EmoteAI Technical Report®

Top Brands and Consumer Trends

WHITEPAPER

Psychology is trendy in market research these days.

There are a number of AI-powered psycholo gy-based platforms on the market. The question is, which one of those platforms are substantive vs just for show? Or, which one will provide you with insights that give you a real business advantage? In the following paper, we will review the psychometrics behind EmoteAI, highlighting its validity and reliability. Our hope is that by the end of this paper, you will be able to see:

How much scientific rigor was put into the construction of the platform EmoteAI

How trustworthy the results are

How to compare the rigor of our platform with other platforms on the market

EMOTEAI

BY WOO

In today's world, consumers have so many undifferentiated choices, so brands must connect with consumers more deeply than before. Brands that tap into a consumer's feelings, by identifying or empathizing with their consumers emotions are more likely to stand out. WOO helps brands develop brand empathy. In other words, WOO helps brands develop a deeper understanding of the emotions that drive consumers to act. Focusing on increasing brand empathy, enables brands to achieve greater clarity, achieve long-lasting consumer relationships, and ultimately increase long-term profitability.

EmoteAI is a new platform that uses **patent-pending systems** for AI-powered projective tests. This platform helps brands identify their brand empathy score (Ex-Score). In other words, how consumers perceive the brands ability to empathize with them and their values. The EmoteAI platform offers a true barometer of a consumer's relationship with the brand.

How do we do it? EmoteAI uses a unique combination of psychological science, data science, and machine learning algorithms to produce intelligent AI-powered projective test technology built on the following underlying conceptual principles:

- There exists an emotional relationship between a brand and a consumer
- Tapping into and enhancing this emotional relationship can impact a brands ability to form and sustain long-term profitability
- EmoteAI surveys consumers on their perception of the extent consumers feel an emotional connection to a specific brand and their competitors
- The EmoteAI platform offers brands solutions and detailed suggestions to enhance their emotional relationship with consumers

What can you learn? By using the EmoteAI platform, a brand can get access to insights about their:

1. Brand empathy score or their Ex-Score
2. What the scores mean
3. Deep dive into their Ex-Score
4. Recommendations for changing a brand's Ex-Score
5. Simulations to showcase the impact of increasing their Ex-Score on relevant outcomes (e.g., consumer likelihood of repurchase).

Key Benefits of The EmoteAI Platform

Why use our platform? While there are a number of ways the EmoteAI platform is beneficial, there are three primary benefits of EmoteAI:

Automated Predictive AI. The EmoteAI platform automatically creates predictive algorithms unique to each brand. The predictive AI not only provides brands with their brand empathy score and recommends solutions for improvement, but it also predicts how increasing a brands Ex-Score will (1) increase consumer satisfaction, (2) increase number of products purchased, (3) increase the likelihood of consumers recommending the brand to their network, and (4) increase brand likability. The predictive AI grows better each time it is used.

Less Questions, More Insights. With the EmoteAI platform, brands answer less questions and get more insights. For years market researchers have been saying surveys in our industry are too long, leading to poor data quality from burnt out survey respondents. So at Inkblot Analytics, we wanted to create a solution that allows researchers to get the same amount of data by asking less questions.

Both Quantitative and Qualitative. EmoteAI studies both quantifiable data and emotional insight using a visual library to uncover secret sentiments that consumers harbor towards a brand. This enables brands to uncover consumers' deep-seated thoughts and feelings above and beyond a typical survey or interview. Concurrently, brands have access to quantitative data with a tangible brand empathy score (Ex-Score) through the platform. The combination of quantitative and qualitative insights offers a 360 visualization of their target audience.

How Does EmoteAI Work?

