Displaying Latent Classes in Figures: Consideration of Practices

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Abstract ■ While latent class analysis (LCA) has gained popularity in social sciences, including psychology, the visualization of latent classes has been the subject of limited discussions. This article reviews the elements of LCA figures, covering issues such as graph type, axis labels, and subgroup naming. Bar charts and line graphs have been identified as two major visualization approaches in LCA studies. It is concluded that LCA figures serve as an important visual vehicle to display subgroup characteristics. However, the elements of LCA figures need careful consideration as they could furnish the text with additional information. A checklist is summarized for LCA figure preparation.

Keywords ■ visualization; latent class analysis; subgroup.

Introduction

Latent class analysis (LCA) is increasingly applied in social sciences, including psychology (Jung & Wickrama, 2008; Nylund-Gibson & Choi, 2018). With numerous names, LCA is typically used to discern unobserved latent classes (also known as "subgroups" or "clusters") based on a set of indicators (McLachlan & Peel, 2000). This identification of heterogeneity in a sample is often referred to as person-centered analysis; in contrast, most previous analyses are considered as variable-centered as they primarily focus on the relationships among variables (Jung & Wickrama, 2008). Subgroups with different magnitudes for indicators could highlight unobserved theoretical and clinical findings.

It is important to clarify the terms used in this article. LCA can be applied in both cross-sectional (i.e., heterogenous subgroups based on a set of variables assessed at one time point) and longitudinal (i.e., distinct developmental patterns based on one or more variables with repeated-measures) designs. Terms like "trajectory" and "growth" are often used in longitudinal studies. In some contexts, LCA can be termed differently depending on, for example, the data distributions of indicators (for a summary of LCA's other names, see Masyn, 2013). Some methodologists use LCA specifically for categorical indicators, while latent profile analysis (LPA) is employed for continuous indicators. In this article, LCA is used as an umbrella name for all finite mixture models that generate segments in data because it merely focuses on the practices of visualizing latent classes. Furthermore, the present article is useful for other clustering analyses, such as k-means (MacQueen, 1967) and two-step cluster analysis (Chiu et al., 2001).

Purpose

The existing methodological discussions mainly focus on statistical mechanisms of LCA. There are guidelines on how to generate an optimal latent class solution using statistical metrics as well as suggestions on how to include covariates in LCA (Vermunt, 2010; Wickrama et al., 2022). However, little attention has been paid to the visualization of LCA figures. There are few discussions about figure use for statistics that form segments in the data. For example, a mainstream handbook that covers visual presentation in scientific writing only provides brief guidelines for dendrograms, which is a particular type of graph for cluster analysis (Nicol & Pexman, 2010). The present article discusses the elements needed in an LCA figure and provides a practical checklist for LCA figure reporting.

Elements of LCA Figures

As its other name—latent profile analysis—suggests, the visualization of LCA is expected to profile the distinct characteristics of subgroups beyond numeric narration. An LCA figure usually includes estimated means or probabilities of indicators in each subgroup, enabling readers to grasp the

between-subgroup differences efficiently. Notably, some researchers report LCA without a figure. For example, in a study by Chen et al. (2018), 14 dysmenorrhea symptoms were used as the LCA indicators and the authors compared the three identified subgroups with numbers in a table. The large number of indicators could be a reason for the authors' decision not to include a figure. Nevertheless, there are several benefits to reporting LCA findings with a figure.

Is a Figure Needed?

Visualization of data provides effective information, enabling readers to understand and "feel" the data; such a communicative function is especially useful for people with less statistical and mathematical literacy (Kongsted et al., 2016). As such, a well-designed LCA figure primarily and efficiently portrays the discrepancies between its subgroups. As a "technique" with a long history, scientific illustration itself has multiple hidden ways to express unexpected information easily. For instance, Feudtner et al. (2015) cleverly incorporated ranking information into their LCA figure so that the belief orders in each subgroup are vividly shown. Due to this intuitive feature, it is possible to compare figures across LCA-generated phenotypes, especially when standardized measures are used (Kongsted et al., 2016). Such cross-study comparisons provide concrete "flesh" to these latent "bones" as they show the generalizability of certain classification patterns.

