Determining Cutting Points of the Maslach Burnout Inventory for Nurses to Measure Their Level of Burnout Online

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Abstract: This study is to determine cutting points for the Chinese version of the MBI-HSS and to design an online assessment tool that instantly measures a nurse’s burnout level. We illustrate (1) the traditional way for determining the cutting points of a scale when the binary classification groups was still known, and (2) the norm-reference approach without groups of binary classifications was used to determine the cutting points on three subscales for the MBIO-HSS. An online MBIO-HSS assessment APP for smartphones was incorporated with the cutting points to instantly display the level of burnout for nurses. The cutoff points of the MBI-HSS were ≤ 21 and ≤ 32 for the Emotional subscale, ≤ 23 and ≤ 30 for the Reduced Personal Accomplishment subscale, ≤ 6 and ≤ 12 for the Depersonalization subscale, and ≤ 15 and ≤ 17 (i.e., low, moderate, and high level) for the overall scores. An available-for-download online MBI-HSS APP for nurses was developed and demonstrated.

Keywords: Nurse Burnout, MBI-HSS Chinese Version, Cutting Points, Prevalence

1. Introduction

Burnout is a critical syndrome and problem in high-tech service-oriented societies, especially for nurses in healthcare settings [1-3]. Many studies have addressed that burnout affects employee’s physical and psychological status [4-6], institute well-being [7-10], and indirect to the patient outcomes if the professionals are nurses [5, 9]. According to Maslach [11], burnout is a syndrome of emotional exhaustion (EE), reduced personal accomplishment (PA), and depersonalization (DP) that can occur in individuals who work much more with people-related jobs such as healthcare and education.

1.1. The Maslach Burnout Inventory

The Maslach Burnout Inventory-Human Services Survey (MBI-HSS) [12] is an instrument that has been used most widely for measuring the burnout climate of healthcare providers [10, 13-15]. The original version of the MBI-HSS is a 22-item domains with a 7-point scale (from never = 0 to every day = 6) to measure burnout for workers in a recent week. The three subscales of burnout include nine items for EE, eight opposite items for PA, and five items for DP. Despite its popularity in social science, not only does the
factor structure (i.e., the item-total correlation based on their variances) differ between cultures and healthcare among provider systems [14, 16-20], but so do the cutting points substantially differ between each other. Maslach et al. [21], accordingly, claimed that the levels of burnout (low, moderate, high) with their respective cutting points might differ across countries. Schaufeli and Van Dierendonck [22] suggested that nation-specific and clinically derived cutting points that should be determined and used for healthcare providers so as to easily compare each other.

Maslach and Jackson [12] said that the subscale total scores were 54 for EE, 48 for PA, and 30 for DP. They also claimed that the level of burnout was high if EE was ≥ 27, PA was ≤ 21, and DP was ≥ 13; moderate if EE was 17-26, PA was 38-22, and DP was 7-12; and low if EE was ≤ 16, PA was ≥ 39, and DP was ≤ 6. Schaufeli and Van Dierendonck [22] wondered whether these three sets of scores were arbitrary when the three groups contained an equal number of members [23]. Maslach and Jackson [12] suggested that valid criteria are in urgent need required to classify levels of burnout for use in literature, but no any one till now is present in published papers. This is, no large and rigorous quantitative studies have reported cutting points that can objectively classify levels of burnout and can be generalized to other worksites and other samples within a relatively homogeneous nation.

1.2. Cutting Points of the MBI-HSS Are Required

Many papers report burnout scores for individuals but translating the numerical scores into the degree or type of their burnout relative to cutting points. The purpose is to be possible for other worksites and other ethnic samples in comparison. However, the burnout golden standard (i.e., ensuring the binary classification groups before the study) is costly, is subject to a small sample size, and would, therefore, be inappropriate generalize to any other population of interest. If we use population information generalized by study sample analyzed to determine cutting points, the result can theoretically be more widely used for other worksites and other ethnic samples than can traditional approaches directly analyze ethnically or culturally specific study samples.

