Accounting for the Hierarchical Structure in Veterans Health Administration Data: Differences in Healthcare Utilization between Men and Women Veterans

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Abstract: Women currently constitute 15% of active United States of America military service personnel, and this proportion is expected to double in the next 5 years. Previous research has shown that healthcare utilization and costs differ in women US Veterans Health Administration (VA) patients compared to men. However, none have accounted for the potential effects of clustering on their estimates of healthcare utilization. US Women Veterans are more likely to serve in specific military branches (e.g. Army), components (e.g. National Guard), and ranks (e.g. officer) than men. These factors may confer different risk and protection that can affect subsequent healthcare needs. Our study investigates the effects of accounting for the hierarchical structure of data on estimates of the association between gender and VA healthcare utilization. The sample consisted of data on 406,406 Veterans obtained from VA's Operation Enduring Freedom/ Operation Iraqi Freedom roster provided by Defense Manpower Data Center — Contingency Tracking System Deployment File. We compared three statistical models, ordinary, fixed and random effects hierarchical logistic regression, in order to assess the association of gender with healthcare utilization, controlling for branch of service, component, rank, age, race, and marital status. Gender was associated with utilization in ordinary logistic and, but not in fixed effects hierarchical logistic or random effects hierarchical logistic regression models. This points out that incomplete inference could be drawn by ignoring the military structure that may influence combat exposure and subsequent healthcare needs. Researchers should consider modeling VA data using methods that account for the potential clustering effect of hierarchy.

Keywords: Hierarchical Logistics Models, Random Effects, GLIMMIX, GENMOD, Generalized Estimating Equations, Gender Differences, Veterans.

1. INTRODUCTION

Women currently constitute 15% of active United States of America military service personnel, and this proportion is expected to double in the next 5 years [1]. Women Veterans of Operation Enduring Freedom/Operation Iraqi Freedom (OEF/OIF) are using Veterans Health Administration (VA) healthcare services more frequently than any previous cohort [2]. These new women Veterans are younger, more likely to identify as belonging to a racial minority, and are less likely to be married than their male counterparts [3]. They have a high prevalence of mental health disorders [4], higher rates of exposure to combat trauma than previous cohorts of women Veterans, and may have high rates of exposure to sexual trauma [5].

Previous research has shown that healthcare utilization and costs differ in women VA patients compared to men [4-6]. For example, Frayne *et al*. [4] found that women Veterans had 11% more outpatient encounters, 26% fewer inpatient days, and 11% lower total cost than men. When policymakers use aggregate data to plan VA health services, the special needs of women Veterans may be obscured because they represent a numerical minority compared with their male counterparts.

While the number of publications on gender differences in VA healthcare has increased steadily since 2000 [7-10], none have accounted for the potential effects of clustering on their estimates. In this case, women Veterans healthcare utilization may in part be a function of military service, and women more likely to serve in specific military branches (e.g. Army), components (e.g. Guard), and ranks (e.g. officer) than men. Each of these factors may confer different risk and protection that can affect subsequent healthcare needs. In addition, the association between gender and utilization may vary by each of these factors; for instance women enrolled in VA healthcare who served in one branch may be more likely than men to utilize care, while women in another branch may be less likely

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to utilize care. Furthermore, Veterans are likely to be more correlated within these factors than between, therefore the assumption of independence of observations is violated, and the probability of rejecting the true null hypothesis (of no association) incorrectly may be increased by using traditional regression models [11].

The ordinary logistic regression model is a simple and straightforward method commonly used to analyze data on binary outcomes such as healthcare utilization. But it does not account for the structure of clustered data, and lacks the ability to accommodate heterogeneity of associations that occur when relationships between individual characteristics and outcomes vary across higher order factors. The hierarchical linear model, also referred to as multilevel model, mixed model, or variance component model, has a wide range of application in public health and other clinical studies [12-14]. In contrast to the ordinary logistic model, it is considered a more appropriate method to fit clustered data because it takes into account the variability derived from the data structures [15-17].

The purpose of this study was to examine the effect of accounting for the hierarchical structure of recent military service on estimates of the association between gender and VA healthcare utilization. We wished to see if the odds of utilization for women Veterans differed after taking into account the clustered nature of this data. We used data from a large cohort of Veterans who served during Operation Enduring Freedom (OEF) and/or Operation Iraqi Freedom (OIF) to examine gender differences in VA healthcare utilization using two statistical models: the ordinary logistic regression model and the hierarchical logistic regression model.

2. METHODS

Study Population

The population consisted of the list of Veterans obtained from VA's OEF/OIF roster provided by Defense Manpower Data Center—Contingency Tracking System. The roster contains information on all personnel discharged from the U.S. military from October 1, 2001 to November 30, 2007 who enrolled for VA healthcare or received VA healthcare before January 1, 2008 (N = 406,802). We limited the sample to Veterans who had 1 year of observation after their last deployment end date in order to standardize the time between potential exposures and health care utilization. We further excluded Veterans who served in the Coast Guard as the limited number of observations (N = 396) would not allow for fitting the military hierarchical structure. The analytic sample thus included 406,406 Veterans.

