These associations are observed across the three delay outcomes, cost-related decisions, medical care, and mental-health care, under a common modeling strategy with identical controls. Full coefficients, standard errors, z–statistics, p–values, and 95% confidence intervals are reported in the accompanying tables.

Table 1: Logistic Regression Results for DELAYCOST

Variable	**Coefficient**	**Std. Err.**	**z**	**P** $>\|z\|$	**[95% Conf. Interval]**
DEPFREQ	-0.1616	0.0348	-4.65	0.000	[−0.2297, −0.0934]
DEPRX	-0.4907	0.0779	-6.30	0.000	[−0.6433, −0.3380]
DEPFEELVL	0.1617	0.0363	4.46	0.000	[0.0906, 0.2327]
PHQSLEEP	0.1406	0.0329	4.28	0.000	[0.0762, 0.2050]
PHQENGY	0.1214	0.0371	3.27	0.001	[0.0486, 0.1942]
PHQEAT	0.1458	0.0358	4.07	0.000	[0.0756, 0.2160]
PHQBAD	0.1739	0.0400	4.35	0.000	[0.0956, 0.2522]
PHQCONC	0.1236	0.0378	3.27	0.001	[0.0495, 0.1976]
Constant	-2.0704	0.1932	-10.71	0.000	[−2.4492, −1.6917]

Table 2: Logistic Regression Results for YDELAYMEDYR

Variable	**Coefficient**	**Std. Err.**	**z**	**P** $>\|z\|$	**[95% Conf. Interval]**
DEPFREQ	-0.1604	0.0399	-4.02	0.000	[−0.2386, −0.0822]
PHQENGY	0.2068	0.0432	4.79	0.000	[0.1222, 0.2914]
PHQEAT	0.1879	0.0416	4.52	0.000	[0.1064, 0.2694]
PHQBAD	0.1777	0.0462	3.84	0.000	[0.0869, 0.2686]
PHQCONC	0.1810	0.0438	4.13	0.000	[0.0948, 0.2668]
PHQMOVE	0.1223	0.0503	2.43	0.015	[0.0237, 0.2209]
Constant	-2.7348	0.1609	-17.00	0.000	[−3.0501, −2.4194]

Table 3: Logistic Regression Results for YDELAYMENTAL

Variable	**Coefficient**	**Std. Err.**	**z**	**P** $>\|z\|$	**[95% Conf. Interval]**
DEPFREQ	-0.0980	0.0346	-2.83	0.005	[−0.1660, −0.0310]
DEPRX	-0.1989	0.0748	-2.66	0.008	[−0.3455, −0.0522]
DEPFEELVL	0.3124	0.0375	8.33	0.000	[0.2386, 0.3854]
PHQSLEEP	0.1349	0.0318	4.25	0.000	[0.0727, 0.1973]
PHQEAT	0.1716	0.0347	4.95	0.000	[0.1036, 0.2395]
PHQBAD	0.3642	0.0386	9.43	0.000	[0.2885, 0.4399]
PHQCONC	0.2193	0.0364	6.02	0.000	[0.1479, 0.2906]
Constant	-3.0164	0.1940	-15.55	0.000	[−3.3967, −2.6361]

Anxiety (Tables 4–6) Across outcomes, ever having an anxiety disorder (`ANXIETYEV`) is positively related to delay. In contrast, reporting frequent worry (`WORFREQ`) and taking medication for worry or nervousness (`WORRX`) are linked to fewer delays, which is consistent with more active management of symptoms. Higher symptom load is associated with more postponement, including difficulty controlling worry (`GADWORCTRL`), worrying too much (`GADWORMUCH`), trouble relaxing (`GADRELAX`), restlessness (`GADRSTLS`), irritability (`GADANNOY`), and feeling afraid (`GADFEAR`). The composite GAD severity indicator (`GADCAT`) is negatively related to delay in the medical care and mental health models, which is consistent with greater engagement among respondents with identified severity. These patterns appear under the common modeling strategy and control set, and full coefficients, standard errors, z–statistics, p–values, and 95% confidence intervals are reported in the tables.

