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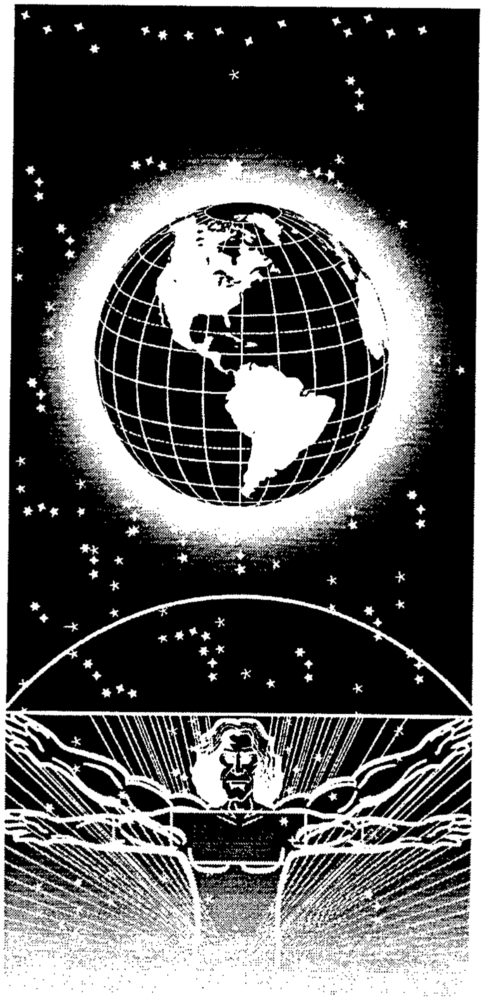

UNITED STATES AIR FORCE
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Health Enrollment Assessment Review 1.0 (HEAR): High Resource Utilization (HRU)

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13. ABSTRACT *(Maximum 200 words)*

The Health Enrollment Assessment Review 1.0 (HEAR) is a self-report health assessment instrument. The HEAR incorporates the high resource utilization (HRU) algorithm to categorize respondents by their expected level of future health care resource utilization ("High," "Medium," or "Low").

This study examined a cohort of 7,596 beneficiaries who completed the HEAR and were continuously enrolled in TRICARE during the succeeding twelve months. Total health care costs were mostly derived from the Corporate Executive Information System (CEIS).

The findings indicate that the HRU algorithm is not sensitive enough to correctly identify high-cost enrollees. It is a poor tool for identifying individuals for utilization/case management or other cost-control interventions. However, it can identify which groups are likely to incur relatively higher or lower costs. Thus, the HRU algorithm could be used to risk-adjust different groups or populations.

The HRU could most likely be improved by modifying the algorithm and categorization scheme. Future studies should use multiple regression analysis to derive a mathematical model for determining an HRU score. The HEAR HRU algorithm should include coding to identify missing and conflicting responses, and produce an "invalid" HRU outcome. Coding should also "flag" specific questions to allow primary care teams to evaluate and follow-up.

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List of Figures

List of Tables

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EXECUTIVE SUMMARY

Introduction

The Health Enrollment Assessment Review 1.0 (HEAR) is a self-report health assessment instrument originally developed for TRICARE Regions 6 and 4 by the USAF Office for Prevention and Health Services Assessment (OPHSA) and Battelle Memorial Institute. The HEAR incorporates an algorithm intended to categorize respondents as to the expected level of future health care resource utilization. This High Resource Utilization (HRU) algorithm uses responses to questions covering 17 health-related variables to assign the individual to one of three categories ("High," "Medium," or "Low"). The algorithm was closely derived from an HRU-type algorithm developed by Yen et al. to predict the cost of medical claims based on behavioral health risk factors. This study evaluated the validity of the HRU algorithm in a population of TRICARE Prime beneficiaries.

Methods

The study examined a cohort consisting of 7,596 Region 6 TRICARE Prime beneficiaries, 17 to 64 years of age, who completed the HEAR during a four-month period (September 1996-December 1996) and who maintained a continuous enrollment in TRICARE Region 6 during the succeeding twelve months (October 1996-December 1997). Total health care costs for each individual were mostly derived from Corporate Executive Information System (CEIS) cost estimates. Preliminary descriptive analysis was done using per person health care costs and HRU categories of "High," "Medium," or "Low." For the main analysis, the "High" and "Medium" HRU categories were collapsed into one category designated as "HIGH HRU" due to the low numbers of individuals in the "Medium" and "High" categories. The "Low" HRU category was redesignated as "LOW HRU." Individuals were subsequently grouped into either "HIGH COST" (top 20% of individuals by cost) or "LOW COST" (bottom 80% of individuals by cost) groups. Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), relative risk, and risk difference were calculated using HIGH/LOW HRU categories as the exposure and HIGH/LOW COST as the outcome.

Results

Among those enrollees classified as HIGH HRU, there was only a 41% probability that they were in the HIGH COST group. Of those in the HIGH COST group, only 13% were classified as HIGH HRU. The relative risk was 2.2 (95% CI: 2.0 – 2.5), indicating that individuals with HIGH HRU were 2.2 times more likely to be HIGH COST than those categorized as LOW HRU. Even though the relative risk was statistically significant, the magnitude of the difference (risk difference: 22.4%) was relatively small. Results of the relative risk analysis were similar to the findings of Yen et al. Adjusting the "cut points" for HIGH and LOW COST grouping (for example, top 10% or top 30% in terms of cost) did not change the association markedly.

The HRU algorithm categorized 2.4% (181) of the 7,596 individuals in the study cohort as "High," 4.0% (301) as "Medium," and 93.7% (7,114) as "Low." The median yearly medical cost for "High" HRU individuals ($1,318) was over three times higher than for "Low" HRU individuals ($409). After controlling for gender, age, and duty status, median yearly medical costs of "High" HRU individuals remained two to three times higher than those of "Low" HRU individuals. The HIGH COST individuals (top 20% in per person costs) accounted for 74% of the cohort's total medical cost.

Conclusions

The findings of this study indicate that the HRU algorithm is not sensitive enough to correctly identify high-cost enrollees. This makes it a poor tool for identifying individuals for utilization/case management or other cost-control interventions. However, the HRU algorithm is successful at identifying which groups are likely to incur relatively higher or lower costs. Thus, the HRU algorithm could be used to risk-adjust different groups or populations. For example, changes in the percentage of HIGH HRU enrollees over time could indicate parallel changes in health resource utilization. Resource managers could use this information for planning and budgetary purposes. Likewise, comparison of HIGH HRU prevalence in different populations could be used as the basis for risk-adjusting capitation rates or outcome measures. For example, Per Member Per Month capitation rates for different TRICARE regions or MEDICARE HMOs could be adjusted by a factor derived from the percentage of HIGH HRU enrollees in the population. Also, outcome measures derived from two empanelled populations could be adjusted by a factor derived from the percentage of HIGH HRU enrollees, thus controlling for differences in case mix.

Although this study did not track changes in HRU status and cost over time, Yen et al showed that regardless of age and gender, people with positive behaviors (or low HRU status) cost less in medical claims. They also showed that medical costs followed changes in risk status over time, both higher and lower. This implies that lowering a person's HRU score should lower future medical costs. Thus, traditional health promotion interventions targeted at lowering HRU-type risks, such as tobacco use or alcohol misuse, could be considered investments that positively impact the fiscal bottom line, as well as improving health outcomes.

In its present form, performance of the HRU algorithm is comparable to the health resource utilization instrument developed by Yen and associates. It should be noted that the Yen algorithm was designed to predict health resource utilization over a three-year period and was validated over a three-year period. The HEAR HRU algorithm was evaluated using only one year's worth of data. The performance of the HEAR HRU algorithm could be significantly different if the analysis is repeated with three years of data.

