

# Comparison of the Utility of Two Assessments for Explaining and Predicting Productivity Change

## *Well-Being Versus an HRA*

William M. Gandy, EdD, Carter Coberley, PhD, James E. Pope, MD, and Elizabeth Y. Rula, PhD

**Objective:** To compare utility of employee well-being to health risk assessment (HRA) as predictors of productivity change. **Methods:** Panel data from 2189 employees who completed surveys 2 years apart were used in hierarchical models comparing the influence of well-being and health risk on longitudinal changes in presenteeism and job performance. Absenteeism change was evaluated in a nonexempt subsample. **Results:** Change in well-being was the most significant independent predictor of productivity change across all three measures. Comparing hierarchical models, well-being models performed significantly better than HRA models. The HRA added no incremental explanatory power over well-being in combined models. Alone, nonphysical health well-being components outperformed the HRA for all productivity measures. **Conclusions:** Well-being offers a more comprehensive measure of factors that influence productivity and can be considered preferential to HRA in understanding and addressing suboptimal productivity.

“What we measure affects what we do.”—J. Stiglitz<sup>1</sup>

Health risk assessment or HRA was a measurement tool borne of the worksite health management industry in the 1980s and has largely remained a tool of choice for employers.<sup>2</sup> These tools were designed to identify employees with health risks like smoking, high blood pressure, chronic conditions, etc, who would benefit from support or intervention. HRAs were important in helping employers and employees recognize the relationship between health risks and increased health care costs.<sup>3,4</sup> Furthermore, researchers established a relationship between increased health risk and poor physical health with reduced productivity in the form of absenteeism and more recently presenteeism.<sup>5–7</sup> Not only has more health risks been associated with higher absenteeism and presenteeism, but changes in health risk have shown to be associated with presenteeism change over time, making health risk a recognized opportunity for employers who wish to improve productivity.<sup>8,9</sup> Presenteeism has previously been more narrowly defined as reduced productivity or performance at work because of illness or other medical conditions.<sup>10,2</sup> Presenteeism is, however, now more broadly thought of as occurring when employees show up for work even if they are too sick, stressed, or distracted to be productive.<sup>11–14</sup> There is growing evidence that factors beyond physical health impact productivity. Although HRAs can include

some nonphysical items as part of their inventory, they remain, as their name implies, primarily oriented toward physical health and the behaviors that influence physical health.

Emerging research on well-being is revealing that employee well-being is associated with absenteeism and presenteeism in the workplace.<sup>12,15–20</sup> This body of research on well-being and productivity has established well-being as a multidimensional construct comprising a range of factors that together define an individual's experience of well- (or ill-) being; the measure used was the Individual Well-Being Score (IWBS). The primary constructs measured within the IWBS include emotional health, physical health and behavioral risks, community quality, access to basic needs, work environment, and evaluation of current and future life situation. Defining well-being as multidimensional is consistent with prior research in the field of well-being.<sup>21,22</sup> Measuring multiple domains that contribute to an individual's or community's overall well-being is also beneficial for identifying areas of opportunity, or targets for interventions to improve well-being and associated outcomes such as productivity. Well-being assessment (WBA), similar to HRA, acknowledges the important role of physical health, but well-being research takes a much broader view of factors that influence the outcomes of an individual or population.<sup>21,23</sup>

A well-recognized theory of productivity is the happy productive worker thesis, which posits that happy employees have higher job-performance behaviors. In this body of literature, researchers have operationalized happiness in different ways—narrowly as job satisfaction or affect or more broadly as one of various definitions of well-being.<sup>24</sup> Two definitions of “happy” were compared by Wright and Cropanzano<sup>25</sup> who examined the influence of job satisfaction and psychological well-being on job performance. Both initial correlational analysis and a series of hierarchical regression models evaluated the incremental contribution of job satisfaction and well-being in predicting job performance found support for the contribution of well-being to job performance above the influence of job satisfaction, which was not a significant contributor to supervisor performance ratings. The small sample size and single measure of productivity, however, limited generalizability. Other studies have found support for job performance as an independent indicator, including a large meta-analysis examining the relationship between job satisfaction and job performance.<sup>26–31</sup> In addition, Koopman et al<sup>32</sup> in conducting the development and validation work on the Stanford Presenteeism Scale (SPS-6) found a statistically significant relationship between job satisfaction and presenteeism as measured by their instrument.

As delineated, both HRAs and the IWBS have demonstrated relationships with productivity; however, it has yet to be shown whether the HRA as an inventory of observed health information sufficiently captures the factors that influence productivity relative to the broader set of constructs measured as part of well-being. To date, the two instruments have not been directly compared in the literature to determine which one is a stronger predictor of productivity change, and thus a better source for developing interventions with a goal of improving productivity. This question is important because a more accurate assessment of the areas that

From the Center for Health Research (Dr Gandy, Dr Coberley, Dr Pope, Dr Rula), Healthways, Inc, Franklin, Tennessee.

