ARTICLE

Statistical methods for developing index measures of compassion

Allen W. Hightower · David G. Addiss

Abstract: Compassion is a complex, multi-dimensional concept. As a result, measuring compassion is a complex task. The measurements can be subjective, varying by person and context. Often, the questions used to create measures of compassion are indirect or incomplete due to their multi-dimensional aspects. Quantifying compassion utilizes statistical tools not commonly used in the field of epidemiology.

This paper reviews two families of statistical methods (primarily Principal Components Analysis and Factor Analysis) that can be used to meet these challenges. The review will cover the central concepts of each method and reference sources with data, annotated output, and code using several popular products (R, SPSS, STATA, SAS). Several currently used compassion indices are discussed, using a simple conceptual framework designed to illustrate typical challenges in the process of index development. The framework is composed of three components: the caregiver, the environment, and the recipient, with the environment broadly defined to include management policies, the type of health care facility, and other factors external to the caregiver and patient.

Summary discussions include the challenges associated with these methods and those associated with integrating results from these analyses into the statistical and mathematical modeling processes.

Keywords: Compassion Index, factor analysis, principal components analysis, well-being

1. Introduction

Compassion is a complex, multi-dimensional concept. This is well-illustrated by reviewing attempts by researchers to define the concept over the years (1). Some scholars attempt to define vital components of compassion, for example: awareness (of suffering), empathy, and commitment to alleviation (1-4). The upshot is that compassion is indeed complex, so measuring compassion is also a complex task. The measurements can be subjective, varying by person and context. They also often are incomplete in that they only measure a subset of many elements of compassion, such as motivation or behavior.

Quantifying compassion utilizes statistical tools not commonly used in the field of epidemiology. In general, compassion is assessed by self-report of the ‘compassion-giver’ (1st-person) or the compassion-recipient (2nd-person) using multi-question indices that examine various dimensions or components of compassion. The composite index ‘score’ is interpreted as a quantitative measure of compassion. Mascaro et al. cover the issues associated with perspective in depth (4).

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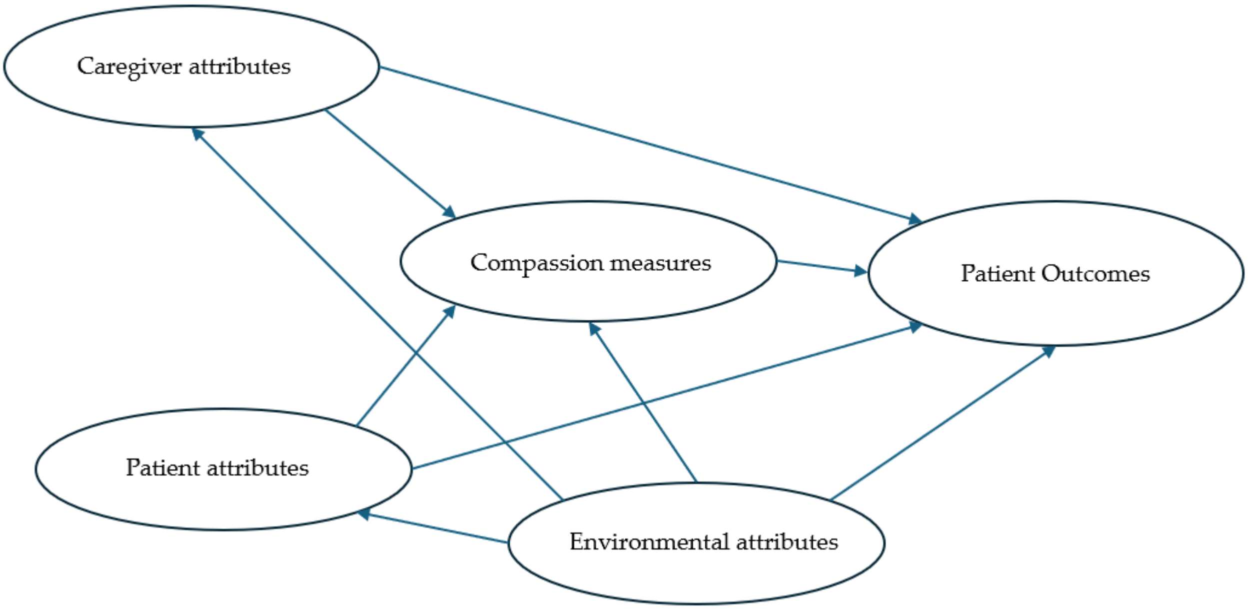
For simplicity, consider the challenge of measuring compassion in a medical caregiving setting. Attributes of the caregiver, the environment in which care is given (including not only the facility or climate, but also the social and organizational environment), and the attributes and experience of the care-recipient (i.e., patient). A simple framework (Figure 1) is presented, composed of the above three components, to illustrate potential complexities in this process: the factors may affect each other (i.e., confound) and may modify the relationship between compassionate care (as measured by a compassion index) and patient outcome. For this paper, a compassion index can be considered as either an outcome (for studies to create this index) or an explanatory variable (e.g., for studies of patient outcomes). Patient attributes and environmental factors could both be confounders or effect modifiers of a compassion index or of patient interventions. This simple conceptual framework has complexities that illustrate the utility of some statistical variable reduction and variable creation procedures and demonstrates the complexities of creating an index.