Recommendations

The validity, sensitivity, and positive predictive value of the HRU algorithm could most likely be improved by modifying the algorithm and categorization scheme. An improved HRU algorithm should be able to identify cohorts for case management or risk-adjusting populations for capitation rates or provider empanelment. The HEAR HRU algorithm should not be used to identify high cost individuals. However, its use as a resource planning and risk-adjustment tool for populations should be explored further.

Future studies should include using multiple regression analysis to derive a mathematical model for determining an HRU score. The score should then be validated against total cost over a multi-year period in a different population. Statistical methods for accounting for individuals who die during the study period or are otherwise lost to follow-up should be used. Future studies should also track changes in HRU score and cost over time to test the findings of Yen et al. Future studies are warranted and should include actual pharmacy costs and dental costs, if at all possible.

Validation of a sample of CEIS data and certain HEAR data, such as chronic disease burden, using actual medical treatment records should be considered if time and resources permit.

Changes to the HEAR HRU algorithm should include coding to identify missing and conflicting responses, and produce an "invalid" HRU outcome. Coding should also "flag" the specific questions to allow primary care teams to evaluate and follow-up as necessary.

INTRODUCTION

The HEAR instrument was developed through the collaborative efforts of the USAF Office for Prevention and Health Services Assessment (OPHSA), TRICARE Region 6, and Battelle Memorial Institute. The HEAR is a voluntary, self-administered health questionnaire given to TRICARE Prime enrollees who are 17 to 64 years old. The 82 questions cover demographics, behavioral health risks, chronic disease burden, cholesterol status, mental health, activity limitations, life satisfaction/family conflict, women's health, clinical preventive services, stress, absenteeism, and medical utilization history. The two main objectives of the HEAR instrument were: 1) assessing the health status, risks, and needs of the population, and 2) predicting resource utilization and appropriate primary care manager level.

Pertaining to the first objective, the HEAR identifies behavioral health risk factors, clinical preventive services needs, and chronic disease burden at the individual and aggregate levels. This information can then be used to target individuals or groups for further evaluation, intervention, and disease or condition management.

The second objective involved developing new predictive models for resource utilization and appropriate level of primary care provider. Both models were developed with the expectation that they would be validated sometime after deployment.

The HRU algorithm was developed based on a body of work done by Yen, Edington, and others at the University of Michigan who hypothesized that health resource utilization was directly related to behavioral health risk factors.[1-5] They showed that health-related measures could be used to predict health costs. Furthermore, they showed that changes in average health costs directly correlated with changes in health risk levels. Their findings provided strong evidence that improving individual health status was associated with financial benefits. Their research identified specific demographic and health risk measures that were the basis for the component elements considered for the HRU algorithm. Aside from the Yen and Edington work, there were relatively few published studies in this area.

The HRU algorithm utilizes 17 risk variables (shown in Figure 1) derived from 31 items in the HEAR questionnaire. (See Table 1 for a list of the 31 HEAR questionnaire items.)

Figure 1: 17 HRU Algorithm Risk Variables

1. Gender	2. Marital status
3. Perceived health status	4. History of high blood pressure
5. History of angina, heart disease, or heart attack	6. History of chronic bronchitis/emphysema
7. Smoking status	8. Family issues
9. Mental health issues	10. History of arthritis
11. Alcohol use	12. Job absenteeism
13. Prescription drug use	14. Outpatient visits
15. Emergency room visits	16. Stress
17. Inpatient visits	

Originally, two HRU categories were developed: "High" and "Low." Those in the "High" HRU category had five or more positive answers to any of the 17 risk variables. "Low" HRU individuals had four or fewer positive answers to any of the 17 risk variables. After pilot testing, a third category was added: "High" HRU with six or more positive answers, "Medium" HRU with five positive answers, and "Low" HRU with fewer than five positive answers.

The HEAR HRU algorithm is intended to be used by DoD TRICARE regions, but could be used by any managed care organization to identify individuals who would likely be high resource utilizers in the future. To validate this algorithm in a managed care population, it was necessary to deploy the HEAR and collect follow-on health resource utilization data. The goal of this study was to validate the HEAR HRU algorithm using the TRICARE Region 6 population.

METHODS

The study uses a retrospective cohort design to evaluate the association between HRU category and per person medical cost (as a surrogate for health resource utilization). The study timeframe was selected based on two considerations: 1) the earliest date that reasonably complete Standard Ambulatory Data Record (SADR) data could be expected, and 2) the latest date that complete Civilian Health And Medical Program of the Uniformed Services (CHAMPUS) data was available. TRICARE Region 6 was selected for this study because it was the first region to deploy the HEAR and represented the most robust data sources. The study cohort consisted of all TRICARE Region 6 Prime enrollees, aged 17 to 64 years, who completed a HEAR questionnaire between September 1996 and December 1996, and who remained enrolled as Prime members in the Region for twelve months. HEAR respondents were identified using data obtained from TRICARE Region 6 managed care support contractor, Foundation Health Federal Services. Continuous enrollment was confirmed by using the Defense Eligibility Enrollment Registration System (DEERS) capitation data at the end of the 12-month follow-up period (see Table 2). Exclusion criteria of improbable costs and missing HRU components were used to define different sub-cohorts for subsequent analysis.

Cost data were derived using all inpatient and outpatient episodes in the Corporate Executive Information System (CEIS). Fifteen percent of direct care episodes and 1% of CHAMPUS episodes had no associated costs in CEIS. These zero-cost episodes occurred in 31% of the study cohort. Since the large number of zero-cost episodes could have had a significant impact on the results of this study, costs were imputed. The imputation was only applied to direct care episodes, not CHAMPUS, due to the absence of variables necessary for imputation. For clarification, those subjects with no CEIS episodes were assigned a total cost of zero.

For zero-cost inpatient stays (n=23), the Associated Standard Area (ASA) cost algorithm was used to impute costs. These costs represent a standard dollar figure that the MTF would receive as revenue from a paying patient based on the Diagnosis Related Group (DRG), locality, and length of stay. For zero-cost outpatient visits (n=6,875), costs were imputed using the same formula used in CEIS, which is based on MTF and the first three characters of the Medical Expense and Performance Reporting System for Fixed Military Medical and Dental Treatment Facilities (MEPRS) code.

Study Cohort

The DEERS capitation files corresponding to the HEAR completion timeframe were not available; therefore, a later data set was used. This reference population (N=175,404) was taken from the October 1997 DEERS capitation file. This population was used only to examine the demographic representativeness of the study cohort.

The study cohort consisted of all HEAR respondents during September-December 1996. This Study Cohort (n=8,131) was used to represent the demographics of the TRICARE Region 6 population. Three records with excessively high cost were found in this cohort. These three outliers ranged in cost from over $650,000 to over $1.9 million (the record with the next highest cost was $111,224). All three were associated with inpatient episodes coded as "knee procedures without principal diagnosis of infection" (DRG 503),[6] and the stays ranged from two to four days. Since DRG 503 was not expected to have such high cost, errors in CEIS were suspected and thus these records were deleted. The resulting sub-set (Cohort 1; n=8,128) was used for cost analysis that did not include HRU category. An additional 532 records were excluded due to missing HRU component data. The resulting sub-set (Cohort 2; n=7,596) was used for all analyses related to HRU category and cost.

