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Evaluation of the Work Capacity: a Case Study in Brazil

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ABSTRACT

The Work Capacity Index (WCI) also known in the literature as WAI (Work Ability Index) is a self-assessment tool for employees to measure their ability to work. It was developed in Finland, but recent studies have shown it is applicable to Brazil. This article analyzes whether some covariates as measured by the WCI related to a set of Brazilian workers affect their ability to work under a Production Engineering approach. The covariates associated with the employees are: age, segment of the economy where they works, gender, marital status and educational level. The data analysis used classical statistical techniques such as ANOVA (analysis of variance) and multiple linear regression models, and statistical techniques using a Bayesian approach, assuming a beta regression model. The results show a lower capacity for work for women, the elderly, and rural workers with low levels of education.

Keywords: Index of Ability to Work, multiple linear regression, Bayesian inference, prediction.

INTRODUCTION

The population is aging worldwide, but it is more pronounced in developing countries. One great concern arising from this phenomenon is a loss of the ability to work for the economically active population. One of the factors that contribute to the decline of working capacity is the age of the workers and the health problems they suffer, such as arthritis, high blood pressure, failing eyesight and hearing, and slowing response time. However, other factors are also associated with a loss of their ability to work [8, 18, 14, 23, 17]. One of the pioneering studies in the assessment of ability to work was developed by the Finnish Institute of Occupational Health, Finland, from 1981 to 1992, involving local workers. This study assessed the health and continued ability to work for individuals who were close to retirement [1, 11, 20, 24]. This study led to the development of an instrument to assess ability to work called the Work Capacity Index (WCI) also known in the literature as WAI (Work Ability Index). Basically, the WCI is a tool that gauges people's perceptions of the requirements to do their jobs. Although the instrument was developed in a country with its own distinct characteristics, Brazil has used it as a basis on which to evaluate its older workers, and recent studies have suggested that there is a lot of confidence in the results obtained by the instrument when applied to the situation in Brazil [11]. Brazil's population is aging faster than most contries, aging faster than the populations of developed countries and China [27]. This paper's main goal is to analyze whether some covariates measured for Brazilian workers affect their ability to work, measured by the WCI, as their age, segment of the economy where they work, their gender, marital status and educational levels. Classical statistical techniques, such as ANOVA and multiple linear regression, as well as statistical techniques using a Bayesian approach, assuming a beta regression model, are used in the data analysis.

WORK CAPACITY INDEX (WCI)

As briefly presented, the WCI is a self-assessment tool of a worker's ability. It is based on a questionnaire designed to gauge the perception of respondents with regard to their ability to work considering the physical, mental and social demands involved. Studies suggest that the WCI is a good estimate of a worker's ability, providing early identification of workers and working environments that require ergonomic support [2,7,14, 25]. The tool comprises seven items, each one assessed by one or more questions as shown in Table 1. The WCI is the sum of the scores assigned by each worker to each question in the tool, depicting the worker's assessment of their own ability [25]. Hence, the WCI shows a worker’s perception of their ability to do their job. After completing the questionnaire, the sum of the values assigned to each question produces a final score ranging from 7 to 49 [26].

Table1. *Work Capacity Index (WCI)*

ITEM	No. of questions	No. of points (score) for answers
1. Current capacity for work compared with lifetime best	1	0-10 points (number indicated in the questionnaire)
2. Capacity for in relation to job requirements	2	Number of points weighted according to the nature of the work
3. Number of current illnesses diagnosed by a physician	1 (list of 51 illnesses)	At least: 5 illnesses = 1 point 4 illnesses = 2 points 3 illnesses = 3 points 2 illnesses = 4 points 1 illness = 5 points (only illnesses diagnosed by a physician are counted)
4. Estimated loss of work to illness	1	1-6 points (value circled in the questionnaire - the worst value is chosen)
5. Absenteeism due to illness in the past year (12 months)	1	1-5 points (value circled in the questionnaire)
6. Prognosis of work capacity in 2 years	1	1, 4 or 7 points (value circled in the questionnaire)
7. Mental resources (this item relates to life in general, both at work and during leisure time)	3	The points from the questions are added up and the result is counted as follows: 0-3 = 1 point 4-6 = 2 points 7-9 = 3 points 10 - 12 = 4 points

