TECHNICAL REPORT: BRAND MOMENTUM VALIDATION AND PREDICTION ACCURACY

DOUBLE E ANALYTICS

BRAND MOMENTUM SCORE

Scale Validation and Prediction Accuracy

Psychology is trendy in market research these days. There are a number of AI-powered psychology-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 the Brand Momentum Score, 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 Brand Momentum AI Platform
- How trustworthy the results are
- How to compare the rigor of our platform with other platforms of the market

Introduction

Overview: What do we do?
The last several years have impacted consumers' lives in so many ways—socially, technologically, physically, environmentally, financially, and emotionally. As a result, consumers are tired of the repetitive and uninspired messages they receive from advertisers and the businesses they engage with. To overcome these barriers, brands must demonstrate relevant messages that energize and create new, meaningful ways to engage and connect with the consumers. People are no longer responsive to "messages without substance" or "business as usual." What they respond to is momentum. Brand Momentum is about creating the right combination of energy and mindshare to grow a brand. The Brand Momentum AI Platform helps brands identify opportunities to craft new, emotive, engaging messaging by utilizing the proprietary Brand Momentum Score. This tool evaluates how effectively brands create awareness and connect with consumers, providing guidance on optimizing and energizing brand messaging to drive higher conversions.

The Brand Momentum AI Platform offers a true barometer of a consumer's relationship with the brand.

Brand Momentum AI Platform is a new platform that uses patent-pending systems for AI-powered projective tests. This platform helps brands identify their Brand Momentum Score, which measures the effectiveness of brand growth. The Brand Momentum AI Platform offers a true barometer of a consumer's relationship with the brand.

How do we do it?
The Brand Momentum AI Platform 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:

- Brands have the ability to energize and connect with consumers in new and meaningful ways.
- Tapping into what generates energetic, fresh, and meaningful experiences for consumers, while keeping the consumer as a whole in mind, can impact a brand's ability to form and sustain long-term profitability.

- The Brand Momentum AI Platform surveys consumers on their perception of a brand's "energy" behind its growth.
- The Brand Momentum AI Platform offers brands solutions and detailed suggestions, with consumer perceptions in mind, on how to increase and sustain relationship with their consumers

What insights can you learn? What can you learn?

By using the Brand Momentum AI Platform, a brand can get access to insights about their

1. Brand Momentum Score
2. What the Brand Momentum Score means
3. Deep dive into their Brand Momentum Score
4. Recommendations for improving a Brand Momentum Score
5. Simulations to showcase the impact of increasing their Brand Momentum Score on relevant outcomes (e.g., consumer likelihood of repurchase).

Key Benefits of Brand Momentum AI Platform

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

Benefit 1

Automated Predictive AI**.** The Brand Momentum AI Platform automatically creates predictive algorithms unique to each brand. The predictive AI not only provides brands with their brand momentum score and recommends solutions for improvement, but it also predicts how increasing a brand's momentum score will (1) increase consumer's emotional connectivity to the brand, (2) increase positive consumer perception of brand, and (3) increase brand engagement. The predictive AI grows better each time it is used.

Benefit 2

Less Questions, More Insights. With the Brand Momentum AI Platform, brands answer fewer questions and gain more actionable insights. By leveraging computerized adaptive testing, the platform dynamically adjusts the complexity and number of questions based on each respondent's previous answers, ensuring that only the most relevant questions are asked. This approach not only reduces survey fatigue, but also enhances data quality, providing researchers with precise and valuable information. The Brand Momentum Survey was designed to overcome the challenges of lengthy surveys, offering the same depth of data with a streamlined approach.

Benefit 3

Both Quantitative and Qualitative. The Brand Momentum AI Platform 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 sensitivity score through the platform. The combination of quantitative and qualitative insights offers a 360 visualization of their target audience.

How Does the Brand Momentum AI Platform Work?