Data Sources

The OEF/OIF roster includes information on sex, date of birth, race, education, marital status, military rank, branch of service (e.g., Army, Marine Corps), and deployment start and end dates. Information on VHA visits and ICD-9 codes used to determine medical and psychiatric conditions were ascertained from the VA national data, including the Corporate Data Warehouse. The study was approved by the VA West Haven, CT, HSS and the Yale University IRB.

Measures

The binary outcome of healthcare utilization was defined as any healthcare visit in the VA Healthcare System within one year after the end of military deployment. The military service related covariates were: branch (Army, Air Force, Navy, Marine Corps); component (Active, Reserve, National Guard); rank (Enlisted, Commissioned/Warrant Officers). The demographic covariates were: gender (women/men), age as a continuous variable, married (yes/no), and race (white/non-white).

Analyses

Given the large dataset the hypotheses were tested at a two-sided significance level of $\alpha = 0.01$.

Bivariate Analysis of Association

To investigate variation in the association between gender and healthcare utilization by military service related characteristics, using logistic regression unadjusted odds ratios were calculated overall and for each branch, component within branch, and rank within branch-component combination.

Ordinary Logistic Regression Model

We next used ordinary logistic regression to model the association between gender and utilization, controlling for military service and demographic characteristics. The parameter estimates of the model were interpreted such that each factor was independent in predicting healthcare utilization when the other factors were controlled. Variations were modeled as the residual from the mean (i.e., the intercept) for each individual unit.

For example, if y is the binary outcome variable of healthcare utilization, then y follows the *Bernoulli* distribution with a success probability π; i.e., $y \sim Bin(1, \pi)$. The model is given as

$$logit[E(y_i)] = logit(\pi) = log[\pi/(1-\pi)]$$
$$= \alpha + \Sigma_j \beta_j I_j + \gamma Age \quad (1)$$

where $i = 1, \ldots, N$ is the individual indicator; $j = 1, \ldots, 9$ is a dummy variable indicator; I_j are dummy variables of risk factors ($I_1 = 1$ if Navy, $I_2 = 1$ if Marine, $I_3 = 1$ if Air Force, $I_4 = 1$ if National Guard, $I_5 = 1$ if Reserves, $I_6 = 1$ if Commissioned and Warrant Officers, $I_7 = 1$ if woman, $I_8 = 1$ if married, and $I_9 = 1$ if white; the reference categories are; Army, Active, Enlisted, man, not married, and non-white, respectively); β_j are regression slopes corresponding to each of I_j for $j = 1, \ldots, 9$; γ is slope coefficient of age; α is the intercept of regression line. We used SAS 9.2 procedure GENMOD [18] to perform the ordinary logistic regression analysis.

Hierarchical Logistic Regression Model – Fixed Effects

We next used a fixed effect hierarchical logistic regression model to account for the clustering effects given the structure of the data. This is a special case of the hierarchical linear model (a.k.a. linear mixed model or multi-level model), which takes into account the variability associated with each level of the hierarchy [13, 19]. To fit the OEF/OIF Veteran data, we used a 4-level hierarchical model: the top level was branch; the level under branch was component; the level under component was rank; and the lowest level was individual Veteran. The 4-level hierarchical logistic model is given as:

$$logit[E(y_i)] = logit(\pi) = log[\pi/(1-\pi)]$$
$$= \alpha + \gamma_j B_j + \tau_k C_k + \rho_l R_l + \beta_1 F_{jkli}$$
$$+ \beta_2 A_{jkli} + \beta_3 M_{jkli} + \beta_4 W_{jkli} \quad (2)$$

where B_j is the effect of branch (j = 1/Navy, 2/Marines, 3/Air Force, and 4/Army; 4/Army is the reference); C_k is the interactive effect between branch and component (k = 1-2/Navy * (Reserve, Active), 3-4/Marines * (Reserve, Active), 5-7/Air Force * (Guard, Reserve, Active), and 8-10/Army * (Guard, Reserve, Active); 10/Army * Active is the reference); R_l is the 3-way interactive effect among branch, component, and rank (1/Navy * Reserves * Enlisted, 2/Navy * Reserves * Officer,…, 5/Marines * Reserves * Enlisted, 6/Marines * Reserves * Officer, …, 9/Air Force * Guard * Enlisted, 10/Air Force * Guard * Officer, …, 19/Army * Active * Enlisted, and 20/Army * Active * Officer; 20/Army * Active * Officer is the reference); F_{jkli} is the effect of woman (gender) for the ith individual in the jth branch, kth component, and lth rank; A_{jkli} is the effect of age; M_{jkli} is the effect of the marital status; W_{jkli} is the effect of the white (race).

In comparison with (1) that models branch, component, and rank as independent at one level, (2) models the 4-level hierarchical effects of branch, component, and rank that are inter-correlated. This accounts for the clustering effect of a hierarchical structure of data. We used SAS 9.2 PROC GENMOD with the generalized estimating equation (GEE) method [20] with an exchangeable covariance structure to account for the similarity of individuals within the clusters to fit the hierarchical logistic regression model.