Data Sources

The study used three sources of data: HEAR, DEERS, and CEIS. Enrollees' sponsor SSAN and enrollees' dates of birth were used as unique identifiers to link records across all three sources. Information used from the HEAR data included HRU variables and the component question-by-question responses. Demographic data were taken from DEERS. CEIS was the source for cost data.

CEIS data is derived from the following three sources: the Standard Inpatient Data Record (SIDR), the Standard Ambulatory Data Record (SADR), and CHAMPUS. SIDR data reflects "direct care" (MTF) inpatient stays, while SADR data reflects "direct care" (MTF) outpatient visits. CHAMPUS data reflects inpatient and outpatient claims submitted for care provided outside the MTF. The CEIS data provided clinical codes, length of stay, and cost information at the episode-of-care level for this study.

The study derived a total cost per person during the twelve-month follow-up period. This was the sum of an enrollee's costs over all episodes. Subjects with no episodes were considered to have zero cost. Direct care costs were derived from the standard CEIS "Patient Level Cost Accounting (PLCA)" algorithms developed by Systems Research and Application (SRA) International, Inc., that are designed to estimate a dollar amount of resource utilization. CHAMPUS cost data reflected the actual sum of claims paid by CHAMPUS, a third party insurer, and/or any balance paid by the patient.

Data Analysis

The data analysis consisted of 1) descriptive statistics of cost and other utilization measures stratified by demographic strata, 2) descriptive statistics of cost and other utilization measures stratified by demographic strata and HRU category, and 3) measures of the association between HRU category and cost group. Cost was the primary surrogate measure of utilization in this study. Other utilization measures were the counts of inpatient/outpatient episodes of care per individual. Demographic strata were gender, duty status (active duty/other), and age (17-34, 35-44, 45-64 years).

HRU categories were "Low," "Medium," and "High." The "High" and "Medium" HRU categories were collapsed into a single category, HIGH HRU, due to the infrequent occurrence of both HRU categories (2.4% and 4.0%, respectively). Where the HIGH HRU category was used, the "Low" HRU category was referred to as LOW HRU.

In order to validate the HRU algorithm, which predicts categorical outcomes, it was necessary to convert the continuous cost variable to a categorical variable. The authors used the top 20% of individuals, by per person cost, to define the HIGH COST category. The LOW COST category encompassed the remaining individuals. We also investigated other cut points (1%, 5%, 10%, 30%, 40%, and 50%) for comparison purposes.

Positive predictive value (PPV), negative predictive value (NPV), sensitivity, specificity, relative risk, and risk difference were used as measures of association between HRU and COST categories. Risk was defined as the probability of being HIGH COST. Relative risk is defined as the ratio of the risk of being HIGH COST, given HIGH HRU status, to the risk of being HIGH COST, given LOW HRU status. Risk difference is defined as the magnitude of the absolute difference in the risk of being high-cost between low and high HRU levels.

RESULTS

The Study Cohort incurred 53,142 episodes of care, of which 85% were direct care at MTFs, and 15% were CHAMPUS. Fifteen percent (n=1,192) of the cohort had no recorded episodes of health care.

DEMOGRAPHIC COMPARISON

Table 3 presents descriptive statistics on gender, age, marital status, and duty status for the TRICARE Region 6 reference population (N=175,404), Cohort 1 (n=8,128), and Cohort 2 (n=7,596). In Cohort 1, the subjects ranged from 17 to 64 years old (mean 34, s.d. ±11), 57% were males, and 43% were females. The majority was active duty (64%), married (71%), and 17 to 34 years old (59%). Cohort 1 consisted of 72 % sponsors, 26% spouses, and 2% children. The proportion of active duty enrollees was slightly higher in Cohort 1 (64%) than in the reference population (56%). There were also slight differences in gender and age composition. The demographic composition of Cohort 2 was similar to that of Cohort 1.

Relative contribution of subjects by MTF to the reference population, Cohort 1, and Cohort 2 are shown in Table 4. The possible effects of the small differences in relative contribution by each site to the study cohorts are unknown.

COMPARISON OF COST AND OTHER UTILIZATION MEASURES BY DEMOGRAPHICS

Table 5 shows the summary statistics for annual cost per enrollee by demographics for Cohort 1. Since the cost distributions were highly skewed (did not fit a normal distribution) overall and in every demographic stratum, we used median annual costs rather than mean annual costs. The overall median annual cost was $429, with females having a substantially higher median cost ($627) than males ($314). The median cost for individuals 45 years or older ($544) was greater than that for persons 35 to 44 years old ($420) or younger ($409).

We further stratified the data by gender, duty status, and age subgroups. Females consistently showed higher costs than males in each stratum. Males and females showed different trends in median annual costs by age strata. For females, the lowest median cost ($567) was found in the 35 to 44 year stratum. For males, the lowest median cost ($284) was found in the 17 to 34 year stratum. This difference may have resulted from including pregnancy costs, which tend to be incurred by females in their childbearing years (ages 17 to 34).

The median annual cost for active duty enrollees ($406) was lower than for other enrollees ($475). This difference was attributed to the fact that 74% of the active duty enrollees were males, while only 27% of other enrollees were males. After stratifying for gender, the direction was reversed. The median total cost for active duty males ($322) was slightly higher than for other males ($295), and the median total cost for active duty females ($788) was higher than that for other females ($556).

Relationships between demographics and other utilization measures were examined and are shown in Table 6. The median number of outpatient episodes was higher for females (6) than males (3), and the proportion of females with four or more outpatient episodes was also higher (65% vs. 45%). The proportion of individuals with at least one inpatient stay was higher for females (13%) than males (4%). These three trends occurred consistently across all other strata as well.

Comparison of Cost and Other Utilization Measures by Demographics and HRU Categories

Summary statistics for cost and other utilization measures by demographics and HRU categories for Cohort 2 (n=7,596) are presented in Tables 7 and 8, respectively. The vast majority of the Cohort (93.7%) was in the "Low" HRU category. Only 4.0% of the cohort were in the "Medium" and 2.4% were in the "High" HRU categories.

Overall, the median costs increased with each higher HRU category. The median cost was $409 in the "Low" category, $903 in the "Medium" category, and $1,318 in the "High" category. The same trend was observed for females and across the three age strata. For males, the median costs of the "Medium" and "High" categories differed only slightly ($850 vs. $825). These two categories were substantially higher than the "Low" category ($308). The similar increasing trend was observed in the non-active duty stratum, but not in the active duty stratum. Due to the difference in gender composition between the duty strata, further stratification on gender was necessary. However, after this stratification, the sample sizes for the "Medium" and "High" HRU categories in the males were so small that no further comparisons were made. Just as for cost, each of the other utilization measures (inpatient episodes and outpatient episodes) showed an increasing trend across HRU categories in the gender and age strata (Table 8). The minimum annual cost in the HIGH COST category was $1,378, and the total cost in this category accounted for 74% of the overall cost.

Association between Cost and HRU Categories

Figure 2 shows the association between HIGH/LOW HRU category and HIGH/LOW COST category using the 20% cut point.