There are some cases in which LCA figures are unnecessary. The interpretability of LCA is an important criterion for both model selection (Wickrama et al., 2022) as well as visualization. For example, when the patterns or structures of all the indicators are homogeneous, one can usually obtain several almost identical lines or bars. In this case, it is perhaps simpler to call them high, medium, and low levels as these adjectives apply to all indicators. As mentioned above, when the indicator number is large, displaying LCA findings visually can be challenging. It might be more appropriate to report latent classes with tables (Chen et al., 2018). Moreover, when there are too many subgroups in the sample, the figure can be unclear.

Pictorial information tends to be more powerful than texts. As displayed in Figure 1, when the same information is shown in a figure rather than a table, readers can immediately capture the key visual differences and similarities across subgroups. For instance, compared with the table information, the bar chart clearly shows that most members—regardless of their subgroup memberships—reported no symptoms. In addition, the "severe multiple symptom group" has markedly more members with moderate and severe symptoms than other subgroups. Thus, the simple bar chart quickly translates the "severe" sense in the last subgroup.

Graph Type: Line Graph and Bar Chart

Line graphs and bar charts are the major types of LCA figures. Line graphs visually render a continuous or growing impression as statisticians traditionally use them to summarize trends. Following this convention, line graphs are used to delineate the cross-time changes in a variable among several subgroups. Researchers tend to use "trajectory" rather than "subgroup" to describe such longitudinal changes in a variable. For example, a 20-year longitudinal study (Byers et al., 2012) used a line graph to depict four trajectories of depressive symptoms over time. Figure 2 compares the charts illustrating three trajectories over 10 years; the line graph appears to be more suitable given the longitudinal design and trend-oriented narration. Although line graphs are conventionally used to express cross-time trends, LCA figures based on cross-sectional designs also use line graphs (Nylund-Gibson & Choi, 2018).

In addition, although not mentioned in the figure captions, Byers et al. (2012) used shaded areas around the lines to indicate the confidence interval of the curves. Similarly, some articles have used dotted lines (Patel et al., 2020) or error bars (Pierce et al., 2021) to represent the confidence interval in a line graph. Standard error bars can be a visual tool to indicate imprecision in group mean scores. However, extra effort may be necessary to produce an LCA graph with standard error bars because the default graphs of some software do not include this representation. Researchers can easily draw a graph with error bars in Microsoft Excel by specifying the values of the standard error values obtained from Mplus. Figure 3 is an LCA bar chart showing three clusters. The error bars in this graph provide the imprecision in each group mean value. Additional information in Figure 3 is the p-values resulting from inter-cluster comparisons of intention. According to the graphic information, not only do these intention bars look different but also the observable differences have statistical significance. As Nicol and Pexman (2010) suggested, once the standard error bars are included, corresponding explanations are needed in the figure caption.

Traditionally, bar charts have been used to represent categorical data, such as the properties of each subgroup. This discrete grouping nature is well in line with LCA figures. In practice, bar charts may seem to be repetitive as all the indicator names are used for each subgroup. The LCA figure by Feudtner et al. (2015) is a clever example of the use of bar charts. In their figure, the authors did not simply repeat the importance scale and 12 indicators; they displayed the ranks of those indicators in each subgroup so that the salient beliefs in each subgroup are immediately observable. Figure 4 compares bar charts using both indicator-centered and class-centered approaches. Follow-

Figure 1 ■ Comparing Subgrouping Information in both Table and Figure Formats

(a)

Indicator	Mild Localized Pain Group (26.5%)				Severe Localized Pain Group (54.1%)				Severe Multiple Symptom Group (19.4%)			
	None	Mild	Moderate	Severe	None	Mild	Moderate	Severe	None	Mild	Moderate	Severe
Pain in the upper thighs	0.91	0.07	0.01	0.01	0.80	0.06	0.07	0.07	0.57	0.01	0.14	0.28
Vomiting	1.00	0.00	0.00	0.00	0.96	0.03	0.01	0.00	0.76	0.03	0.07	0.14
Reduced appetite	0.84	0.15	0.00	0.01	0.76	0.10	0.11	0.03	0.50	0.04	0.18	0.28
Constipation	0.84	0.09	0.07	0.00	0.81	0.05	0.07	0.08	0.60	0.02	0.09	0.29
Fewer bowel movements	0.89	0.08	0.01	0.02	0.94	0.01	0.02	0.04	0.87	0.01	0.06	0.07

