

# The Household Water Insecurity Experiences Scale: answer patterns and cutoffs in Mexico

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## Abstract

**Objective.** To investigate the degree in which answer patterns in the Household Water Insecurity Experiences Scale (HWISE) relate to scores aiming at identifying latent groups with different water insecurity levels in a nationwide representative sample of the Mexican population. **Materials and methods.** Based on data from the 2021 National Survey on Health and Nutrition (*Estudio Nacional de Salud y Nutrición 2021, Ensanut 2021*), sequence data representations, and a latent class analysis (LCA), in this article we estimate the likely misclassification errors of different cutoffs proposed for the HWISE scoring system. **Results.** The main results suggest that a 5-item subset of the HWISE may exhibit a more reliable and cost-effective behavior than the complete 12-item set for a 2-level partition of the sample. **Conclusions.** Our methodological approach provides new insights regarding the efficiency and likely errors in distinguishing between levels of water insecurity based on the Mexican chapter of the HWISE.

Keywords: factor analysis; latent class analysis; health inequality monitoring

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## Resumen

**Objetivo.** Investigar la asociación entre patrones de respuestas a la *Household Water Insecurity Experiences Scale* (HWISE) y los puntajes utilizados para identificar grupos con diferentes niveles de inseguridad del agua, en una muestra representativa de la población mexicana. **Material y métodos.** Con base en datos de la Encuesta Nacional de Salud y Nutrición 2021 (Ensanut 2021), representaciones de la secuencia de los datos y Análisis de Clases Latentes, en este artículo se estimaron los probables errores de clasificación al usar diferentes puntos de corte bajo el sistema de puntajes propuesto para la HWISE. **Resultados.** Los principales resultados sugieren que, para una partición de la muestra de dos niveles, un subconjunto de cinco ítems de la HWISE podría exhibir una conducta más confiable y costo efectiva vis a vis con el conjunto completo de 12 ítems. **Conclusiones.** El presente abordaje metodológico ofrece nuevas pistas en lo que se refiere a la eficiencia y los probables errores involucrados en distinguir entre niveles de inseguridad del agua con el capítulo mexicano de la HWISE.

Palabras clave: análisis factorial; análisis de clases latentes; monitoreo de las desigualdades en salud

Experienced-based scales are becoming increasingly popular for assessing different aspects of people's living conditions and target interventions to specific population groups.<sup>1-3</sup> Based on the methodological insights gained from the application of food insecurity experience scales, the Household Water Insecurity Experiences Scale (HWISE) has been proposed as a new

tool to quantitatively assess, compare and measure experiences of household water insecurity across low and middle-income countries.<sup>4</sup>

In the pursuit of tools that are efficient and user-friendly for data collection via survey modules, as well as simple to interpret and comprehend in both research and policy settings, it is highly atypical to rely exclu-

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sively on raw/observed scores (obtained from simple functions or factor estimates) in order to make inferences about the studied population. Instead, the prevalent practice involves employing these raw scores to classify households into distinct severity level groups (e.g. high, moderate, mild) using theoretical and statistical criteria.

In line with this common practice, for example, the multi-site study that launched the HWISE<sup>4</sup> classified a sample of 8 127 households into two levels of water insecurity. However, more detailed groupings have been proposed. As part of the Mexican chapter, for example, Jepson and colleagues<sup>5</sup> grouped 498 households into 5 levels of water insecurity (marginal, low, moderate, high, and extreme).

Group classification requires both substantive theoretical knowledge and exhaustive empirical scrutiny to ensure that inferences about the respondents' classification lead to valid conclusions.<sup>6</sup> It is clear that not every classification makes theoretical sense. Furthermore, even those classifications that seem theoretically sound might not make empirical/statistical sense in every sample (theoretical-empirical consistency).

A necessary but not sufficient condition for any partition of the population to be useful is for it to be statistically grounded, i.e., the expected answering pattern must not only be statistically detectable in the data at hand (by whatever means or black-box algorithm) but also recognizable through an easy-to-communicate scoring function (usually a simple sum of points). This is a question not only of sample size -although small samples do stand in the way of statistical inference-, but, fundamentally, of the amount of information an instrument is able to pick up (coverage) in its interaction with a specific system under measurement,<sup>7</sup> and the existence of a sufficient (simple) statistic for a useful partition. Indeed, all measurement is befuddled with error, even when census data is used.