This study was funded by Healthways and all authors are employees and shareholders of this company.

This is an open-access article distributed under the terms of the Creative Commons Attribution-Non Commercial-No Derivatives License 4.0, where it is permissible to download and share the work provided it is properly cited. The work cannot be changed in any way or used commercially.

Address correspondence to: Elizabeth Y. Rula, PhD, Center for Health Research, Healthways, Inc, 701 Cool Springs Boulevard, Franklin, TN 37067 (elizabeth.rula@healthways.com).

Copyright © 2015 American College of Occupational and Environmental Medicine

DOI: 10.1097/JOM.0000000000000598

impact productivity allows for more informed and complete interventions to improve productivity.

The current study directly compares the utility of the IWBS versus HRA to provide empirical evidence to guide employers or other organizations seeking to improve productivity. In this context, the preferred measure should best identify the root causes of productivity loss in a population to inform interventions to improve productivity and, in turn, change in the measure should predict change in productivity. If a measure predicts an outcome, it captures factors that explain change in the outcome of interest. These become the factors to address as part of an intervention to improve that outcome.

Given that a measure that is more comprehensive and more predictive offers greater opportunity to address factors that impact productivity, the study had two specific goals: (1) to directly compare the IWBS and HRA in models predicting three types of productivity change: presenteeism, job performance, and absenteeism; (2) to determine if the nonphysical constructs within the IWBS that make this measure more comprehensive than the HRA are influential in explaining the change in productivity measures.

**METHODS**

**Study Design**

The study used a longitudinal, retrospective panel study design, using survey data collected in 2010 (T1) and 2012 (T2). The data for the panel were composed of 2189 exempt and non-exempt employees from a large employer. Study eligibility required valid scores for all included survey measures at T1 and T2 and a documented age between 18 and 64 years. A subsample of 677 nonexempt employees with available unscheduled paid-time off (PTO) employer records was evaluated in absenteeism analyses.

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 (45 CFR §46.101).

**Data**

Self-reported data including the IWBS, HRA, presenteeism, and job performance measures were collected using a single survey, the WBA. The WBA was developed as an extension of the Well-Being Index (WBI) community survey<sup>33</sup> for use by employers and organizations managing health and productivity through well-being improvement. The survey was offered as part of a broader well-being improvement program, and WBA completion was incentivized with a \$100 health savings account or health reimbursement account deposit. Unscheduled PTO data were provided by the employer. Specific independent and dependent measures are detailed below.

**Independent Measures**

**Well-Being: IWBS**

IWBS was developed and validated<sup>34</sup> as a scoring method for items collected on the WBI, for use in measuring the well-being of individuals in a population. The IWBS is calculated using 40 questions from the following six domains of well-being that are included in the WBI and WBA: physical health, emotional health, healthy behaviors, work environment, basic access, and life evaluation.<sup>34</sup> Each domain is weighted equally in the calculation of the IWBS, as in the WBI, and scores range from 0 to 100 for each respondent.

**Job Satisfaction**

Job satisfaction was measured by a three option response to the question “Are you satisfied or dissatisfied with your job or the work you do?”: satisfied, dissatisfied, or don’t know. The item was originally from the Gallup Healthways WBI and was the only job

satisfaction indicator in the WBA and is a scored item in the IWBS.<sup>33,34</sup>

**HRA**

Traditional HRA inventories typically collect physical health information about a combination of health conditions and health risk behaviors. The number of conditions and risks, type of conditions and risks examined, as well as the criteria for those conditions and risks are not consistent in the literature. The specific set of risks used in the current study (Table 1) were drawn from available WBA items and were a composite modeled after the 10 behavioral and biometric health risks used by Yen et al<sup>35</sup> and the existing medical problems used by Loeppke et al.<sup>36</sup> The evaluated set of risk factors largely matched seminal research by Dee Edington.<sup>37,38</sup> All risks meeting noted criteria were summed to a total HRA score ranging from 0 to 11, and HRA change was calculated as the difference in risk count from T1 to T2.

**Dependent Measures**

**Productivity (Presenteeism): Well-Being Assessment for Productivity (WBA-P) Overall Score**

The primary measure of productivity in the study was the WBA-P, a validated presenteeism measure collected as an extension of the WBA that provides an informative evaluation of on-the-job productivity loss (presenteeism) because of well-being-related barriers. The WBA-P was chosen as the primary productivity measure for this analysis because of its multidimensionality, which has the advantages of measuring more variance in a population. Criterion-related validity of the WBA-P has been established through multivariate analysis to a number of health and well-being measures.<sup>12</sup> The WBA-P score is composed of 11 items with the shared question stem “During the past 4 weeks (28 days), how often have you had trouble at work concentrating or doing your best because of . . . ” and then lists 11 possible reasons or barriers. Scoring of this measure ranges from 0 (not at all) to 100 (a lot for all 11 reasons).<sup>12</sup> Change in the WBA-P score, the difference from T1 to T2, was used as the outcome variable.