(b)
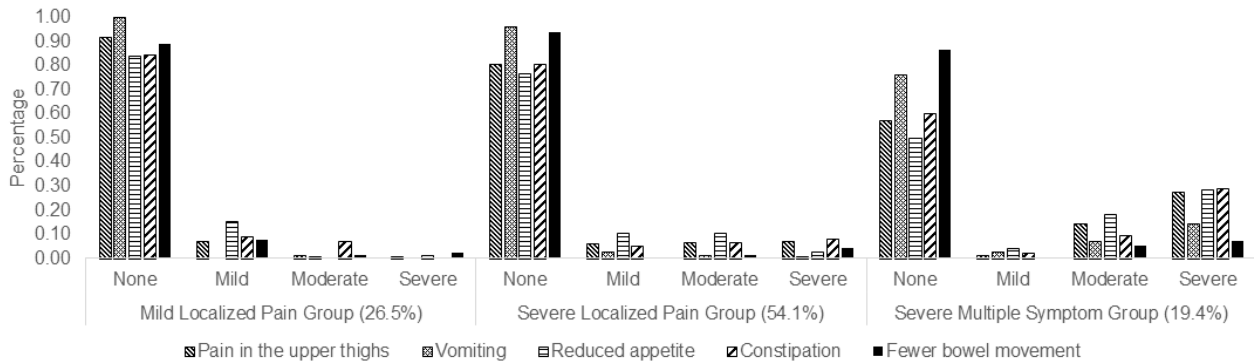
Note. N = 762. The data in this figure are reproduced from Chen et al. (2018). For brevity, values are rounded to two decimal places. Notice that, in table (a), two vertical borders are inserted to separate the subgroups; shading can be used here too, but it is generally recommended to avoid using shading because some print quality may cause reading difficulties (e.g., fonts are not discernible).

ing the representation by Feudtner et al. (2015), plate (b) orders indicators by rank in each class. As such, readers can easily see that socialization and stress coping seem to be dominant in Classes 1 and 2, respectively. In contrast, plate (a) seems to be less informative as it does not use any ranking information. Figure 4 also shows that bar charts are suited to profiling detailed class characteristics. If necessary, p-value comparisons and error bars can further be incorporated, as shown in Figure 2.

LCA visualization uses several types of graphs. Statistical packages may play a role here. For instance, the default visual output from Mplus and Latent GOLD for LCA is a line graph. It is not uncommon for researchers to publish this figure directly in their articles. Apart from the program preference, space parsimony may be a reason. Line graphs can save a considerable amount of space as subgroups can be illustrated by simply overlapping lines within the same space. This feature is especially useful when researchers conduct LCA separately for different subsamples. For instance, a set of health behaviors was examined by gender and a combined figure with two line graphs efficiently illustrates the heterogeneity in both boys and girls in tandem (Davey & Zhao, in press; Fleary, 2017). Conversely, some

within-subgroup characteristics, such as ranking, that can be incorporated into bar charts are not likely to be included in line graphs. Based on the bar chart family, several variations can be considered. For example, stacked bar charts could save space, as in line graphs, and box and violin plots (see Figure 3) could include further details, such as the median and data shape in each subgroup.

Issues Concerning the X-axis and Y-axis

Regardless of the choice of graph type, estimated means on the Y-axis and indicator names on the X-axis are essential elements of an LCA figure. These elements should be presented clearly so that readers can understand the meaning of the indicator scores (e.g., percentage or likelihood). A common pitfall in LCA figures is the use of abbreviations. As space is limited in the figures, the use of abbreviations under the X-axis is understandable. However, necessary figure captions explaining the abbreviations are needed as the figure is a standalone part of the article (see Figure 5).