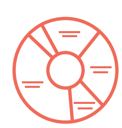
This paper is focusing specifically on the Ex-Score scale. Obtaining brand empathy scores involves a four step process:

The Testing Step

Taking the Ex-Score scale

The Scoring Step

Scoring responses to the projective test



The Profiling Step

Identifying which factor is predominant for the individual

The Predicting Step

Predicting outcomes and solutions for brands

Each one of these steps has a scientific process built into them. For the **testing step** (i.e., when the participant takes the Ex-Score scale), we want to make sure the data is good quality. So we use an algorithm that measures the extent to which a respondent is intentionally trying to deceive the test, not take it seriously, or enter in bad quality data. For the **scoring step** we use measures of inter-rater reliability. For the **profiling step**, we use classic psychometric measures of validity and reliability to know the traits we're measuring are trustworthy. For the **predicting step** we use the model's error (the difference from the predicted score and actual score) to know how accurate/precise the model's predictions are. Over the course of the rest of this paper, we'll go in depth on each of these aspects so that you can see just how science-based this tool is.

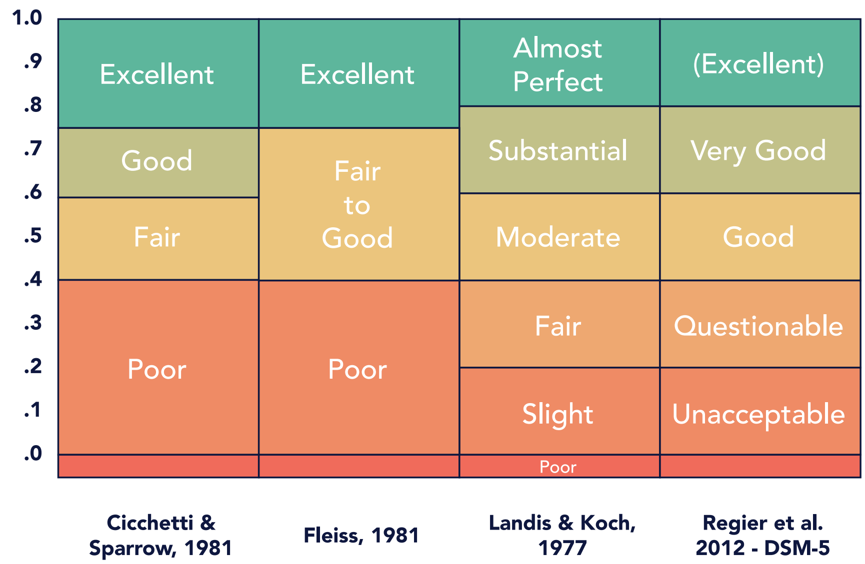
The Scoring Step: Measuring Inter-rater Reliability

Due to the high velocity of data we sometimes receive, we have multiple coders who apply a specific scoring scheme to the secret sentiments portion. However, as you may suspect, everyone has a slightly different way of interpreting ambiguous data. As a result, all coders are put through a training program for how to score the secret sentiments portion. Once the coders have sufficiently passed a scoring test, they are allowed to work on scoring project data. For any given project, we have 2 coders score the responses separately. No coder is able to see how any other coder has scored the responses, keeping all parties independent of possible scoring influences. However, to continually check that all coders are scoring the responses similarly, we calculate inter-rater reliability on all projects, and overall, on an ongoing basis.

Inter-rater reliability (IRR) is a statistic that measures the consistency of our coding methods. Basically, it's a check to see if our trained coders are applying the same codes to the same responses.

Historically, there are a few different approaches as to what is considered a "good" versus "bad" reliability score. You can see these approaches, and their references, in the accompanying chart. At Inkblot Analytics, we traditionally follow the inter-rater reliability approach outlined by Regier et al (2012), shooting for .80 reliability or above. This means that we always expect our coders to agree on a minimum of 80% of the scoring they do.

This section is an add-on service.



The Profiling Step: Psychometrics of Brand Empathy

Once the test data is collected, we are able to use our proprietary algorithms to help build brand empathy scores. First, however, we have to make sure that our prosperity scales accurately and consistently measures each aspect or construct of brand irresistibility. In other words, we have to make sure that our scales have strong psychometric properties. Without assessing the psychometric properties of constructs, we can't be certain if we are "tapping into" the construct we are interested in. For example, we may think we are "tapping into" the construct of adoration for a brand, but in reality we might be measuring the "general likability of the brand."