Figure 1. Conceptual framework used to assess compassion indices



Each arrow in Figure 1 will have data challenges in common with the other arrows. There could be many attributes or sub-components within each component of the framework. For example, multiple personal, interpersonal, environmental, historical, and systemic factors have been associated with caregivers' capacity for compassion. For many of these factors, separate indices or assessment tools have been developed (e.g., for empathy or personality). Rather than include all the measures for each component in a model, Principal Components Analysis (PCA) can be employed to summarize a group of related observed variables into a single, combined variable to simplify analyses, followed by an evaluation of how effectively this new variable accomplishes this task.

An alternative statistical approach to understanding compassion – and compassionate caregiving – is best captured as a latent or unmeasured variable that shows itself through its impact on the correlation structures of measured variables. While this may sound impossible, Factor Analysis (FA) does precisely that using methods that are both intuitively reasonable and statistically sound.

There have been considerable efforts to devise compassion indices for use in a variety of environments employing different types of caregivers and patients (5-12). While there are several compassion indices that have been developed and validated using appropriate methods, there still may be novel environments, caregivers, or patient types that require development of new indices.

Integration of PCA and FA will be critical to summarizing the many attributes related to compassion and creating an index that incorporates the vast array of measured and unmeasured attributes in a statistically efficient manner.

1.1 Indices and variable reduction in studies of compassion

How should we make a compassion index? For example, how do we incorporate 25 different measures of personal or environmental characteristics relevant for compassionate care into as few summary variables as possible for use in further models? Consider that one or more questions can be asked to address each of the many aspects of patient care. For example, detailed and relevant information on the type of caregiver (nurse, physician, etc.), circumstances of the patient (ER visit, short-term or long-term care), and multiple caregiver-patient interactions could challenge a single assessment tool. Also, consider that compassion is not a simple measure of any one of these factors. Consider further that there are external factors, such as attributes of the buildings, management policies, or culture where the care is being given, that might impact the ability of the staff to care for the patient compassionately. A more difficult challenge might be the patient's ability to appreciate the level of compassion being delivered by the staff. Are there structured approaches that we can use to address these issues, so we can have a simple toolkit that solves each of these problems consistently?

First, consider an ad hoc or a Delphi panel approach. In this case, experts assign multiplier coefficients to each variable under consideration, with the sum being the value of the index. This process has flaws that are easy to discern: coefficients chosen by experts may not utilize statistical processes with known desirable properties, inconsistency across changing environments, inability to deal with underlying correlational structures, and inconsistencies due to a changing panel of experts. Similar problems arise in defining how to use multiple observed variables to define a multifaceted concept such as compassion or intelligence**.** Fortunately, there are statistical methods (PCA and FA) that deal with these problems in a consistent and arguably optimal manner.

