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Well-Being and Employee Health—How Employees' Well-Being Scores Interact with Demographic Factors to Influence Risk of Hospitalization or an Emergency Room Visit

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Abstract

The goal of this study was to determine the relationship between individual well-being and risk of a hospital event in the subsequent year. The authors hypothesized an inverse relationship in which low well-being predicts higher likelihood of hospital use. The study specifically sought to understand how well-being segments and demographic variables interact in defining risk of a hospital event (inpatient admission or emergency room visit) in an employed population. A retrospective study design was conducted with data from 8835 employees who completed a Well-Being Assessment questionnaire based on the Gallup-Healthways Well-Being Index. Cox proportional hazards models were used to examine the impact of Individual Well-Being Score (IWBS) segments and member demographics on hazard ratios (HRs) for a hospital event during the 12 months following assessment completion. Significant main effects were found for the influence of IWBS segments, sex, education, and relationship status on HRs of a hospital event, but not for age. However, further analysis revealed significant interactions between age and IWBS segments ($P=0.005$) and between age and sex ($P<0.0001$), indicating that the effects for IWBS segments and sex on HRs of a hospital event are mediated through their relationship with age. Overall, the strong relationship between low well-being and higher risk of an event in employees ages 44 years and older is mitigated in younger age groups. These results suggest that youth attenuates the risk engendered in poor well-being; therefore, methods to maintain or improve well-being as individuals age presents a strong opportunity for reducing hospital events. (*Population Health Management* 2014;17:13–20)

Introduction

Health care costs are expected to grow to 20% of the gross domestic product in 2016[1] and continue to outstrip gains in worker wages.[2] Costs for health insurance provided by employers for families jumped 9% for 2011 compared to 2010.[2] Inflation continues to fuel the rise in medical and pharmacy expenditures.[2] This has led many large and mid-sized companies to look to wellness programs to hold down rising health care costs and to improve productivity among their employees.[2]

Two leading contributors to the rising trend in health care costs are hospital admissions and emergency room (ER) visits. The Standard and Poor's Healthcare Economic Indices reported a 7.2% annual growth rate in their Hospital Commercial Index in July, 2012.[3] The Centers for Disease Control and Prevention reported that approximately 17% of privately insured adults aged 18 to 64 had an ER visit in 2009.[4] ER services are routinely higher cost compared to other outpatient service areas or office-based settings.[5] Both inpatient admissions and hospital ER visits result in direct (medical costs) and indirect (loss of productivity) costs to employers.[6]

Research on risk assessment models based on medical and pharmaceutical claims to predict future health care costs has a long tradition.[7] Risk assessment of employees to predict future health care costs and utilization is widely marketed among health care providers and has gained increasing acceptance among employers as a part of health care management programs for high-risk cases. Most commercial predictive models rely on sophisticated proprietary algorithms based on health care claims to identify individuals at risk for high costs. However, the expense associated with the use of these commercial algorithms and the claims on which they depend have led employers to seek lower cost

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alternative approaches. In addition, this approach is not an option for the many employers who do not have access to employee health care claims. An additional complicating factor for groups who wish to manage risk in their entire population, as opposed to only among diseased individuals, is the absence of claims for a large portion of the population, obscuring the identification of risk that has not yet manifested as a chronic condition or associated acute health care event. In these cases, an alternative route for risk assessment is necessary.

Self-reported ratings of health status have been found to contribute significantly to the prediction of health outcomes.[8–11] The most accurate of predictive models employ a combination of claims data, clinical severity indexes, and demographic variables, among others, in addition to self-reported health assessment.[8,12] Again, the applicability of these models often is restricted because many employers may not be able to afford or gain access to the claims and other data resources these complex models require. The advantage of self-rated measures is in the currency of information they provide and the ease of administration in that they can be auto-administered by phone or online, making them more cost-effective than claim feeds and other data sources.[13] Traditionally, these self-rated measures are risk assessments limited to questions about an individual's experience of disease or observable physical health problems. Increasing evidence indicates that there is value in using a measure that assesses an individual's overall well-being, which includes but is much broader than just one's physical health.[14–16]