1.3. Online Assessment Using Smartphones Is Required

As with all forms of Web-based technology, advances in mobile health (mHealth) and health communication technology are rapidly increasing [24]. Till now, there is no any online APP for smartphones that measures nurse burnout levels in healthcare industry. If the cutting points are used with the MBI-HSS, the online assessment can thus alert individual APP users to alleviate their mental strain before it becomes a serious burnout problem.

1.4. Study Aims

The aims of the current study were thus to (i) determine the cutting points of the MBI-HSS person strata according the literature, and (ii) design an online burnout assessment APP for smartphones.

2. Methods

2.1. Data Source

The data was collected from three different levels hospitals in Southern Taiwan. Staff nurses (n = 1,000) were recruited, and 970 (93%) completed the MBI-HSS Chinese version.

2.2. Ethics

The current study was approved and monitored by the Chi Mei Medical Center Institutional Review Board before we began to retrieve data. All hospital and study participant identifiers were stripped from the data.

2.3. Instruments

The factor structure of the MBI-HSS for nurses in Taiwan was examined using exploratory factor analysis and confirmatory factor analysis [3]. The modified factor structure included the original three factors (i.e., subscales) with 20 items (i.e., removing items # 14 and #22 [3] from the MBI-HSS). The three subscales of burnout consist of 8 items for EE, 8 opposite items for PA, and 4 items for DP. The subscale total scores for EE, PA, and DP were 48, 48, and 24, respectively. The indices of the model fit were GFI = 0.92, AGFI = 0.90, and RMSEA = 0.05. The data collected using the MBI-HSS Chinese version [21] were used to determine the cutting points in the current study.

2.4. Traditional Method for Determining Cutting Points

Traditionally, researchers in clinical practice use ROC (receiver operating characteristic) curves to plot the true-positive rate (sensitivity) against the false-positive rate (1 - specificity) at various threshold settings [25] (Figure 1). The preliminary condition is to know the patient’s classification (i.e., stratum) (e.g., separating person burnout strata with low, moderate, and high level) before conducting the ROC.

![Figure 1. The cut-points of person strata determined using a norm referred method.](image-url)
However, we usually do not know the patient’s true- and 
false-positive disease-specific status, as in this study, unless 
we have done another costly diagnostic intervention to obtain 
the so-called gold standard test (e.g., a cutting point) before 
doing a study. The area under the ROC curve is comp 
uted by 
the so-called gold standard test (e.g., a cutting p oint) before 
we have done another costly diagnostic intervention  to obtain 
false-positive disease-specific status, as in this study, unless 
sensitivity across all possible scores. 

determined at the maximal summation of specificity and 
sensitivity (Table 1 last column).

2.5. A Norm-Reference Approach for Determining Cutting 
Points

According to the literature [26-28], as a scale’s reliability 
(i.e., Cronbach’s α) increases, so does the person-number of 
ranges that can be confidently distinguished. Measures from 
two instruments with reliabilities of 0.67 will tend to vary 
within two groups that can be separated with 95% confidence; 
0.80 will vary within three groups; 0.90, within four groups; 
0.94, within five groups; 0.96, within six groups; 0.97, within 
seven groups; and so on [29].

To compute the number of the strata, pick up any two 
adjacent normally distributed samples using the Microsoft 
Excel function =NORMDIST (mean, standard deviation [SD], 
TRUE); the mean is the cluster center obtained using the 
k-mean method when the number of strata is known according 
to the Cronbach’s α scale [26], and the SD is obtained from 
the individual scores of the specific cluster. Using a brute force 
search of the two adjacent samples, the cutting points can be 
determined at the maximal summation of specificity and 
sensitivity across all possible scores.