Hierarchical Logistic Regression Model – Random Effects

Lastly, we used a random effects hierarchical logistic regression model to account for the clustering effects given the structure of the data. Similarly to the fixed effects model, we used a 4-level hierarchical model: the top level was branch; the level under branch was component; the level under component was rank; and the bottom level was individual Veteran. There were three random effects of branch, component, and rank respectively, and four fixed effects of gender, age, marital status and race. The 4-level hierarchical logistic model is given as

$$logit[E(y_i)] = logit(\pi) = log[\pi/(1-\pi)]$$
$$= \alpha + \delta_j f_j + \zeta_{jk} f_{jk} + \theta_{jkl} f_{jkl} + \beta_1 F_{jkli} + \eta_j a_j + \kappa_{jk} a_{jk} + \lambda_{jkl} a_{jkl} +$$
$$\beta_2 A_{jkli} + \nu_j m_j + \xi_{jk} m_{jk} + \rho_{jkl} m_{jkl} + \beta_3 M_{jkli} + \upsilon_j w_j + \varphi_{jk} w_{jk} +$$
$$\psi_{jkl} w_{jkl} + \beta_4 W_{jkli} \quad (3)$$

where F_{jkli} is the fixed effect of female (gender) for the ith individual in the jth branch, kth component, and lth rank; A_{jkli} is the fixed effect of standardized age; M_{jkli} is the fixed effect of the married (marital status); W_{jkli} is the fixed effect of the white (race); f_j, a_j, m_j, w_j are random effects of branch with respect to gender, age, marital status, and race (j = 1/Army, 2/Air Force, 3/Marines, and 4/Navy); f_{jk}, a_{jk}, m_{jk}, w_{jk} are random effects of branch * component (k = 1/active, 2/reserve, and 3/National Guard); f_{jkl}, a_{jkl}, m_{jkl}, w_{jkl} are random effects of branch * component * rank (l = 1/enlisted and 2/officer). f_j, f_{jk}, and f_{jkl} are weighted as

$f_j = (S_{j...} - S_{....}) + \varepsilon_j$, $\varepsilon_j \sim N(0, \sigma_b^2)$

$f_{jk} = (S_{jk..} - S_{j...}) + \varepsilon_{jk}$, $\varepsilon_{jk} \sim N(0, \sigma_c^2)$

$f_{jkl} = (S_{jkl.} - S_{jk..}) + \varepsilon_{jkl}$, $\varepsilon_{jkl} \sim N(0, \sigma_r^2)$

where $S_{....}$ is the fraction of either females (while individual is female) or males (while individual is male) in the whole sample; $S_{j...}$ is the fraction of either females (while individual is female) or males (while individual is male) in the *j*th branch; $S_{jk..}$ is the fraction of either females or males in the *j*th branch and *k*th component; $S_{jkl.}$ is the fraction of either females or males in the *j*th branch, *k*th component, and *l*th rank; ε_j, ε_{jk}, and ε_{jkl} are mutually independent. The random effects of marital status (m_j, m_{jk}, m_{jkl}) and race (w_j, w_{jk}, w_{jkl}) are all formulated using the same formula as for gender, but substituting the fractions of male/female by the fractions of married/unmarried and white/non-white. The a_j, a_{jk}, and a_{jkl} are random effects of standardized age with regards to branch, component, and rank, respectively. They are weighted as

$a_j = (Age_{jkli} - Age_{j...})/sd(Age_{j...}) + e_j$, $e_j \sim N(0, \tau_b^2)$

$a_{jk} = (Age_{jkli} - Age_{jk..})/sd(Age_{jk..}) + e_{jk}$, $e_{jk} \sim N(0, \tau_c^2)$

$a_{jkl} = (Age_{jkli} - Age_{jkl.})/sd(Age_{jkl.}) + e_{jkl}$, $e_{jkl} \sim N(0, \tau_r^2)$

The model (3) can now be written in the form

$$logit[E(y_i)] = logit(\pi) = log[\pi/(1-\pi)]$$

$$= \alpha + \delta_j(S_{j...} - S_{....}) + \zeta_{jk}(S_{jk..} - S_{j...}) + \theta_{jkl}(S_{jkl.} - S_{jk..}) + \beta_1 F_{jkli} + \eta_j(Age_{jkli} - Age_{j...})/sd(Age_{j...}) + \kappa_{jk}(Age_{jkli} - Age_{jk..})/sd(Age_{jk..}) + \lambda_{jkl}(Age_{jkli} - Age_{jkl.})/sd(Age_{jkl.}) + \beta_2 A_{jkli} + \nu_j(M_{j...} - M_{....}) + \xi_{jk}(M_{jk..} - M_{j...}) + \rho_{jkl}(M_{jkl.} - M_{jk..}) + \beta_3 M_{jkli} + \upsilon_j(W_{j...} - W_{....}) + \varphi_{jk}(W_{jk..} - W_{j...}) + \psi_{jkl}(W_{jkl.} - W_{jk..}) + \beta_4 W_{jkli} \quad (3a)$$

We ran a SAS 9.2 PROC GLIMMIX [21-22] fitting the random effects hierarchical logistic regression model.