This paper is focusing specifically on the Brand Momentum Score. Brand Momentum AI Platform adopts a four step process:

- **The Testing Step**
    - Taking the Brand Momentum Survey
- **The Scoring Step**
    - Analyzing survey responses and generating Brand Momentum Scores
- **The Profiling Step**
    - Breakdown of Scores into factors and facets to profile a brand
- **The Predicting Step**
    - Predicting outcomes and solutions to improve a brand's score

Each one of these steps has a scientific process built into them. For the testing step (i.e., when the participant takes the Brand Momentum survey), we want to make sure the data are 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 a proprietary algorithm to derive scores based on consumer data. For the profiling step, we use classic psychometric measures of validity and reliability and breakdown brand scores into factors and facets to profile a brand.

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.

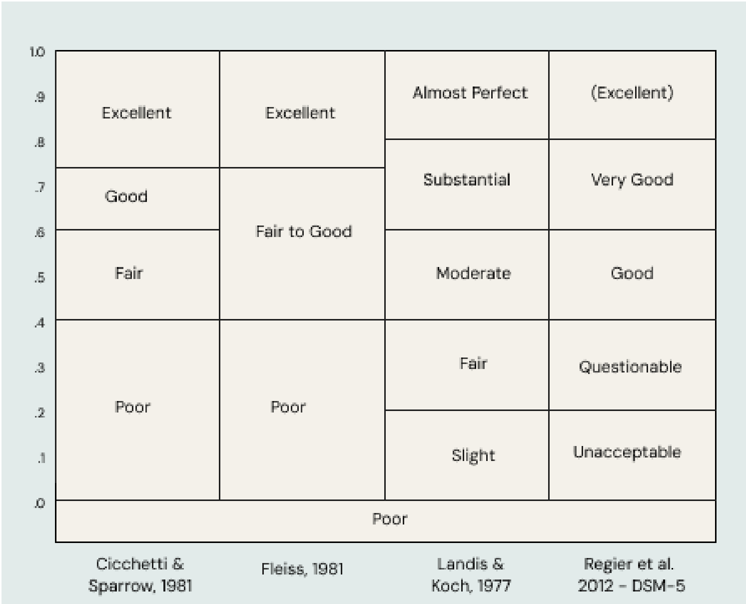
The Scoring Step: Measuring Inter-rater Reliability

Due to the high velocity of data we sometimes receive, we have multiple coders who apply a specific scoring scheme to the Brand Momentum survey responses.

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 Brand Momentum survey responses. 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 Double E 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.



The Profiling Step:

Psychometrics of Measured Constructs

Once the test data is collected, we are able to use our proprietary algorithms to help build brand score profiles. First, however, we have to make sure that our scales are accurately and consistently measuring each of the intended constructs. 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 extraversion, but in reality we might be measuring the "likelihood to talk to strangers."

The Brand Momentum Score measures how a brand utilizes emotions, energy, and cultural relevance to generate momentum and establish meaningful, engaging connections with consumers. The Brand Momentum Score measures three primary factors: Brand Animation, Brand Attention, and Brand Amplification. Each of these factors can be further divided into two facets each:

1. Brand Animation
    a. Refreshing Energy
    b. Rebel Energy
2. Brand Attention
    a. Feeling Moved
    b. Good Buzz
3. Brand Amplification
    a. Cultural Change
    b. Dispersion

In this section, we walk you through the scientific process of how we evaluated the psychometric properties of the Brand Momentum Score, using the Brand Attention factor as an example.

Brand Momentum Score

The Brand Momentum scale measures three primary factors: Brand Energy, Brand Attention, and Brand Amplification.

The **Brand Animation** construct measures a brand's energy level, assessing whether the brand exhibits vitality and freshness. Key questions include: Is it new? Is it unusual? Does it evoke curiosity? Does it create a distinct emotional response? Brand Animation includes two key parts:

- Refreshing Energy
    - Refreshing Energy is a facet of the Brand Animation factor. It represents a brand's capability to captivate audiences with

inventive, forward-thinking ideas that ignite curiosity and spark interest. This facet captures the brand's potential to introduce groundbreaking concepts, evoke excitement for the unknown, and encourage consumers to envision themselves engaging with pioneering products or services.