There have been considerable efforts to develop and validate standardized compassion indices using these methods, particularly in the last decade. These indices are available for a wide range of caregivers, health care facilities, leadership, nationalities, and patient types (5-12). We will review a few.

Additionally, there are several review articles and websites that evaluate these indices (13-16). Notably, Addiss et al. (14) discuss six themes or domains for classifying the compassion indices reviewed.

The SCQ (Sinclair Compassion Questionnaire) consists of 15 questions designed to assess patients' perceptions of compassion and health care providers. The SCQ has been adapted for use in different settings, such as long-term care, hospice, and outpatient clinics (7-9). It has been adapted for specific patient populations, such as those with short-term hospital stays. There is a five-question short form. In both the 15 and 5 question versions, the patient is asked about care over the past 7 days. There are versions of the questions adapted for other care environments (including institutional assessment), self-assessments, and other related topics, such as patient-based assessment of the importance of various aspects of compassionate care. This permits the use of SCQ in a variety of environments, caregiver roles, and types of patients, which addresses many of the concerns raised by our conceptual framework. Incorporation of these 5-15 questions should not be a significant challenge for most projects. The index in its various states has been developed and validated using methods we will discuss later.

One of the earlier and widely applicable tools, the Compassionate Care Assessment Tool (5), is a 28-item tool that uses a 4-point scale. It was developed for patients to rate elements representing compassionate care. Notably, the Compassionate Leadership Questionnaire includes an assessment of the Healthcare Institution.

The Bolton Compassion Strengths Indicators (BCSIs) go in a different direction. They are focused on conducting detailed assessments by caregiving nurses with the objective of self-assessment and empowerment (6). It is comprised of indices covering Self-Care, Character, Empathy, Connection, Interpersonal Skills, Engagement, Competence, and Communication. It was also developed and validated using robust psychometric tools.

In summary, there are several compassion index options for a wide variety of environments, caregivers, and patient types that have been developed and validated using proper tools. Consideration of the issues presented in Figure 1, along with review articles and toolboxes (2), should help an investigator sort out if there is an existing index that fits their needs, as well as the challenges of developing a new one.

2. Statistical methods used to summarize variables and develop indices

Researchers seeking to either develop a new index to measure compassion, validate an existing compassion measure, or summarize multiple observed variables into one or more linear combinations of the component variables to facilitate use in other statistical modeling efforts will use statistical tools arising from two families of statistical procedures. These methods have conceptual differences but share a common analytic engine. We will now review these methods while both comparing the similar analytic approaches and contrasting the conceptual differences.