RESULTS

Table **1** describes the sample characteristics by gender**.** There were 49,045 women and 357,361 men

Table 1: Demographic Characteristics of Operation Enduring Freedom and/or Operation Iraqi Freedom Veterans (n = 406,406)

Characteristic	Women (n=49,045)	Men (n=357,361)
Branch		
Army	32,483 (66%)	231,962 (65%)
Air Force	8,340 (17%)	41,570 (12%)
Marine	1,681 (3%)	46,326 (13%)
Navy	6,541 (13%)	37,503 (10%)
Component		
Active	13,093 (27%)	69,785 (20%)
Reserve	24,335 (50%)	168,150 (47%)
National Guard	11,617 (24%)	119,426 (33%)
Rank		
Enlisted	44,193 (90%)	324,840 (91%)
Officer	4,852 (10%)	32,521 (9%)
Race		
White	26,483 (54%)	246,402 (69%)
Non White	22,562 (46%)	110,959 (31%)
Marital Status		
Married	16,226 (33%)	173,180 (48%)
Not married	32,819 (67%)	184,181 (52%)
Age (mean/median)	30/26	32/29
Healthcare Utilization	19,524 (40%)	144,232 (40%)

Note that percentages within characteristic may not sum to 100% due to rounding.

Veterans in the sample. A lower proportion of women Veterans served in the Marine Corps than male Veterans, a higher proportion served in active components, and similar proportions to be officers. Women Veterans were slightly younger, more likely to be non-white, and a lower proportion were married than male Veterans. Overall**, s**imilar proportions of women and men Veterans used VA healthcare services.

Figure **1** shows the unadjusted percentages of healthcare utilization and suggests that women who served as Army Reservists were less likely to utilize than male Army Reservists; on the other hand women who served in the Guard were more likely to utilize than their male counterparts, while women who served as Marine Reserve officers were less likely to utilize than their male counterparts. Figure **2** further demonstrates the variation in the stratified odd ratios and leads us to suspect that there might be a difference in the results of the hierarchical logistic model compared to the multivariable ordinary logistic model. The overall unadjusted odds ratio for healthcare utilization in the first year after discharge for women Veterans versus men was 0.98 (p=0.02 NS) (Figure **2**) suggesting that women were not significantly but slightly less likely than men Veterans to use healthcare.

Results of the multivariable ordinary logistic regression are shown in Table **2**. In contrast to the unadjusted OR, these results indicate that women Veterans were significantly more likely to have used VA healthcare than men (OR=1.06, p<0.001). In addition, Veterans who were married, white, officers, Reservists, and have served in the Air Force, Marine Corps, or Navy were less likely to have used VA healthcare, while increasing age and having served in the Guard were significantly more likely to have used VA healthcare services.

Figure **2** also reinforces this conjecture in that the odds ratios change direction with respect to the effect of gender depending on branch, component, and rank. Thus, to adjust for the clustering effects, we modeled the OEF/OIF data using a hierarchical logistic regression.

Table **3** presents the results of the fixed effects hierarchical logistic regression. In this model, the