**Productivity (Job Performance): Health and Work Performance Questionnaire Self-Rated Performance Scale**

The Health and Work Performance Questionnaire (HPQ) contains a global, self-rating of job performance measured on a 0- to 10-point scale that is considered an absolute measure of

**TABLE 1. Health Risk Assessment Risks and Criteria**

Measure	Risk Criteria
Smoking status	Current smoker
Physical activity	<1 time/wk
Alcohol consumption	>14 drinks/wk
Seat belt usage	<90% of the time
Blood pressure	Systolic >139 mm Hg or diastolic >89 mm Hg
Total cholesterol	>239 mg/dL
High density cholesterol (HDL)	<35 mg/dL
Body weight	≥BMI 27.8 for men or 27.3 for women
Illness days	≥5 d/yr
Self-assessment of health	Fair or poor
Existing medical problems	Heart problems, diabetes, cancer, or past stroke

BMI, body mass index; HDL, High Density Lipoprotein.

presenteeism<sup>39</sup>; this question was included in the WBA. This HPQ item was included as a secondary outcome to ensure conclusions were not sensitive to the specific measure used to assess on-the-job productivity. The item reads, “Using the same 0-to-10 ladder, how would you rate your overall job performance on the days you worked during the past 4 weeks (28 days)?” Change in the HPQ score, the difference from T1 to T2, was used as the outcome variable.

**Productivity (Absenteeism): Unscheduled PTO**

Change in the level of unscheduled PTO usage, available for nonexempt employees only, was used as an objective measure of absenteeism. Only unscheduled PTO (as opposed to scheduled PTO) were included to ensure that vacations and other preplanned time off were not included in this outcome measure. Change for this variable was represented by a three-level ordinal outcome: 1 = increase in usage; 0 = no change in usage; -1 = decrease in usage. Change in the level of unscheduled PTO usage on this scale from T1 to T2 was used as the outcome variable.

**Statistical Methods**

Drawing from the method of Wright and Cropanzano,<sup>25</sup> a series of hierarchical regression models were used to assess the unique and additive value of the HRA and IWBS in explaining productivity change over a base model (Model 1) consisting of age, sex, and job satisfaction. Although job satisfaction is included as a scored item in the IWBS, it was included separately in the models to ensure that this aspect of well-being shown to be independently associated with productivity<sup>31</sup> was not driving any incremental benefit of well-being over an HRA. Both the HRA and IWBS models consisted of two variables each: an initial score (2010) and a change score (2010 to 2012). The HRA (Model 2) and IWBS (Model 3) variables were each added independently to the base model to determine the unique variance explained by each measure over the base model variables. Then, both the HRA and IWBS variables were included in a combined model (Model 4) to evaluate the additive value over the base model and the incremental value of the IWBS over the HRA and vice versa through comparison to Model 2 and Model 3, respectively. Table 2 contains the specification of all modeled variables.

**Hierarchical Ordinary Least-Squares Regression Models**

To evaluate the contributions of the HRA and IWBS in explaining changes in presenteeism and performance, as measured

**TABLE 2.** Study Variables

Variable	Type	Category/Range
Age, yrs	Continuous	18–64
Sex	Dichotomous	Male = 0, female = 1
Job satisfaction	Ordinal	1 = yes, 0.5 = don't know, 0 = no
HRA initial	Continuous	0–10
HRA change score	Continuous	-11 to +11
IWBS initial	Continuous	0–100
IWBS change score	Continuous	-100 to +100
Job performance change*	Continuous	-10 to +10
Presenteeism change (WBA-P)*	Continuous	-100 to +100
Absenteeism change (unscheduled PTO)*	Ordinal	+1 = increase, 0 = no change, -1 = decrease

HRA, health risk assessment; IWBS, Individual Well-Being Score; PTO, paid-time off.

\*Dependent productivity measures.

by the WBA-P and HPQ respectively, hierarchical ordinary least-squares (OLS) modeling was conducted on the entire sample of 2189 employees. Model performance was assessed using  $R^2$  values, which were statistically compared between models using the  $F$ -test. The relative strength of the contributions of each IWBS and HRA variable within a given model was assessed using its  $t$ -statistic. The  $t$ -statistic, the coefficient divided by its standard error, reflects how many standard deviations the true value of the coefficient is from zero. The larger the absolute value of  $t$ , the less likely that the actual value of the parameter could be zero. Thus, the magnitude of the  $t$ -statistic allows for direct comparison across variables with different scales to provide a measure of the strength of a variable's effect size relative to other variables in the model.