2.1 Principal component analysis (PCA)

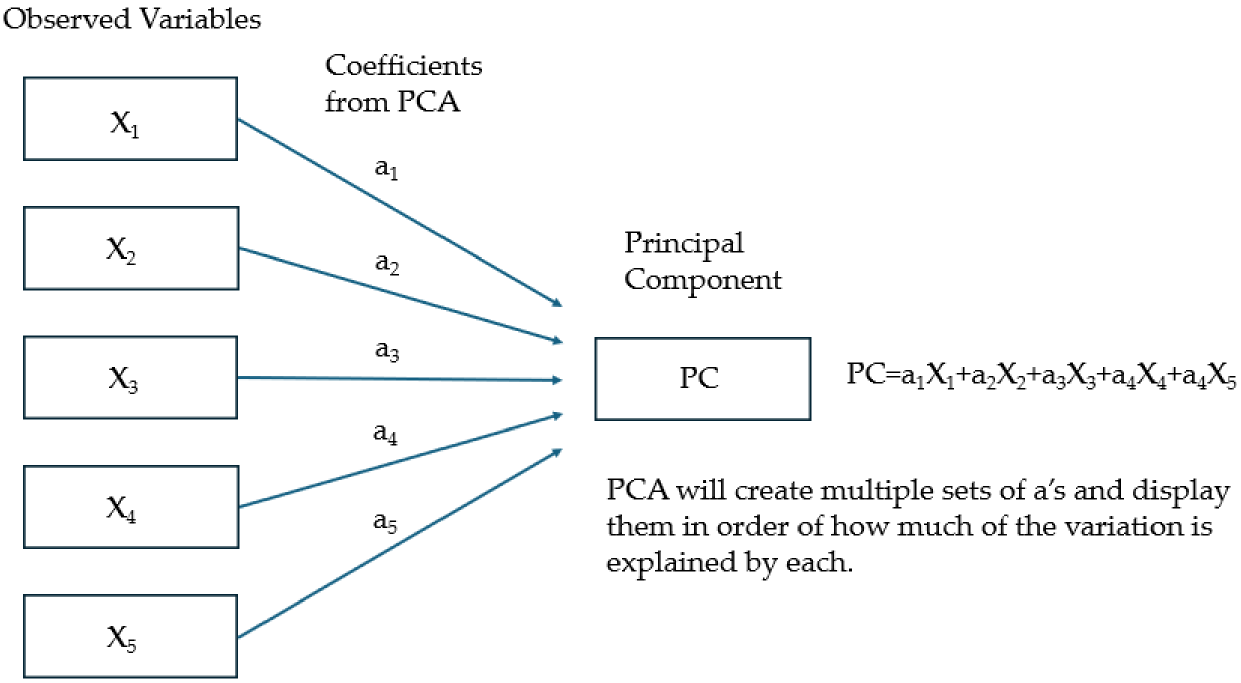
PCA is a method to summarize many, often correlated, observed into a few uncorrelated summary variables (often a single summary variable). PCA's approach to data reduction is to create one or more summary variables from a larger set of measured variables. These summary variables are each linear combinations (weighted sums) of the original variables multiplied by different sets of PCA-computed coefficients (Figure 2). These coefficients are computed using: (1) a matrix of covariances between each observed variable under consideration, (2) the vectors of coefficients (also called eigenvectors) that describe the relative importance of each observed variable in the weighted sum (the set of coefficients to be used in the linear combination or principal component), and (3) the amount of overall variation explained by each resulting principal component (the eigenvalue for that eigenvector). The overall variation explained by the weighted sum is simply the sum of the variances of all our measured variables prior to any transformation created by PCA (15, 16). In our case, we might wish to combine different questions about compassion or other topics into a single variable to be used in further models.

The linear combinations are presented in sorted order of the magnitude of the eigenvalues (i.e., the ones that explain the most are shown first). The ratio of the eigenvalue to the total variation is the proportion of overall variation explained by the weighted sum, which is a good way to describe how well a particular linear combination variable captures the larger set of observed variables. The linear combination that has the largest eigenvalue (i.e., explains more of the variation than any other linear combination) is known as the first principal component. Notice that other sets of coefficients for our measured variables exist, but the amount of variation that they explain will be less than the set at the top of our sorted list. A researcher may feel that the first principal component does not explain the measured variables sufficiently well. In that case, the second principal component could be used in addition to the first. The total amount of variation explained by the first two principal components together is simply the sum of their eigenvalues since eigenvectors have the nice property of being orthogonal or statistically uncorrelated (17). No matter how many principal components we decide to use, it is straightforward to assess what percentage of the overall variation is explained.

Figure 2 shows how PCA combines 5 observed variables into a single principal component. One can see from the direction of the arrows that the X variables contribute to the component variable. The coefficients allow this linear combination to emphasize some X variables more than others.

The point of the PCA is to do this using a statistically valid procedure that produces a logically optimal result (i.e., a weighted sum of the original variables that explains the most variation among the possible combinations considered). After we perform PCA on the set of observed variables, we will know how much of the overall variation each component explains, indicating the effectiveness of the best-performing linear combination, and of course, the coefficients in the linear combination to form each component.