The inferential nature of measurement opens a gap between what analysts and policy makers would like to "see" in terms of population groups with different characteristics, and what an instrument actually allows to infer for a given sample. That is, measurement error is simple defined as the amount of unwanted variance (noise) of the scores or resulting classifications- just as the resulting image or pixel resolution of the measurement outcome.<sup>8</sup>

This paper aims at assessing the theoretical-empirical consistency of group configurations (i.e. latent sub-populations with distinct levels of severity) based on the HWISE scoring system. Drawing upon the work of Reichenheim and colleagues, and Interlenghi and colleagues,<sup>9,10</sup> this article uses latent class analysis (LCA) to identify (internally similar yet comparatively distinct) types of answer patterns and cutoff points of the HWISE

that result in low-error group configurations with distinctive degrees of severity of water insecurity as per Ensanut 2021.

## Materials and methods

### Data

Data were obtained from Ensanut 2021,<sup>11</sup> carried out on a national cross-section of 12 619 households across nine broad regions where the 12-item HWISE was included for the first time (publicly available online<sup>12</sup>). The HWISE probes experiential dimensions of water insecurity (table I).<sup>4,11,12</sup>

The 12 items elicited frequency of experiences within the prior four weeks: 'never' (0 times), 'rarely' (1-2 times), 'sometimes' (3-10 times), 'often' (11-20 times), 'always' (more than 20 times), 'not applicable', 'don't know' or refused. This study treats both the 'not applicable' and 'don't know' responses as missing values.

### Methods

The full HWISE scale (i.e. 12 items with five mutually possible responses) leads to five<sup>13</sup> response patterns from which it is expected to derive clear (mutually exclusive and exhaustive) population groups with distinctive degrees of severity of water insecurity. Visual inspections by means of answer distribution graphs were used to assess the variation and concentration of answer patterns across the 12 items of the HWISE.

This paper relies on LCA to identify the most sensible group partitions given the observed response patterns among the five<sup>13</sup> possible sequence of answers,<sup>13</sup> as well as related cutoff points that result in the lowest classification error as per the HWISE scoring system. LCA is a latent variable method that assigns response patterns to its most likely group, i.e. the resulting classes reflect particular series of responses. As latent classes are, by definition, unobserved, such a task requires an assumption of the number of groups to be estimated. However, being a probabilistic method, LCA allows to assess the most likely number of groups in the data by means of fit statistics, along with its respective configuration in terms of their answer patterns. Following the standard approach,<sup>14</sup> a series of LCA models with an increasing number of latent classes (from 1 to 5) were fitted to the data using Mplus 8.0<sup>15</sup> for their comparison.

In order to assess model fit across solutions we compared the following indices: the Bayesian Information Criterion (BIC), where lower values indicate a better model fit; Entropy, whose values approaching 1 indicate clear delineation of classes<sup>16</sup> (values below 0.8