Figure 2: HRU Category vs. Cost Category

	HIGH COST	LOW COST	Total
HIGH HRU	198	284	482 (6%)
LOW HRU	1326	5788	7114 (94%)
Total	1524 (20%)	6072 (80%)	n=7596

Figure 3: Statistical Analysis of HRU Algorithm at 20% Cut Point

Positive Predictive Value	41%
Negative Predictive Value	81%
Sensitivity	13%
Specificity	95%
Relative Risk	2.2
Risk Difference	22.4%

Among those enrollees classified as HIGH HRU, there was only a 41% probability that they were in the HIGH COST group, as shown in Figure 3. Of those in the HIGH COST group, only 13% were classified as HIGH HRU. The relative risk was 2.2 (95% CI: 2.0 – 2.5), indicating that individuals with HIGH HRU were 2.2 times more likely to be HIGH COST than those categorized as LOW HRU. Even though the relative risk was statistically significant, the magnitude of the difference (risk difference: 22.4%) was relatively small. Results of the relative risk analysis were similar to the findings of Yen et al.[1]

For comparison, results based on other cut points are presented in Tables 9 and 10. Results were highly dependent on the cut points. As the cut point moved from 1% to 50%, the sensitivity and NPV decreased, while the specificity and PPV increased. While relative risk trended downward (4.5 – 1.4) as the cut point increased, risk difference was greatest at a 30% cut point (26%).

CONCLUSIONS

STUDY FINDINGS

The findings of this study indicate that the HRU algorithm is not sensitive enough to correctly identify high-cost enrollees. This makes it a poor tool for identifying individuals for utilization/case management or other cost-control interventions targeted at high-cost utilizers. However, the HRU algorithm is successful at identifying which groups are likely to incur relatively higher or lower costs. Thus, the HRU algorithm could be used to risk-adjust different groups or populations. For example, changes in the percentage of HIGH HRU enrollees over time could indicate parallel changes in health resource utilization. Resource managers could use this information for planning and budgetary purposes. Likewise, comparison of HIGH HRU prevalence in different populations could be used as the basis for risk-adjusting capitation rates or outcome measures. For example, Per Member Per Month capitation rates for different TRICARE regions or MEDICARE HMOs could be adjusted by a factor derived from the percentage of HIGH HRU enrollees. Also, outcome measures derived from two empanelled populations could be adjusted by a factor derived from the percentage of HIGH HRU enrollees, thus controlling for differences in case mix.

Although this study did not track changes in HRU status and cost over time, Yen et al showed that regardless of age and gender, people with positive behaviors (or low HRU status) cost less in medical claims.[1] They also showed that medical costs followed changes in risk status over time, both higher and lower.[5] This implies that lowering a person's HRU score should lower future medical costs. Thus, traditional health promotion interventions targeted at lowering HRU-type risks, such as tobacco use or alcohol misuse, could be considered investments that positively impact the fiscal bottom line as well as improving health outcomes.

In its present form, performance of the HRU algorithm is comparable to the health resource utilization instrument developed by Yen and associates. It should be noted that the Yen algorithm was designed to predict health resource utilization over a three-year period and was validated over a three-year period. The HEAR HRU algorithm was evaluated using only one year's worth of data. The performance of the HEAR HRU algorithm could be significantly different if the analysis is repeated with three years of data.

The validity, sensitivity, and positive predictive value of the HRU algorithm could most likely be improved by modifying the algorithm and categorization scheme. An improved HRU algorithm should be able to identify cohorts for case management or risk-adjusting populations for capitation rates or provider empanelment. Future research is warranted and should focus on developing a predictive model with weighted risk factors using multiple regression techniques and validating the model on a full three years of data.

STUDY LIMITATIONS

Study Design and Analysis

The study cohort consisted of enrollees who responded to the HEAR questionnaire during four months (September 1996-December 1996). This represented approximately 4.6% of the enrolled eligible population. Because the actual number of HEAR questionnaires mailed out during this period is unknown, we cannot calculate the actual response rate. However, findings from this small, non-random cohort may not be generalizable to the reference population.

When defining HIGH COST in the analysis of association, ideally the reference group should be the entire TRICARE Prime Region 6 enrollee population aged 17 to 64. However, due to time considerations, we used the cost distribution of our study Cohort 1 to define HIGH COST. Since the cohort and population differed demographically, we believe that if we had applied the same percentile definition of HIGH COST to the reference population, HIGH COST might have been a different dollar figure and changed the study results.

A strict evaluation of the association of HRU category and cost category would involve three of each. However, after collapsing the three HRU categories into two due to small sample sizes, corresponding cost categories were also dichotomized.

Length of Follow-Up

Most outcome studies of health risks involve a multi-year follow-up to allow for development of the disease state. This timeframe would also be necessary to accurately assess subsequent health-care costs. Yen et al. used three years of data to validate their original algorithm, and six years of data to show the association of health risk status and cost over time. However, this study was limited to a one-year follow-up because the customer for the project requested a more immediate report. Follow-on studies, including more HEAR respondents and a longer follow-up period, may show a stronger association between HRU status and cost.

HRU Algorithm

The HEAR HRU algorithm equally weights all the risk factors and, therefore, does not distinguish which risks contribute more or less to the predictive model. Using multivariate analysis to determine the most significant predictors and their relative weights would most likely result in a better algorithm. Also, the cut points between "Low," "Medium," and "High" HRU categories determined by the original HEAR developers appeared to be somewhat arbitrarily determined. The cut points between the HIGH/LOW COST groupings were arbitrary as well. This resulted in less precise categorical variables that limited statistical analysis. Using HRU and cost score as continuous variables may improve the performance of the algorithm.

Two issues associated with scoring were found. First, the algorithm does not distinguish between a missing response and an actual negative response, and codes both as a negative response. For example, a respondent who both smokes and drinks, yet declines to answer the relevant smoking and drinking questions, and otherwise answers four of the remaining risk factors affirmatively, will have a score of 4 and an HRU category "Low," rather than a true HRU category "High," corresponding to a score of 6. This is particularly troublesome, given that some respondents, particularly active duty members, might leave sensitive questions blank out of concerns regarding confidentiality. This current methodology would tend to underestimate HRU status and may reduce the ability of the algorithm to predict resource utilization. It would also tend to lessen the magnitude of the association between HRU and cost within this study.

Second, the HEAR algorithm does not use skip-pattern logic to identify conflicting responses. For example, one leading question for alcohol use is followed by four subsequent questions. An individual who answers negatively to "ever using alcohol" and who proceeds to answer affirmatively to any of the subsequent drinking questions will have an increase in their HRU score. Coding logic is needed to identify missing or conflicting responses and create an "invalid" HRU category. Also needed would be a "flag" noting such occurrences for the primary care team to evaluate.

Age is a recognized risk factor in the literature and in the Yen algorithm,[2,4] and is identified in the HEAR project final report as an HRU risk variable.[7, 8] However, age was omitted from the HRU algorithm for unknown reasons. Including age in the algorithm might have improved the association between HRU and cost.

Quality of Data

Due to time and resource constraints, no attempt was made to validate data quality and integrity in the various data sources used in this study. We accepted the data as given, except where noted below.

Actual pharmacy costs are not collected in CEIS and thus were not readily available. Therefore, only average estimated pharmacy costs from the Patient Level Cost Accounting (PLCA) algorithm were used. Unfortunately, true pharmacy costs may be substantially different from estimated average costs; therefore, the true contribution of pharmacy costs to total costs is unknown. Dental costs were not readily available and were not included in this study.
In general, all sources of data used during this study had some issues concerning data completeness. These center on completeness of reporting and completeness of coverage. In direct care data (SIDR and SADR), we have inferred the completeness of reporting from ratios of

SIDR and SADR episodes to MEPRS counts (Tables 11 and 12). However, these ratios may be unreliable, since their range is wide and often overlaps 100%. CHAMPUS data may also be incomplete due to lags in reporting claims.

There is additional data that is not collected in CEIS: treatment outside the MTF for enrollees paid for by either a managed care contract or third-party insurance. This missing data leads to underestimation of the total cost for individuals receiving such care, thereby weakening the association between HRU and cost.