**Hierarchical Multinomial Logistic Models**

To evaluate the contributions of the HRA and IWBS in explaining changes in utilization of unscheduled PTO (absenteeism), a hierarchical multinomial logistic model with ordered polytomous outcome was used. A subsample ( $n = 677$ ) of nonexempt only employees was used. Model performance was assessed using the Akaike information criterion (AIC) to compare performance to the base model or other models in hierarchical modeling of a given outcome. No statistical test of AIC is available; however, differences of 3 to 7 suggest that the base is considerably worse, more than 10 indicates it is highly unlikely the base model is preferable.<sup>40</sup> The relative strength of the contributions of each IWBS and HRA variable within a given model was assessed using Wald chi-square values.

**RESULTS**

Of the 2189 employees who qualified for the data panel, 677 (31%) were identified as nonexempt. Participant demographics for the entire sample and the nonexempt employees are shown in Table 3. Both samples have a high percentage of females.

Examining the results for the first outcome measure, WBA-P change, all three hierarchical models were found to provide significant improvement in  $R^2$  compared with the base model and thus added incremental advantage over demographics and job satisfaction in explaining presenteeism (Table 4). Model 2, adding HRA variables only, reflected a 2% overall increase in the explained variance, from 3% to 5%, a 67% relative improvement over the base model alone. Model 3, adding IWBS variables only, evidenced an  $R^2$  of 14%, more than a five-fold improvement relative to the Base model (Model 2). It is important to note that Model 4 (IWBS and HRA) evidences no  $R^2$  improvement compared with Model 3 (IWBS only). This comparison between Models 3 and 4 reveals that not only is the IWBS a superior predictor, it captures all of the variance also explained by the HRA plus explains significantly more variance. Also, shown in Table 4, a similar pattern was observed in

**TABLE 3.** Sample Demographics

Employee Characteristic	Total Sample (N = 2,189)	Nonexempt (n = 677)
Percent female	67.0%	89.5%
Level of Education		
High school	37.0%	39.1%
Tech/vocational	7.3%	4.6%
College	46.6%	51.5%
Post college	7.8%	2.1%
Missing	1.4%	2.7%
Average age	45.0	44.9
Time points	T1 = 2010; T2 = 2012	T1 = 2010; T2 = 2012

**TABLE 4.** Summary of Model Performance

Outcome variable	Models			
	1 (Base)	2 <sup>a</sup> (Base + HRA)	3 <sup>a</sup> (Base + IWBS)	4 <sup>b</sup> (Base + IWBS and HRA)
Presenteeism change ( $R^2$ )	0.03	0.05**	0.14**	0.14**
Job performance change ( $R^2$ )	0.01	0.01	0.04**	0.04**
PTO change (AIC) <sup>c</sup>	697.9	691.9	681.8	681.6

AIC, Akaike information criterion; HRA, health risk assessment; IWBS, Individual Well-Being Score; PTO, paid-time off. \*\* $P < 0.0001$ .

<sup>a</sup> $R^2$  significance tested to base model using  $F$ -test.

<sup>b</sup> $R^2$  significance tested incrementally relative to Model 2.

<sup>c</sup>A lower AIC indicates higher model performance; no statistical test of AIC available. AIC differences from base model interpretation<sup>40</sup>: -3 to -7, base model considerably worse; <-10, highly unlikely the base model is preferable.

modeling changes in job performance with the IWBS providing a multifold improvement in  $R^2$  relative to the HRA, but the HRA adding no incremental advantage to prediction over the IWBS. In the case of job performance, the HRA, however, also added no significant advantage in prediction over the base model.

To evaluate changes in levels of unscheduled PTO usage, the AIC was used to assess model fit. Although both the HRA (Model 2) and the IWBS models (Model 3) have a lower AIC than the base model, indicating an improvement in model performance, the IWBS provides a much better fit in predicting absenteeism. Including both the IWBS and HRA in Model 4 does not meaningfully improve the AIC over Model 3, demonstrating again for absenteeism that there is no advantage to adding HRA variables once IWBS variables are included in the model.

The contribution of specific IWBS and HRA variables was evaluated in each of the combined models (Model 4 for each outcome, base + IWBS and HRA) to compare the relative strength of these independent variables in explaining changes in the three productivity measures (Table 5). In support of overall model performance results, the IWBS variables, and IWBS change in particular, play a dominant role in explaining change in all three outcome variables. The HRA change variable only plays a statistically significant role in explaining presenteeism; however, its impact on presenteeism change is far less than the impact of the IWBS change variable.