The World Health Organization has broadly defined health as ''a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity.''[17] Well-being as measured by the Well-Being Assessment (WBA) adopts this broader definition of health advocated by the World Health Organization.[15] Items from the WBA are used to calculate Individual Well-Being Scores (IWBSs), a global well-being measure that encompasses both evaluative and experienced well-being.[15] Poorer well-being, as measured by the IWBS, has been shown to be predictive of higher medical costs, inpatient admissions, and ER visits.[14]

In a large-scale study conducted using the Gallup-Healthways Well-Being Index (WBI), from which the domains and items on the WBA were drawn, Coughlin examined the potential moderating effect of age on overall well-being and found that the distribution of scores across age groups resembled a U-shaped distribution in which well-being is lowest among the middle-aged.[18] He urged additional research aimed at better understanding the role of moderating variables on well-being over the life span.

To date, no studies of well-being have attempted to conduct a detailed examination of the moderating effects of other variables on the relationship of well-being with an outcome variable of interest. The goal of this study was to better understand the relationship between well-being segments and risk of a hospital-based event (admission or ER visit) by testing the well-being measure and other individual characteristics as independent and interacting variables in predicting the occurrence of such events in the year following the survey. The authors hypothesized that the relationship between well-being and the likelihood of a hospital event varied based on an individual's characteristics; the study sought to understand how these variables interact in defining risk of hospital utilization.

Methods

Well-Being Assessment and Individual Well-Being Score

The WBA was developed as an extension of the WBI community survey for use with employer populations and with health plans. The WBA can be administered by phone or computer. An IWBS was developed from WBI/WBA items and domains to allow calculation of well-being at the individual level.[15] The IWBS is calculated using 40 questions from the following 6 domains of well-being that are included in both the WBI and WBA: physical health, emotional health, healthy behaviors, work environment, basic access, and life evaluation. The items comprising the IWBS were derived from research conducted by Diener (subjective well-being), Kahneman (evaluative vs. experienced well-being), and Cantril (life evaluation).[19–21] Each domain is weighted equally in the calculation of the IWBS, as they are in the WBI, and scores range from 0 to 100 for each respondent.[15]

IWBS risk segments

Although the IWBS is considered a continuous measure, recent research has demonstrated the utility of segmenting the IWBS into discrete segments based on score thresholds at which shifts in risk for an adverse health or productivity outcome were observed.[16] The research grouped IWBSs into 5 ordinal segments, in which lower score segments indicated lower levels of well-being and higher score segments reflected higher levels of well-being: low (<53), low medium (53 to <66), medium (66 to <75), high medium (75 to <88), and high (≥ 88). These score ranges were used as the IWBS variable in this study, which hereafter is referred to as IWBS segments.

Study design

The study employed a retrospective, fixed effects study design using Cox proportional hazards to model the relationship between IWBS segments and study covariates on the time until first hospital-based medical event (inpatient admission or ER visit) using data from 8835 employees of a large commercial insurance company. For inclusion in the study, employees had to complete the WBA during June or July of 2010 and have 1 to 12 months of health plan eligibility following completion of the WBA. Health care claims of study participants covering the 12-month period following completion of the WBA were used for analyses. All participants who failed to experience a hospital event or were lost to observation prior to the conclusion of the study were right censored. Because of the negligible risk, retrospective design, and use of de-identified data, this study was exempt from institutional review board approval based on exclusion criteria outlined in the US Code of Federal Regulations.

Study Variables

Table 1 shows the finalized covariates available for modeling main effects and their categories. In addition to the

Table 1. Finalized Modeling Variables

Variable	*Type*	*Categories*	*Cutpoint*
Hospital event	Dependent	No event	0
(Inpatient admission or ER visit)		Event	1
Time	Independent	Continuous	NA
IWBS segments	Independent	High	≥88
		High Medium	75 to <88
		Medium	66 to <75
		Low Medium	53 to <66
		Low	<53
Age	Independent	Younger	<44
		Older	≥44
Sex	Independent	Male	0
		Female	1
Education	Independent	No college	0
		College	1
Relationship status	Independent	In a relationship	0
		Other	1

ER, emergency room; IWBS, individual well-being score.