Which LCA indicators should be included is a theoretical question. For interdisciplinary studies, these indicators can be ontologically different. For instance, the inclusion of biomarkers and genetics in conventional nursing datasets

Figure 2 ■ Displaying Latent Trajectories in both a Bar Chart and a Line Graph

(a)

(b)
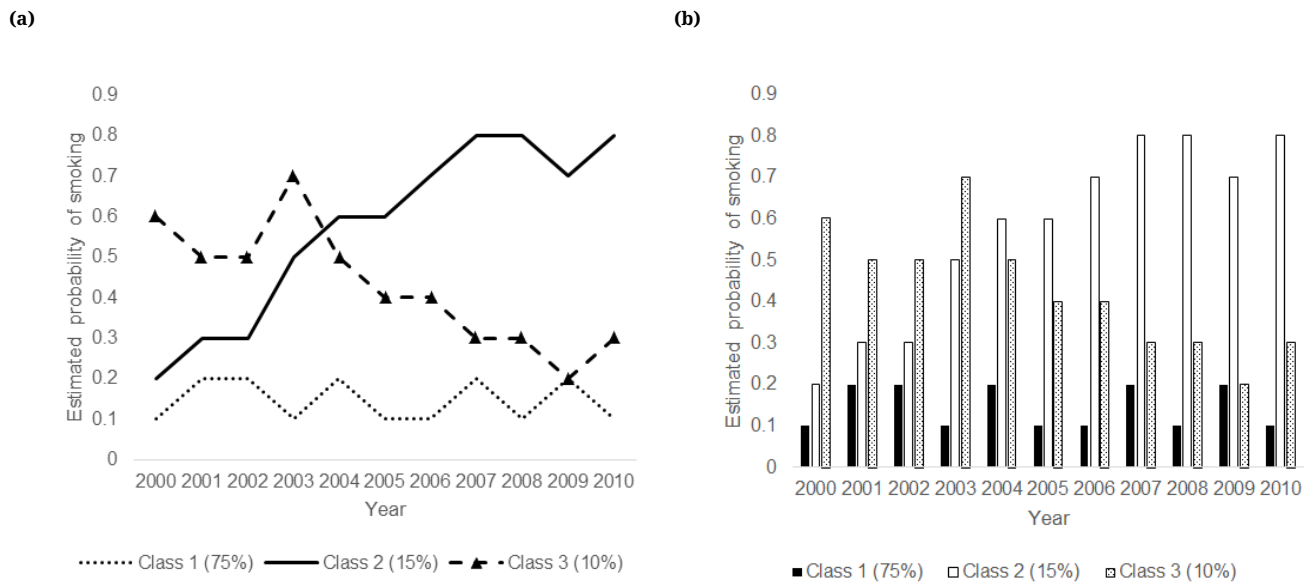
Note. In a hypothetical longitudinal study ($N = 9800$), three trajectories of smoking behavior were identified in the sample. When several dashed lines are used in a graph, it can be useful to add markers (e.g., ●, ■, and ▲) on the line. All the figures produced in this article use the black/white mode because journals tend to charge an extra fee for color printing. When using a black/white mode, subtle textures rather than shading are better [as in plate (b)] because shading can be undistinguishable in print.

has been recommended to examine the underlying clusters (Conley, 2017). Using a diverse combination of indicators facilitates divergent thinking, but it may lead to difficulty in understanding the scores on the Y-axis. If the LCA figure reports a set of variables using similar scales, such as percentages, the interpretation would be straightforward and the scores would be somewhat comparable. However, researchers sometimes face indicators using scales that differ in either ranges or intervals. Tricky cases like this often occur in lifestyle medicine research in which researchers are dealing with multiple forms of scales. For example, an LCA including cigarette use quantity, alcohol use amount, and perceived stress would have a Y-axis that is used to quantify three qualitatively different things for each indicator (e.g., number of cigarettes used, liters of alcohol consumed, and total score on a stress scale). Researchers have obviously noticed this issue and used transformations such as the z-score. As a perennial issue in applied statistics, researchers should use transformed variables with greater discretion. Take the z-score for example. While the use of the z-score has been suggested for comparisons of the relative standings of variables (Wang & Chen, 2012), z-scores do not translate information well because (1) the original scales, especially those with cutoff values that no longer exist (e.g., Figure 5), and (2) the negative numbers produced in z-score transformation may give a wrong impression to

uninitiated readers (Soloman & Sawilowsky, 2009). For example, a population-based survey on cigarette use quantity is likely to be positively skewed; thus, nonsmokers and nonfrequent smokers will obtain a negative z-score, which will seem like the "worse" cases in smoking. As pointed out by Horst (1931), when we compare variables with different types of skewness, z-score transformation is likely to give weights unevenly. While other transformations, such as rank-based normalization (Soloman & Sawilowsky, 2009), serve as alternative methods, more studies are needed to clarify the impact of transformed data on class enumeration in LCA.