The IWBS contains two of six domains that relate directly to physical health, whereas the other four measure aspects of well-being that are less commonly evaluated in the health sciences. To evaluate the contribution of these four nonphysical domains of well-being for their contribution to changes in productivity, the overall IWBS was recalculated (modified IWBS) removing the physical health and the healthy behavior domains, which capture content similar to and have some overlap with the HRA. By calculating the

score without these domains, it is possible to determine not only the extent to which the additional aspects of well-being are contributing to productivity change, but also to confirm that the differences observed in models of the HRA and IWBS do not arise solely from differences in their measurement of physical health-related factors.

Model performance for presenteeism and job performance are presented in Figure 1 for the modified IWBS with comparison to the hierarchical model results for the base model and models with unmodified IWBS and HRA scores (Models 2 and 3, respectively). Results reflect the multifold improvement of the IWBS over the HRA in predicting productivity change, both when the full IWBS and modified IWBS are modeled. Also, not shown in the figure, model performance for absence change was AIC = 687.3 for the modified IWBS, over a 10-point improvement over the base model (AIC = 697.9). The modified IWBS also outperformed the HRA (AIC = 691.9), but not the full IWBS (AIC = 681.8). These comparisons indicate that physical health and health behaviors may play a stronger role for predicting absence than on-the-job productivity/performance.

## DISCUSSION

Lost productivity because of poor health continues to be a major concern among employers (CDC 2015). Traditionally, many employers have elected to address this problem through the use of HRAs and wellness programs for employees at risk of productivity loss because of health risks and/or existing medical conditions.<sup>2</sup> Here we show that well-being, measured by the IWBS, offers greater utility than an HRA in measuring the factors that influence three types of worker productivity—presenteeism, absenteeism, and job performance. A guiding principle for this study was that a measure useful for influencing an outcome should provide an assessment of the factors associated with that outcome to inform intervention and, importantly, when employers/employees affect

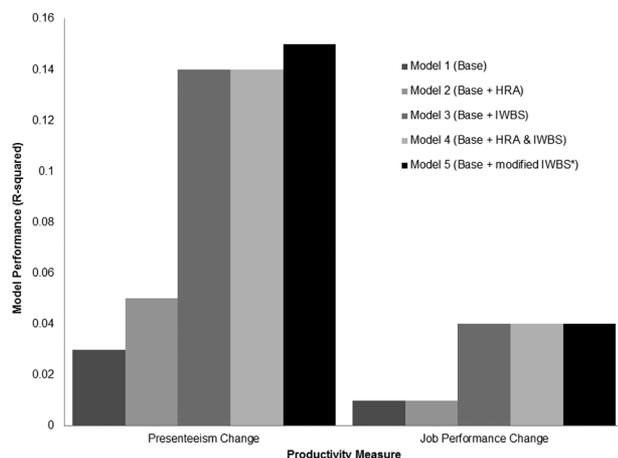
**TABLE 5.** Instrumental Variable Contribution to Productivity Outcomes in Model 4 (Combined Model With IWBS and HRA Variables)

Outcome Variable	Predictor			
	IWBS	IWBS Change	HRA	HRA Change
Presenteeism change <sup>a</sup>	NS	-13.62***	NS	2.88**
Job Performance change <sup>a</sup>	NS	6.25***	NS	NS
PTO change <sup>b</sup>	7.89**	13.13***	NS	NS

IWBS, Individual Well-Being Score; HRA, health risk assessment; PTO, paid-time off. Statistical significance: \*\* $P < 0.01$ ; \*\*\* $P < 0.001$ .

<sup>a</sup> $t$  values, adjusted for effects of age, sex, and job satisfaction.

<sup>b</sup>Wald chi-square, adjusted for effects of age, sex, and job satisfaction.



**FIGURE 1.** Summary of model performance in predicting presenteeism and job performance. \*"modified IWBS" is the individual well-being score calculated as the average of the 4 nonphysical domains, omitting the physical health and health behaviors domains. IWBS, Individual Well-Being Score; HRA, health risk assessment.

change in the predictor measure they should expect near-term change in the outcome of interest (ie, productivity/performance). Accordingly, well-being proved to more comprehensively assesses the factors that are associated with productivity compared with an HRA, and well-being change was also a much stronger predictor of 2-year productivity change. This study fills a gap that remained between productivity research focusing on health risk and recent literature on employee well-being; it also provides empirical evidence to guide efforts to improve productivity, which should have a broader focus on well-being and not just physical health.