To measure brand empathy or the extent to which consumers feel an emotional connection to the brand, we created the Ex-Score Scale. The Ex-Score Scale measures three primary factors: Empathy, Expression, and Engagement. Together, the three E's create the Ex-Score.Each of these factors is further broken down into two facets: Identification and Emotion are the facets for Empathy, Impression and Empowerment are the facets for Expression, and Enthusiasm and Interest are the facets for Engagement.

In this section, we walk you through the scientific process of how we evaluated the psychometric properties of the Ex-Score Scale, using the Empathy factor as an example.

We determined what makes a consumers' emotional connection to a brand by measuring three E's: Empathy, Expression, and Engagement

For the Empathy construct:

Empathy Identification

A high score indicates that an individual feels that the brand understands how they feel and therefore feel an emotional connection to the respective brand.

Empathy Emotion

A high score indicates that the brand makes the individual feel good and therefore they feel an emotional connection to the respective brand.

We determine the extent to which individuals feel a brand is high on Empathy adding up scores on Empathy Identification and Empathy Emotion. We repeat this process for the remaining Ex-Score factors. Brands can use this information to target specific constructs within the three E's to improve how consumers relate and feel towards their brand.

Ex-Score Part 1: Scale Validity

For the Ex-Score Scale to work, we had to train and test how responses to the scale were related to scores on each of the constructs and if the scale had acceptable psychometric properties. The first psychometric property we looked at was construct validity.

Construct Validity

Validity corresponds to the extent to which the scale accurately measures reality. Construct validity is an assessment as to whether or not the measure we created is measuring what we want it to measure. For example, is our measure of Empathy truly assessing the extent to which a brand understands their consumers? Or is it measuring something else? To test construct validity, we look at four areas:

Structural Validity
Does the factor structure support that items are all measuring the same construct?

Convergent Validity
Does the construct, Empathy, relate to other constructs it should be theoretically related to?

Divergent Validity
Is the construct, Empathy, unrelated to constructs it shouldn't be related to?

Nomological Validity
Does the network of constructs around the construct, Empathy, show relationships that are expected?

Construct Validity: Structural Validity.

For the Empathy construct, we want to make sure that the items for Empathy Identification are measuring the extent to which a brand understands the consumer and items for Empathy Emotion are measuring the extent to which a brand makes the consumer feel positively, and all items together are measuring the Empathy construct. To do so, we assess structural validity by using both exploratory factor analysis and confirmatory factor analysis.

Exploratory Factor Analysis.

- Step 1: Correlation Check

  » To determine which items to include or exclude in factor analysis, we first examined the **bivariate correlations** to identify any items with small bivariate correlations (r <.30). Items with correlations below this threshold As you can see in the example below, the three items included in Empathy Identification all have correlations, on average, around .65 with each other. Similarly, all three items Empathy Emotion have correlations around .50 with each other. Together, the items have correlations above the threshold of .30. Therefore, all items for the Empathy construct were retained.

	IDEN_1	IDEN_2	IDEN_3	EMO_1	EMO_2	EMO_3
IDEN_1	1.00	0.68	0.71	0.53	0.57	0.58
IDEN_2	0.68	1.00	0.65	0.53	0.48	0.59
IDEN_3	0.71	0.65	1.00	0.54	0.47	0.57
EMO_1	0.53	0.53	0.54	1.00	0.68	0.66
EMO_2	0.57	0.48	0.47	0.68	1.00	0.66
EMO_3	0.58	0.59	0.57	0.66	0.66	1.00

  » Traditional bivariate correlations only provide a part of the picture, so we also examined **partial correlations.** Partial correlations refer to the correlation between two items after controlling for the effect of all other items. In other words, partial correlations are the correlations that are left over after the common variance is extracted. As a rule of thumb, we include items with a partial correlation <.70 in the analysis and exclude items that exceed this threshold. As you can see in the example below, the three items included in Empathy Identification all have partial correlations below .7 with each other. Similarly, all three items in Empathy Emotion have partial correlations below .7 with each other. Together, all items have partial correlations below .7 with each other. Therefore, all items for the Empathy construct were retained.