Source: *[25]*

STATISTICAL MODELING

Use of ANOVA (Analysis of Variance) and Multiple Linear Regression Analysis

Analysis of variance (ANOVA) is a statistical methodology that tests whether a particular factor has a significant effect on a dependent variable, Y. Assuming μ_j represent the true value of the dependent variable mean for group j (defined by levels of a given factor), the ANOVA technique tests the hypothesis that there are no differences between μ_j assuming that there are no differences between the variability of observations in each group. It is important to observe that the statistical analysis of data considering one-factor ANOVA models allows significant differences between the different levels of each factor to be proved, or not, but it does not allow the verification of a set and simultaneous effect of many factors. To check this joint effect of all the covariates it is important to use a multiple linear regression model [9,19]. Multiple linear regression (MLR) is a statistical technique used to verify hypotheses about the relationships between variables [16]. In general, the main goal of MLR is to evaluate the joint relationship of a dependent variable (or response) Y_i with some independent variables X_j (covariates or regressors), j = 1, 2,. . . , K. The multiple linear regression model is given by:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots\ldots + \beta_k x_{ik} + \varepsilon_i \tag{1}$$

where i = 1,2,...n; n is the number of observations, y_i is the ith response, $\mathbf{X}_i = (x_{i1}, x_{i2},..., x_{ik})$ is a vector of observations of the independent variables for the ith response, $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, \ldots, \beta_k)$ is a vector of regression coefficients (parameters) to be estimated and the ε_i component is a random error. The MLR assumes that the errors are independent and normally distributed with mean zero and unknown variance σ^2.

For some situations it is an interesting idea to transform the dependent variable Y, to set it within a given range that facilitates interpretations [3], for example in the interval [0,1]. Another common transformation employed in multiple linear regression applications is the logit transformation, given by (2). Such a transformation is often useful for the analysis of a variance model or RLM assumptions, such as normality and constant variance. The logit transformation is given by:

$$Z = \log[Y/(1-Y)] \qquad (2)$$

Use of a Beta Regression Model

For statistical analysis of the data, assume that the response Y (transformed or not) is defined in the interval (0,1). In this case, we consider a transformation of the data to be defined in the interval (0,1). Since the response data Y is defined for values in the interval (0,1) we could consider using a beta regression model to analyze a data set in the original scale Y, rather in the logit scale given by (2).

The beta probability distribution is defined by the following probability density function:

$$f(y/p,q) = \Gamma(p+q)/[\Gamma(p)\Gamma(q)]\, y^{p-1}(1-y)^{q-1} \qquad (3)$$

where $0 < y < 1$, $p > 0$, $q > 0$ and $\Gamma(.)$ denotes a gamma function. If Y is a random variable with a beta distribution, the mean and the variance of Y are given, respectively by, $\mu = p/(p+q)$ and $\sigma^2 = pq/[(p+q)^2(p+q+1)]$.

Inferences for the beta regression models have been discussed by many authors using a classical inference approach [10, 21] or using a Bayesian approach [5] considering different reparametrizations for the parameters p and q. For a regression model considering the beta distribution of density (3), we assume the reparametrization μ and $\Phi = p + q$, that is, $p = \mu\Phi$ and $q = (1-\mu)\Phi$, and the following regression models for both parameters μ and Φ:

$$\text{logit}(\mu_i) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots\ldots + \beta_k x_{ik} \text{ and } \log(\Phi_i) = \alpha_0 + \alpha_1 x_{i1} + \alpha_2 x_{i2} + \ldots\ldots + \alpha_k x_{ik} \qquad (4)$$

where the covariates $x_{i1}, x_{i2},..., x_{ik}$ were defined assuming the linear regression model (1).