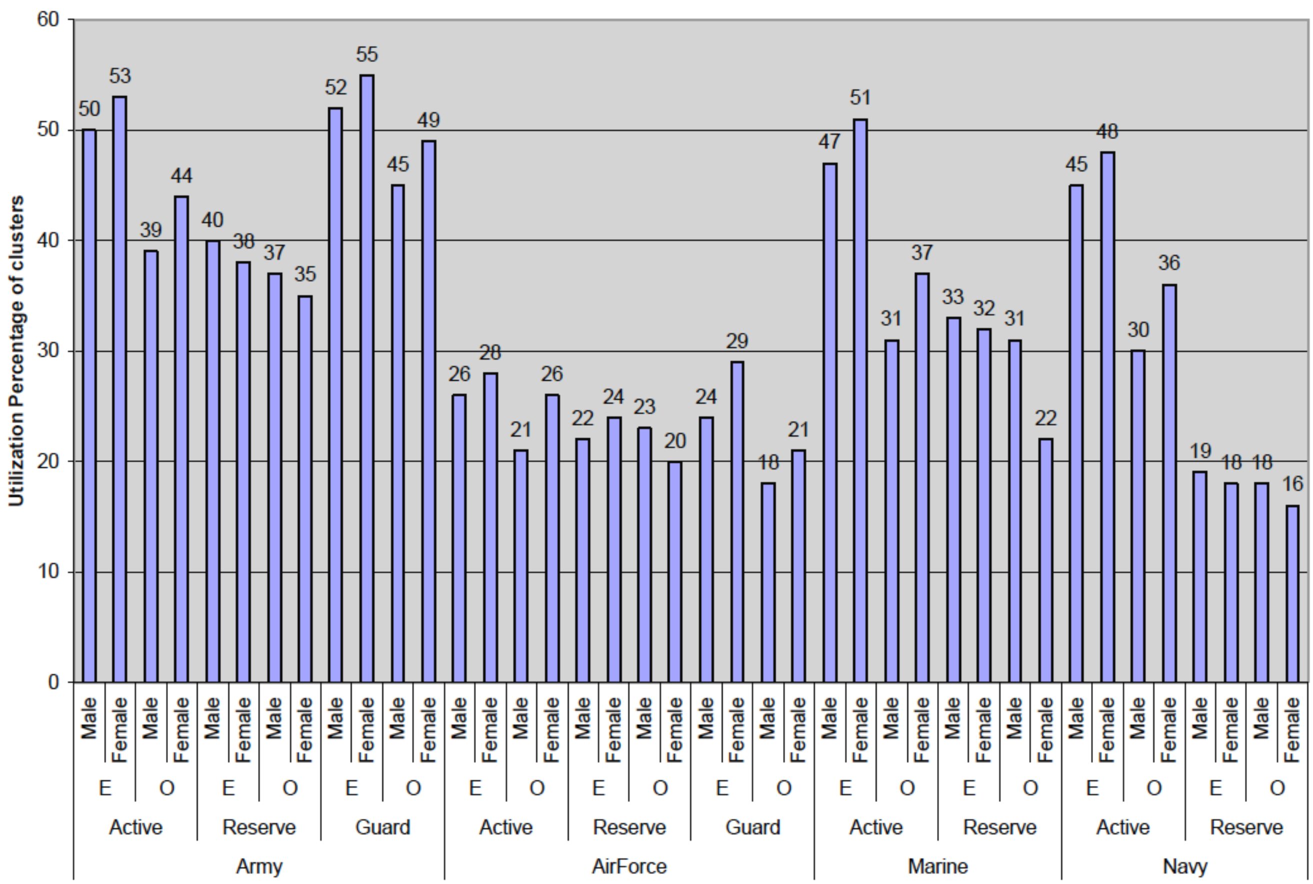

Figure 1: United States of America's Veterans Health Administrations Healthcare Utilization Percentage of Operation Enduring Freedom and/or Operation Iraqi Freedom Veterans.

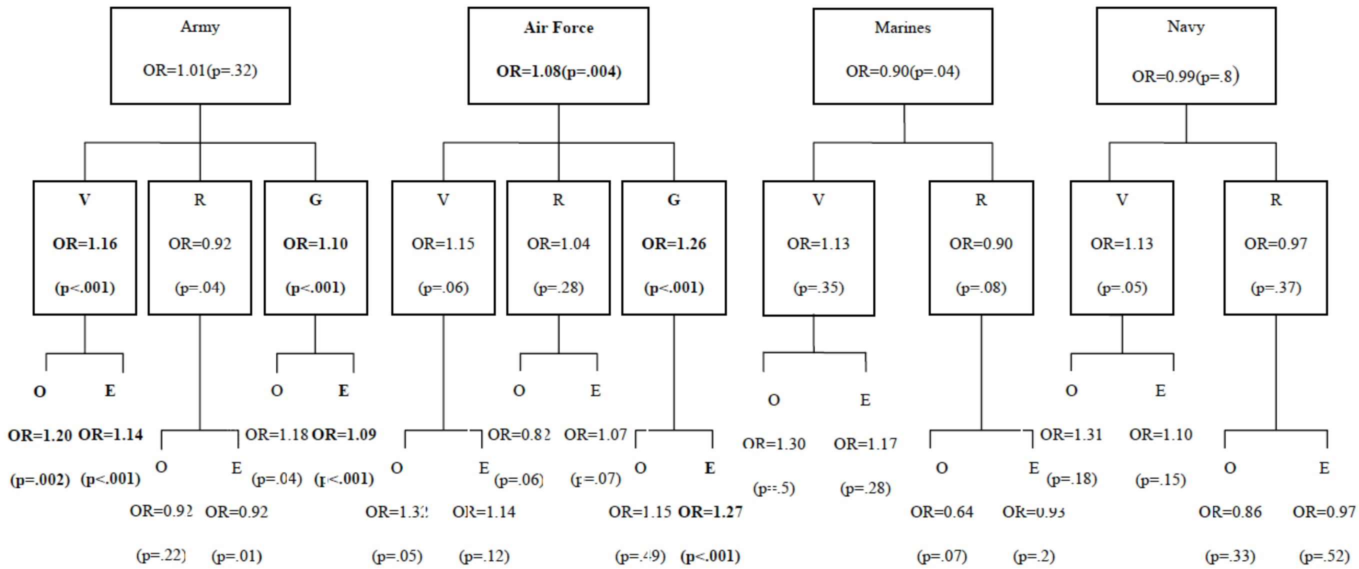

Figure 2: Odds ratios for women relative to men's Veterans Healthcare Administrations utilization using the military hierarchical structure of Operation Enduring Freedom and/or Operation Iraqi Freedom Veterans. Bold odds ratios (OR) are statistically significant at p<0.01. Key: V: active; R: reserve; G: National Guard; O: officer; E: enlisted.