	IDEN_1	IDEN_2	IDEN_3	EMO_1	EMO_2	EMO_3
IDEN_1	1.00	0.32	0.42	-0.04	0.25	0.06
IDEN_2	0.32	1.00	0.24	0.09	-0.04	0.20
IDEN_3	0.42	0.24	1.00	0.17	-0.10	0.12
EMO_1	-0.04	0.09	0.17	1.00	0.42	0.25
EMO_2	0.25	-0.04	-0.10	0.42	1.00	0.31
EMO_3	0.06	0.20	0.12	0.25	0.31	1.00

  » We also look at the **anti-image correlation matrix**, which contains the negatives of the partial correlation coefficients. Consequently, these values are the magnitude of the variable that can't be regressed on, or predicted by, the other variables. If variables can't be regressed on, or predicted by, the other variables, then the variables are not likely related. If variables aren't related, then they will not likely load on the same factor. Consequently, large magnitudes indicate the possibility of a poor factor solution. However, as you can tell from the light colors in the corrogram heat map, majority correlations in the ant-image correlation matrix are close to 0. This means all items on both constructs are retained.

	IDEN_1	IDEN_2	IDEN_3	EMO_1	EMO_2	EMO_3
IDEN_1	1.00	-0.13	-0.17	0.02	-0.10	-0.02
IDEN_2	-0.13	1.00	-0.10	-0.04	0.02	-0.09
IDEN_3	-0.17	-0.10	1.00	-0.07	0.04	-0.05
EMO_1	0.02	-0.04	-0.07	1.00	-0.18	-0.11
EMO_2	-0.10	0.02	0.04	-0.18	1.00	-0.13
EMO_3	-0.02	-0.09	-0.05	-0.11	-0.13	1.00

- **Bartlet test of sphericity** compares the correlation matrix to the identity matrix, checking to see if there is any redundancy between the variables. High redundancy is indicative that the variables have common variance and therefore can be loaded on similar factors. If there is high redundancy, then the correlations in the correlation matrix should be higher in magnitude. Therefore, when it's compared to the identity matrix (where values are mainly 0), the two matrices will not be similar. If there is little redundancy, then the correlations in the correlation matrix should be close to zero. This means when it is compared to the identity matrix, the two matrices will be similar, indicating the possibility of a poor factor solution. In the case of the Empathy construct, the correlation matrix was significantly different from the identity matrix.

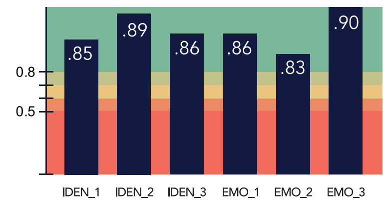
	IDEN_1	IDEN_2	IDEN_3	EMO_1	EMO_2	EMO_3
IDEN_1	1.00	0.68	0.71	0.53	0.57	0.58
IDEN_2	0.68	1.00	0.65	0.53	0.48	0.59
IDEN_3	0.71	0.65	1.00	0.54	0.47	0.57
EMO_1	0.53	0.53	0.54	1.00	0.68	0.66
EMO_2	0.57	0.48	0.47	0.68	1.00	0.66
EMO_3	0.58	0.59	0.57	0.66	0.66	1.00

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]
[1,]	1.00	0.00	0.00	0.00	0.00	0.00
[2,]	0.00	1.00	0.00	0.00	0.00	0.00
[3,]	0.00	0.00	1.00	0.00	0.00	0.00
[4,]	0.00	0.00	0.00	1.00	0.00	0.00
[5,]	0.00	0.00	0.00	0.00	1.00	0.00
[6,]	0.00	0.00	0.00	0.00	0.00	1.00

- Lastly, the **Kaiser-Meyer-Olkin Measure of sampling adequacy** measures the extent to which the variance of the items might be caused by an underlying factor. The higher proportion of variance caused by underlying factors, the better your factor solution might be. Consequently, the following is what we use to determine whether or not to continue with the factor analysis.