Enrollees who died during the year following completion of a HEAR questionnaire were excluded from the study. Since health costs tend to escalate immediately prior to death, some of these excluded subjects may have been high-cost utilizers, but the impact of their exclusion from this study is unknown.

Costs

Total cost per person over twelve months was used as a surrogate for resource utilization. Three types of cost were used in the study: the Patient Level Cost Accounting (PLCA) algorithm costs, CHAMPUS claims, and cost imputations (for zero-cost episodes). CEIS provides PLCA and CHAMPUS costs. The PLCA algorithm estimates costs for three types of direct care episodes: 1) inpatient stays, where there are several factors for staffing, physician salary, bed days, and DRG case complexity; 2) same-day surgery, which is based on physician time estimates, work center, and MTF; and 3) outpatient visits, which depend only on average pharmacy cost and overall staffing expense for the work center. For example, every patient seen in a family practice clinic would be given the same cost estimate, regardless of diagnosis, level of care, or number of prescriptions. This has the effect of homogenizing the outpatient cost and probably reduces the power of this study, especially since the overwhelming majority of episodes were outpatient. CHAMPUS data reflected the actual sum of claims paid by CHAMPUS, any third party insurer, and any balance paid by the patient. The effect of the imputation of costs for inpatient zero-cost episodes is unknown, but since it represents claims reimbursement amounts, it might be expected to be higher than actual cost accounting amounts. Cost imputations for outpatient visits would be the same as those in CEIS, as they use the same formula.

HEAR Administration Issues

When comparing the study cohort to the TRICARE Prime Region 6 reference population, differences in the relative population contribution by MTFs were observed (Table 4). These were most likely due to varying HEAR response rates by MTF, or differences in assigned MTF between DEERS and HEAR data.

RECOMMENDATIONS

The HEAR HRU algorithm should not be used to identify high cost individuals. However, its use as a resource planning and risk-adjustment tool for populations should be explored further.

Future studies should use multiple regression analysis to derive a mathematical model for determining an HRU score. The score should then be validated against total cost over a multi-year period in a different population. Statistical methods for accounting for individuals who die during the study period or are otherwise lost to follow-up should be used. Future studies should also track changes in HRU score and cost over time to test the findings of Yen et al.[5] Estimates of cost should include actual pharmacy costs and dental costs, if at all possible.

Validation of a sample of CEIS data and certain HEAR data, such as chronic disease components, using actual medical treatment records should be considered if time and resources permit.

Changes to the HEAR HRU algorithm should include coding to identify missing and conflicting responses, and produce an "invalid" HRU outcome. Coding should also "flag" the specific questions to allow primary care teams to evaluate and follow-up as necessary.

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TABLES

Table 1: Risk Variables Affecting High Resource Utilization (HRU) Category

Risk Variables*	Relevant HEAR Questions	Positive HRU Responses
1. Gender	*Gender?*	Female
2. Marital status	*Marital status?*	Never married
3. Perceived health status	*Would you say that your health in general is...*	Fair OR Poor
4. History of high blood pressure	*Have you been told two or more different times that you had hypertension or high blood pressure?*	Yes
5. History of angina, heart disease, or heart attack (any one of the 3)	*a) Have you ever been told by a health care provider that you have...had a heart attack?* *b) Have you ever been told by a health care provider that you have...had a stroke?* *c) Have you ever been told by a health care provider that you have...heart disease or angina?*	a) Yes OR b) Yes OR c) Yes
6. History of chronic bronchitis/emphysema	*Have you ever been told by a health care provider that you have...chronic bronchitis/emphysema?*	Yes
7. Smoking status	*Do you now smoke cigarettes every day, some days, or not at all?*	Some days OR Every day
8. Family issues (either of the 2)	*a) In general, how satisfied are you with your life (e.g., work situation, social activity, accomplishing what you set out to do)?* *b) How often do you have serious problems dealing with your husband or wife, parents, friends or with your children?*	a) Not satisfied OR b) Often
9. Mental health issues (any one of the 6)	*a) In the past month, have you often been bothered by little interest or pleasure in doing things?* *b) In the past month, have you often been bothered by feeling down, depressed, or hopeless?* *c) In the past month, have you often been bothered by "nerves" or feeling anxious or on edge?* *d) In the past month, have you often been bothered by worrying about a lot of different things?* *e) During the past month, have you had an anxiety attack (suddenly feeling fear or panic)?* *f) During the past 12 months, have you been treated by a mental health professional?*	a) Yes OR b) Yes OR c) Yes OR d) Yes OR e) Yes OR f) Yes
10. History of arthritis	*Have you ever been told by a health care provider that you have...had arthritis?*	Yes

* = Each variable can only contribute "1" to the HRU score.

Table 1: Risk Variables Affecting High Resource Utilization (HRU) Category, cont.

Risk Variables*	Relevant HEAR Questions	Positive HRU Responses
11. Alcohol use (any one of the 4)	*a) During the past month, have you thought you should cut down on your drinking of alcohol?*	a) Yes OR
	b) During the past month, has anyone complained about your drinking?	b) Yes OR
	c) During the pass month, have you felt guilty or upset about your drinking?	c) Yes OR
	d) During the past month, was there at least one day on which you had five or more drinks of beer, wine, or liquor?	d) Yes
12. Job absenteeism (either of the 2)	*a) During the past two weeks, how many days did you stay in bed for more than half of the day because of illness or injury?*	a) 5 or more days OR
	b) During the past two weeks, how many days did you miss more than half of the day from job business because of illness or injury?	b) 5 or more days
13. Prescription drug use	*How many different prescription medications are you currently taking?*	6 or more medications
14. Outpatient visits	*Excluding visits for pregnancy, medication refills, and dental care, how many times did you see a doctor, nurse, or other health care professional for an office visit or clinic appointment? (Include both civilian and military health care professionals. Only include visits for yourself.) During the past 12 months.*	21 or more visits
15. Emergency room visits	*During the past 12 months, how many times have you gone to an emergency room or urgent care clinic?*	5 or more visits
16. Stress (any one of the 3)	*a) How often do you feel that your present work or lifestyle is putting you under too much stress?*	a) Often OR
	b) During the past 2 weeks, would you say that you experienced...?	b) A lot of stress OR
	c) In the past year, how much effect has stress had on your health?	c) A lot
17. Inpatient visits (either of the 2)	*a) During the past twelve months, how many nights have you spent in the hospital?*	a) 4 or more times OR
	b) During the past twelve months, on how many different occasions did you enter the hospital and stay for at least one night?	b) 2 or more times

* = Each variable can only contribute "1" to the HRU score.