Figure 2. *Principal component analysis concepts*



2.2 Factor analysis (FA)

Suppose one does not have indices to measure compassion directly, or suspects that current measures will not adequately capture key elements of compassion in particular settings. Yet, at the same time, one has identified a set of measured variables that, as a group, should measure some components of this concept. The goal would be to identify the underlying one or more forces that explain correlations between all these observed variables. FA examines the nature of these unobserved forces that result in the correlation matrix between the variables that we observe. While this sounds impossible at first glance, finding the effect of unmeasured factors by their influence on a group of variables is a plausible statistical task. The method we use to do this is (exploratory) factor analysis, and these underlying forces are sometimes referred to as "latent constructs" or "factors". While this sounds different from PCA, FA uses a similar analytic engine (17,18).

However, compared to PCA, FA approaches data reduction in a fundamentally different way. It estimates the effect of a latent or unmeasured variable on the set of observed variables. This latent variable cannot be directly measured with a single variable. Instead, it is seen through the relationships it causes in a set of observed variables.

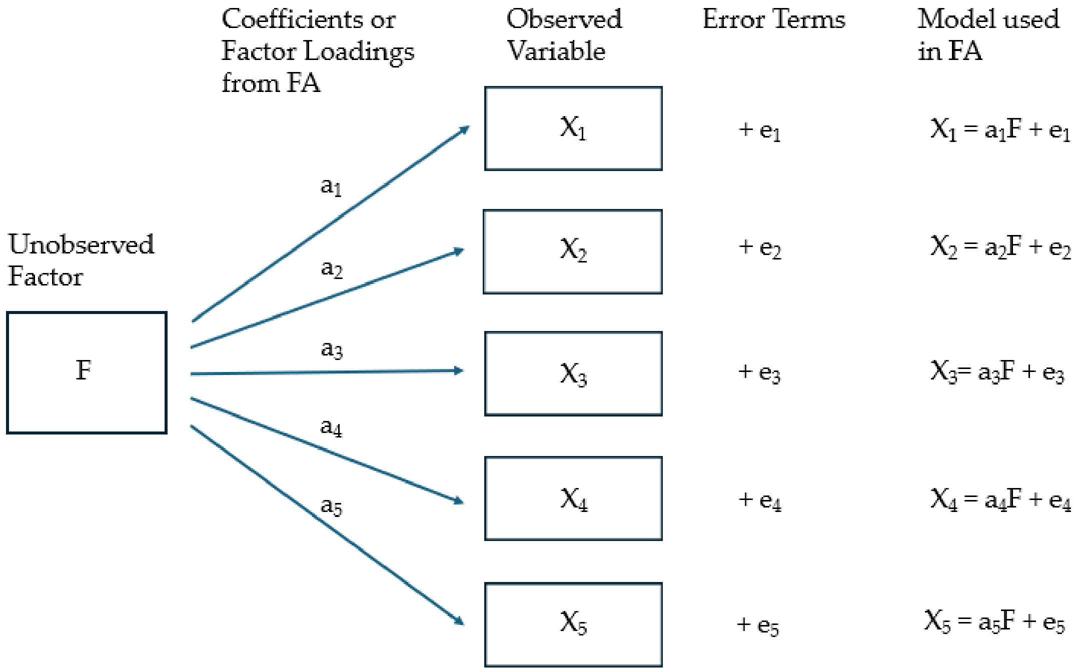
We may not be able to measure compassion directly. However, we can measure whether compassion is high or low with a set of observed variables. For example, respondents with higher levels of compassion would be more likely to agree with the individual questions: "It is important to explain the reasons for a treatment plan" and "Staff at my hospital are helpful in the admission process" than less compassionate individuals. This idea can be extended to the patterns of responses to a larger group of observed variables that can reflect the hidden effect of compassion. Physicians with high compassion levels will give similar responses to these observed variables *because of* their high compassion levels. Likewise, physicians with low compassion levels will give similar low responses to these observed variables.