    - A high score indicates that consumers feel an elevated sense of excitement and curiosity toward the brand, highlighting its ability to attract attention through novelty, originality, and cutting-edge innovation.

- Rebel Energy

    - The Rebel Energy facelt reflects a brand's daring, boundary-pushing personality and its readiness to challenge conventional norms. This facet resonates with consumers who value originality and appreciate a brand that doesn't conform to traditional standards.
    - A high score indicates that consumers are drawn to the brand's fearless approach, signifying strong appeal for audiences who seek brands willing to disrupt established norms and deliver bold, unconventional experiences.

The **Brand Attention** construct measures a brand's ability to capture and maintain consumer engagement, assessing whether the brand creates meaningful connections and generates active interest. Key questions include: Does it create buzz? Does it resonate emotionally? Does it inspire engagement? Does it foster lasting connections? Brand Attention includes two key parts:

- Feeling Moved

    - Feeling Moved is a facet of the Brand Attention factor. It represents a brand's ability to forge deep emotional connections through meaningful impact and personal resonance. This facet captures the brand's capacity to enhance consumer self-worth, create authentic emotional bonds, and develop genuine understanding that motivates sustained engagement with the brand's offerings.

    - A high score indicates that consumers experience profound emotional connection and personal significance with the brand, highlighting its ability to create lasting impact through meaningful, emotionally resonant experiences.

- Good Buzz

    - Good Buzz is a facet of the Brand Attention factor. It represents a brand's ability to generate genuine excitement and enthusiasm that drives proactive engagement. This facet captures the brand's power to inspire active participation, stimulate organic discussions, and motivate consumers to deeply explore and connect with its offerings.

    - A high score indicates that consumers display strong initiative and enthusiasm in engaging with the brand, signifying powerful appeal for audiences who seek brands that naturally command attention and inspire active participation.

We can determine how a brand scores on the construct of Brand Attention by using a proprietary algorithm to conjoin scores from Feeling Moved and Good Buzz. We repeat this process with the remaining constructs. Brands can use this information to target specific constructs to improve how consumers relate and feel towards their brand.

The **Brand Amplification** construct measures a brand's cultural resonance and community engagement, assessing whether the brand creates meaningful societal impact and fosters active participation. Key questions include: Does it shape cultural conversations? Does it inspire social change? Does it build vibrant communities? Does it encourage meaningful interaction? Brand Amplification includes two key parts:

Cultural Change

    - Cultural Change is a facet of the Brand Amplification factor. It represents a brand's power to influence and reshape societal perspectives, inspiring consumers to examine their beliefs and embrace positive social transformation. This facet captures the brand's ability to catalyze meaningful cultural shifts, champion important causes, and weave its values into the fabric of everyday life.

- A high score indicates that consumers actively embrace and champion the brand's social initiatives, highlighting its ability to drive cultural evolution and create lasting societal impact through authentic value alignment.

Dispersion

- Dispersion is a facet of the Brand Amplification factor. It represents a brand's ability to cultivate dynamic, multi-faceted community engagement across diverse audiences. This facet captures the brand's success in sparking meaningful interactions, fostering authentic connections, and inspiring consumers to become active participants in its growing network of advocates.

- A high score indicates that consumers enthusiastically engage with and promote the brand within their communities, signifying strong appeal for audiences who seek brands that create vibrant, inclusive spaces for meaningful connection and shared experiences.

We can determine how a brand scores on the construct of by using a proprietary algorithm to conjoin scores from the two facets within the construct. We repeat this process with the remaining constructs. Brands can use this information to target specific constructs to improve how consumers relate and feel towards their brand.

In this section, we walk you through the scientific process of how we evaluated the psychometric properties of the Brand Momentum Score, using the Brand Attention factor as an example.