> .80	Meritorious
> .70	Middling
> .60	Mediocre
> .50	Miserable
< .49	Unacceptable

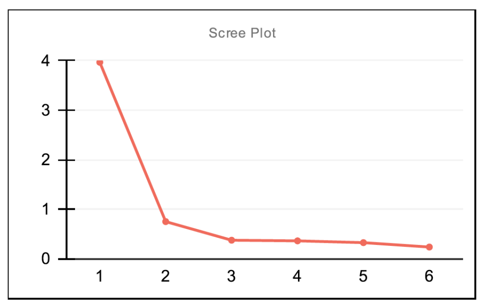
There is cause for concern, if the KMO drops below .60. All items for the Empathy construct have values above .80, indicating that they are meritorious.



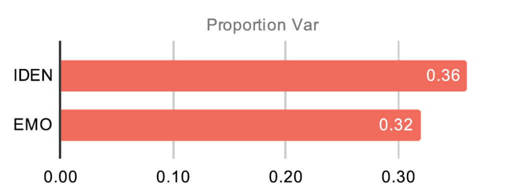
- **Step 2: Factor Check.** Once the correlations check out for each construct, and a final list of items are retained, we then run the factor analysis. The first thing to consider in this process is how many factors to retain in the solution. To determine this, we use two general principles:
  - Only retain factors with eigenvalues > 1.

Eigen values

3.97	0.75	0.37	0.36	0.32	0.23



  - Only retain factors with variance > 5% OR factors whose variance sum to 60% or more

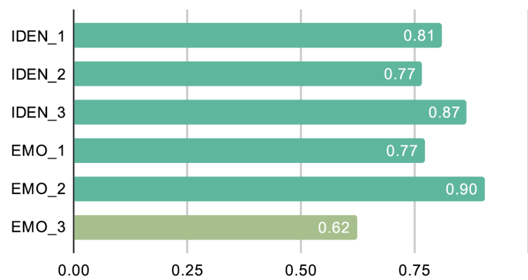


  - While the eigenvalues present evidence for a one-factor solution, in that all six items come together to represent Empathy, the proportion of variance for the two facets indicate that items measuring the Empathy can also be further divided and represented with the Identification facet and Emotion facet.

- Step 3: Item Check. Once we've decided on the number of factors that should be retained, the question becomes what items are associated with the factors (and which items are not).
  - » For practical significance of factor loadings, we follow the below approach:

> .70	Indicative of a well-defined structure
.50 - .69	Practically significant
.30 - .49	Minimally viable for a factor structure
< .30	Unrelated

You can see the following example:



» Items for measuring Empathy have factor loadings above .60.

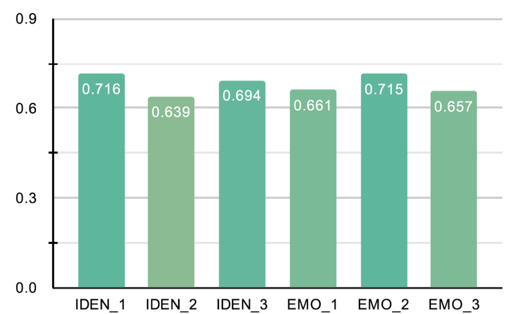
» For statistical significance of factor loadings, there are a few different approaches that researchers can take. However, factor loadings significance changes as a function of sample size. Consequently, we generally adhere to the following significance of factor loadings given the sample size.