IWBS segments described, age also was categorized into 2 categories, <44 (younger) and ≥44 (older) years of age, based on distributional characteristics (ie, median and mean) and plots of kernel density estimates. Usually, categorization of continuous variables is discouraged because of potential loss of information, among other reasons.[22,23] More importantly, it may substantially alter covariate relationships in the model as well as the models that achieve convergence. To address this concern, all models were run with IWBS and age treated as continuous as well as categorical variables to establish model validity before accepting the categorical version of the model. Transforming continuous variables into categorical ones is not without precedent and is often done in medical and epidemiological research for efficient data summarization and to improve the ease of interpretation.[24–27] This is particularly true when interpreting relative risks or hazard ratios.

Main effects were modeled first. The process of variable selection began with individual modeling of covariates in combination with the dependent variable. All covariates with *P* values less than 0.25 were retained for main effects modeling. The 1 exception to these criteria was the variable age. Because of the role that aging plays in the evolution of disease morbidity, it was expected that age would be found to have a significant relation with the dependent variable, hospital event. However, the lowest *P* value obtained for age, in continuous or categorical form, was 0.468. Normally, such a large *P* value would disqualify it from further consideration, but the expectation was so strong that, despite the failure of age to meet statistical criteria in the main effects model, it was retained for further modeling and assessment.

Statistical methods

Cox proportional hazards models were used to estimate the relative risk for a first hospital event, either an inpatient admission or an ER visit.[28–30] Variable selection for Cox models was conducted via the log-rank test for categorical variables and proportional hazards regression was used for continuous form variables. The main effects only models were evaluated via the likelihood ratio test. Proportional hazard models were used to test all first-order interactions for entry into the main effects model. Testing for conditional marginal effects with interactions were conducted via a custom design matrix in SAS 9.2.[31] All reported models were assessed for proportionality. Final main effects with interaction models were determined through likelihood ratio tests. All statistical analyses were conducted using SAS 9.2 (SAS Institute Inc, Cary, NC).

Results

Of the 8835 employees who qualified for the study, 647 (7.3%) experienced a qualifying hospital event, with the other 92.7% being censored over the course of the 12-month observation period. Participant demographics are presented in Table 2. The study group was largely female and over half were 44 years of age or older. Most participants reported at least some college and endorsed being in a relationship.

The use of Cox proportional hazards models to examine the relationship between IWBS segments, study covariates, and time until first hospital-based event (inpatient admission or ER visit) was performed in stages. Results are thus presented

Table 2. Participant Demographics (N = 8835)

Variable	*Response category*	*%*
Inpatient admission or ER visit	Had an Event	7.3
Age	≥44	52.6
Sex	Female	61.9
Education	College	63.8
Relationship status	In a relationship	64.3
Minority status	Minority	27.1
IWBS segments	Low (<53)	9.0
	Low medium (53 to <66)	19.3
	Medium (66 to <75)	22.3
	High medium (75 to <88)	34.7
	High (≥88)	14.7

ER, emergency room; IWBS, individual well-being score.

in stages starting with main effects only and progressing to main effects with interactions.

Main effects

All models reported met tests of the proportionality assumption for Cox regression. Results of the Type 3 Test for main effects are presented in Table 3. The results indicate that all variables in the main effects only model are significant with the exception of age. Again, the decision was made to retain age for further modeling as it was hypothesized that the influence of age might show up in the interaction with other variables in the model. Interpretation of main effects was deferred until interaction terms had been added and assessed, as they were likely to mitigate or obviate their interpretation.

Main effects with interactions

Once the main effects only model was derived, all pairwise interactions from the variables comprising the main effects only model were individually tested by entering them 1 at a time into that model to assess their contribution to the model and their impact on the other variables. From this process, 2 interactions were found to be statistically significant: IWBS segments x age and age x sex. These 2 interactions were added to the model and the model was rerun. Results of this combined model, main effects with interactions, are presented in Table 4.