PART 1
Score Validity

For the Brand Momentum Score 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 the factor of Brand Attention really assessing the extent to which a brand holds a consumer's attention? 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, Brand Attention, relate to other constructs it should be theoretically related to?
- Divergent Validity
  - Is the construct, Brand Attention, unrelated to constructs it shouldn’t be related to?
- Nomological Validity
  - Does the network of constructs around the construct, Brand Attention, show relationships that are expected?

Construct Validity: Structural Validity.

First, we want to make sure that items for Feeling Moved and Good Buzz measure what they are supposed to be measuring and that together all items are measuring the Brand Attention construct as a whole. 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 were removed from the analysis and all others were retained. As you can see in the example below, the three items included in Feeling Moved all have correlations above .3 with each other. Similarly, all three items in Good Buzz have correlations above .3 with each other. Together, the items have correlations above .3 with each other. Therefore, all items for Brand Attention were retained.

	A_FM_1	A_FM_2	A_FM_3	A_FB_1	A_FB_2	A_FB_3
A_FM_1	1	0.584	0.511	0.45	0.406	0.366
A_FM_2	0.584	1	0.601	0.519	0.519	0.465
A_FM_3	0.511	0.601	1	0.509	0.509	0.486
A_FB_1	0.45	0.519	0.509	1	0.606	0.577
A_FB_2	0.406	0.492	0.462	0.606	1	0.635
A_FB_3	0.366	0.465	0.486	0.577	0.635	1

- 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 Feeling Moved all have partial correlations below .7 with each other. Similarly, all three items in Good Buzz have partial correlations below .7 with each other. Together, all items have partial correlations below .7 with each other. Therefore, all items for Brand Attention were retained.

	A_FM_1	A_FM_2	A_FM_3	A_FB_1	A_FB_2	A_FB_3
A_FM_1	1	0.339	0.191	0.116	0.058	-0.019
A_FM_2	0.339	1	0.312	0.124	0.114	0.067
A_FM_3	0.191	0.312	1	0.136	0.039	0.156
A_FB_1	0.116	0.124	0.136	1	0.29	0.229
A_FB_2	0.058	0.114	0.039	0.29	1	0.389
A_FB_3	-0.019	0.067	0.156	0.229	0.389	1

- 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 correlogram heat map, all correlations in the ant-image correlation matrix are close to 0. This means all items on both constructs are retained.

	A_FM_1	A_FM_2	A_FM_3	A_FB_1	A_FB_2	A_FB_3
A_FM_1	0.603	-0.185	-0.109	-0.064	-0.032	0.01
A_FM_2	-0.185	0.492	-0.161	-0.062	-0.056	-0.034
A_FM_3	-0.109	-0.161	0.542	-0.071	-0.02	-0.082
A_FB_1	-0.064	-0.062	-0.071	0.509	-0.145	-0.117
A_FB_2	-0.032	-0.056	-0.02	-0.145	0.491	-0.196
A_FB_3	0.01	-0.034	-0.082	-0.117	-0.196	0.515

1
0
-1

	A_FM_1	A_FM_2	A_FM_3	A_FB_1	A_FB_2	A_FB_3
A_FM_1	1	0.584	0.511	0.45	0.406	0.366
A_FM_2	0.584	1	0.601	0.519	0.492	0.465
A_FM_3	0.511	0.601	1	0.509	0.462	0.486
A_FB_1	0.45	0.519	0.509	1	0.606	0.577
A_FB_2	0.406	0.492	0.462	0.606	1	0.635
A_FB_3	0.366	0.465	0.486	0.577	0.635	1

1
0
-1

- 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 Brand Attention construct, the correlation matrix was significantly different from the identity matrix.