**Table I**  
**HWISE ITEMS AS PER ENSANUT 2021**

| Names/Context | Questions<br>En las últimas 4 semanas, ¿con qué frecuencia...<br>In the last 4 weeks, how frequently...  | Label        |
|---------------|--|--------------|
| h0801         | <i>usted o alguien en su hogar se preocupó de no tener suficiente agua para todas las necesidades de su hogar?</i><br>did you or anyone in your household worry that you would not have enough water for all of your household needs?  | Worry        |
| h0802         | <i>se ha interrumpido o disminuido el suministro de las fuentes principales de agua en su hogar (por ejemplo, menor presión o interrupción del agua entubada, menor caudal en el río donde se abastece el agua, etc.)?</i><br>has your household water supply from your main water source been interrupted or limited (e.g., water pressure, less water than expected)?  | Interruption |
| h0803         | <i>no ha habido suficiente agua en el hogar para lavar la ropa?</i><br>has there not been enough water in the household to wash clothes?   | Clothes      |
| h0804         | <i>usted o alguien en su hogar tuvo que cambiar sus horarios o planes debido a problemas con el agua? (Las actividades que pueden haber sido interrumpidas incluyen cuidar a otros, hacer tareas domésticas, llegar tarde al trabajo o a la escuela, etc.)</i><br>have you or anyone in your household had to change schedules/plans due to problems with your water situation, such as problems getting or distributing water within the household? (Activities that may have been interrupted include caring for others, doing household chores, and so on.) | Plans        |
| h0805         | <i>usted o alguien en su hogar, ha tenido que cambiar lo que iba comer porque había problemas con el agua (por ejemplo, para lavar los alimentos, cocinar, etc.)?</i><br>have you or anyone in your household had to change what was being eaten because there were problems with water (eg. for washing foods, cooking, and so on)?   | Food         |
| h0806         | <i>usted o alguien en su hogar, no pudo lavarse las manos después de actividades antihigiénicas (como después de ir al baño o cambiar pañales, limpiar desechos de animal) porque no tenía suficiente agua?</i><br>have you or anyone in your household had to go without washing hands after dirty activities (e.g., defecating or changing diapers, cleaning animal dung) because of problems with water?  | Hands        |
| h0807         | <i>usted o alguien en su hogar no pudo bañarse porque no había suficiente agua? (por ejemplo, no hay suficiente agua, está sucia, difícil acceso)</i><br>have you or anyone in your household had to go without washing their body because of problems with water (e.g., not enough water, dirty, unsafe)?   | Body         |
| h0808         | <i>no hubo suficiente agua para beber para usted u otro integrante de su hogar?</i><br>has there not been as much water to drink as you would like for you or anyone in your household?  | Drink        |
| h0809         | <i>usted o alguien en su hogar se sintió molesto(a) por alguna situación referente al agua?</i><br>did you or anyone in your household feel angry about your water situation?  | Angry        |
| h0810         | <i>usted o alguien en su hogar se durmió con sed porque no había agua para beber?</i><br>have you or anyone in your household gone to sleep thirsty because there wasn't any water to drink?   | Sleep        |
| h0811         | <i>hubo en su hogar agua no potable o que no se puede tomar?</i><br>has there been no useable or drinkable water whatsoever in your household?   | No water     |
| h0812         | <i>usted o alguien en su hogar sintió vergüenza o rechazo a causa de los problemas con el agua?</i><br>have problems with water caused you or anyone in your household to feel ashamed/excluded/stigmatized?   | Shame        |

HWISE: Household Water Insecurity Experiences Scale  
Ensanut 2021: Encuesta Nacional de Salud y Nutrición 2021  
Source: Ensanut 2021<sup>11,12</sup>

are typically considered problematic); and the  $p$  value of the Vuong-Lo-Mendell-Rubin test (LRT, comparing models with  $k$  and  $k-1$  latent classes) was used to examine whether there was a significant improvement in model fit with the inclusion of an additional class, where the null hypothesis ( $H_0$ ) assumes the  $k-1$  model as the prevailing one and lower  $p$  values make it less likely (values below 0.05 are typically considered reasonable evidence against the null).<sup>14</sup>

As LCA allows comparing observed raw scores with the model-based groups, the degree of agreement

between the expectations of the validation protocol (i.e. proposed scoring) of the HWISE with the empirical results of the LCA was assessed with contingency tables, based on which misclassification rates were calculated for several cutoff points.

A byproduct of the LCA analysis is an estimate of the items with the highest information contribution (item entropy), i.e. items that track the largest amount of variance of the latent variable.<sup>17</sup> Based on these estimates, and related item discrimination, a potential narrower subscale was derived in order to compare the

resulting partitions with the full scale. The predictive validity was assessed by means of receiver operating curves (ROC) -a graph of sensitivity versus one minus specificity as the cutoff  $c$  is varied- where two markers of water access were used.<sup>18</sup>

## Results

Figure 1<sup>11,12</sup> shows the relative frequency of the 3 458 different answer patterns to the HWISE in the Ensanut 2021, far less than  $5^{13}$  of the possible patterns. Such multiplicity is shrunken not only because some of the patterns are quite unlikely, but also because 48% of the sample (6 059 households) answered 'never' to all 12 items -seen in lighter color at the bottom of the figure.

It is important to keep in mind that figure 1 shows not the bar chart of item frequencies, but the general pattern of the whole set of answer sequences observed in our data (transversal aggregated views read horizontally). A state distribution plot that shows jumps in the sequence of answer distributions.