While the optimal way of including qualitatively different LCA indicators remains an open question, it does not mean that Y-axis values should be totally overlooked. The heights in a bar chart, for example, show the estimated means across subgroups visually. To utilize the Y-axis information further, researchers could even consider providing a cutoff score, say, from the national norm or a clinical criterion. Although these concepts are based on variables, they help readers to identify the vulnerable or at-risk subgroups quickly. Figure 5, for example, illustrates three clusters based on several health-related indicators. A critical guideline for insomnia severity has further been included. Compared with other subgroups, the "Risk" subgroup clearly had an elevated level of insomnia, along with

Figure 3 ■ Bar Chart and Violin Plot Showing Three Clusters with Standard Error Bars and Inter-cluster Comparisons

(a)

(b)
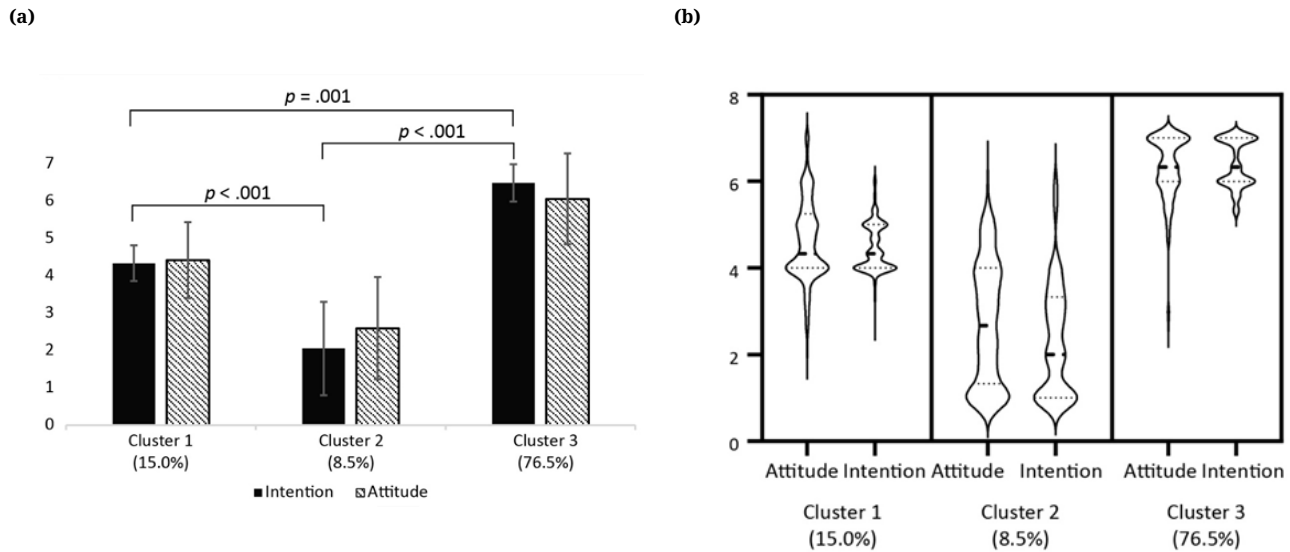
Note. In a hypothetical survey ($N = 1230$) of public perceptions about receiving a COVID-19 vaccine, three clusters were found and illustrated. Both intention and attitude questions were assessed using a 7-point Likert scale (disagree [1] to agree [7]). Standard error bars are included in the bar chart. Intention was compared between clusters using independent t-tests, the exact p-values of which are displayed in the figure. The Y-axis title is not displayed here because the figure notes explained the scale. Alternatively, a Y-axis title such as "Value" or "Degree of Agreement" could be added. Plate (b) demonstrates a violin plot produced with GraphPad Prism 9.5.1. Compared with plate (a), the violin plot provides more information of data distribution in each cluster. For instance, Cluster 2 members had lower mean scores on both indicators, but the variability seems to be larger as their 'violins' look longer.

other issues.