Table 2: Study Timeframes by Data Source

Cohort (by month) HEAR File (Import date)	Costs from CEIS	Enrollment DEERS Capitation File
Sep 96	Oct 96 to Sep 97	Oct 97
Oct 96	Nov 96 to Oct 97	Nov 97
Nov 96	Dec 96 to Nov 97	Dec 97
Dec 96	Jan 97 to Dec 97	Jan 98

Table 3: Demographic Composition of the Reference Population and Cohorts

Variable	Category	Percent of Reference Population (N=175,404)	Percent of Cohort 1 (n=8,128)	Percent of Cohort 2 (n=7,596)
Gender	Male	61%	57%	56%
	Female	39%	43%	44%
Age	Years	mean 33, s.d. ±12	mean 34, s.d. ±11	mean 34, s.d. ±11
	17-34	64%	59%	58%
	35-44	20%	25%	25%
	45-64	16%	16%	17%
Marital Status	Single	21%	24%	24%
	Married	74%	71%	72%
	Unknown	5%	5%	4%
Beneficiary Category	Active Duty (AD)	56%	64%	61%
	AD Family	22%	17%	18%
	Retiree	8%	7%	8%
	Retiree Family	11%	8%	8%
	Other	3%	0%	1%
	Unknown		4%	4%
Family Relationship	Sponsor	67%	72%	70%
	Spouse	28%	26%	28%
	Child	5%	2%	2%

Table 4: Composition of Reference Population and Cohorts According to Medical Treatment Facility (MTF) of TRICARE Prime Enrollment

Defense Medical Information System (DMIS) ID and MTF Name	Percent of Reference Population* (N=175,404)	Percent of Cohort 1 (n=8,128)	Percent of Cohort 2 (n=7,596)
0013 Little Rock AFB, AR	1.5%	9.1%	8.5%
0062 Barksdale AFB, LA	2.2%	5.9%	6.2%
0064 Bayne-Jones ACH, Ft. Polk, LA	7.0%	2.3%	2.4%
0096 Tinker AFB, OK	7.9%	4.2%	4.1%
0097 Altus AFB, OK	2.7%	0.9%	0.9%
0098 Reynolds ACH, Ft. Sill, OK	11.5%	2.7%	2.9%
0109 Brooke AMC, Ft. Sam Houston, TX	2.5%	3.9%	3.5%
0110 Darnall ACH, Ft. Hood, TX	3.5%	4.5%	4.8%
0112 Dyess AFB, TX	0.8%	1.2%	1.2%
0113 Sheppard AFB, TX	0.8%	5.5%	4.9%
0114 Laughlin AFB, TX	1.2%	0.5%	0.5%
0117 Wilford Hall Medical Center, TX	9.0%	4.9%	5.1%
0118 NH Corpus Christi, TX	3.4%	4.5%	4.8%
0338 Vance AFB, OK	0.3%	1.0%	1.0%
0363 Brooks AFB, TX	1.4%	2.7%	2.8%
0364 Goodfellow AFB, TX	1.0%	1.2%	1.2%
0365 Kelly AFB, TX	3.3%	1.2%	1.2%
0366 Randolph AFB, TX	6.3%	4.8%	4.8%
0369 NBMC, Kingsville TX	0.7%	2.5%	2.7%
0656 Ingleside Navy, Corpus Christi, TX	1.6%	2.3%	2.3%
1587 TMC McWethy-Ft. Sam Houston, TX	6.5%	8.2%	7.0%
1588 TMC-1, Ft. Hood, TX	0.0%	0.0%	0.0%
1592 Monroe Consolidated-Ft. Hood, TX	9.1%	2.4%	2.4%
1593 TMC-6, Ft. Hood, TX	4.0%	1.6%	1.6%
1597 TMC-10, Ft. Hood, TX	1.0%	0.3%	0.4%
1599 TMC-12, Ft. Hood, TX	1.3%	0.3%	0.3%
1745 USAF Troop Clinic Lackland, TX	3.3%	7.1%	7.3%
6906 FHFS Network Region 6	0.0%	12.3%	13.0%
7236 Bennett HC, Ft. Hood, TX	6.1%	2.2%	2.1%

*Source of data: DEERS capitation file as of October 1997

Table 5: Summary Statistics for Annual Cost per Enrollee by Demographic Variables in Cohort 1

Demographic Variable	Category	Sample Size	Annual cost ($) per enrollee		
			Median	Interquartiles*	Range
All		8,128	429	124-1,102	0-111,224
Gender	Male	4,626	314	89-773	0-111,224
	Female	3,502	627	227-1,696	0-74,732
Age (years)	17-34	4,781	409	116-1,027	0-43,264
	35-44	2,050	420	124-1,037	0-48,352
	45-64	1,297	544	185-1,497	0-111,224
Duty Status	Active Duty (AD)	5,164	406	118-979	0-43,264
	Other	2,964	475.	147-1,369	0-111,224
Gender/ Duty Status	Male/AD	3,837	322	94-755	0-43,264
	Male/Other	789	295	57-876	0-111,224
	Female/AD	1,327	788	295-1,956	0-28,622
	Female/Other	2,175	556	194-1,545	0-74,732
Gender/ Age (years)	Male/17-34	2,760	289	73-684	0-43,264
	Male/35-44	1,237	364	94-856	0-25,186
	Male/45-64	629	385	110-1,239	0-111,224
	Female/17-34	2,021	654	233-1,847	0-26,650
	Female/35-44	813	567	197-1,427	0-48,351
	Female/45-64	668	655	272-1,664	0-74,732
Gender/ Duty Status/ Age (years)	Male/AD/17-34	2,591	295	82-697	0-43,264
	Male/AD/35-44	1,078	390	113-890	0-25,186
	Male/AD/45-64	168	406	126-1,007	0-15,390
	Male/Other/17-34	169	153	0-474	0-4,382
	Male/Other/35-44	159	169	50-589	0-6,116
	Male/Other/45-64	461	377	107-1,334	0-111,224
	Female/AD/17-34	938	823	314-2,061	0-26,650
	Female/AD/35-44	328	728	259-1,631	0-28,622
	Female/AD/45-64	61	845	348-1,618	0-12,454
	Female/Other/17-34	1083	547	186-1,623	0-26,027
	Female/Other/35-44	485	442	147-1,323	0-48,351
	Female/Other/45-64	607	642	256-1,670	0-74,732

* Interquartiles range encompasses the 50% of individuals between the 25th and 75th percentiles

Table 6: Summary Statistics for Other Utilization Measures by Demographic Variables in Cohort 1

Demographic Variable	Category	Sample Size	Median Number of Outpatient Episodes per Enrollee	Range of Number of Outpatient Episodes per Enrollee	Enrollees with 4 or more Outpatient Episodes (%)	Enrollees with 1 or More Inpatient Episodes (%)
All		8,128	4	0-122	54%	8%
Gender	Male	4,626	3	0-97	45%	4%
	Female	3,502	6	0-122	65%	13%
Age(years)	17-34	4,781	4	0-113	52%	8%
	35-44	2,050	4	0-122	52%	6%
	45-64	1,297	5	0-67	61%	7%
Duty Status	Active Duty (AD)	5,164	4	0-122	52%	6%
	Other	2,964	4	0-97	57%	10%
Gender/ Duty Status	Male/AD	3,837	3	0-97	45%	3%
	Male/Other	789	3	0-67	45%	6%
	Female/AD	1,327	7	0-122	71%	15%
	Female/Other	2,175	5	0-97	61%	12%
Gender/ Age (years)	Male/17-34	2,760	3	0-97	43%	3%
	Male/35-44	1,237	3	0-54	47%	4%
	Male/45-64	629	4	0-67	53%	7%
	Female/17-34	2,021	5	0-113	65%	16%
	Female/35-44	813	5	0-122	60%	11%
	Female/45-64	668	6	0-61	68%	8%

Table 7: Summary Statistics for Annual Cost per Enrollee by Demographic Variables and HRU Categories in Cohort 2