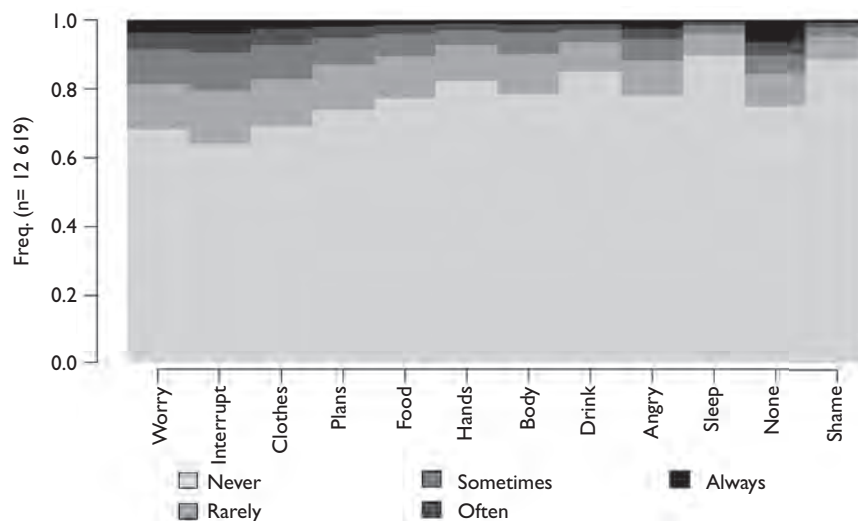
When comparing the global fit of the five LCA models (results not shown, available from the authors upon request), we found the 5-level severity classification feasible in that it exhibits good entropy and high classification probabilities. However, the Vuong-Lo-Mendell-Rubin likelihood ratio test suggests that a 4-level severity solution offers a better fit. Also, the group 3 solution showed larger sample sizes than the group 4 solution (levels grow unstable and suspiciously idiosyncratic/overfitted as they grow smaller), while

the group 2 solution exhibited the highest "resolution" (detectability) according to the entropy and probabilities of classification.

Based on the results of the "validation protocol", the team behind it suggested a score of 12 or higher as a "reasonable provisional indicator for water insecurity", with a scoring system of 0 for all those items answered 'never', 1 for 'rarely', 2 for 'sometimes', and 3 for 'often/always'.<sup>19</sup> According to our latent class estimates for the best 2-level partition of the sample, a 12+ threshold would result in 12% of level 2 (more water-insecure) households being misclassified as level 1; that is, some 1 538 households were classified as level 2 (having a <12 score). This is because their answer pattern is closer (under the model) to those with 12+ scores with rather high probabilities (0.96 on average). Patterns like answering 'rarely' to items Worry, Interruption, Clothes, and Plans (table I), with a score of 4, are (statistically) more 'alike' to those with more precise answering patterns than to the 48% who answer 'never' to all 12 items.

While the same 12+ threshold results in misclassification rates of little over 5% of the sample under other partitions, this comes at the cost of higher levels of misclassification for some estimated levels of water insecurity -25% of the sandwich class under the class 3 solution, and over half of level 3, right-over-the-threshold households, under both class 4 and class 5 solutions-, which speaks of random variations in answering patterns around the middle of the scoring system.

Figure 2<sup>11,12</sup> shows the answer pattern underlying the 2-level solution for our latent class estimates. At the



HWISE: Household Water Insecurity Experiences Scale

Source: Prepared by the authors with data from the Encuesta Nacional de Salud y Nutrición 2021<sup>11,12</sup>