We assume a Bayesian approach [4] to analyze the data assuming the beta regression model defined by (3) and (4). For a Bayesian analysis of the data, we can assume normal prior distributions with means equal to zero and specified values for the variances for the regression parameters α_j and β_j where $j = 0,1, \ldots, 10$. We further assume prior independence among the parameters of the models. The posterior summaries of interest can be obtained using standard MCMC (Markov Chain Monte Carlo) methods [6, 13]. The simulation of samples of the joint posterior distribution for the regression parameters α_j and β_j can be simplified by using the free available software OpenBugs [22], which only requires the specification of the distribution for the data and the prior distributions for the parameters.

DATA SET AND STUDY DESCRIPTION

A sample of workers in different segments of the Brazilian economy in the São Paulo province, Brazil, was used in this study. Several covariates associated with each individual in the sample were measured (quantified values in parentheses) given by:

- Segments of the economy: industry (1); commerce (2), services (3); rural activity (4), construction (5); domestic service (6).
- Gender: female (1), male (2).

- Marital status: single (1), married (2).
- Education: primary school (1), high school (2), university (3).

RESULTS

The data was first analyzed using ANOVA and multiple regression models under a classical statistical approach and the MINITAB® software; a second analysis was considered assuming a beta regression model under a Bayesian approach. The response variable is given by the WCI measured on a scale ranging from 7 to 49 points where: 7 to 27 points represent a low ability to work, 28 to 36 points represent a moderate ability to work, 37 to 43 points represent a good ability to work, and 44 to 49 points represent a very good ability to work (see Table 2).

Table2. *Work Capacity Index classification*

Score	Work ability	Actions
7 – 27	Low	Recover the work ability
28 -36	Moderate	Improve the work ability
37 - 43	Good	Support the work ability
44 – 49	Very good	Keep the work ability

Source: *[25]*

A descriptive preliminary data analysis of the selected data is presented in Table 3 where it can be observed that the segment with level equal to 4 (rural activity) presents an average WCI that is smaller than for the other levels of the segment. We also observe different means for the WCI in the different levels of the other factors (gender, marital status and education).

Statistical Analysis with Transformed Data

It is observed from the results of the descriptive preliminary analysis of the data that a more carefully statistical analysis is needed. For the statistical analysis of the data, the following data transformation was used: denoting by X, the WCI measured on a scale of 7 to 49 points, let us consider the transformation:

$$Y=(X-7)/(49-7) = (X-7)/42, \quad (5)$$

that is, Y is defined in the interval (0,1). This transformation facilitates statistical modeling, since we could assume Y as a random variable defined in the interval (0,1). Besides the transformation (6), we also consider a logit transformation for the transformed response Y, given by (2), that is the variable Z.

With the logit transformation (2), some usual assumptions needed for statistical analysis assuming an analysis of a variance model or a linear regression model are better verified [3, 16] such as data normality and constant variance. Besides the logit transformation given by (2) we also eliminated some discordant observations (possibly overvalued) to achieve better representativeness of the sample where the statistical assumptions are more appropriate considering a final sample of size n = 1772 observations for the statistical analysis. Figure 1 presents a histogram and normal probability plot (QQ plot) of the transformed data Z (given by (2)). We observe good normality for the transformed data.

Table3. *Descriptive statistics*

Factor	Descriptive Variable Statistics WCI				
segment	N	Average	SD	Maximum	Minimum
1	512	43.4060	4.0950	18.0000	49.0000
2	421	42.6690	4.6990	21.5000	49.0000
3	812	42.4390	4.8450	20.0000	49.0000
4	69	38.9780	7.0710	18.0000	48.0000
5	31	42.4500	5.8400	26.0000	49.0000
6	53	40.1600	5.9040	21.0000	48.0000

gender	N	Average	SD	Maximum	Minimum
1	1087	42.192	4.887	18.0000	49.0000
2	811	43.057	4.767	18.0000	49.0000
marital status	N	Average	SD	Maximum	Minimum
1	779	43.4940	4.0640	23.0000	49.0000
2	1119	41.9120	5.2400	18.0000	49.0000
educational level	N	Average	SD	Maximum	Minimum
1	409	40.5670	6.1500	18.0000	49.0000
2	1072	42.9800	4.3460	21.5000	49.0000
3	417	43.4410	4.0710	27.0000	49.0000