2.6. An Online Burnout Assessment APP Was Designed for 
Use on Smartphones

An online routine was designed for patients to report their 
burnout scores. In addition to 20 items from a previous study 
[3], we added three items from a new scale of Satisfaction 
with Nursing (SN) [30]. High scores indicate more 
satisfaction with being a nurse. All the opposite responses are 
automatically transferred to a burnout score (e.g., the higher 
the score on the PA and the SN scales, the greater the 
tendency for burnout using the formula of 6 – response). The 
overall score is the mean of the EE, PA, and DP scale scores. 
There are five bins to record the count of interest for the study 
(bins (i.e., EE, PA, DP, SN, and overall).

To help examinees recognize whether burnout is present, 
we set two indices for ensuring the occurrence: (i) the revised 
Ferguson (δ) coefficient [31-35] (= 
g((g-1)×(sum^2 − \sum \text{observed}_i^2) / \text{sum}^2)) in a range from 0 to 1, and 
(ii) the $\chi^2$ ( = $\sum \text{observed}_i$ − $\text{Expected}_i$) / $\text{Expected}_i / g$) from 
zero to infinite, where g denotes the five bins, the observed 
= round(scorei / pscorei×100,0) , $\sum \text{observed}_i$ , the 
Expected represents the first cutting point (i.e., the upper limit 
of low-level burnout) of each bin; scorei, and pscore are the 
response summation score and the possible total summation 
score of each bin, respectively. When the $\delta > 0.9$ (toward 
a uniform distribution [31,35]) and $\chi^2 < 3.84 (= 1.96^2)$ are 
corrently true, we confirm that the examinee is at the low 
burnout level. Otherwise, the responses might be distraction, 
careless, mistaken, cheating, or awkward if the $\delta < 0.9$ or less. 
That is because the score ratios across subscale are not 
inconsistent (i.e., toward a non-uniform distribution [31,35]).

2.7. Statistical Tools and Data Analyses

SPSS 15.0 for Windows (SPSS Inc., Chicago, IL) was used to 
calculate Cronbach’s α for the three subscales of response 

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Note: a: Area under ROC curve (AUC) summing the area of trapezoid with curved edge referred to columns F and G; b: Sensitivity+ Specificity; c: cutting point; c:summing values of the total rows; d: the maximum of the summation of sensitivity and specificity.

Table 1. The cutting point is determined when the binary classification groups are known.