Table 4: Logistic Regression Results for DELAYCOST

Variable	**Coefficient**	**Std. Err.**	**z**	**P** $>\lvert z\rvert$	**[95% Conf. Interval]**
ANXIETYEV	0.2490	0.0753	3.31	0.001	[0.1014, 0.3967]
WORFREQ	-0.2669	0.0285	-9.37	0.000	[−0.3228, −0.2111]
WORRX	-0.4201	0.0788	-5.32	0.000	[−0.5749, −0.2653]
GADWORCTRL	0.1320	0.0381	3.44	0.001	[0.0569, 0.2070]
GADRELAX	0.1722	0.0394	4.37	0.000	[0.0943, 0.2496]
GADRSTLS	0.1189	0.0394	3.02	0.002	[0.0417, 0.1961]
GADANNOY	0.1338	0.0358	3.74	0.000	[0.0682, 0.2086]
Constant	-1.9153	0.1425	-13.44	0.000	[−2.1946, −1.6359]

Table 5: Logistic Regression Results for YDELAYMEDYR

Variable	**Coefficient**	**Std. Err.**	**z**	**P** $>\lvert z\rvert$	**[95% Conf. Interval]**
ANXIETYEV	0.2414	0.0815	2.96	0.003	[0.0814, 0.4011]
WORFREQ	-0.2685	0.0374	-7.18	0.000	[−0.3418, −0.1953]
WORFEELVL	-0.1986	0.0464	-4.28	0.000	[−0.2896, −0.1077]
GADWORMUCH	0.2458	0.0604	4.07	0.000	[0.1274, 0.3642]
GADRELAX	0.2539	0.0554	4.58	0.000	[0.1453, 0.3625]
GADRSTLS	0.2053	0.0515	3.99	0.000	[0.1045, 0.3061]
GADANNOY	0.1846	0.0479	3.85	0.000	[0.0908, 0.2784]
GADFEAR	0.2368	0.0524	4.52	0.000	[0.1342, 0.3394]
GADCAT	-0.4409	0.1087	-4.06	0.000	[−0.6541, −0.2278]
Constant	-1.9407	0.2291	-8.47	0.000	[−2.3896, −1.4917]

Table 6: Logistic Regression Results for YDELAYMENTAL

Variable	**Coefficient**	**Std. Err.**	**z**	**P $>|z|$**	**[95% Conf. Interval]**
ANXIETYEV	0.6383	0.0777	8.22	0.000	[0.4861, 0.7905]
WORFREQ	-0.4475	0.0344	-13.02	0.000	[−0.5148, −0.3801]
WORRX	-0.3439	0.0788	-4.36	0.000	[−0.4938, −0.1894]
GADANX	0.2069	0.0482	4.29	0.000	[0.1123, 0.3013]
GADWORMUCH	0.2208	0.0508	4.35	0.000	[0.1213, 0.3204]
GADRELAX	0.2148	0.0464	4.63	0.000	[0.1238, 0.3058]
GADRSTLS	0.1147	0.0439	2.61	0.009	[0.0284, 0.2003]
GADANNOY	0.1855	0.0445	4.18	0.000	[0.1061, 0.2648]
GADFEAR	0.1216	0.0444	2.74	0.006	[0.0345, 0.2088]
GADCAT	-0.3479	0.0993	-3.50	0.000	[−0.5428, −0.1530]
Constant	-2.1754	0.1705	-12.76	0.000	[−2.5095, −1.8413]

V Conclusion

This study shows that mental health symptoms meaningfully shape the timeliness of health –related decision making. Using NHIS micro-data and comparable survey–weighted logistic models across three outcomes (cost–related delays, medical care, and mental–health care), we find a clear pattern: indicators consistent with treatment and symptom management are associated with fewer delays, whereas higher symptom burden, captured by depression severity and GAD components such as difficulty controlling worry, trouble relaxing, restlessness, irritability, and fear—is associated with more delays. These associations are robust across outcomes under a common specification and align with mechanisms linking cognitive load and affective regulation to reduced follow–through in care seeking.

The policy message is straightforward; integrating mental-health support into routine care pathways—through screening and referral, facilitated access to counseling and medication management, and navigation supports that lower administrative and cost frictions—can help mitigate avoidable delays. Practical steps include brief screening in primary care, warm handoffs to mental-health services, reminders and scheduling assistance, and targeted help for patients reporting severe symptoms.

Several limitations qualify the findings: First, the data are observational and primarily self-reported, limiting causal interpretation and raising the possibility of measurement error. Second, while models harmonize covariates, unobserved confounding may remain. Third, our classification rule relies on a mean-probability threshold; alternative cutoffs (e.g., ROC-based) could be explored. Future work should leverage longitudinal designs or quasi-experimental variation, examine mediation through cognitive and behavioral channels, and assess heterogeneity by socioeconomic status and access to care. Together, these steps would strengthen causal claims and inform more precise interventions aimed at reducing delays and improving health outcomes.

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