The measurement model for a simple, one-factor model looks like the diagram in Figure 3 (below). In this situation, F, the latent Factor, is *causing* the responses on the five measured X variables. So, the arrows go in the opposite direction from PCA. Just like in PCA, the relationships between F and each X are weighted by the coefficients (the a_i's, called factor loadings in this case), with the factor analysis process figuring out the optimal weights.

In this model, we have a set of error terms, designated by the e_i's. This is the deviation in each X that is unexplained by the Factor.

As seen in Figure 3, one can interpret this model as a set of regression equations.

Figure 3. *Factor analysis concepts*



FA will create the a's and tell what percentage of the variation is explained by the factor. The procedure also will offer additional sets of coefficients and indicates how much additional variation is explained by including additional solutions, typically in a scree plot.

The F is the unmeasured Factor and is characterized by the observed correlations between the measured variables (the x_i's).

Above, the coefficients a_i's are known as "factor loadings". They are the correlations between the observed variables and the underlying Factor. Computer output typically contains the factor loadings for the observed variables and the eigenvalues for the first 10 or so Factors, sorted by the amount of shared or common variation explained. The common variation is a measure of the amount of variance that is shared among a set of observed variables. This common variation among a particular set of observed variables contrasts with the reduction in overall or total variance that is considered in PCA (17). Highly correlated observed variables will share much variance, since the knowledge of the value of one variable is predictive of the value of the other variable with little error.

An observed variable's total variance is made up of two parts: common variance (explained by the factors) and unique variance (specific to the variable plus any random error). Communality is the value of the common variance for an observed variable. It will range between 0 and 1. FA software often requires users to specify prior communality estimates. The SMC (squared multiple correlation of each variable with the others) option is a common default choice. Loadings are used to choose or eliminate variables in a factor. The magnitude of the loading signals whether the associated measured variable is a necessary part of the Factor, so a loading near zero means the associated variable is playing a minor role in the Factor (17-19).

One can assess if there is one Factor (F) that explains enough of the shared variation between the variables that are measured. One can compute the shared variance that is explained by the solution using one or more factors by simply adding their eigenvalues. This can be graphically displayed in a scree plot, which shows the amount of variance explained vs. Factor number being considered. Recall that factor numbers are presented in the order of the amount of variation explained. Typically, a significant drop in the eigenvalue followed by a levelling off as the factor number increases is a sign of when to stop adding factors (also called the elbow) (22-25). The stopping point for adding factors (or components for PCA) would be at the eigenvalue preceding the significant drop.

Both Factor Analysis and Principal Component Analysis use similar mathematical methods to obtain and evaluate solutions. However, the methods solve different problems. In Factor Analysis, one is trying to quantify unmeasured forces that explain the observed correlations between the observed variables. In PCA, the goal is to summarize many observed variables into one or two summary variables, often on a known topic. In both cases, the result is summarizing the data and reducing the number of variables. Both approaches assess how well factors or principal components explain the variation or correlation in the measured variables, although the measure of variation is different in FA than PCA. It is possible to assess whether it is realistic to use only a single factor or the first principal component. Both FA and PCA are recommended to be only used in situations where there are a substantial number of observations, typically 150 or more. However, there is no real agreement on a magic sample size number.

2.3 Factor rotation

Rotations aim to make factors more interpretable by maximizing the variance of factor loadings, resulting in each Factor having a smaller number of observed variables with meaningful loadings. Factor rotations are typically specified as a part of the FA process. FA's can be run several times using different rotations to assess their impact and determine which rotation results in the most straightforward results.

Rotations can be orthogonal, like Varimax rotation, or oblique. With oblique factor rotations, the new factors are correlated; with orthogonal rotation, the factors are *not* correlated. Of the two types, orthogonal rotations have the "…greatest scientific utility, consistency, and meaning" (19). Varimax, along with the quartimax, are two of the most common types of orthogonal rotations (20). The key question is which type of rotation (or no rotation) results in factors that are easier to interpret or use a smaller number of observed variables.

