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MEASURING CULTURAL AWARENESS AND BELONGING IN AN ORGANIZATION

Abstract

This study presents the development and validation of a quantitative instrument designed to measure cultural awareness and belonging within the context of diversity, equity, and inclusion (DEI) in organizations. The Cultural Awareness and Belonging Survey (CABS) aims to fill the research gap by offering a reliable tool for assessing these constructs. Drawing on theoretical frameworks such as the theory of generative interactions, the CABS survey was constructed with three initial dimensions: Embrace, Engage, and Enact. Data were collected from 403 U.S.-based participants using a cross-sectional survey design. Exploratory and confirmatory factor analyses indicated a two-dimensional model consisting of Embrace and Enact, with strong internal consistency reliability (Cronbach's α = .91 for Embrace and .91 for Enact). The fit indices (CFI = 0.98, TLI = 0.97, RMSEA = 0.05, SRMR = 0.02) confirmed the robustness of the measurement model. The findings suggest that cultural awareness and belonging are critical factors in organizational performance and psychological safety, with practical implications for DEI initiatives. This study contributes a validated tool for organizations to understand better and enhance their DEI efforts, fostering a more inclusive workplace environment.

Keywords: cultural awareness, belonging, diversity, equity, inclusion, DEI, survey development, factor analysis, organizational culture

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Introduction to the Problem and Gap In Practice

Cultural awareness and belonging have been the focus of a wide range of recent diversity, equity, and inclusion (DEI) workplace studies, though the research in this arena has evolved over decades. A 2021 BetterUp survey found that the return on investment from increasing a sense of belonging in organizations can drive a 56% improvement in performance on the job, a 75% reduction in time off due to illness, and a 50% decrease in the likelihood that employees will leave ("The Value of Belonging at Work," 2021). However, Stamps (2024) concluded that creating an inclusive culture can only be perpetuated by ongoing efforts and commitment to addressing core DEI issues. In addition, Schwartz et al. (2020) revealed that almost 80% of companies conceptually understand that creating a culture of belonging in the workplace is vital to organizational success in the near to mid-term, yet under 15% of those firms believe they are prepared to achieve it or evaluate how well they did it. To address this gap in the research, we set out to develop a quantitative instrument that measures cultural awareness and belonging within the context of DEI.

Background

Our initial thinking around designing a model from which our cultural awareness and belonging assessment tool would evolve was based on a review of key studies and reports such as McKinsey and Company's *Diversity Matters Even More* (Hunt et al., 2023). This report stipulated that financial performance significantly improves when organizations prioritize belonging and inclusion and cultivate DEI mentors, champions, and sponsors. The Schwartz et al. (2020) study, conducted for Deloitte, also emphasized that fostering a culture of belonging entails more than fair and respectful treatment of others, such that connection to people and contribution to organizational results are also essential. Similarly, articles by Kennedy and Jain-Link (2021) and Westover (2020) informed our work from the perspective that creating a culture of belonging requires active participation, involvement, and innovation outside of simple awareness. Cross et al. (2021) additionally emphasized the importance of personal networks in building an inclusive culture. Perhaps Google's 2023 Diversity Annual Report summed it up best regarding how a sense of belonging amplifies and extends cultural awareness in their organization: "Embedding belonging in all we do" ("Google Diversity Annual Report," p. 4).

Terms and Definitions

Belonging. Belonging is a human desire to feel that humans are not alone in this world, and belonging is essential for human connections (Filstad et al., 2019). Belonging is when awareness becomes visceral and takes DEI to new levels of connection and contribution.

Cultural Awareness. **"**Cultural awareness is the foundation of communication, and it involves the ability to stand back from ourselves and becoming aware of our cultural values, beliefs and perceptions" (Quappe & Cantatore, 2005, p. 1). Cultural awareness moves DEI to a conscious level within an organization.

Diversity. "Refers to who is represented in the workforce" (Sternfels et al., 2022, para. 5).

Equity. "Refers to fair treatment for all people so that the norms, practices, and policies in place ensure identity is not predictive of opportunities or workplace outcomes" (Sternfels et al., 2022, para 11).

Inclusion. "Refers to how the workforce experiences the workplace and the degree to which organizations embrace all employees and enable them to make meaningful contributions" (Sternfels et al., 2022, para. 12).

Theoretical Framework and Literature Review

The theory of generative interactions (Bernstein et al., 2020) serves as the theoretical framework for our study despite other DEI research that has leveraged frameworks such as organizational justice and stakeholder theories (see, for example, Im et al., 2023). Generative interactions theory suggests that

> to facilitate inclusion, multiple types of exclusionary dynamics (self-segregation, communication apprehension, and stereotyping and stigmatizing) must be overcome through adaptive cognitive processing and skill development, and engagement in positive interactions must occur ...to facilitate inclusion that is created and sustained by contextually relevant sets of organizational practices." (Bernstein et al., 2020, p. 395).