Table 2: Odd Ratios for Healthcare Utilization from Multivariable Ordinary Logistic Regression

Factor	Odds Ratio (95% CI)	p-value
Gender – Men as reference		
Women	1.06 (1.04, 1.08)	<.001
Branch – Army as reference		
Navy	0.42 (0.41, 0.43)	<.001
Marines	0.82 (0.78, 0.87)	<.001
Air Force	0.36 (0.35, 0.39)	<.001
Component – Active as reference		
National Guard	1.06 (1.04, 1.08)	<.001
Reserve	0.67 (0.66, 0.68)	<.001
Rank		
Officer vs. Enlisted	0.69 (0.67, 0.71)	<.001
Age (years)	1.01(1.01, 1.02)	<.001
Race - Non-white as reference		
White	0.99 (0.98, 1.00)	<.001
Marital Status - Not Married as reference		
Married	0.91 (0.90, 0.92)	<.001

within-group correlation due to the clustering from the hierarchy of branch-component-rank has been taken into account in the GEE estimates and is apparent in the standard error estimates. Hence, there are effect estimates for branch, component, and rank combinations. The estimates of the effects of gender, age, race, and marital status are similar to those in Table **2**, but the standard errors are larger in the fixed effects hierarchical model. The most important difference in the results of the two models is that gender (OR=1.06, p=0.11), race (OR=0.99, p=0.70) and marital status (OR=0.90, p=0.02) effects are non-significant in the fixed effects hierarchical logistic regression. However, almost all of branch, rank, and

Table 3: Odd Ratios for Healthcare Utilization from Fixed Effects Hierarchical Logistic Regression

Factor	Odds Ratio (95% CI)	p-value
Gender – Men as reference		
Women	1.06 (0.99, 1.15)	0.11
Branch - Army as reference		
Navy	0.66 (0.64, 0.68)	<.001
Marines	0.71 (0.70, 0.72)	<.001
Air Force	0.41 (0.41, 0.42)	<.001
Component – Army Active as reference		
Navy Reserve	0.53 (0.51, 0.55)	<.001
Marines Reserve	1.00 (0.98, 1.01)	0.63
Air Force Guard	0.85 (0.84, 0.85)	<.001
Air Force Reserve	1.14 (1.12, 1.16)	<.001
Army Guard	1.33 (1.31, 1.34)	<.001
Army Reserve	0.97 (0.94, 0.99)	0.008
Rank - Army Active Officer as reference		
Navy Reserve Enlisted	1.17 (1.13, 1.21)	<.001
Navy Active Enlisted	2.02 (1.93, 2.11)	<.001
Marines Reserve Enlisted	1.34 (1.28, 1.40)	<.001
Marines Active Enlisted	2.34 (2.22, 2.48)	<.001
Air Force Guard Enlisted	1.48 (1.46, 1.50)	<.001
Air Force Reserve Enlisted	1.09 (1.06, 1.13)	<.001
Air Force Active Enlisted	1.30 (1.28, 1.32)	<.001
Army Guard Enlisted	1.46 (1.42, 1.50)	<.001
Army Reserve Enlisted	1.24 (1.20, 1.29)	<.001
Army Active Enlisted	1.70 (1.63, 1.78)	<.001
Age	1.01 (1.01, 1.02)	<.001
Race - Non-white as reference		
White	0.99 (0.93, 1.05)	0.70
Marital Status - Not Married as reference		
Married	0.90 (0.83, 0.98)	0.02

component effects remain statistically significant with the exception of Marine Reservists Veterans which did not differ from Army Active duty Veterans.

Table **4** presents the results of the random effects hierarchical logistic regression. The effect of women on VA healthcare utilization (OR = 1.00034, p=0.89) was not significant. The effects of branch, component, and rank, however, were significant. In addition, the random effects hierarchical model also assessed deviations (unexplained variations) from each branch, each component in branch, and each rank in component in branch. Several but not all of these random effects met statistical significance. Summarily, the random effects hierarchical logistic regression obtained two results: (1) there was no difference in the odds for female veterans to use VA healthcare system; (2) there were some interactive effects between branch and gender, component and gender, or rank and gender.

DISCUSSION

In this study, the multivariable ordinary logistic regression and hierarchical logistic regression methods were applied to model the effects of military service related characteristics (*i.e.,* branch, component, and

Table 4: Odd Ratios for Healthcare Utilization from Random Effects Hierarchical Logistic Regression

Effect	Odds Ratio (95% CI)	p-value
Fixed		
Gender - Men as reference		
Women	1.0034 (1.0033, 1.0035)	0.89
Branch – Army as reference		
Navy	0.3967 (0.3967, 0.3968)	<.001
Marines	0.8655 (0.8654, 0.8667)	<.001
Air Force	0.3608 (0.3607, 0.3610)	<.001
Component – Active as reference		
Guard	1.1600 (1.1599, 1.1601)	<.001
Reserve	0.6985 (0.6983, 0.7007)	<.001
Rank – Officer as reference		
Enlisted	0.7050 (0.7050, 0.7051)	<.001
Age	1.0313 (1.0312, 1.0314)	0.36
Race – Non-white as reference		
White	1.0342 (1.0341, 1.0343)	0.04
Marital Status – Not Married as reference		
Married	0.9133 (0.9132, 0.9134)	<.001
Random[1]		
$Married_j$ - Marines	1.6553 (1.6548, 1.6558)	<.001
Age_{jk} - Navy(Reserve)	0.6063 (0.6062, 0.6065)	<.001
Age_{jk} - Navy(Active)	0.5004 (0.5003, 0.5006)	<.001
Age_{jk} - Air Force(Guard)	1.5362 (1.5356, 1.5368)	0.008
Age_{jk} - Air Force (Active)	1.7133 (1.7126, 1.7139)	<.001
$Gender_{jk}$ - Air Force(Guard)	0.0259 (0.0258, 0.0259)	<.001
$Gender_{jk}$ - Air Force(Reserve)	10.22 (10.19, 10.25)	<.001
$Gender_{jk}$ - Army(Guard)	0.2282 (0.2279, 0.2285)	<.001
$Gender_{jk}$ - Army(Active)	2.8123 (2.8100, 2.8145)	<.001
$Race_{jk}$ - Army(Guard)	0.5399 (0.5397, 0.5401)	<.001
$Race_{jk}$ - Army(Active)	2.9096 (2.9078, 2.9113)	<.001
$Married_{jk}$ - Navy(Active)	2.0788 (2.0765, 2.0790)	<.001
$Married_{jk}$ - Army(Guard)	2.4427 (2.4412, 2.4442)	<.001
$Married_{jk}$ - Army(Reserve)	2.0234 (2.0224, 2.0245)	<.001
Age_{jkl} – Army(Reserve, Enlisted)	0.8434 (0.8433, 0.8435)	<.001