2.4 Varimax rotation

Varimax rotation (also called Kaiser-Varimax rotation) maximizes the sum of the variance of the squared loadings, where 'loadings' means correlations between observed variables and factors (21). This rotation usually results in high factor loadings for a smaller number of observed variables and low factor loadings for the rest. All remaining components have eigenvalues of more than one (22). In simple terms, the result is that a small number of important observed variables are highlighted, which makes it easier to interpret results.

Promax oblique rotation is often used when either the researcher suspects that factors should be correlated, or when the factors produced are complex and the researcher is attempting to find simpler factors. It can offer a more realistic representation of the data. The first step of a promax rotation is to perform a varimax rotation. Then, power transformations are used that produce correlated factors (23). The names usually indicate which power transformation is used. For example, the quartimax rotation maximizes the variance of squared factor loadings across the observed variables. The process of squaring the coefficients makes them closer to zero or 1, which simplifies the number of observed variables materially contributing to the Factor.

2.5 Exploratory vs confirmatory factor analysis

So far, we have discussed exploring data using FA to discover hidden relationships. This process is also known as Exploratory Factor Analysis (EFA), since we have no preconceived notion about the specifics of these latent relationships. Suppose we have performed an EFA, but want to see if similar relationships exist in other datasets? We may want to validate an index by using another data set collected under similar conditions. In this case, we could use CFA or Confirmatory Factor Analysis. EFA and CFA are not the same. CFA is not just using new data to see if we get similar results to our EFA results. In CFA, we fit the hypothesized model and assess its goodness of fit. We have a clear hypothesis to test in CFA vs exploring for latent factors and their meanings in EFA (25). In CFA, we specify a previously known model or a hypothesized structure that we wish to confirm. CFA then utilizes measures of internal reliability such as Cronbach's alpha, goodness of fit, utilizing a variety of measures of mean square error (25).

2.6 Using the FA results to create an index

Once the factor structure is determined, one can calculate factor scores for each observation in the dataset. For each respondent, multiply the value of a variable by its factor loading and sum them for all observed variables. These are called Factor Scores. These scores can show what the role of the underlying factors is for the respondent. The Factor scores are computed either by the regression or Bartlett's method (26). Factor-based scores are calculated by summing or averaging the items for a particular factor. The Factor-based scores approach is more straightforward and often easier to understand (27). One can rescale Factor scores to specific ranges (e.g., 0-100, 0-1, or z-scores).

In summary, creation of an index using FA will involve selecting the observed variables to be used, performing a FA (either EFA or CFA), deciding if a rotation is appropriate, removing observed variables from the FA with small or near zero loadings, if desired, and using either Factor Scores or Factor-based Scores to form an index that can be scaled as desired.

Table 1 compares PCA and FA with respect to methodologies, inputs, outcomes, other topics discussed here.

Table 1. *Comparison of PCA and FA*

	PCA	FA
Typical Input Data	A set of related observed variables to be summarized.	A set of observed variables affected by a hidden or latent variable
Outcome	A new variable that is a linear combination of the original set of variables.	A new variable (factor) that explains the underlying correlation structure in the observed variables.
Analytic goal	Choosing the best sets of coefficients for a linear combination of the observed variables in a statistically justifiable manner.	Choosing the best sets of regression coefficients for a series of models predicting the observed variables based on the hidden variable multiplied by coefficients.
Computational Process	Matrix algebra to find eigenvalues	Matrix algebra to find eigenvalues
Graphical Aid for assessment	Scree plot of eigenvalues vs Component number	Scree plot of eigenvalues vs Factor number
Statistic used to assess optimal outcome of process	Percent of variation in observed variables explained by summary combination variable.	The proportion of the shared variation between the measured variables that is explained by the hidden variable.
Sample size requirements	Substantial (at least 30 observations per observed variable)	Substantial (at least 30 observations per observed variable)
Limitations	Only applies to specific environment studied (i.e., type of respondent, environment, point in time)	Only applies to specific environment studied (i.e., type of respondent, environment, point in time)

3. Discussion

Compassion indices have been developed and validated for a wide range of caregivers and environments (e.g., type of health care facilities, international settings). While the majority focus on caregivers, there are indices for evaluating the patient's perspective or management's role in compassionate care. Researchers interested in these areas are well advised to consider literature reviews or web tools for listings and evaluations of previous work in this area.