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
<th>K</th>
<th>Max^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Score</td>
<td>Count</td>
<td>Accumulation</td>
<td>D/56</td>
<td>E/9</td>
<td>1-G</td>
<td>1-F</td>
<td>Sum</td>
<td>Max^2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>8</td>
<td>14</td>
<td>0</td>
<td>0.14</td>
<td>0.00</td>
<td>1.00</td>
<td>0.86</td>
<td>0.14</td>
<td>1.14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>6</td>
<td>14</td>
<td>0</td>
<td>0.25</td>
<td>0.00</td>
<td>1.00</td>
<td>0.75</td>
<td>0.11</td>
<td>1.25</td>
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<td></td>
</tr>
<tr>
<td>17</td>
<td>2</td>
<td>16</td>
<td>0</td>
<td>0.29</td>
<td>0.00</td>
<td>1.00</td>
<td>0.71</td>
<td>0.04</td>
<td>1.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>7</td>
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<td>0</td>
<td>0.41</td>
<td>0.00</td>
<td>1.00</td>
<td>0.59</td>
<td>0.13</td>
<td>1.41</td>
<td></td>
<td></td>
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<tr>
<td>19</td>
<td>11</td>
<td>34</td>
<td>0</td>
<td>0.61</td>
<td>0.00</td>
<td>1.00</td>
<td>0.39</td>
<td>0.20</td>
<td>1.61</td>
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</tr>
<tr>
<td>20</td>
<td>8</td>
<td>42</td>
<td>1</td>
<td>0.75</td>
<td>0.11</td>
<td>0.89</td>
<td>0.25</td>
<td>0.13</td>
<td>1.64</td>
<td></td>
<td></td>
</tr>
<tr>
<td>21^c</td>
<td>13</td>
<td>55</td>
<td>1</td>
<td>0.98</td>
<td>0.11</td>
<td>0.89</td>
<td>0.02</td>
<td>0.21</td>
<td>1.87</td>
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<td>22</td>
<td>1</td>
<td>55</td>
<td>2</td>
<td>0.98</td>
<td>0.22</td>
<td>0.78</td>
<td>0.02</td>
<td>0.00</td>
<td>1.76</td>
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</tr>
<tr>
<td>23</td>
<td>1</td>
<td>56</td>
<td>3</td>
<td>1.00</td>
<td>0.33</td>
<td>0.67</td>
<td>0.00</td>
<td>0.01</td>
<td>1.67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>1</td>
<td>56</td>
<td>4</td>
<td>1.00</td>
<td>0.44</td>
<td>0.56</td>
<td>0.00</td>
<td>0.00</td>
<td>1.56</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>2</td>
<td>56</td>
<td>6</td>
<td>1.00</td>
<td>0.67</td>
<td>0.33</td>
<td>0.00</td>
<td>0.00</td>
<td>1.33</td>
<td></td>
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</tr>
<tr>
<td>26</td>
<td>1</td>
<td>57</td>
<td>7</td>
<td>1.00</td>
<td>0.78</td>
<td>0.22</td>
<td>0.00</td>
<td>0.00</td>
<td>1.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>1</td>
<td>56</td>
<td>8</td>
<td>1.00</td>
<td>0.89</td>
<td>0.11</td>
<td>0.00</td>
<td>0.00</td>
<td>1.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>28</td>
<td>1</td>
<td>56</td>
<td>9</td>
<td>1.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sum</td>
<td>56</td>
<td>9</td>
<td>0.96^a</td>
<td>1.87^a</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
datasets. The comparisons between demographic variables were measured using descriptive statistics, $\chi^2$, and analysis of variance (ANOVA). Data were analyzed using SPSS and Microsoft Excel. Cutting points were determined at maximal summations of specificity and sensitivity for each person stratum when strata central points were determined using k-mean cluster analysis.

### 3. Results

The sample of 970 nurses was obtained from the study. The mean age of the participants was $31 \pm 4.3$ years, more than 99% ($n = 962$) were female, more than 74% ($n = 725$) were unmarried (Table 2).

#### Table 2. Demographic characteristics of the participants ($n = 970$).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>n</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>8</td>
<td>0.8</td>
</tr>
<tr>
<td>Female</td>
<td>962</td>
<td>99.2</td>
</tr>
<tr>
<td>Marital status</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unmarried</td>
<td>725</td>
<td>74.7</td>
</tr>
<tr>
<td>Married</td>
<td>235</td>
<td>24.3</td>
</tr>
<tr>
<td>Others</td>
<td>10</td>
<td>1.0</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Under College</td>
<td>304</td>
<td>31.3</td>
</tr>
<tr>
<td>Above University</td>
<td>666</td>
<td>68.7</td>
</tr>
<tr>
<td>Nurse competence</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Under N1</td>
<td>589</td>
<td>60.7</td>
</tr>
<tr>
<td>N2</td>
<td>279</td>
<td>28.8</td>
</tr>
<tr>
<td>Above N3</td>
<td>102</td>
<td>10.5</td>
</tr>
<tr>
<td>Hospital seniority</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;2 years</td>
<td>344</td>
<td>35.5</td>
</tr>
<tr>
<td>2-5 years</td>
<td>335</td>
<td>34.5</td>
</tr>
<tr>
<td>&gt;5 years</td>
<td>291</td>
<td>30.0</td>
</tr>
</tbody>
</table>

### 3.1. Cutting Points of MBI-HSS Chinese Version

The Cronbach’s $\alpha$ of the three-burnout subscales ranged from 0.74 to 0.84 in the current study. Thus, the number of person strata for the MBI-HSS Chinese version can be divided into three groups: low, moderate, and high. For each subscale, ANOVA showed significant differences ($p < 0.001$) between the three levels. The cutting point sensitivity and specificity ranged from 0.82 to 0.97. The area under the curve (AUC) ranged from 0.97 to 0.99 (Table 3).