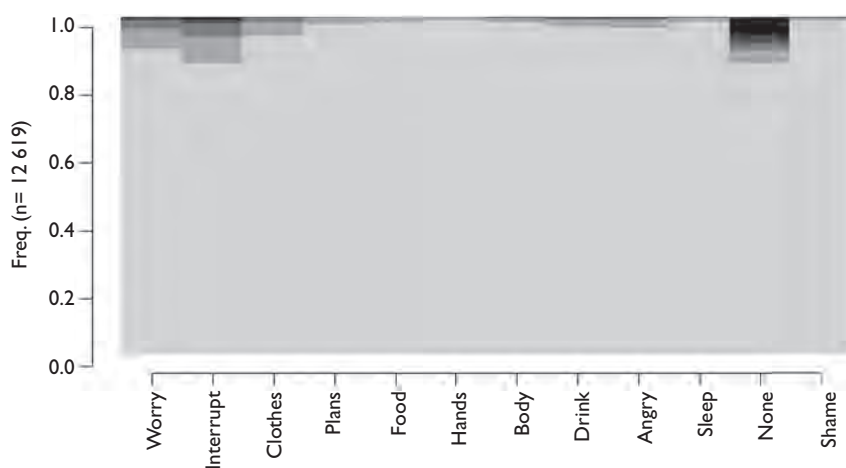
**FIGURE 1. ANSWER PATTERNS TO HWISE. MEXICO 2021**

top of panel (a), in darker colors, one can see the patterns considered 'like' those of respondents who answered 'never' to all items i.e., within discriminant error under the model. There we can see some degree of randomness in households' answers across all 12 items, particularly to items 'Interruption' and 'None'.

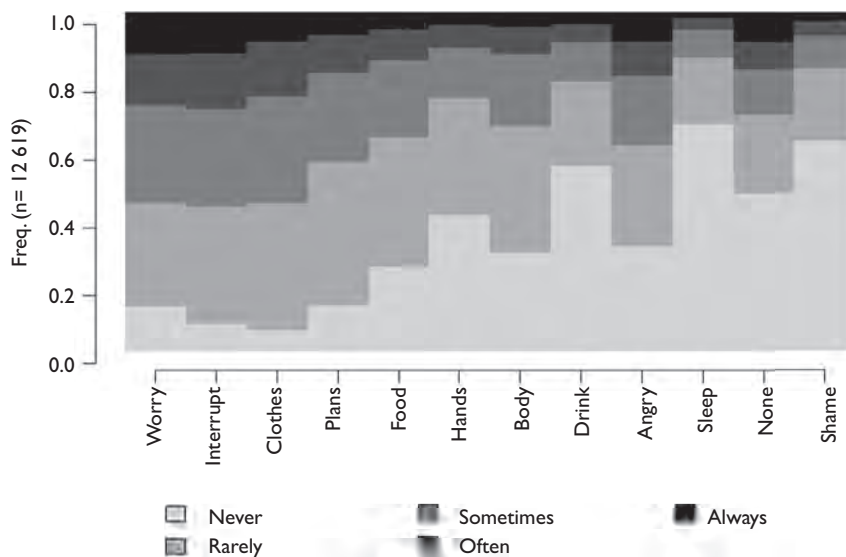
Table II<sup>11,12</sup> shows the distribution of households according to the proposed scoring system and the 2-level class estimates. Under the full scale heading (columns 2 and 3), one can see that a cutoff point of 6 or higher would yield a smaller misclassification rate of 4% of the data, versus the 12+ cutoff point.

One would be right in assuming that going through all 12 items for a 6+ cutoff is a bit of an overkill, not to say a waste of time and resources. Indeed, Young and colleagues<sup>20</sup> have persuasively argued on the advantages of a shortened version of the HWISE, among them, its inclusion in surveys with stringent criteria for adding new items, as well as its use in emergency contexts where minimal time burdens are of the utmost importance. If the researchers, considering the Item Response Theory<sup>19</sup> to be the foundation of the scale, were interested in a reliable 2-level partition of the population based on estimated item discrimination and the related

(a) Class I (71% of the sample)



(b) Class 2 (29% of the sample)



Legend:  
 Never (light gray), Rarely (medium gray), Sometimes (dark gray), Often (black), Always (black)

HWISE: Household Water Insecurity Experiences Scale  
 Source: Prepared by the authors with data from the Encuesta Nacional de Salud y Nutrición 2021<sup>11,12</sup>

**FIGURE 2. ANSWER PATTERNS TO HWISE BY LATENT CLASS OF WATER INSECURITY. MEXICO 2021**

univariate entropy from the class 2 model, their asking only about items 3-7 (Clothes, Plans, Food, Hands, Body) with a 3+ cutoff would result in a clearer partition (with < 4% misclassified households), as shown in columns 4 and 5 of table II under the 'Reduced scale' heading.