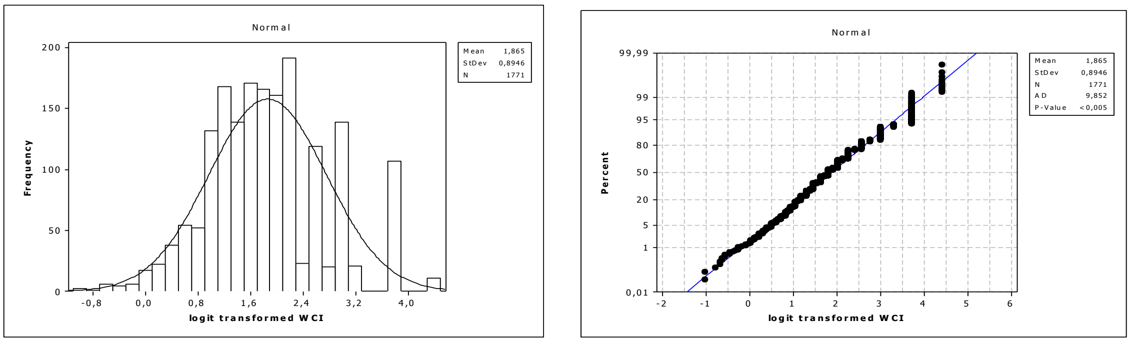

Figure1. *Histogram and normal probability plot for the transformed data Z*

Use of an ANOVA Model

We first consider an analysis of variance (ANOVA with one classification) for the transformed WCI data considering the classifications within each factor: segments of the economy, gender, marital status and education. The results of this analysis are given in Table 4.

From the results in Table 4, we have the following conclusions:

- There is a significative difference between the levels of segments. This is confirmed by the p-value (< 0.05, a usual significance level) for the hypothesis test for equality of means of transformed WCI for workers in each segment level of the economy. We also observe from the 95% confidence intervals for each segment mean, the difference between the estimated mean for WCI at level 5 (rural activity) when compared to the estimated means of the other levels which indicates values lower than for levels 1,2,3 and 5.
- There is a significative difference between men and women. This is confirmed by the p-value (< 0.05, a usual significance level) for the hypothesis test for equality of means of WCI for men and women workers. This is also observed from the 95% confidence intervals for the means of WCI for men and women. Men have a higher WCI.

Table4. *ANOVA for the transformed WCI data*

Source	DF	SS	MS	F	p
Segment	6	30.295	5.049	6.43	< 0.001
Error	1766	1386.545	0.785		
Total	1772	1416.84			
Gender	1	12.534	12.534	15.81	< 0.001
Error	1771	1404.305	0.793		
Total	1772	1416.84			
Marital status	1	30.651	30.651	39.16	< 0.001
Error	1771	1386.191	0.783		
Total	1772	1416.841			
Educ level	2	36.581	18.29	23.45	< 0.001
Error	1770	1380.261	0.78		
Total	1772	1416.841			

(DF is degree of freedom; SS is the sum of squares; MS is the mean square; F is the value of the Snedecor F statistics and p is the observed p-value).

- There is a significative difference between married and single workers. This is confirmed by the p-value (< 0.05) for the hypothesis test for equality of means of transformed WCI for single workers and married workers. This is also observed from the 95% confidence intervals for the means. Singles have a higher WCI.
- There is a significative difference among workers with different levels of education. This is confirmed by the p-value (< 0.05) for the hypothesis test for equality of means of transformed WCI for workers with different educational levels. This is also observed from the 95% confidence intervals for the means. Workers with a lower educational level (primary school) have a lower WCI than workers with higher educational levels. Workers with higher educational levels (high school and university) have a higher WCI. In these two levels (high school and university) we observe that the means are statistically equal.