There are substantial differences between the main effects only model and the main effects with interactions model. First, IWBS segments, which is the most potent variable in the main effects only model, becomes statistically nonsignificant as a main effect once interactions are added. The influence of IWBS segments is now captured through its interaction with age. Age, by contrast, previously insignificant in the main effects only model, emerges as significant in the model with interactions, plus it shares significant interactions with IWBS segments and sex. The hypothesized masking of age by other variables in the main effects only model appears to be validated by the main effects with interactions model. Two variables not involved in interactions, education and relationship status, are statistically significant and can be interpreted as main effects (ie, unconditional marginal effects). The beta for education (-0.17049) when exponentiated (exp ß) converts to a hazard ratio of 0.84, indicating that college attendance is associated with a 16% reduction in the hazard of a hospital event, compared to no college. The beta for relationship status (-0.23014) converts into a hazard function of 0.794 or a 20% decrease in the hazard of a hospital event for individuals not in a relationship compared to individuals who identified themselves as being in a relationship.

The interactions between IWBS segments × age and age × sex require examination and testing of conditional marginal effects for interpretation via their partial likelihoods.

Table 3. Results of Main Effects Only Model Evaluating the Effect of Individual Well-Being Score Segments and Demographic Variables on Risk of a Hospital Event

Variable	*Wald Chi-Square*	P *value*
IWBS segments	42.07	< 0.0001
Age	0.42	0.5169
Education	4.51	0.0338
Sex	17.04	< 0.0001
Relationship status	6.53	0.0106

IWBS, individual well-being score.

Table 4. Results of Final Main Effects with Interactions Model Evaluating the Effect of Individual Well-Being Score Segments and Demographic Variables on Risk of a Hospital Event

Variable	*Wald Chi-Square*	P *value*
IWBS segments	6.67	0.1543
Age	24.32	< 0.0001
Education	4.48	0.0343
Sex	37.52	< 0.0001
Relationship status	7.87	0.005
IWBS segments x age	14.77	0.0052
Age x sex	23.44	< 0.0001

IWBS, individual well-being score.

IWBS segments x age interactions

To allow for interpretation of the interaction between age group and IWBS segments, partial likelihoods were used to conduct pairwise comparisons among score segments within each age group. Tables 5 and 6 present the hazard ratios for all comparisons of lower to higher IWBS segments in the < 44 and ≥ 44 age groups, respectively, thus representing the likelihood of having a hospital event for people in lower IWBS segments relative to people in higher score segments. These tables are similar in appearance to a diagonal correlation matrix. The cells of the matrix represent the hazard ratio values of the comparison segments (ie, the values displayed) relative to the reference segment, which always has a hazard ratio of 1. Hazard ratios for the comparison segments represent positive values and can be less or greater than 1.0. For example, the hazard ratio of 0.865 in the top left cell of Table 5 indicates that the hazard of an event for younger study members with a low medium IWBS (reference segment) is 86.5% relative to those younger members with a low IWBS (comparison segment), or 13.5% lower risk of an event.

In the younger age group (< 44), Table 5 shows that there are no significant differences between any of the comparison segments scoring lower than high (ie, low medium, medium, and high medium) relative to the reference segments; however, the high IWBS segment of the comparison shows a significant reduction in hazard relative to 3 of the 4 lower reference segments. The largest difference in risk was found when comparing the low segment of the reference to the high segment for the comparison, which revealed a hazard ratio of 0.519, indicating nearly half the risk of having a hospital event during the study period.

More dramatic and significant differences emerged among comparisons between IWBS comparison and reference segments in the older group (≥ 44); hazard ratios for these pairwise comparisons are shown in Table 6. All higher

Table 5. Pairwise Comparisons of Hazard Ratios for a Hospital Event for Higher Scoring IWBS segments (Comparison) Relative to Lower Scoring IWBS segments (Reference) for Ages <44 Years

	Reference IWBS segments (1.0 HR)			
Comparison IWBS segments	*Low (<53)*	*Low medium (53 to <66)*	*Medium (66 to <75)*	*High medium (75 to <88)*
Low medium	0.865			
Medium	0.788	0.912		
High medium	0.852	0.986	1.081	
High (≥88)	0.519*	0.601*	0.659	0.609*

*Indicates hazard is statistically significant at $P<0.05$
HR, hazard ratio; IWBS, individual well-being score.

scoring comparison segments demonstrated statistically significant reductions in hazard relative to the low and low medium reference segments. Evaluation of the high and high medium comparison segments relative to the medium reference segment found slight declines in the hazard ratios that were not significant. The high segment for the comparison evidenced a slight but nonsignificant increase in hazard relative to the high medium segment for the reference.