Variable	Category	HRU Category	Sample Size	Annual Cost($) per enrollee Median	Interquartiles	*Range
All		Low	7,114	409	119-1,020	0-91,793
		Medium	301	903	258-2,220	0-41,944
		High	181	1,318	315-3,358	0-111,224
Gender	Male	Low	4,102	308	89-747	0-91,793
		Medium	93	850	201-2,616	0-33,109
		High	44	825	183-1,968	0-111,224
	Female	Low	3,012	590	221-1,561	0-74,732
		Medium	208	921	293-2,027	0- 41,944
		High	137	1519	388-4,125	0-49,972
Age (years)	17-34	Low	4,195	398	113-995	0- 43,264
		Medium	166	788	258-1,790	0-33,109
		High	75	822	170-2,550	0- 16,132
	35-44	Low	1,811	395	119-955	0-25,186
		Medium	59	942	232-1,986	0-7,845
		High	38	1,465	470-2,558	0-48,351
	45-64	Low	1,108	491	166-1,283	0-91,793
		Medium	76	972	263-3,283	0-41,944
		High	68	1,636	744-5,243	0-111,224
Duty Status	Active Duty (AD)	Low	4,434	391	116- 928	0-43,264
		Medium	155	1,013	282-2455	0-33,109
		High	71	947	199-2,228	0-28,622
	Other	Low	2,680	439	139-1263	0-91,793
		Medium	146	807	218-1,984	0-41,944
		High	110	1,561	497-4,882	0-111,224
Gender/ Age (years)	Male/17-34	Low	2,436	285	74-670	0-43,264
		Medium	57	658	187-1,917	0-33,109
		High	16	698	91-976	0-3,358
	Male/35-44	Low	1,097	337	94-805	0-25,186
		Medium	21	942	285-2,347	0-7,845
		High	12	1,241	367-1,968	0-2,558
	Male/45-64	Low	569	375	207-1,179	0-91,793
		Medium	15	1,348	259-4,793	0-16,046
		High	16	830	142-8,012	0-111,224

* Interquartiles range encompasses the 50% of individuals between the 25th and 75th percentiles

Table 7: Summary Statistics for Annual Cost per Enrollee by Demographic Variables and HRU Categories in Cohort 2, cont.

Variable	Category	HRU Category	Sample Size	Annual Cost($) per enrollee		
				Median	Interquartiles	*Range
Gender/ Age (years), cont.	Female/17-34	Low	1759	616	226-1,800	0-26,650
		Medium	109	921	345-1,756	0-17,596
		High	59	965	170-3,170	0-16,132
	Female/35-44	Low	714	521	188-1,315	0-22,675
		Medium	38	877	232-1,526	0-6,748
		High	26	1,905	552-4,283	0-48,352
	Female/45-64	Low	539	595	235-1,416	0-72,732
		Medium	61	961	266-2,845	0-41,944
		High	52	2,106	968-5,111	0-49,972
Gender/ Duty Status	Male/AD	Low	3,369	311	94-736	0-43,264
		Medium	70	809	201-2,474	0-33,109
		High	23	827	264-1,699	0-3,358
	Male/Other	Low	733	287	50-791	0-91,793
		Medium	23	1,348	188-3,978	0-16,046
		High	21	671	180-2,258	0-111,224
	Female/AD	Low	1,065	766	289-1,852	0-26,650
		Medium	85	1,072	384-2,322	0-17,596
		High	48	1,013	184-2,242	0-28,622
	Female/Other	Low	1,947	530	183-1,415	0-74,732
		Medium	123	777	218-1,937	0-41,944
		High	89	1,994	852-4,882	0-49,972

* Interquartiles range encompasses the 50% of individuals between the 25th and 75th percentiles

Table 8: Summary Statistics for Other Utilization Measures by Demographic Variables and HRU Categories in Cohort 2

Demographic Variable	Demographic Category	HRU Category	Sample Size (n=7,596)	Median Number of Outpatient Episodes per Enrollee	Range of Number of Outpatient Episodes per Enrollee	Enrollees with 4 or more Outpatient Episodes (%)	Enrollees with 1 or More Inpatient Episodes (%)
All		Low	7,114	4	0-113	52%	7%
		Medium	301	7	0-97	66%	14%
		High	181	10	0-122	76%	18%
Gender	Male	Low	4,102	3	0-88	45%	3%
		Medium	93	6	0-97	57%	16%
		High	44	7.5	0-67	68%	9%
	Female	Low	3,012	5	0-113	63%	13%
		Medium	208	7	0-61	71%	13%
		High	137	11	0-122	78%	21%
Age (years)	17-34	Low	4,195	4	0-113	51%	8%
		Medium	166	6	0-97	65%	13%
		High	75	8	0-56	71%	13%
	35-44	Low	1,811	4	0-59	51%	6%
		Medium	59	7	0-54	59%	10%
		High	38	9.5	0-122	76%	16%
	45-64	Low	1,108	4.5	0-61	59%	6%
		Medium	76	7.5	0-55	75%	18%
		High	68	11	0-67	81%	25%
Duty Status	Active Duty (AD)	Low	4,434	4	0-113	51%	6%
		Medium	155	9	0-97	68%	14%
		High	71	8	0-122	73%	14%
	Other	Low	2,680	4	0-72	56%	10%
		Medium	146	6	0-55	65%	14%
		High	110	12	0-97	77%	21%
Gender/ Duty Status	Male/AD	Low	3,369	3	0-88	45%	3%
		Medium	70	5.5	0-97	56%	17%
		High	23	7	0-29	78%	4%
	Male/Other	Low	733	3	0-49	44%	5%
		Medium	23	9	0-39	61%	13%
		High	21	8	0-67	57%	14%

Table 8: Summary Statistics for Other Utilization Measures by Demographic Variables and HRU Categories in Cohort 2, cont.

Demographic Variable	Demographic Category	HRU Category	Sample Size (n=7596)	Median Number of Outpatient Episodes per Enrollee	Range of Number of Outpatient Episodes per Enrollee	Enrollees with 4 or more Outpatient Episodes (%)	Enrollees with 1 or More Inpatient Episodes (%)
Gender/ Duty Status, cont.	Female/AD	Low	1,065	7	0-113	69%	15%
		Medium	85	11	0-61	78%	12%
		High	48	9.5	0-122	71%	19%
	Female/Other	Low	1,947	5	0-72	60%	11%
		Medium	123	6	0-55	66%	14%
		High	89	12	0-97	82%	22%

Table 9: Measures of Association According to Different Definitions of HIGH COST in Cohort 2

Definition of HIGH COST (Cut point)			Frequencies				Measures of Association			
			LOW HRU		HIGH HRU					
Percent of total sample by enrollees	Annual cost ($) per enrollee	Percent of total cost accounted for	LOW COST	HIGH COST	LOW COST	HIGH COST	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value
Top 1%	≥11,067	20%	7,055	59	464	18	23%	94%	4%	99%
Top 5%	≥4,657	42%	6,795	319	418	64	17%	94%	13%	96%
Top 10%	≥2,890	57%	6,459	655	370	112	15%	95%	23%	91%
Top 20%	≥1,378	74%	5,788	1,326	284	198	13%	95%	41%	81%
Top 30%	≥882	83%	5,083	2,031	219	263	11%	96%	55%	71%
Top 40%	≥604	89%	4,363	2,751	180	302	10%	96%	63%	61%
Top 50%	≥428	94%	3,647	3,467	152	330	9%	96%	68%	51%

Table 10: Relative Risk and Risk Difference According to Different Definitions of HIGH COST in Cohort 2

Definition of HIGH COST (Cut point)		"Risk" of HIGH COST		Relative Risk with 95% Confidence Interval (CI)	Risk Difference with 95% Confidence Interval (CI)
Percent of total sample by Enrollees	Annual Cost ($) per Enrollee	In LOW HRU	In HIGH HRU		
Top 1%	≥11,067	0.8%	3.7%	4.5 (2.7-7.6)	2.9% (1.3 % - 7.1%)
Top 5%	≥4,657	4.5%	13.3%	3.0 (2.3-3.8)	8.7% (5.4 % - 12.2%)
Top 10%	≥2,890	9.2%	23.2%	2.5 (2.1-3.0)	14.0% (11.0% - 17.1%)
Top 20%	≥1,378	18.6%	41.1%	2.2 (2.0-2.5)	22.4% (20.0% - 25.1%)
Top 30%	≥882	28.5%	54.6%	1.9 (1.8-2.1)	26.0% (23.6% - 28.4%)
Top 40%	≥604	38.7%	62.7%	1.6 (1.5-1.8)	24.0% (21.8% - 26.2%)
Top 50%	≥428	48.7%	68.5%	1.4 (1.3-1.5)	19.7% (17.6% - 21.9%)