Normality and constant variance for the errors, was verified from standard plots for the residuals of the model.

Use a Multiple Linear Regression Model

Note that statistical analysis assuming an ANOVA model with one classification (see Table 4) allows us to show (or not) the significant differences among the different levels of each factor (segments of the economy, gender, marital status and education) but this modeling approach does not allow us to verify a joint and simultaneous effect of all the factors. As a special case, it was found that married workers have a lower WCI than unmarried workers, but we could have a large number of older workers among the married ones. That is, we could have a correlation between elderly and married workers. To check this joint effect of all the covariates it is important to use a multiple linear regression model [9, 19]. Thus, for joint statistical analysis of all the covariates in the transformed WCI response Z, we assume a multiple regression model given by:

$$Z_i = \beta_0 + \beta_1 gender + \beta_2\, age_i + \beta_3 marital.status_i + \beta_4 industry_i + \beta_5 commerce_i + \beta_6 services_i \\ + \beta_7\, rural.activities_i + \beta_8 construction_i + \beta_9\, high.school_i + \beta_{10}\, university_i + \epsilon_i \quad (6)$$

where i = 1, ..., 1772; ϵ_i are random errors assumed to have a normal probability distribution with mean equals to zero and constant variance σ^2. The covariates are quantified as follows: gender is equal to 1 for women and is equal to 2 for men. Marital status is equal to 1 for singles and equal to 2 for married people. Industry is equal to 1 for workers in industry and zero for other sectors. Commerce is equal to 1 for workers in commerce and zero for the other sectors. Service is equal to 1 for service workers and zero for the other sectors. Rural activity is equal to 1 for workers in rural activity and zero for other cases. Construction is equal to 1 for workers in construction and zero for the other sectors. Domestic services is considered as reference. High school is equal to 1 for workers with high school education and zero for the other educational levels. University is equal to 1 for workers with university education and zero for the other levels of education. Elementary school is considered as a reference. From the results obtained using the multiple regression model we have the following prediction model obtained from the least squares estimators of (6):

$$\hat{Z} = 1.99 + 0.203\, gender - 0.0154\, age - 0.0128\, marital.status + 0.0881\, industry + 0.0499\, commerce + \\ 0.0321\, services - 0.181\, rural.activity + 0.146\, construction + 0.0970\, high.school + 0.218\, university \quad (7)$$

From the fitted model, we get some important interpretations:

- Gender: we have a positive and significant estimator considering women (1) and men (2). We observe that men have higher WCI values (p-value < 0.05). Significant at a significance level equal to 0.05.

- Age: we have a negative estimator indicating that older workers have lower WCI values when compared to the other workers (p-value < 0.05). Significant at a significance level equal to 0.05.
- Rural activity: we have a negative estimator. That is, when compared to the other activities, workers in rural activity have a lower WCI (p-value < 0.06).
- University: we have a positive estimator. That is, university-educated workers when compared to other workers have higher values of WCI (p-value < 0.05).Significant at a level of significance equals to 0.05.
- The other factors are not significant for WCI (p-values > 0.05).

Use a Beta Regression Model

For a regression model considering the beta distribution with density (3), we assume the reparametrization μ and $\Phi = p + q$, that is, $p = \mu\Phi$ and $q = (1 - \mu)\Phi$, and the following regression models for both parameters μ and Φ:

$$\text{logit}(\mu_i) = \beta_0 + \beta_1\text{gender} + \beta_2\,\text{age}_i + \beta_3\text{marital.status}_i + \beta_4\text{industry}_i + \beta_5\text{commerce}_i + \beta_6\text{services}_i$$

$$+ \beta_7\,\text{rural.activities}_i + \beta_8\text{construction}_i + \beta_{9\text{high}}\,\text{school}_i + \beta_{10}\text{university}_i\,,$$

$$\log(\Phi_i) = \alpha_0 + \alpha_1\text{gender} + \alpha_2\,\text{age}_i + \alpha_3\text{marital.status}_i + \alpha_4\text{industry}_i + \alpha_5\text{commerce}_i + \alpha_6\text{services}_i$$

$$+ \alpha_7\,\text{rural.activities}_i + \alpha_8\text{construction}_i + \alpha_9\text{high school}_i + \alpha_{10}\text{university}_i \qquad (8)$$