An earlier study conducted by the authors<sup>19</sup> examined the relationship between well-being and chronic disease status with employee productivity. Well-being was more predictive of productivity loss than either demographic factors or the presence of one or more chronic disease. This finding led to the conclusion that well-being provides a broader framework for understanding and explaining changes in employee productivity. The current study served as a logical extension of our prior study, focused on chronic disease only, by directly comparing the utility of well-being with an HRA, the latter being a commonly used workplace tool and a broader measure of physical health risk than our evaluation of disease status. Together the two studies make a compelling case for addressing well-being as a preferential means to improve productivity among all employees, including those without existing physical risk factors captured on an HRA. The magnitude of difference in explanatory power observed between well-being and the HRA is striking. Well-being was found superior relative to the HRA in explaining 2-year change in productivity loss (presenteeism) with five-fold advantage over the HRA. A similar pattern was observed among the models when examining job performance change, with a three-fold increase in explained variance for the IWBS over the HRA. The IWBS model also provided a substantially better fit in explaining change in unscheduled PTO usage compared with the HRA. The strongest support for the IWBS instrument across all three productivity measures was evidenced by combining this measure with the HRA in the final model of the hierarchy, which added no additional advantage over modeling the IWBS alone, indicating that there would be no benefit in collecting both measures—the IWBS explains the same proportion of productivity that the HRA does plus significantly more. In sum, although the HRA does provide meaningful

information about productivity, the IWBS exhibits far greater utility in explaining worker presenteeism, job performance, and absence.

An added strength of the current study was the opportunity to compare the IWBS and HRA metrics, both collected at the same time within the broader WBA, in the same sample over time. Comparison within the same sample prevented any confounding or bias as a result of different sample characteristics that could otherwise contribute to differences in model performance. Similarly, time is not a factor because of collection of data at the same points in time for the entire sample.

As noted previously in the introduction, a large amount of research has been done to understand the link between health risk and productivity. Research linking HRA data to outcomes provided the scientific evidence that laid the groundwork for employers to address health risk as means to reduce costs from health care and lost productivity.<sup>3–6,8,9,38,41</sup> This foundational work has also benefited workers whose employers, as a result of this evidence, have provided access to wellness programs to help them maintain or improve their health. The results of the current study support prior work in demonstrating the value of health risk in predicting change in presenteeism and absenteeism; however, the results also reveal that health risk represents too limited a view. In fact, well-being is more predictive of these outcomes and represents a more comprehensive set of individual factors that programs can address to influence productivity, thereby providing greater opportunity for productivity improvement. Recently published employer case studies offer real-world examples of successful well-being improvement strategies that have impacted productivity.<sup>20,42</sup>

To specifically test the extent to which aspects of well-being not captured in the HRA contribute to productivity, IWBS domains measuring physical health and healthy behaviors were removed and the models reanalyzed using the other four domains. Results clearly demonstrate the role nonphysical factors play in explaining changes in productivity. Because explanatory power was undiminished by removal of the two domains relating to physical health risk, this analysis also confirmed that the advantage of the IWBS over the HRA was because of the additional constructs measured within well-being, as opposed to the IWBS being simply a better measure of the factors relating to physical health.

Well-being as measured by the IWBS is not limited to targeting the effects of productivity loss because of poor health, but recognizes psychosocial, environmental, and emotional factors associated with levels of productivity and performance. Furthermore, an advantage of using a validated psychometric instrument over an inventory is that it measures a multifaceted construct. This means that a parsimonious sample of items from a larger universe of items can be used to represent the construct.<sup>43</sup> This allows the IWBS to capture information beyond the immediate items surveyed, which may further contribute to the ability of the measure to explain employee productivity. In other words, it exposes a larger domain of related items beyond those used in the subscale that can then be explored with an individual and, if confirmed, tailor interventions to address them.

As Joseph Stiglitz said "What we measure affects what we do." This admonition has clear implications for how we approach and measure productivity in light of the current study findings. At one time, work was primarily defined by physical activity. In contrast, the modern workplace is largely defined by cognitive activities. An accruing body of evidence is finding that a host of nonphysical factors can influence productivity beyond medical conditions and health risks. The current study provides evidence that both new paradigms and measurement instruments offer greater promise for measuring and impacting sources of

productivity loss. Well-being as measured by the IWBS has the ability to explain both greater variance and directional change in productivity measures than traditional HRAs. As Loeppke<sup>14</sup> argued that HRAs were an advancement over claims because the focus on a broader set of business relevant outcomes, the current study offers evidence that well-being, as measured by the IWBS, is an advancement over traditional HRAs in addressing productivity issues. The multidimensional construct of well-being allows the employer to expand the opportunities for optimizing employee productivity and performance by not only through addressing physical health, but also through psychosocial and environmental factors that are known to influence higher-order mental processes and in turn productivity. Future research should explore the properties of well-being related to cognitive processes associated with higher levels of productivity such as complex problem solving, innovation, and creativity.