	[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

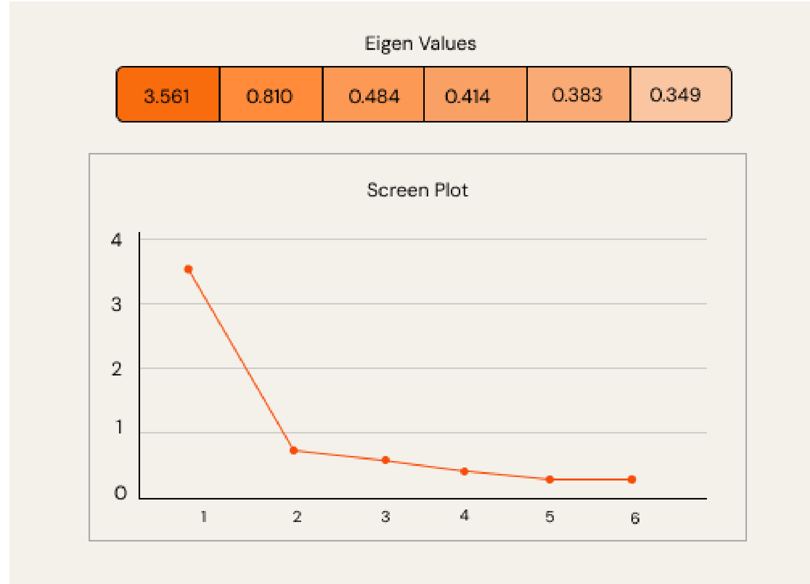
- Lastly, the Kaiser-Meyer-Olkin Measure of sampling adequacy measures the extent to which the variance of the items might be caused by an underlying factor. The higher proportion of variance caused by underlying factors, the better your factor solution might be. Consequently, the following is what we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

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

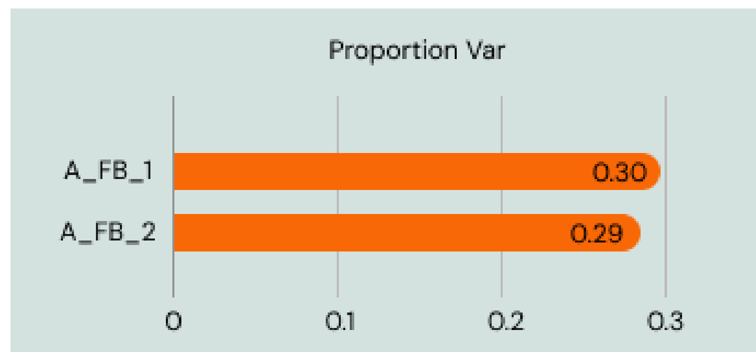
There is cause for concern, if the KMO drops below .60. For Feeling Moved and Good Buzz, all items have values above .80, indicating that they are meritorious and providing little cause for concern.

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



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



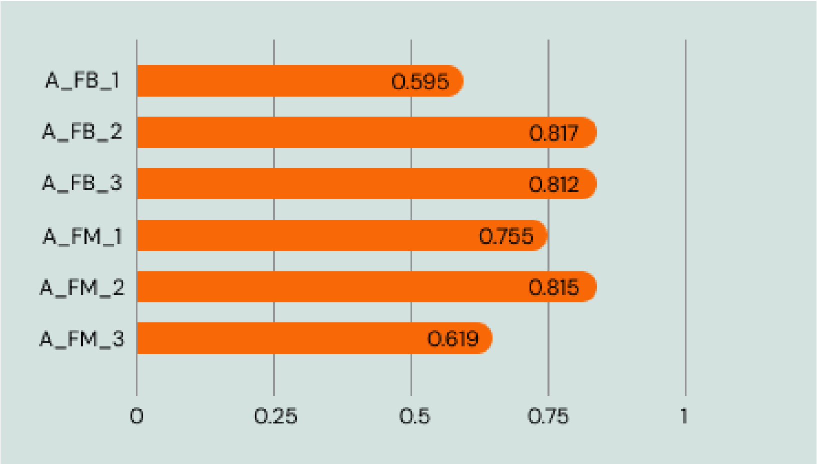
- In this case, the data represent a solution for one factor: Brand Attention indicating that the items are measuring a collective underlying factor. While a two-factor solution was expected for this measure, a one-factor solution indicates cohesion of items for the targeted overall construct.