Factor Loading	Sample Size Needed for Significance*
.30	350
.35	250
.40	200
.45	150
.50	120
.55	100
.60	85
.65	70
.70	60
.75	50

*Significance is based on a .05 significance level (α), a power level of 80 percent, and standard errors assumed to be twice those of conventional correlation coefficiencies

» With a sample size of 319 participants we can safely conclude that factor loadings for Empathy Identification and Empathy Emotion are statistically significant.

- Lastly, when determining what items to retain, we look at communalities. Communalities are the proportion of each variable's variance that can be explained or accounted for by the factors. As a general rule of thumb, we shoot for Communalities > .5 (i.e., retaining items in which a half of the variance of each variable should be accounted for by the factor solution).



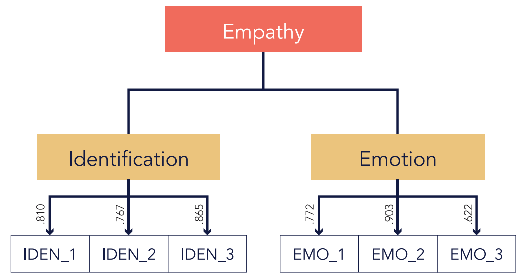
» All items have communalities above .60, except for one item, indicating that items are accounting for more than half of the variance in the factor solution.

Confirmatory Factor Analysis.

Exploratory Factor Analysis is only half of the equation. At Inkblot Analytics, we also use Confirmatory Factor Analysis to help with structural validity. While exploratory factor analysis was a data-driven approach, confirmatory factor analysis is a theory-based approach that helps us "confirm" if our theory matches the data. There are four things we look for in a confirmatory factor analysis that supports structural validity:

- Standardized loading estimates should be high. Standardized loading estimates are the same as standardized regression coefficients—they quantify the magnitude and direction of the relationship between the item and the factor. We want the relationship between the item and the factor to be high, therefore standardized loadings estimates must be high to be retained for adequate structural validity. More specifically, we use the accompanying rule. Notice, items for Empathy Identification and Empathy Emotion load highly and ideally on their respective factors.

> .50	Ideal
.30 - .49	Minimally Viable
< .30	Unacceptable



- Standardized residuals should be small. Standardized residuals are a calculation of the error in a model. Basically, it is a calculation of the magnitude of difference between observed and expected values. If our factor structure is not valid, then there is likely to be more error. Consequently, for items to be retained, we look for low values.
  - Notice that the values for both Empathy Identification and Empathy Emotion are less than .20. This means that the expected values are a close match to the observed values. Very little error was produced when we estimated our theoretical model.

< .20	No problem
.21 - .39	"Red flag"
> .40	Unacceptable

	IDEN_1	IDEN_2	IDEN_3
EMO_1	0.000	0.032	-0.018
EMO_2	0.032	0.000	-0.009
EMO_3	-0.018	-0.009	0.000

	IDEN_1	IDEN_2	IDEN_3
EMO_1	0.000	-0.006	0.006
EMO_2	-0.006	0.000	-0.002
EMO_3	0.006	-0.002	0.000

- Model Indices should be small. Modification indices represent the improvement a model would see (that is, improvement in units of chi-square values) if a particular relationship was added or deleted to the model. For a factor structure to be structurally valid, we want to minimize the number of modification indices and their values. Our current rule of thumb is that modification indices > 4 suggests improvements can be made to the model and therefore represent a poor factor structure.
  - CFA is a theoretically guided analysis. So the researcher must be selective in what modification indices to use. The algorithm will give any/all modifications that can be made to your model, not just the ones that are theoretically relevant. In this case, two modification indices were flagged. The pathways recommended were to add correlation paths between items of Identification and Emotion. This is not surprising, as all items are related to each other and adding any of these paths would not change the interpretation of the model. The modification suggestions are theoretically trivial. To be through, we tested each modification suggestion and did not find a significant improvement in model fit for all. In other words, adding any of the four recommended paths had a minimal (non-significant) impact on our final conclusions, so we retained our hypothesized model.