This result also contrasts with the reduced four-item proposal (Worry, Plans, Hands, Drink; 4+ cutoff) by the HWISE Research Coordination Network,<sup>20</sup> which, according to the LCA estimates, would likely result in misclassifying roughly 10% of the Ensanut 2021 sample.

Figure 3<sup>11,12</sup> shows misclassification rates for the 12+ and 6+ cutoffs across all 9 regions in which Ensanut 2021 is representative for the full scale, and the 3+ cutoff with the 5-item reduced scale.

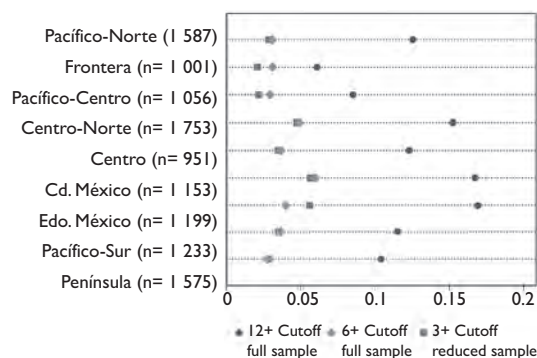
While our results suggest a better fit (higher power) for the 4-level partition than for the 5-level one. According to the LCA estimates (results not shown, available from the authors upon request), the 5-level partition proposed by Jepson and colleagues<sup>5</sup> would likely result in misclassifying roughly 20% of the sample.

**Table II**  
**PERCENTAGE OF HOUSEHOLDS BY RAW SCORE OF THE HWISE ACCORDING TO LATENT CLASS MEMBERSHIP. MEXICO 2021**

| Raw score | 12-Item Latent Class |       |               |       |
|-----------|----------------------|-------|---------------|-------|
|           | Full scale           |       | Reduced scale |       |
|           | C1                   | C2    | C1            | C2    |
| 0         | 48.45                | 0     | 64.36         | 0.13  |
| 1         | 5.53                 | 0     | 4.43          | 0.54  |
| 2         | 4.45                 | 0     | 1.91          | 2.33  |
| 3         | 7.42                 | 0     | 0.56          | 2.64  |
| 4         | 2.26                 | 0     | 0.06          | 3.18  |
| 5         | 1.19                 | 1.01  | 0             | 5.67  |
| 6         | 1.14                 | 1.67  | 0.01          | 2.59  |
| 7         | 0.44                 | 1.71  | 0             | 1.87  |
| 8         | 0.21                 | 1.80  | 0             | 1.71  |
| 9         | 0.16                 | 1.81  | 0             | 1.61  |
| 10        | 0.05                 | 1.78  | 0             | 2.13  |
| 11        | 0.02                 | 1.78  | 0             | 0.84  |
| 12        | 0.01                 | 2.61  | 0             | 0.64  |
| 13        | 0                    | 1.21  | 0             | 0.60  |
| 14        | 0                    | 1.33  | 0             | 0.44  |
| 15+       | 0                    | 11.31 | 0             | 1.75  |
| Total     | 71.32                | 28.68 | 71.32         | 28.68 |

HWISE: Household Water Insecurity Experiences Scale  
The reduced scale includes only five items: Clothes, Plans, Food, Hands, and Body.

Source: Authors' calculations based on data from the *Encuesta Nacional de Salud y Nutrición 2021*<sup>11,12</sup>



Source: Prepared by the authors with data from the *Encuesta Nacional de Salud y Nutrición 2021*<sup>11,12</sup>

**FIGURE 3. 2-LEVEL PARTITION MISCLASSIFICATION RATE BY CUTOFF. MEXICO 2021**

It is important to note that the results of the 2-level model are based on the assumption that similar experiences elicit similar answer patterns. This would, in principle, offer better statistical contrasts (predictive validity) in distinguishing between groups with different water situations and related illnesses. Our regression results show this is indeed the case, if only marginally, for piped water inside the household and having fallen ill (the last time in the past three months) with diarrhea or a stomach infection (results not shown, available from the authors upon request).