Figure 1 provides a graphical representation of the interaction between IWBS segments and age based on the proportion of individuals with a hospital event, and illustrates the differences in risk that emerge between the age groups at lower IWBS segments.

Age x sex interactions

To allow for interpretation of the interaction between age and sex, the influence of age on hazard ratios of having an event was evaluated for each sex separately. The results of this analysis are shown in Table 7. Compared to younger males, older males demonstrated a significantly higher hazard ratio, indicating more than twice the risk of having an event. In contrast, older females compared to younger females demonstrated a 10% lower risk of an event, although the difference between the age groups was not significant. Within the older age group there is no significant difference in hazard between males and females.

Figure 2 illustrates the convergence of the 2 sexes in the older age group. We can see that if the main effects only model for sex was interpreted directly, one would draw the simple conclusion that females have a higher risk ratio for a hospital event than males. However, the interaction reveals that this difference is only significant in the younger age group because risk increases substantially among males in the older age group compared to males in the younger age group.

Discussion

The goal of the present study was to determine the relationship between individual well-being, as measured by IWBS segments, and the risk of a hospital event in the subsequent year. In addition, it was hypothesized that the relationship between well-being and the risk of a hospital event, as reflected by the first occurrence of a hospital admission or ER visit, would vary based on an individual's characteristics. Study results revealed a strong mitigating effect for age on the relationship of well-being to the risk of a first hospital-based event. In the younger group of employees (<44 years), it was found that those with well-being in the high (≥88) IWBS segment were the only subgroup of this age category that evidenced significantly lower risk of a hospital event; no significant differences in risk were found among the other lower-scoring IWBS segments. This suggests that among younger employees, only those with the highest personal well-being experience a significantly lower hazard for a hospital event. However, among those in the older (≥44) age group, a very different picture emerged. It was found that significant differences in the hazard for a hospital event can occur between adjacent segments, such as from the lowest IWBS segment (<53) to the next higher segment (53-<66). This suggests that even modest changes in well-being may be associated with significant reductions in the hazard of a hospital event in this older age group.

The relationship between well-being and age has been examined previously. In 2 large-scale studies that

Table 6. Pairwise Comparisons of Hazard Ratios for a Hospital Event for Higher Scoring IWBS segments (Comparison) Relative to Lower Scoring IWBS segments (Reference) for Ages ≥44 Years

	Reference segments (1.0 HR)			
Comparison segments	*Low (<53)*	*Low medium (53 to<66)*	*Medium (66 to<75)*	*High medium (75 to<88)*
Low medium	0.553*			
Medium	0.396*	0.716*		
High medium	0.343*	0.621*	0.867	
High (≥88)	0.358*	0.647*	0.904	1.043

*Indicates hazard is statistically significant at $P<0.05$.
HR, hazard ratio; IWBS, individual well-being score.

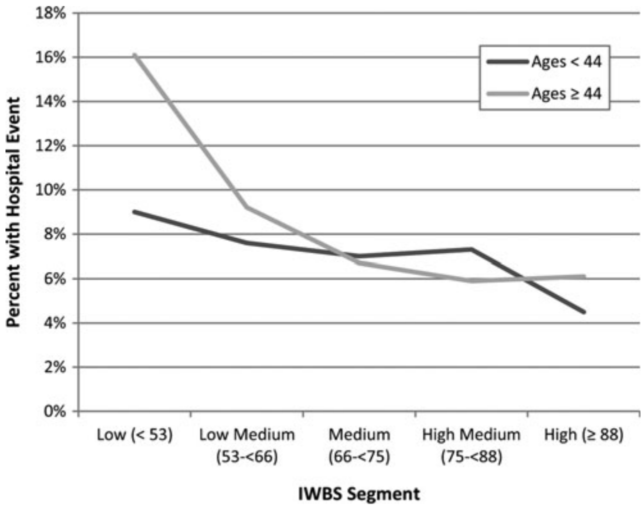

FIG. 1. Proportion of study population with a hospital event (admission or emergency room visit) by Individual Well-Being Score (IWBS) segment and Age Group.