- Model Fit Indices should indicate a good fit. Lastly, there are a number of model fit values that provide an overall assessment of how well the model fits the data. We use many of these to assess model performance and overall structural validity. The table below will show you what values we use for our cutoff.

Factor Loading	Standard for Acceptable Fit
TLI	> .90 (marginal fit) ; > .95 (good fit)
CFI	> .90 (marginal fit) ; > .95 (good fit)
RMSEA	< .08
PClose	> .05 (i.e., not statistically significant)
SRMR	< .08
CD	The closer to 1, the better the fit
AIC	When comparing models, the lower the better
BIC	When comparing models, the lower the better

CFI	0.984
TLI	0.969
RMSEA	0.084
SRMR	0.025

Notice that our model fits the data very well, with the exception of RMSEA. The RMSEA is slightly greater than the .08 threshold. This is likely a function of the sample size. It is likely that in another sample this value may be lower. Since all other empirical evidence points to a good fit, we move forward.

- AVE > .5. With CFA, the average variance extracted is calculated by the average of the variance explained by the factor for each item that loads on it. Said differently, it's the sum of the squared standardized loadings of all items on a factor, divided by the number of items on that factor. If an AVE < .50, then it suggests that error explains more about the item's variance than is explained by the factor structure. For both, Empathy Identification and Empathy Emotion, the average variance extracted was greater than .50.

Construct Validity: Convergent & Divergent Validity.

Other forms of construct validity are known as convergent and divergent validity. Convergent validity refers to the relationship between variables that should be theoretically related. Divergent validity refers to the relationship between variables that should not be theoretically related.

With Regular Bivariate Correlations.

When looking to support convergent and divergent validity, the use of bivariate correlations can show us just how related different measures are. At Inkblot Analytics, we use the accompanying rules of thumb.

> .90	Indicates the same construct
.70 - .89	Convergent validity for highly related constructs
.50 - .69	Convergent validity for somewhat related constructs
.40 - .49	No man's land
.20 - .39	Divergent validity for somewhat unrelated constructs
.10 - .19	Divergent validity for highly unrelated constructs
0 - .09	Indicates no relationship

With Confirmatory Factor Analysis.

- AVE > Correlation. Convergent validity is supported by finding two constructs are related, but are NOT the same construct. For this to be shown, the variance extracted by a factor should be GREATER than the variance explained by the related construct. So when doing a CFA, we're looking for the AVE for two factors to be greater than the correlation between the two factors.
- A model with cross-loadings should be a poorer fitting model. When performing a CFA, if construct validity is to be theoretically supported, there should not be any cross-loaded items. If there were to be cross loaded items, removing them should make the model better. To test this out, we force some items to cross-load (that is, load on to the original construct and the related construct). By doing this, your model should get worse. If it gets better, then you know both constructs might be measuring the same thing.

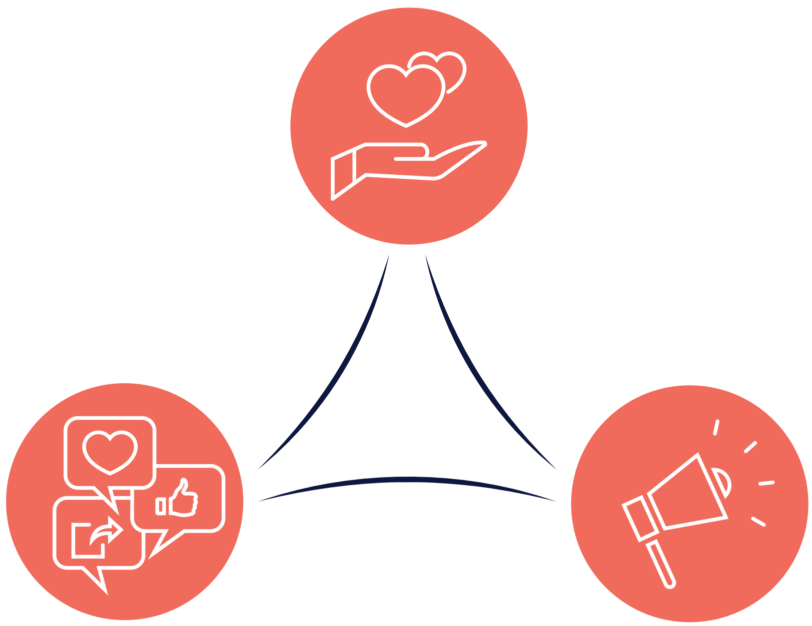
With Bifactor Modeling.