## Discussion

In scale development, it is quite common to categorize individuals by applying score-based cutoff points. However, the determination of the criteria for this categorization and the assessment of the suitability of a proposed approach are not always straightforward. Specifically, researchers lack compelling reasons to anticipate, beforehand, that utilizing a specific quantile of the score distribution as a cutoff point would yield a statistically meaningful grouping. In other words, such a grouping should be distinguishable within the given sample beyond the effects of sampling and measurement errors, as outlined by the metrological model.

This paper draws upon model-based approaches and latent variable methods (LCA) to provide a statistical assessment of the cutoffs and group partitions that can be derived from the HWISE scale. The results suggest that holding the provisional 12+ cutoff for a 2-level partition, as proposed by the team behind the development and validation protocol of the HWISE, may not be the best partition as per the answering patterns in the Ensanut 2021 sample. In fact, when aiming for a 2-level

partition of the Ensanut 2021 sample, significant cost savings in data collection could be achieved by using only five items (Clothes, Plans, Food, Hands, Body) and a 3+ cutoff. This also suggests that, in all likelihood, whenever the target involves partition with more than 2 sub-populations, the number of items required for the task will increase. Determining whether this is indeed the case remains pending empirical work.

Several differences in our approach can explain this misalignment with current recommendations from HWISE Research Coordination Network, chiefly among them our use of LCA as a systematic way to assess a particular grouping of a population in light of the informational content offered by an instrument in a particular context; in this case, the Ensanut 2021. That is, unlike Young and colleagues,<sup>20</sup> we do not take the 12+ partition as a reference to evaluate the predictive accuracy of our five-item proposal, but the most likely latent class membership according to our class 2 LCA model. This also allowed us to use the related univariate entropy (as a measure of information content) as an additional criterion to select a subset of the HWISE items. Also, we used a 2-parameter IRT model on the raw HWISE to estimate separate item discrimination parameters –instead of a 1-parameter IRT or Rasch model–, which we also used as a criterion in our selection of items. Finally, here we used a different and larger sample for Mexico. It is well known that no instrument is equally reliable for all classification purposes everywhere. After all, reliability is always a property of the scores, not of the instrument, and this alone could also lead to different results, even when using the same instrument. With these notable differences in mind, our results would not suggest “Worry” or “Drink” as natural candidates for a reduced scale given their relative low discrimination, and also low entropy in the case of “Drink”. Particularly, our approach would suggest that item “No water” is a likely candidate to have been considered for a reduced scale by Young and colleagues<sup>20</sup> as the worst option, as already noted by Shamah and colleagues,<sup>21</sup> who have suggested changes to improve the comprehension of this item.

Whether these results would replicate in the data used by Young and colleagues,<sup>20</sup> as well as its full meaning and consequences, should this be the case, remains to be determined. Whatever complementarity may be granted to our approach, as previously argued, quite convincingly, by Reichenheim and colleagues, “[s]ubstantive knowledge on the subject matter is undoubtedly crucial in the process of grouping respondents appropriately, but the search for internally similar yet comparatively distinct groups may gain from using model-based approaches”.<sup>6</sup>

There is a natural concern that by not asking all of the questions, a reduced scale may miss important information and result in biased estimates for specific population groups. The use of a reduced scale with the proposed cutoff points yields consistent results across regions. However, further research is necessary, as this article is limited in that it does not provide answers for other types of cross breaks.

An important limitation of our approach is that it relies exclusively on the observed answer patterns to the HWISE as per the Ensanut 2021 sample and related statistical model assumptions. Unlike the methodology applied by Young and colleagues,<sup>20</sup> we were not able to take into consideration substantive (water insecurity) theoretical knowledge and fieldwork experience with the HWISE. It is important to note that whether a reduced version of the HWISE behaves in the field similarly to the full-scale items is an implicit assumption that requires empirical confirmation.

It is also important for practitioners to keep in mind that even though the data set at hand may admit a given partition reliably, under the measurement model there is no guarantee that there is also a simple and sufficient statistic of this partition; that is, the partition may not be susceptible to be represented by an easy to communicate, whole-number scoring function (e.g., raw sums). Of course, even when such a function exists for a reliable partition of the population under study, when comparing different sub-populations it is always best to test for invariance across groups and evaluate possible inconsistencies due to cultural and economic disparities.<sup>10</sup>

*Declaration of conflict of interests.* The authors declare that they have no conflict of interests.

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