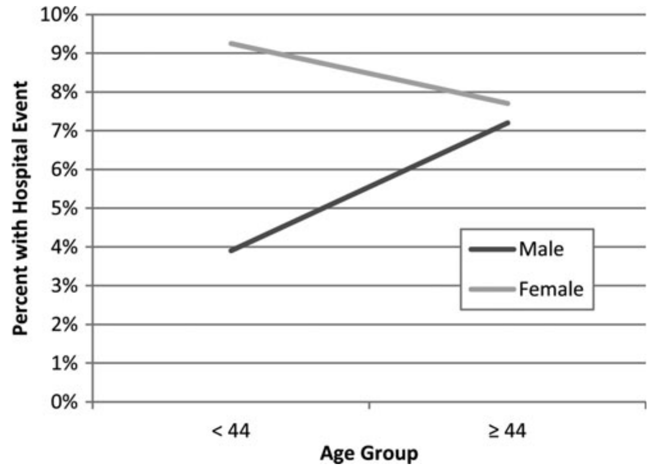

FIG. 2. Proportion of study population with a hospital event (admission or emergency room visit) by sex and age group.

evaluated well-being measures, significant differences in measures of well-being across ages were detected.[18,32] Stone and associates assessed global well-being through a single life evaluation item and hedonic well-being was examined with questions about affect experienced yesterday. Both measures revealed U-shaped age profiles for both men and women.[32] In a second large-scale study conducted by Joseph Coughlin of the MIT Agelab using the Gallup-Healthways Well-Being Index, differences in well-being scores also were observed.[18] This study categorized age into 3 segments: young (18–43 years), midlife (44–64 years), and seniors (≥65 years). The study found that overall well-being was lowest during the midlife years and higher during the younger and senior age periods, thus resembling a U-shaped distribution but with well-being reaching its highest level during the senior years. Interestingly, although these 2 studies used different measures of well-being, both detected a decrease in well-being at around midlife.[18,32] However, no study to date has explored how well-being interacts with age and other variables to impact an outcome.

The first 2 age categories in the Coughlin study closely approximate the age categorizations used with the employee population evaluated in the present study, which were 18–43 years and ≥44 years. Less than 1% of the study population

Table 7. Comparison of Hazard Ratios for a Hospital Event For Ages ≥44 Years (Comparison) Relative to Ages <44 Years (Reference) by Sex

	Reference (1.0 HR)	
	Age<44	
Comparison Age≥44	*Male*	*Female*
Male	2.153*	
Female		0.898

*Indicates hazard is statistically significant at $P<0$ .05.
HR, hazard ratio.

was 65 years of age or older, as would be expected in an employed population. The present evaluation of IWBS segments extends upon the work of Stone and Coughlin, which describes the relationship of age with well-being,[18,32] to quantify the differential risk of an adverse health event imparted by well-being level in these different age groups. It was found that higher well-being scores had a strong mitigating effect on risk of a hospital event in the ≥44 age group, but that only the highest level of well-being was associated with significantly lower risk of an event in the younger age group. The study results, supported by the previous research, strongly suggest that individualized interventions to improve well-being in employee populations need to be informed by age.