#### Table 3. The cutting points of MBI-HSS Chinese version for emotional exhaustion, depersonalization, and reduced personal accomplishment subscales.

<table>
<thead>
<tr>
<th>Subscale</th>
<th>Cronbach’s $\alpha$</th>
<th>Cluster centers</th>
<th>ANOVA F-values</th>
<th>Cutting point$^\dagger$</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emotional exhaustion</td>
<td>0.84</td>
<td>17, 27, 38</td>
<td>3810$^2$</td>
<td>21</td>
<td>0.94</td>
<td>0.94</td>
<td>0.99</td>
</tr>
<tr>
<td>Depersonalization</td>
<td>0.83</td>
<td>4, 10, 16</td>
<td>3742$^2$</td>
<td>6</td>
<td>0.95</td>
<td>0.95</td>
<td>0.99</td>
</tr>
<tr>
<td>Reduced Personal accomplishment</td>
<td>0.74</td>
<td>11, 21, 28</td>
<td>3168$^2$</td>
<td>23</td>
<td>0.94</td>
<td>0.94</td>
<td>0.99</td>
</tr>
</tbody>
</table>

ANOVA: analysis of variance; AUC: area under the curve; $^\dagger$ the scores for personal accomplishment have been reversed to the burnout tendency; $^* p < 0.05$.

### 3.2. Online Burnout Assessment

By scanning a QR-code (Figure 2, top right, bottom) or downloading the APP, the burnout questionnaire appears on the smartphone. We developed a mobile survey procedure to provide a practical demonstration of the newly designed burnout MBI-HSS application in action. The burnout APP processed each nurse item-by-item with audio and visual (Figure 2, top left). The result with a high burnout level across all subscales instantly shows on a smartphone (Figure 2, bottom). The $\delta$ index is 1.0 ($> 0.9$), which means that the scores of the five bins are equal ratios to their respectively corresponding cut-point criteria, and $\chi^2$ is 21.77 ($> 3.84$), which means that the scores of the five bins are different from the low burnout level. These index values indicate that the examinee is not at the low burnout level.
Figure 2. Snapshots shown on a smart phone.
4. Discussion

4.1. Key Findings

The cutoff points of the MBI-HSS Chinese version were ≤ 21 and ≤ 32 for Emotional, ≤ 23 and ≤ 30 for Negative Personal Accomplishment, ≤ 6 and ≤ 12 for Depersonalization, and ≤ 17 and ≤ 15 (i.e., low, moderate, and high level) for the overall scores. An available-for-download online MBI-HSS APP for nurses was suited for smartphones.

4.2. Additional Contribution to Existing Research

The MBI-HSS has been used most widely for measuring burnout in the world [10, 13-15]. The psychometric properties of 20 items of these scales have been validated for use in hospital nurses [3]. However, most of them merely report numerical results that are not translated into the degree (or classification) of their burnout problems relative to a cutting point that can be generalized to other worksites and other ethnic samples.

Maslach and Jackson [12] reported the level of burnout using the criteria of cutting points. Schaufeli and Van Dierendonck [22] disagreed with their methods and wondered why these three cutting points were arbitrary and merely based on an equal sample size of the three groups divided by the high, moderate, and low levels of burnout [23].

Schaufeli & Janczur [36] reported that staff with similar characteristics in Europe undergo lower rates of exhaustion and depersonalization than do staff in North America, and suggested different cultural values as a possible explanation for the different rates. However, all of which should translate those numerical results into the degree (or classification) of their burnout problems. Furthermore, Maslach et al. [21] confirmed that levels of burnout must be different in various countries. However, we have not found any research that reported the cutting points used for the MBI-HSS on hospital nurses and suitable for a nation-based reference when the binary classification groups of burnout were unknown, and no application that incorporates the MBI-HSS has been used for smartphones.