A conceptual framework (Figure 1) can be used for assessing the role of many possible environments and types of caregivers involved in assessing compassionate care, as well as identifying possible pitfalls. In work to date, the problems of confounding and effect modification have been addressed by using different assessment tools for differing types of caregivers or environments. There are a few tools, notably the SCQ, that have been developed and validated in a wide variety of caregivers and environments. However, a researcher will always face trade-offs in using a standardized index versus one tailored to their circumstance. One of these trade-offs is that even when a standardized set of questions are used for creating a compassion index, the observed factor loadings or PCA component coefficients will vary across studies due to both differences in the populations being assessed and random differences in responses. An interesting attempt to address this issue is described in the Global Data Lab's efforts to develop an International Wealth Index (28), essentially creating the index across 97 surveys. Repeating this effort for certain compassion index measures is worth considering. In addition to attempting to create International Compassion Indices, cataloguing the different locations, patient populations, and even coefficients or factor loadings along with the percentage of overall variation explained would appear to be an effort that would be useful to others conducting work in this area.

One aspect of the conceptual framework in Figure 1 is rarely addressed: patient-centric attributes that diminish their ability to perceive or appreciate compassionate care. Reduced capacity to 'receive' compassion may be closely related to 'fears of compassion' described by Gilbert and colleagues (29). There are few studies examining patient attributes associated with capacity for perceiving and accepting compassion, or the impact of this capacity on systems optimized to deliver compassionate care (30). Similarly, relatively few studies consider the impact of the work environment on a caregiver's ability to maintain levels of compassionate care (3, 31).

Whether the researcher decides to use a previously developed compassion index or not, they are still likely to face similar analytic challenges as those used in developing a compassion index. The need to reduce or summarize the number of observed variables to be used in further modeling is a common challenge. PCA is the tool to do this. We have reviewed the concepts and steps involved in using this method. One of the pluses of this approach is that one knows how well the principal components summarize the information in the observed variables they summarize.

Researchers wishing to use their data to characterize hidden factors or to use or develop a compassion index will likely use Factor analysis in either the EFA or CFA approach. It is important to understand that CFA is not simply using another data set to see if the factor loadings are similar. Goodness-of-fit assessments and hypothesis testing are a part of the CFA process.

But there is a lot more to developing a good index than properly using certain statistical methods. Index credibility is not just about explaining a lot of the shared variance. Researchers should realize that a latent variable is evaluated only in the context of the measured variables. Unasked questions could add critical additional information to a compassion index that is not already captured in the percent of the shared variation for a factor used in the index creation. Researchers should be aware that a latent variable that is labeled 'compassion" is not necessarily a complete measure of compassion.

Fortunately, there are substantial resources available to investigate existing work of compassion indices in both the scientific literature and the Task Force FACE Compassion Measures Toolbox website (2).

Additionally, there are online resources for assistance in performing PCA and FA (of both types). These resources typically have an overview of the methodology, data sets, annotated code used to perform the analyses, and annotated output. There are many resources available that have annotated programs written in SPSS, SAS, STATA, and R (17, 32-40). The UCLA resources (17, 32-35) provide a Rosetta-stone approach in which the same dataset and methods are analysed using different statistical tools (SAS, R, SPSS, and STATA).

We have presented two conceptually different but computationally related statistical methods for summarizing observed variables that could be employed either to reduce the number of variables used in further modeling efforts or to create a new, previously hidden variable. Both methods have been used to develop indices of compassion that have been validated for a variety of caregivers and patients in various environments. Going forward, the researcher has the choice of deciding whether to use an existing index in a known environment, validate an existing tool in a novel environment, or develop a new index if necessary.

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Author contribution statement

AH provided statistical information. DA provided context within the area of compassion research. Both authors made substantial contributions to writing the manuscript.

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