The other interesting interaction identified was between age and sex. The risk of a hospital event increased for older men relative to those<44 years of age, as was anticipated. Conversely, there was a small decline in risk of approximately 10% among women in the older age group relative to the<44 years of age group. Although the difference between the age groups was not statistically significant in females, the higher percentage of younger women with hospital events may reflect admissions associated with labor and delivery during these primary childbearing years. These results are directionally consistent with statistics published by the National Center for Health Statistics that indicate a hospital discharge rate of 1247 per 10,000 among females aged 15–44 years, and a rate of 1207 per 10,000 among females aged 45–64 years. The hospital discharge statistics for men, however, increase 2.8 fold in the 45–64 age group compared with the 15–44 age group—an even larger increase than experienced in this study population.[33]

These findings could hold important implications for employers who are seeking means to reduce the burden of health care costs and lost productivity stemming from expensive hospital events. While one might conclude from the results of the present study that employers are more likely to see larger and more immediate gains by focusing on improving the well-being of older employees, it would be a mistake to assume that efforts to improve well-being among younger employees are likely to prove unproductive. In a sense, age can be thought of as a proxy for exposure time to risk. Therefore, intervention with younger employees to improve well-being, and thereby minimize exposure time to risk engendered in suboptimal well-being, can have both short-term as well as long-term dividends. The immediate effects of improving well-being may not have as broad an immediate effect on health care utilization as it would among older, more risk-burdened employees because youth, and thus less exposure time to risk, works to attenuate the negative effects of lower well-being on risk of a hospital event. However, even in the younger age group the high IWBS segment had significantly lower risk of an event, suggesting some potential for minimizing risk by optimizing well-being. Additionally, strategies to improve well-being may have near-term beneficial effects on productivity by reducing sick days and presenteeism[34] that may be independent of age. Future studies should explore how well-being and other variables interact to impact these and other work-related outcomes.

The present study also has implications for researchers seeking to build predictive models to more accurately predict future health care costs and utilization using self-reported measures of well-being in lieu of claims. To predict risk of hospital admission and other health care events accurately, good modeling practice should include testing of marginal effects beyond simple main effects.[35] As this study revealed, simply because a covariate does not evidence significant first order effects for an outcome does not mean that it can be dismissed automatically as unimportant, particularly if theory would suggest otherwise. Moreover, exploring and testing marginal effects is not only important to optimizing prediction but is critical to furthering our understanding of well-being and how it manifests itself through health care metrics. This in-depth knowledge is required if effective interventions to increase well-being, improve health, and foster productivity are to be personalized to individual needs.

Hazard ratios can be a useful method for not only evaluating the influence of covariates on health care outcomes but also communicating the benefits of changes in well-being as it relates to health risks.[36] Hazard ratios may be more intuitive to nonstatisticians than beta coefficients and P values because they relate directly to the likelihood of an outcome. This allows the presentation of complex but important marginal effects in a manner that is more comprehensible for a general audience.

Limitations of this study that should be considered in the interpretation of results include the fact that data represent a nonrandom sample from a single employer and may not be generalizable, as well as the potential for self-report bias and endogeneity between study variables. However, the novelty of the study findings warrants further study using the IWBS segments and subscales of the WBA in order to gain greater insight into the relationship of well-being and other important covariates and the risk of adverse health care outcomes. Future work also should explore the relationship between well-being and other covariates with respect to other costs to employers, such as lost productivity related to presenteeism or absenteeism. Additionally, longitudinal controlled studies are an important future direction of this research to allow an understanding of how changes in well-being relate to changes in risk of a hospital event.

Conclusions

The goal of the present study was to determine the relationship between individual well-being, as measured by the WBA, and risk of a hospital event in the subsequent year. In particular, the study sought to provide a more detailed understanding of how demographic variables interact with IWBS segments to influence the risk of hospital utilization. Results revealed significant relationships between education and relationship status and likelihood of a hospital event. More importantly, the study revealed an important moderating effect of age on the relationships between IWBS segments and sex and the hazard for a hospital event. Among the implications of this study is that, although older employees may reap larger and more immediate benefits from marginal improvements in well-being, strategies to improve and maintain high levels of well-being may serve as a longer-term investment in younger employees with respect to avoiding hospital events. Future research should investigate whether differences in well-being among younger employees are more strongly predictive of other sources of value to employers, such as employee productivity. In general, findings from this study underscore the need to examine the role of moderating variables in future well-being research.

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Disclosure Statement

Drs. Gandy, Coberley, Pope, and Rula are employees and shareholders of Healthways, Inc.

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