Table 11: Ratios for Completeness for Standard Inpatient Data Record (SIDR) by Medical Treatment Facility (MTF) and Month-Year

	Ratio (percent) by Month-Year														
MTF Name	10-96	11-96	12-96	01-97	02-97	03-97	04-97	05-97	06-97	07-97	08-97	09-97	10-97	11-97	12-97
Little Rock AFB, AR	72	33	175	133	100	100	93	100	8	100	100	89	100	100	100
Barksdale AFB, LA	44	102	105	100	101	100	101	107	110	108	108	105	111	114	--*
Bayne-Jones ACH, Ft. Polk, LA	106	105	97	89	106	106	104	105	106	113	104	105	110	102	109
Tinker AFB, OK	100	104	100	100	97	97	99	34	101	105	103	111	124	115	128
Altus AFB, OK	91	92	99	87	93	100	98	95	98	92	92	97	100	98	100
Reynolds ACH, Ft. Sill, OK	105	103	102	115	107	126	108	102	100	80	91	76	74	93	103
Brooke AMC, Ft. Sam Houston, TX	98	101	101	103	80	78	96	98	106	103	102	105	103	--*	--*
Darnall ACH, Ft. Hood, TX	39	62	78	103	91	68	102	100	78	43	106	42	91	96	65
Dyess AFB, TX	87	85	77	77	82	79	74	93	89	83	82	83	81	80	84
Sheppard AFB, TX	99	97	97	98	91	88	87	87	103	96	101	101	12	90	99
Wilford Hall Medical Center, Lackland AFB, TX	91	94	99	98	98	98	98	100	98	97	98	96	98	97	98
NH Corpus Christi, TX	90	106	95	89	93	91	96	95	100	100	94	75	100	--*	--*

Source of data:

Numerator≥ Number of inpatient dispositions, CEIS TRENDPATH from SIDR; as of September 98

Denominator ≥ Number of inpatient dispositions, CEIS QUANTUM from Medical Expense Reporting Performance System (MEPRS); as of September 98

* -- No data reported.

Table 12: Ratios for Completeness for Standard Ambulatory Data Record (SADR) by Medical Treatment Facility (MTF) and Month-Year

	Ratio (Percent) by Month-Year														
MTF Name	10-96	11-96	12-96	01-97	02-97	03-97	04-97	05-97	06-97	07-97	08-97	09-97	10-97	11-97	12-97
Little Rock AFB, AR	60	47	84	78	70	81	76	75	79	79	47	83	111	102	104
Barksdale AFB, LA	38	54	57	59	58	68	83	92	93	89	88	88	94	95	91
Bayne-Jones ACH, Ft. Polk, LA	74	32	80	90	84	88	91	95	90	91	96	57	89	107	101
Tinker AFB, OK	92	69	98	96	93	97	96	93	93	92	95	76	25	79	90
Altus AFB, OK	93	79	96	99	100	96	100	100	107	99	99	86	59	95	77
Reynolds ACH, Ft. Sill, OK	49	4	0	6	17	39	47	52	60	54	49	55	36	68	80
Brooke AMC, Ft. Sam Houston, TX	9	23	39	50	61	65	68	51	77	68	66	75	64	--*	--*
Darnall ACH, Ft. Hood, TX	22	13	34	43	42	42	49	44	53	55	55	61	33	80	81
Dyess AFB, TX	88	89	105	107	107	106	102	101	97	82	104	88	37	102	93
Sheppard AFB, TX	71	5	92	98	100	108	101	109	105	90	97	93	42	103	104
Laughlin AFB, TX	79	78	87	85	91	96	101	98	106	95	94	37	63	100	95
Wilford Hall Medical Center, Lackland AFB, TX	22	8	13	29	36	41	46	45	51	57	59	42	36	69	61
NH Corpus Christi, TX	27	47	47	50	56	53	58	56	51	55	54	43	38	--*	--*
Vance AFB, OK	74	68	79	75	94	96	97	97	97	85	81	71	28	92	89
Brooks AFB, TX	60	79	106	108	113	114	117	112	87	111	109	59	57	104	102
Goodfellow AFB, TX	97	97	102	106	108	106	108	100	108	117	110	98	56	157	122
Kelly AFB, TX	106	106	108	111	103	108	108	103	102	115	111	83	78	105	91
Randolph AFB, TX	70	78	83	82	73	75	104	113	84	104	123	104	52	120	111

Source of data:

Numerator≥ Number of outpatient visits, CEIS TRENDPATH from SADR; as of September 98

Denominator ≥ Number of outpatient visits, CEIS QUANTUM from Medical Expense Reporting Performance System (MEPRS); as of September 98

* -- No data reported.

LIST OF SYMBOLS, ABBREVIATIONS, AND ACRONYMS [9,10]

CEIS	Corporate Executive Information System, the source for medical cost data from direct care inpatient, direct care outpatient, CHAMPUS inpatient, and CHAMPUS outpatient encounters.
CHAMPUS	Civilian Health and Medical Program of the Uniformed Services, a program administered by the Department of Defense that cost-shares for care delivered by civilian health providers to retired members, dependents of active and retired members, certain survivors of deceased members, and certain former spouses of members of the uniformed services of the Unites States.
DEERS	Defense Eligibility Enrollment Registration System, an automated system of verification of a person's eligibility to receive Uniformed Service benefits and privileges.
DMIS	Defense Medical Information System, a medical automated information system that supports the collection, integration, validation, analysis, and reporting of data related to the Military Health System.
DRG	Diagnosis-Related Group, a patient classification system that relates demographic, diagnostic, and therapeutic characteristics of patients to length of inpatient stay and amount of resources consumed. It provides a framework for specifying hospital case mix and identifies classifications of illness and injuries for which payment is made under prospective pricing programs.
Eligible Beneficiaries	For purposes of coordinated care programs, eligible beneficiaries include active duty personnel and their dependents, reserve personnel when on active duty, dependents of reserve personnel when their sponsor's active duty orders are for more than 30 days, retirees and their dependents, and survivors.
HMO	Health maintenance organization, an organization that has management responsibility for providing comprehensive health care services on a prepayment basis to voluntarily enrolled persons within a designated population.
MEPRS	Medical Expense and Performance Reporting System for Fixed Military Medical and Dental Treatment Facilities, a uniform reporting methodology designed to provide consistent principles, standards, policies, definitions, and requirements for accounting and reporting of expense, manpower, and performance data by DoD fixed military medical and dental treatment facilities.
MTF	Medical treatment facility, facilities established to furnish medical and/or dental care to eligible individuals.

SADR	Standard Ambulatory Data Record, data that reflects "direct care" (MTF) outpatient episodes.
SIDR	Standard Inpatient Data Record, data that reflects "direct care" (MTF) inpatient episodes.
SRA	Systems Research and Application International, Inc., a contractor for the Department of Defense who developed patient level cost accounting algorithms that are designed to estimate a dollar amount of health-care resource utilization relative to inpatient care.
TRICARE	The managed health-care program for the uniformed services of the United States of America. Worldwide, there are 12 TRICARE Regions.