[1]Only significant random effects are listed.

rank) on the odds of women utilizing VA healthcare a year post-discharge adjusted by demographic covariates (*i.e.,* age, marital status, and race) among OEF/OIF Veterans who enrolled in VA healthcare. We demonstrate that the odds ratio estimates are sensitive to the models chosen. Graphical methods demonstrate the non-independence of individuals and non-constant effect of branch, component and rank. Assumptions of multivariable logistic regression are that all observations and predictors are independent and results show that all of seven predictor variables are simultaneously significantly associated with the utilization outcome ($p < .001$). The ability to disentangle higher level influences from individual-level characteristics is a key feature of hierarchical models.

There are several forms of hierarchical models. In this analysis we used both a fixed effect and random effects models as we had nearly population level data. Random effect models are useful when there are other sources of variation that needs to be accounted for at each level of the hierarchy. When selecting a modeling approach one should determine the level of independence of observations and predictor variables. Graphical methods may be a useful tool for determining whether there are constant effects across level of a predictor or whether they change within subgroups. Furthermore, there are hierarchical methods for different forms of the outcome, such as continuous measures like expenditures or counts of utilization within a time frame.

This observational study has limitations. To avoid undue computational complexities, we have treated deaths that may occur prior to healthcare utilization as a non-informative censoring event. However, many of these Veterans are young (Table **1**) and 40% did utilize services within a year of discharge. Additionally, if healthcare was received outside of the VA it is not captured in the dataset. Then again, VA healthcare is likely the first choice for healthcare among those who qualify for it. A further limitation of this study is that we had constrained information on other military service related factors and socio-demographic factors. Detailed information about military service exposures may explain differences in Veteran utilization in the first year after discharge. This information increases model complexity, but also may improve the model's explanatory power.

CONCLUSIONS

According to the findings obtained from this study, we conclude that researchers should determine whether there is a hierarchy in the data and if so should model the hierarchical structure to take into account the clustering effect from the hierarchy of data. It is apparent that incomplete inferences could be drawn, underestimation of variance and thus inflated Type I error may occur by ignoring the hierarchical structure of data. Thus, determining whether the hierarchical (multi-level) data is informative should be undertaken.

To summarize this study, both modeling approaches that accounted for the hierarchical structure of data showed no significant difference in the odds of women utilizing the VA healthcare system. In the future, models that could account for additional covariates that address the limitations above, or are specific for types of healthcare utilization should account for the hierarchical structure of data when assess whether there are differences in VA healthcare utilization by Veterans of OEF/OIF.

Secondly, characteristics of military services such as branch, component, and rank are important factors to account for in analyses on Veteran cohorts because different levels of the hierarchical characteristics may cause very different effects on outcomes. For example, a Navy Reserve officer likely has different combat exposure than an active enlisted Marine. Combat exposure has non-trivial direct impact on Veterans' health conditions. It is apparent that incomplete inferences could be drawn by ignoring the structure of the data. Thus, hierarchical methods should be routinely incorporated into statistical analyses of Veteran data.

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DISCLAIMER

The views expressed in this article are those of the authors and do not necessarily reflect the position or policy of the Department of Veterans Affairs.

APPENDIX

SAS version 9.2 codes to fit the three logistic models:

```
title 'GENMOD ordinary logistic
regression';
proc genmod data=work1 desc;
class branchofservice/*(ref='A')*/
component/*(ref='V')*/
      collapserank/*(ref=first)*/
/param=ref;
model utilize=branchofservice component
collapserank
              gender age married
white/dist=bin type3;
run;


title 'GENMOD_GEE Fixed Effect';
proc sort data=work1; by branchofservice
component collapserank studyid; run;
proc genmod data=work1 desc;
class b c r/param=ref;
```

```
model utilize= b c r gender age white
married /dist=bin type3;
repeated subject=r/type=cs covb;
run;

title 'GLIMMIX 4-Level';
proc glimmix data=work1;
class branchofservice component
collapserank;
model utilize= branchofservice
collapserank component gender age white
                married/solution
dist=bin;
random Fj Mj Wj
Aj/subject=branchofservice solution;
random Fjk Mjk Wjk
Ajk/subject=component(branchofservice)
solution;
random Fjkl Mjkl Wjkl
Ajkl/subject=collapserank(component
branchofservice)
       solution;
nloptions tech=nrridg;
run;
```