- Test a bifactor model and see if it gets worse. A bifactor model is usually used when you want to test the presence of a general factor that all items load onto. This approach helps identify the plausibility of a scale having multiple factors that are theoretically uncorrelated.

Convergent and divergent validity analysis are add-on features.

Construct Validity: Nomological Validity.

Typically, at Inkblot Analytics, we use other construct types for convergent and divergent validity, while using variables from the same construct type for nomological variability. For nomological validity we look at a correlation matrix and identify the biggest correlations. In theory these relationships should correspond to how you would theoretically think variables within the same construct type would be related. For example we found the following correlations:



- The higher a consumer rates scores on the Empathy, the higher they score on the Engagement.
- The higher a consumer rates scores on the Empathy, the higher they score on the Expression.
- The higher a consumer rates scores on the Expression, the higher they score on the Engagement.

These relationships between constructs make sense, as a brand that understands how a consumer feels is likely to enable consumers to express how they feel. Similarly, brands that enable consumers to express themselves are likely to keep consumers emotionally engaged.

Ex-Score Part 2: Scale Reliability

Item-to-total correlations > .5.

One of the first things we look at is to what extent each scale item correlates with a composite score of the scale (i.e., with all items for the scale scored properly). Generally speaking, we look for an item-to-total correlation of at least .50. When looking at the scores for Empathy Identification, we get the following:

	Emp
IDEN_1	0.8320
IDEN_2	0.8010
IDEN_3	0.8000

Notice all items are above the .50 threshold. Similarly, when looking at the scores for Empathy Emotion, we get the following:

	Emp
EMO_1	0.8080
EMO_2	0.8000
EMO_3	0.8360

Again all items are above the .50 threshold.

CFA's Composite Reliability >.70.

We calculated the composite reliability of the CFA models. This includes both Alpha and Omega values of reliability. Generally speaking, we use the following criteria:

> .70	Suggests good reliability
.60 - .69	Acceptable

As you can see below, items for Empathy Emotion meet the .70 threshold for reliability. Items for Empathy Identification meet the threshold for acceptable reliability. Additionally, the general Empathy profile meets the reliability threshold.

	IDEN	EMO
Alpha	0.87	0.87
Omega	0.86	0.86

Chronbach's Alpha > .70.

One of the most prolific ways of checking scale reliability is by calculating Chronbach's alpha. When calculating scale reliability at Inkblot Analytics, we use the following standards:

Cronbach's alpha	Internal consistency
$\alpha \geq 0.9$	Excellent
$0.9 \geq \alpha \geq 0.8$	Good
$0.8 \geq \alpha \geq 0.7$	Acceptable
$0.7 \geq \alpha \geq 0.6$	Questionable
$0.6 \geq \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

When looking at Empathy Identification and Empathy Emotion, scale reliability is ~.87 for each, indicating good internal consistency. Similarly, the general Empathy construct has a reliability of .90.

Summary

At this point, I hope you can see just how much rigor goes into the platform, EmoteAI.

From the perspective of scale construction and use, scales must have adequate psychometric properties to be used. Both example scales reported on in this paper--Empathy Identification and Empathy Emotion--have good to excellent psychometric properties.

No matter what part of the tool you're looking at, our results are backed by a rigorous vetting process.