LCA figures share many common "visual language" terms with conventional graphs. For example, when all the bars are tall, one can consider using scale breaks to save the figure scale. Font and color design are also important but often ignored issues in figure illustration. Conventionally, texts in figures should use a sans serif font (e.g., Arial) with a type size between 8 and 14 points. If subgroups are shown in different colors, one should also think about the output in print works—most journals request a fee for color pages. To avoid color prints, subgroups can be presented with patterns, such as grids. Most journals have a figure requirement document in their authors' guidelines. The LCA figure should be tailored to a specific journal before submission.

Subgroup Labeling

Subgroups often tell interesting stories based on the indicators. In lifestyle medicine, for example, a subgroup with high consumption of tobacco and alcohol and low physical activities portrays a risky group. We tend to use a loosely defined construct to describe a prototype as if it means some distinctive behavioral manners (Gibbons &

Gerrard, 1997). While these loose labels are useful in assisting readers to understand the LCA findings, it is sometimes difficult to find a suitable phrase for a subgroup. In an LCA study examining smoking, alcohol use, eating, and other lifestyle variables, Laska et al. (2009) directly used neutral labels, such as "Class 1," along with descriptions of each subgroup in texts. In contrast, specific classification phrases have been suggested when describing the patterns of some scales. For example, Kongsted et al. (2016) tabulated information on how to describe pain trajectories based on pain intensity and variability as an over-time changing pattern. Figure 5 uses "Reference," "Emergence," and "Risk" to label subgroups according to their levels of risk. When deciding which labels to use, one should consider whether they encapsulate the general characteristics of the indicators collectively.

Other Clustering Visualization Approaches

Most LCA figures are bar charts and line graphs, which are the focus of this article. However, there are alternative LCA figures with additional information. For example, patients with chronic pain were classified in a four-dimensional profile in the study by Rovner et al. (2019). In a review
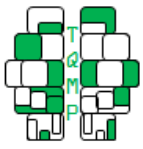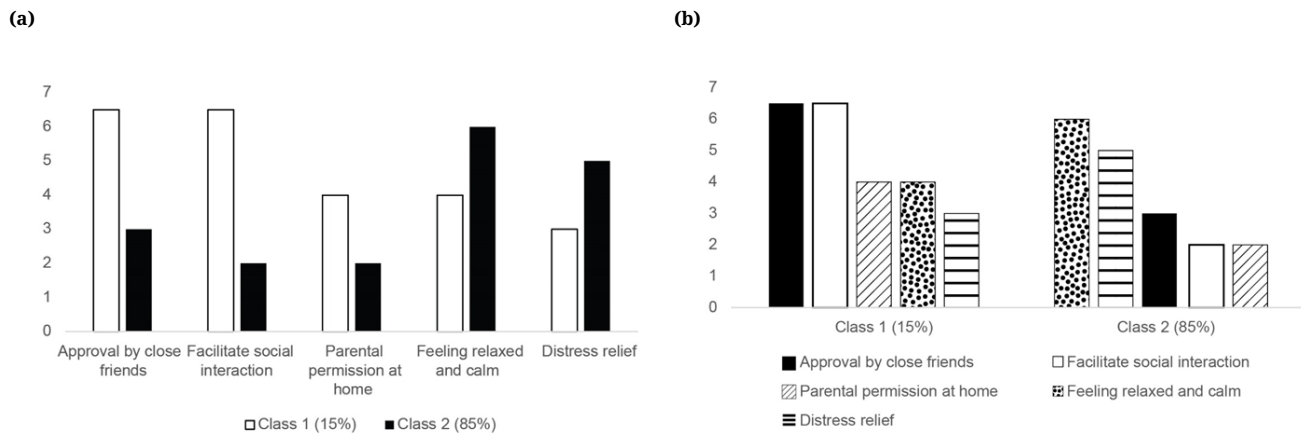
Figure 4 ∎ Bar Charts Illustrating the Estimated Means in Two Subgroups

(a)

(b)

Note. In a hypothetical survey of adolescent smokers ($N = 803$), participants were asked to rate their reasons for smoking (disagree [1] to agree [7]). Two latent classes were found in the hypothetical data. Although both bar charts above summarize the key information, plate (b) ranks the reasons for each latent class.

of cluster analyses used in family psychology (Henry et al., 2005), the radar plots also visually compared 16 variables between two family clusters. This can be a useful visualization tool when the indicator number is large. Magidson and Vermunt (2001) showed plots considering latent classes and factors at the same time, although this application requires readers to have more advanced knowledge about latent class analysis.