Assuming a Bayesian approach and the OpenBugs software, we first simulated a "burn-in-sample" size of 5,000, discarded to eliminate the effect of the initial values in the iterative Gibbs sampling algorithm. After this "burn-in-sample" period, we simulated another 92,000 Gibbs samples taking every 80th sample to have approximately uncorrelated samples, which makes a final Gibbs sample of size 1,150 to be used to get Monte Carlo estimates of the posterior means for each parameter. The posterior summaries (posterior mean, posterior standard deviations and 95% credible intervals) are given in Table 5. Convergence of the simulation algorithm was monitored using standard graphical methods, such as the trace plots of the simulated samples for each parameter [12]. From the results in Table 5, we conclude that the covariates gender, age and workers with a university education affect the means of the index of ability to work (the 95% credible intervals for the regression parameters β_1, β_2, and β_{10}, do not include the zero value). Considering a 90% credible interval for β_4 we also observe that workers in industry also affect the means of the index of ability to work. That is, we have similar results as obtained using the multiple linear regression model with normal errors for the logit transformed data except for the covariate rural activities where zero is included in the 95% credible interval for β_7 (-0.1933; 0,04939) but since the upper limit of this interval is close to the zero value, the beta regression model also indicates some effect of the covariate rural activities on the WCI. In the same way, we observe that the age of workers also affects the parameter Φ since the 95% credible interval for α_2 does not include the zero value.

Table5. *Posterior summaries for the parameters of the beta regression model*

Parameter	mean	SD	95% cred.interval		Parameter	Mean	SD	95% cred.interval	
α_0	2.985	0.1488	2.697	3.292	β_0	1.883	0.09852	1.698	2.092
α_1	0.09159	0.057	-0.02066	0.202	β_1	0.169	0.03371	0.1057	0.2329
α_2	-0.02148	0.002838	-0.02685	-0.01574	β_2	-0.0161	0.001678	-0.01956	-0.0128
α_3	0.04889	0.06407	-0.07332	0.166	β_3	-0.002904	0.03797	-0.07602	0.06954
α_4	0.1021	0.06357	-0.02164	0.2298	β_4	0.08101	0.04109	-0.00215	0.1613
α_5	-0.02045	0.07084	-0.1505	0.1248	β_5	0.0308	0.04252	-0.05219	0.11
α_6	0.03482	0.06571	-0.09502	0.173	β_6	0.02786	0.03974	-0.04748	0.1066
α_7	-0.0231	0.08212	-0.1862	0.1491	β_7	-0.07229	0.06135	-0.1933	0.04939
α_8	0.001531	0.09003	-0.1685	0.1802	β_8	0.05517	0.07142	-0.08379	0.2012
α_9	0.06082	0.06156	-0.05706	0.18	β_9	0.05015	0.04104	-0.03063	0.1282
α_{10}	0.112	0.06964	-0.02651	0.2481	β_{10}	0.1431	0.04818	0.04665	0.2333

CONCLUDING REMARKS

From the results obtained it can be seen that some variables directly affect the work ability of individuals. Among these variables are age, sex, education and the segment worked in. It can be observed that the WCI for men is higher than for women, and also that the as the level of education increases, so does the WCI, suggesting that better educated individuals enjoy better working conditions and are less exposed to factors that decrease the WCI. However, another study to prove this hypothesis would be required. In relation to the work segment, it was observed that rural workers had a lower WCI, suggesting that in this work segment the conditions are worse, being predominantly of a physical nature.

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