4.3. What It Implies and What Should Be Changed

We have provided a way to determine the cutting points of person burnout strata using a norm-referred method. It is because we usually do not know the nurse’s true- and false-positive status. Thus, many studies in their limitations sections caution that their results cannot be generalized to other sites or to other types of sample groups. This is because the data were sample-dependent. How we estimate the population properties using the sample data (e.g., Cronbach’s $\alpha$ coefficient for a scale [29]) before determining cutting points and then make inferences (e.g., the cutting points for a scale) about the population is the main feature of the present study.

Thus, in this study, the norm-referred method was introduced based on suggestions in the literature [26-28]. The cutting points were theoretically determined using an inference based on the study sample. Future studies are suggested to use this way to determine cutting points for other diseases in healthcare settings.

4.4. Strengths of This Study

It is easy to set up the online burnout assessment form if the designer uploads relevant audio and visual files to the corresponding questions of the database. We especially developed two indices (i.e., the revised Ferguson Delta and the $\chi^2$) for helping users (or psychiatrists) discriminate the level of burnout according the graphical result in Figure 2: the higher Delta is, the more confident we are that the responses are not careless, mistaken, cheating, or awkward; the higher the value of $\chi^2$ (> 3.84), the more likely is moderate or even high burnout (e.g., not at the low burnout level).

As with all forms of Web-based technology, advances in mobile health (mHealth) and health communication technology are rapidly emerging [37]. Mobile online burnout assessment is promising and worth considering in many fields of health assessment.

On the other hand, health literacy is increasingly recognized as critical [38]. Adults with below basic or basic health literacy are more likely than adults with higher health literacy to get information about health issues from multimedia graphical representations [39,40] rather than traditional newspapers, magazines, books, brochures, or pamphlets. An online burnout assessment such as the one we developed can be used to inform examinees quickly about when and whether they should take actions or follow-up to see a psychiatrist, and how to improve their behaviors and attitudes given their lifestyle is not changed. Mobile online burnout assessment is promising, and it is worth using for promoting nurses’ health literacy. Interested readers are recommended to scan the QR-code or download the APP in Figure 2 to practice it in their own way and to conduct an online burnout assessment.

4.5. Limitations and Future Studies

Our study has some limitations. First, although we believe that the online burnout assessment is suitable for any normally distributed group, there is no evidence to support our assumption that our sample of nurses is fully normally distributed, which might affect what cutting points are determined. This means that more than one stratum is required if data are not normally distributed [26]. We recommend additional studies using samples with a variety of distributions to see whether different cutting points are arrived.

Second, although the MBI-HSS Chinese version’s Cronbach’s $\alpha$ coefficients ranged from 0.74 to 0.84 [3], we conservatively determined that all the subscales’ nurse strata were three instead of four or more when Cronbach’s $\alpha$ for a scale approached 0.90 [29]. It is convenient, clear, and simple to show the stack bar chart plot, like the one in Figure 2, of a graphical representation for users.

Third, the study was based on a previously published paper...
The presentation of the burnout assessment shows that it is innovative and novel for helping hospital nurses (or psychiatrists) measure burnout engagement. Journal of Nursing Administration 2006; 10 6 (4): 60–71.

5. Conclusion

We found that the online mobile module used for smartphones is promising for assessing nurse burnout. The visualized presentation of the burnout assessment shows that it is innovative and novel for helping hospital nurses (or psychiatrists) measure the level of burnout online in clinical settings.

Competing Interests

The authors declare that they have no competing interests.

References


[27] Wright BD, Masters GN. Number of person or item strata. Rasch Meas Trans 2002; 16 (3): 888.