Limitations to consider when evaluating the results of this study include the potential for self-report bias and the fact that nonrandom samples were used which may restrict generalizability of findings. There is also possibility of omitted variable bias.

## CONCLUSIONS

The current study reveals that employee well-being has greater utility in measuring the factors that predict productivity change than a traditional HRA. The stronger explanatory power of well-being over the HRA is consistent across measures of presenteeism, job performance, and absenteeism. The hierarchical approach to modeling demonstrated that the IWBS explains all of the variance also explained by the HRA, plus significantly more variance that the HRA is unable to account for. Furthermore, the nonphysical factors of well-being as measured by the IWBS are more influential than physical factors in affecting on-the-job measures of productivity. These results support that this well-being measure has the potential to provide greater information for identifying and addressing productivity issues in the modern workplace and as an outcome measure for such initiatives.

## REFERENCES

1. Stiglitz J, Amartya S, Fitoussi JP. *Report by the Commission on the Measurement of Economic Performance and Social Progress*. Paris, France: OECD; 2010. Available at: [http://www.insee.fr/fr/publications-et-services/default.asp?page=dossiers\\_web/stiglitz/documents-commission.htm](http://www.insee.fr/fr/publications-et-services/default.asp?page=dossiers_web/stiglitz/documents-commission.htm). Accessed September 28, 2015.
2. Schultz A, Edington D. Employee health and presenteeism: a systematic review. *J Occup Rehabil*. 2007;17:547–579.
3. Yen L, Edington D, Witting P. Association between employee health-related measures and prospective medical insurance costs in a manufacturing company. *Am J Health Promot*. 1991;6:46–54.
4. Goetzel R, Anderson D, Whitmer R, et al. The relationship between modifiable health risks and health care expenditures: an analysis of the multi-employer HERO health risk and cost database. *J Occup Environ Med*. 1998;40:843–854.
5. Yen L, Edington D, Witting P. Prediction of prospective medical claims costs and absenteeism costs for 1284 hourly workers from a manufacturing company. *J Occup Med*. 1992;34:428–435.
6. Aldana S, Pronk H. Health promotion programs, modifiable health risks and employee absenteeism. *J Occup Environ Med*. 2001;43:36–46.
7. Goetzel R, Long S, Oziminkowski R, Hawkins K, Wang S, Lynch W. Health, absence, disability and presenteeism cost estimates of certain physical and mental health conditions effecting US employers. *J Occup Environ Med*. 2004;46:398–412.
8. Burton W, Chen C, Conti D, Schultz A, Edington D. The association between health risk change and presenteeism change. *J Occup Environ Med*. 2006;48:252–263.
9. Grossmeier JJ, Mangen DJ, Terry PE, Haglund-Howieson L. Health risk change as a predictor of productivity change. *J Occup Environ Med*. 2015;57:347–354.
10. Hump P. At work—but out of it. *Harv Bus Rev*. 2004;82:49–58.
11. Armstrong C. *Presenteeism*. Wiley Encyclopedia of Management. New York, NY: John Wiley & Sons, Inc; 2015. Available at: <http://onlinelibrary.wiley.com/doi/10.1002/9781118785317.wcom110288/abstract>. Accessed September 28, 2015.
12. Prochaska JO, Evers KE, Johnson JL, et al. The well-being assessment for productivity: a well-being approach to presenteeism. *J Occup Environ Med*. 2011;53:735–742.
13. Loeppke R, Taitel M, Richling D, et al. Health and productivity as a business strategy. *J Occup Environ Med*. 2007;49:712–721.
14. Loeppke R, Taitel M, Haufle V, Parry T, Kessler RC, Jinnett K. Health and productivity as a business strategy: a multi-employer study. *J Occup Environ Med*. 2009;51:411–428.
15. Merrill RM, Aldana SG, Pope JE, et al. Presenteeism according to healthy behaviors, physical health, and work environment. *Popul Health Manag*. 2012;15:293–301.
16. Merrill RM, Aldana SG, Pope JE, et al. Self-rated job performance and absenteeism according to employee engagement, health behaviors, and physical health. *J Occup Environ Med*. 2013;55:10–18.
17. Shi Y, Sears LE, Coberley CR, Pope JE. Classification of individual well-being scores for the determination of adverse health and productivity outcomes in employee populations. *Popul Health Manag*. 2012;16:90–98.
18. Sears LE, Shi Y, Coberley CR, Pope JE. Overall well-being as a predictor of health care, productivity, and retention outcomes in a large employer. *Popul Health Manag*. 2013;16:397–405.