Discussion

Although LCA figures only involve estimated means of each indicator in subgroups, the present article concludes that a few issues are worth noting (see Table 1 at the end for a summary). The major choice seems to be the graph type—a bar chart or a line graph. There are no certain preferences for this choice; however, guidelines for considerations are included in Table 1 under this point. Both graph types have strengths and weaknesses. Researchers should make decisions based on their specific cases. Apart from these considerations, researchers should be able to generate figures using computer packages. Microsoft Excel can satisfy most demands. However, GraphPad Prism and Adobe Illustrator could be considered to produce more advanced figures.

Authors' note

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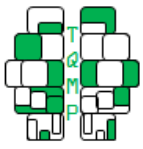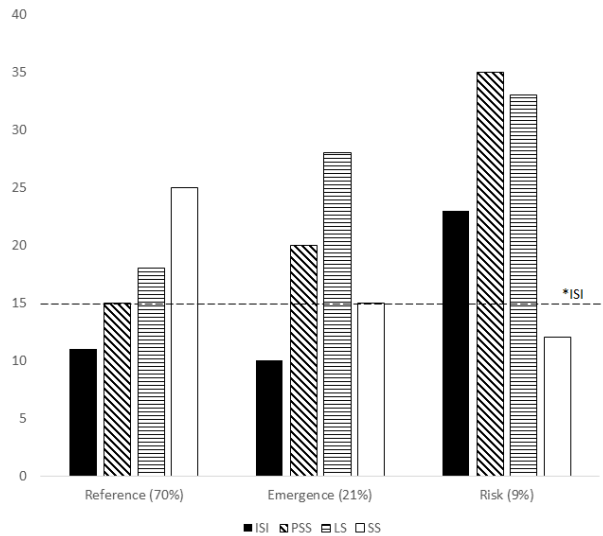
Figure 5 ■ Bar Chart Showing Three Latent Classes with the Critical Guideline of One Indicator

Note. $N = 3490$. ISI = insomnia severity index (range: 0–28). PSS = Perceived stress scale (0–40). LS = loneliness scale (0–40). SS = social support (0–40). * ISI: scores ≥ 15 indicate a clinical insomnia level.

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Table 1 ■ Checklist of Effective Elements of LCA Figures along with Suggestions

Mark	Item
☐	Is an LCA figure needed? Does it add value to the textual information? • Suitable graphic illustrations usually add approachability to the LCA findings. • Even with many indicators, certain types of graphs (e.g., radar plots) could work.
☐	Use a consistent font (preferably a sans serif font, e.g., Arial) with a type size between 8 and 14 points in the figure.
☐	Make sure that the figure is referred in the text (e.g., "Figure 1").
☐	What type of figure? The main choice is between a line graph and a bar chart. • A bar chart takes more space than a line graph, especially one with many indicators. • A bar chart could portray subgroup details such as within-subgroup ranks of indicators. • Longitudinal subgroups (i.e., trajectories) are more intuitive in line graphs. • When LCA is undertaken in subsamples (e.g., men or women), a line graph can give a quick visual comparison in terms of the number of subgroups and patterns across subsamples.
☐	What patterns can be used to distinguish subgroups? Colored or black-and-white patterns? • Black-and-white patterns with subtle textures are highly recommended. • Shading and color should be avoided.
☐	The X-axis shows the indicator names. If abbreviations are used, figure captions should explain them.
☐	The Y-axis shows the meaning of numbers (e.g., percentage or likelihood). If original scores are used, figure captions should note the range and meaning of the scores in each indicator to help readers interpret them.
☐	Indicate subgroup labels and sizes. For example, "Class 1 (14%)."
☐	Auxiliary visual functions to consider: • Ranks of indicators in each subgroup. • Error bars or ranges. • A line indicating a clinically critical threshold. • A scale break for large values.
☐	Use high-quality figures. Preferably, use vector graphs such as *.AI or *.EPS files as per the target journal's guidelines.

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