REFERENCES

[1] Yano EM, Frayne SM. Health and health care of women veterans and women in the military: research informing evidence-based practice and policy. Womens Health Issues 2011; 21(4 Suppl): S64-6. http://dx.doi.org/10.1016/j.whi.2011.04.030

[2] Leslie DL, Goulet J, Skanderson M, Mattocks K, Haskell S, Brandt C. VA health care utilization and costs among male and female veterans in the year after service in Afghanistan and Iraq. Mil Med 2011; 176(3): 265-9.

[3] Actuary Oot: Women Veterans: Past, present, and future. Department of Veterans Affairs, Office of Policy and Planning. (Administration V ed). Washington, DC 2007.

[4] Frayne SM, Yu W, Yano EM, Ananth L, Iqbal S, Thrailkill A, Phibbs CS. Gender and use of care: planning for tomorrow's Veterans Health Administration. J Womens Health (Larchmt) 2007; 16: 1188-99. http://dx.doi.org/10.1089/jwh.2006.0205

[5] Haskell SG, Brandt CA, Krebs EE, Skanderson M, Kerns RD, Goulet JL. Pain among Veterans of Operations Enduring Freedom and Iraqi Freedom: do women and men differ? Pain Med 2009; 10: 1167-73. http://dx.doi.org/10.1111/j.1526-4637.2009.00714.x

[6] Frayne SM, Parker VA, Christiansen CL, Loveland S, Seaver MR, Kazis LE, *et al*. Health status among 28,000 women veterans. The VA Women's Health Program Evaluation Project. J Gen Intern Med 2006; 21(Suppl 3): S40-6.

[7] Borrero S, Kwoh CK, Sartorius J, Ibrahim SA. Brief report: Gender and total knee/hip arthroplasty utilization rate in the VA system. J Gen Intern Med 2006; 21(Suppl 3): S54-57.

[8] Kaur S, Stechuchak KM, Coffman CJ, Allen KD, Bastian LA. Gender differences in health care utilization among veterans with chronic pain. J Gen Intern Med 2007; 22: 228-33. http://dx.doi.org/10.1007/s11606-006-0048-5

[9] Washington DL, Caffrey C, Goldzweig C, Simon B, Yano EM. Availability of comprehensive women's health care through Department of Veterans Affairs Medical Center. Womens Health Issues 2003; 13: 50-54. http://dx.doi.org/10.1016/S1049-3867(02)00195-0

[10] Yano EM, Bastian LA, Frayne SM, Howell AL, Lipson LR, McGlynn G, *et al*. Toward a VA Women's Health Research Agenda: setting evidence-based priorities to improve the health and health care of women veterans. J Gen Intern Med 2006; 21(Suppl 3): S93-101.

[11] Kreft IGG, de Leeuw J. Introducing Multilevel Modeling. London: Sage 1998.

[12] Demidenko E. Mixed Models: Theory and Applications. Hoboken, NJ.: John Wiley & Sons, Inc 2004.

[13] Goldstein H. Multilevel Statistical Models. 3rd ed. London: Edward Arnold 2003.

[14] Hox J. Multi-Level Analysis. London: Lawrence Erlbaum Associates 2002.

[15] Austin PC, Tu JV, Alter DA. Comparing hierarchical modeling with traditional logistic regression analysis among patients hospitalized with acute myocardial infarction: should we be analyzing cardiovascular outcomes data differently? Am Heart J 2003; 145: 27-35. http://dx.doi.org/10.1067/mhj.2003.23

[16] Bowen ME, Gonzalez HM. Racial/ethnic differences in the relationship between the use of health care services and functional disability: the health and retirement study (1992-2004). Gerontologist 2008; 48: 659-67. http://dx.doi.org/10.1093/geront/48.5.659

[17] Tuerk PW, Mueller M, Egede LE. Estimating physician effects on glycemic control in the treatment of diabetes: methods, effects sizes, and implications for treatment policy. Diabetes Care 2008; 31: 869-73. http://dx.doi.org/10.2337/dc07-1662

[18] SAS/STAT 9.2 Production GENMOD Procedure for Windows. Cary, NC: SAS Institute Inc. 2009.

[19] Austin PC, Goel V, van Walraven C. An introduction to multilevel regression models. Can J Public Health 2001; 92: 150-54.

[20] Liang KY, Zeger S. Longitudinal data analysis using generalized linear models. Biometrika 1986; 73: 13-22. http://dx.doi.org/10.1093/biomet/73.1.13

[21] SAS Institute. SAS/STAT 9.2 Production GLIMMIX Procedure for Windows. Cary, NC:SAS Institute Inc. 2009.

[22] Little RC, Milliken GA, Stroup WW, *et al*. SAS System for Mixed Models. Cary, NC:SAS Institute Inc. 1996.

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