19. Gandy WM, Coberley C, Pope JE, Wells A, Rula EY. Comparing the contributions of well-being and disease status to employee productivity. *J Occup Environ Med*. 2014;56:252–257.
20. Rajaratnam A, Sears L, Shi Y, Coberly C, Pope J. Well-being, health and productivity improvement after an employee well-being intervention in large retail distribution centers. *J Occup Environ Med*. 2014;56:1291–1296.
21. Rath T, Harter J. *Well-Being: The Five Essential Elements*. New York, NY: Gallup Press; 2010.
22. Diener E, Lucas R, Scollon C. Beyond the hedonic treadmill: revising the adaptation theory of well-being. *Am Psychol*. 2006;61:305–314.
23. Willingham JG. Managing presenteeism and disability to improve productivity. *Benefits Compens Dig*. 2008;1:11–14. Available at: <http://www.ifebp.org/inforequest/0155525.pdf>. Accessed September 28, 2015.
24. Cropanzano R, Wright TA. When a “happy” worker is really a “productive” worker: a review and further refinement of the happy-productive worker thesis. *J Consul Psychol*. 2001;53:182–199.
25. Wright TA, Cropanzano R. Psychological well-being and job satisfaction as predictors of job performance. *J Occup Health Psychol*. 2000;1:84–94.
26. Iffaldano M, Muchinsky P. Job satisfaction and job performance: a meta-analysis. *Psychol Bull*. 1985;97:251–273.
27. Judge TA, Thoresen CJ, Bono JE, Patton GK. The job satisfaction—job performance relationship: 1939–1998. Paper presented at the Annual Meeting of the Academy of Management, San Diego, CA; 1998.
28. Judge TA, Larsen RJ. Dispositional affect and job satisfaction: a review and theoretical extension. *Organ Behav Hum Decis Process*. 2001;86:67–98.
29. Harter JK, Schmidt FL, Keyes CLM. Well-being in the workplace and its relationship to business outcomes: a review of the Gallup studies. In: Keyes CL, Haidt J, eds. Washington, DC: American Psychological Association; 2003:205–224. Available at: <http://www.apa.org/pubs/books/431686A.aspx?tab=2>. Accessed September 28, 2015.
30. Edwards JR. Person-environment fit in organizations: an assessment of theoretical progress. *Acad Manag Ann*. 2008;2:167–230.
31. Judge TA, Thoresen CJ, Bono JE, Patton GK. The job satisfaction—job performance relationship: a qualitative and quantitative review. *Psychol Bull*. 2001;127:376–407.
32. Koopman C, Pelletier KR, Murray JF, et al. Stanford presenteeism scale: health status and employee productivity. *J Occup Environ Med*. 2002;44:14–20.
33. Gallup. Gallup-Healthways Well-Being Index: Methodology Report for Indexes. Available at <http://wbi.meyouhealth.com/files/GallupHealthways-WBI-Methodology.pdf>. Accessed August 4, 2015; 2009.
34. Evers KE, Prochaska JO, Castle PH, Johnson JL, Prochaska JM, Harrison PL. Development of an individual well-being scores assessment. *Psychol Well-Being*. 2012;2:2. Available at: <http://www.psywb.com/content/2/1/2>. Accessed September 28, 2015.
35. Yen L, McDonald T, Hirschland D, Edington DW. Association between wellness score from a health risk appraisal and prospective medical claims costs. *J Occup Environ Med*. 2003;45:1049–1057.
36. Loeppke R, Edington D, Beg S. Impact of the prevention plan on employee health risk reduction. *Popul Health Manag*. 2010;13:275–284.

37. Edington D, Yen L, Wittting P. Financial impact of changes in personal health practices. *J Occup Environ Med.* 1997;39:1037–1046.
38. Edington DW. Emerging research: a view from one research center. *Am J Health Promot.* 2001;15:341–349.
39. Kessler RC, Ames M, Hymel PA, et al. Using the World Health Organization Health and Work Performance Questionnaire (HPQ) to evaluate the indirect workplace costs of illness. *J Occup Environ Med.* 2004;46:S23–S37.
40. Burnham K, Anderson D. Multimodel inference: understanding AIC and BIC in model selection. *Sociol Methods Res.* 2004;33:261–304.
41. Yen L, McDonald T, Hirschland D, Edington D. Association between well-being score from a health risk appraisal and prospective medical claims costs. *J Occup Environ Med.* 2003;45:1049–1057.
42. Hamar B, Coberley C, Pope JE, Rula EY. Well-being improvement in a midsize employer: changes in well-being, productivity, health risk, and perceived employer support after implementation of a well-being improvement strategy. *J Occup Environ Med.* 2015;57:367–373.
43. Edwards J. Multidimensional constructs in organizational behavior research: an integrative analytical framework. *Organ Res Methods.* 2001; 4:144–192.