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 well-defined structure
.50 - .69	Practically signifigant
.30 - .49	Minimally viable for a factor structure
< .30	Unrelated

You can see the following example:



- One item from each facet, Good Buzz and Feeling Moved, have factor loadings that are practically significant. The other two items in their respective constructs have loadings that are indicative of a well-defined structure. Additionally, items did not cross-load across factors. Analytically, this means that items measuring Feeling Moved didn't have factor loadings greater than .3 for Good Buzz and vice versa. Conceptually, items for Feeling Moved and Good Buzz grouped with their respective constructs and measured what they were supposed to be measuring. Together, the correlation between the factors was .78, indicating that while items can be separated into their respective constructs, they still overlap and collectively measure Brand Attention.

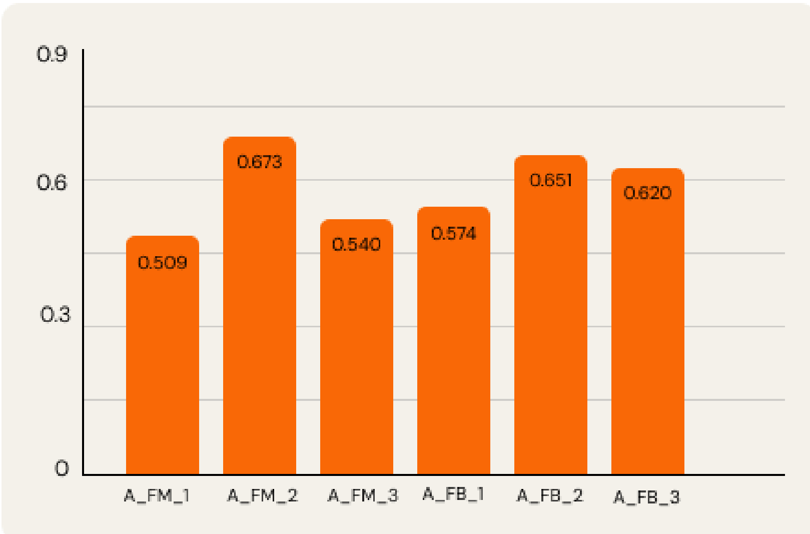
- For statistical significance of factor loadings, there are a few different approaches that researchers can take. However, factor loadings significance changes as a function of sample size. Consequently, we generally adhere to the following significance of factor loadings given the sample size.

Factor Loading	Sample Size Needed for Signifigance*
.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 co-efficiencies

Given the large sample size of 1,022, we can safely conclude that all loadings were 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).

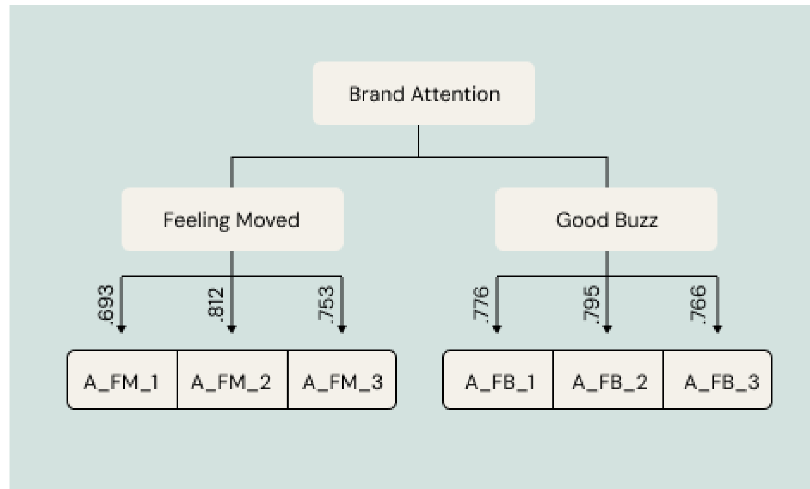


- All items have communalities above .5 indicating that all items should be retained, as a considerable amount of variance is accounted for by the factor solution.

Confirmatory Factor Analysis
Exploratory Factor Analysis is only half of the equation. At Double E 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 Feeling Moved and Good Buzz load highly on their respective factors.

> .70	Ideal
.50-.69	Minimally Viable
< .50	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 Feeling Moved and Good Buzz are less than .2. 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

	A_FM_1	A_FM_2	A_FM_3
A_FM_1	0	0.024	-0.013
A_FM_2	0.024	0	-0.013
A_FM_3	-0.013	-0.013	0

	A_FB_1	A_FB_2	A_FB_3
A_FB_1	0	-0.015	-0.026
A_FB_2	-0.015	0	0.042
A_FB_3	-0.026	0.042	0

- 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, zero modification indices were flagged.
- 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	0.990
TLI	0.980
RMSEA	0.058
SRMR	0.023

Notice that our model fits the data very well. 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 Feeling Moved and Good Buzz, 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 Double E 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 (CFA)

- 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.

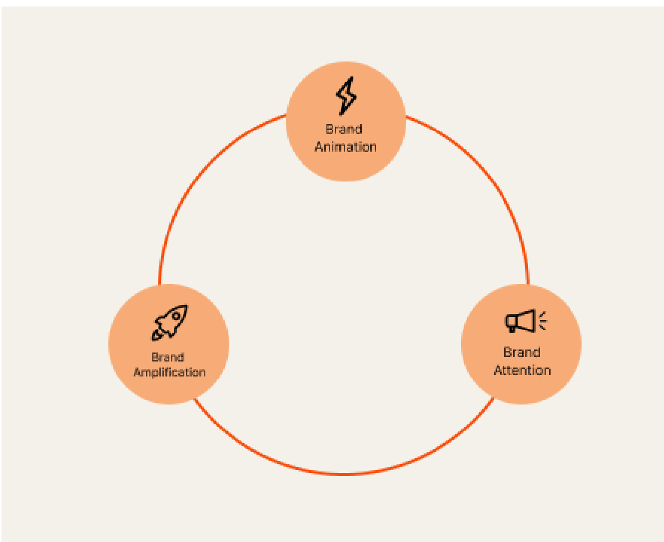
With Bifactor Modeling

- 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 Double E 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 brand scores on the Brand Animation construct, the higher they score on the Brand Attention construct.
- The higher a brand scores on the Brand Attention construct, the higher they score on the Brand Amplification construct.
- The higher a brand scores on the Brand Amplification construct, the higher they score on the Brand Animation construct.

These relationships between constructs make sense, as a brand that understands how to generate momentum in one area is likely able to do the same in other areas.

Problem Profiles 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 Feeling Moved, we get the following:

	Feeling Moved
A_FM_1	0.697
A_FM_2	0.782
A_FM_3	0.766

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

	Good Buzz
A_FB_1	0.798
A_FB_2	0.792
A_FB_3	0.78

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, both Feeling Moved and Good Buzz, meet the .70 threshold for reliability. Additionally, the general Brand Attention meets the reliability threshold. This indicates excellent respondent differentiation.

	A_FM	A_FB	A
Omega	0.80	0.82	0.86

Chronbach's Alpha > 0.70:

One of the most prolific ways of checking scale reliability is by calculating Chronbach's alpha. When calculating scale reliability at Double E 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

	A_FM	A_FB	A
Alpha	0.80	0.82	0.9

The facets Feeling Moved and Good Buzz each have scale reliabilities of .80 or above, indicating good internal consistency. Similarly, the general construct of Brand Attention has a reliability of .86.

Summary

At this point, I hope you can see just how much rigor goes into the Brand Momentum AI Platform and the Brand Momentum Score.

From the perspective of scale construction and use, Scores must have adequate psychometric properties to be used. Both example facets reported on in this paper--Good Buzz and Feeling Moved and the overall factor Brand Attention--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.