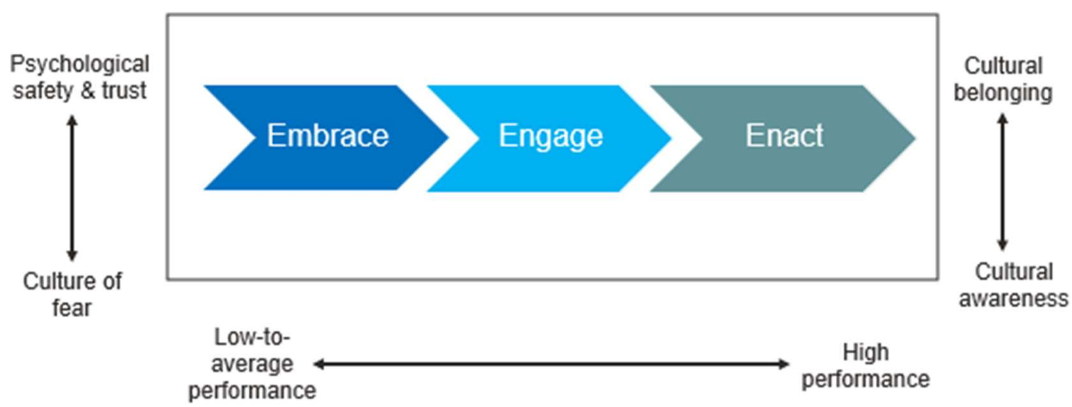
Thus, the generative interactions theory informs our study from the perspective that the *Embrace* subscale represents adaptive cognitive processing and skill development as a measure of the cultural awareness construct, while the *Engage* and *Enact* subscales represent involvement and participation in positive interactions as a measure of belonging.

Warren and Warren (2023) furthered Bernstein et al.'s (2020) seminal work on the theory of generative interactions by showing that if we strive to turn members of the dominant nonminority group into allies – what they call *allyship* – we can bolster an organization's focus on equity and inclusion in a durable way. This notion of building positive interactions through allyship goes beyond initiating cultural awareness to creating a genuine sense of belonging. To that end, Leslie and Flynn (2024) discussed the concept of diversity cognitions as perceptions of how to approach DEI in organizations through diverse ideologies, beliefs, and climates. Essentially, diverse ideologies and beliefs are facets of cultural awareness that can proceed along a directional path toward belonging.

As a result of our exploration of the research, we concluded that cultural awareness and belonging could be measured along a continuum, where the starting point was the former and the finish line was the latter. Our working premise was that awareness included *embracing* DEI concepts whereas belonging consisted of *engaging* in DEI applications and events as well as *enacting* DEI initiatives through behavioral participation. Consequently, we envisioned a three-factor survey instrument to measure the DEI cultural awareness and belonging constructs of Embrace, Engage, and Enact. As a foreshadowing of our results, the final findings showed that our initial premise had overestimated the number of factors. The initial conceptual model is shown in Figure 1.

Figure 1

Conceptual Model



Research Technique Overview: The Instrument

The *Cultural Awareness and Belonging Survey* (CABS; see Appendix) is scored on a 5-point Likert scale ranging from 1 = *strongly disagree*, 2 = *disagree*, 3 = *neither agree nor disagree*, 4 = *agree*, and 5 = *strongly agree*. A panel of academic subject matter experts assessed content validity. The items on the CABS questionnaire began with three domains measuring Embrace, Engage, and Enact. The internal consistency reliability (> .70) for the Cronbach α coefficient of the Embrace dimension was $\alpha = .93$. Similarly, for the Engage Cronbach $\alpha = .92$, and Enact had a Cronbach $\alpha = .94$. Embrace included 10 items that measure the employee's perception of their organization's cultural awareness. Engage included 10 items that measure an employee's perception of their belonging in the organization based on involvement in DEI activities. Enact also included 10 items that measured an employee's perception of creating action to improve the DEI efforts geared towards enhancing a sense of belonging in the organization.

Design

To capture accurate data, a cross-sectional survey design was implemented. In a cross-sectional design, data is collected from individuals or groups at a specific moment or within a relatively short period of time, allowing researchers to examine the prevalence, distribution, and relationships among variables of interest at that time (Spector, 2019).

Study Sample

The sample consisted of 403 U.S.-based participants, grouped by gender, race, remote workers, industry, organization size, income, education level, state, and current living location.

Data Collection

Data was collected online through Saurage Research Inc. Saurage Research Inc. provided a consent form and survey using their online platform. Once the participants consented to participate, they completed screening and demographic questions. The survey took approximately 10-15 minutes to complete. Saurage Research Inc. then provided the final dataset.

Data Analysis

We hypothesized that each factor (Embrace, Engage, and Enact) would separate from each other, offering no cross-loadings after we conducted exploratory factor analysis (EFA). The preliminary data analysis began with data cleaning and accuracy checks. We analyzed the variables using JASP version 0.17.2 (JASP Team, 2023). Descriptive statistics were conducted before we ran EFA. We analyzed the mean, standard deviations, skewness, and kurtosis. We also assessed normality using Kolmogorov-Smirnov. Factor analysis is sensitive to violations of normality assumptions to some extent, but its robustness depends on the specific type of factor analysis being used and the degree of non-normality present in the data. If data exhibit substantial non-normality, it is advisable to consider alternative techniques such as principal axis factoring or minimum rank factor analysis (de Winter & Dodou, 2012).

To evaluate multicollinearity, we calculated the VIF and tolerance values. Additionally, we hypothesized that the Embrace, Engage, and Enact dimensions would correlate. We chose an oblique rotation (oblimin rotation). The optimal number of factors to retain was determined using several methods, including visual examination of the scree plot, parallel analysis based on eigenvalues derived from EFA, confirmatory factor analysis (CFA), and consideration of theoretical perspectives. Various measures were employed to assess the fit of the data to the model and evaluate the fit of individual items to the scales, including total variance explained, communalities, pattern coefficients, and factor correlations. In this initial evaluation of the instrument, items were retained based on a pattern coefficient cutoff of > 0.40, aiming to retain as many items as possible from the original scale. We scrutinized the correlation matrix for the presence of missing data.

We employed the Kaiser-Meyer-Olkin (KMO) test to assess sampling adequacy for factor analysis. The KMO evaluates whether the variables included in the analysis are suitable for factor analysis based on the strength and pattern of their intercorrelations. The KMO test measures the proportion of variance in the variables that can be accounted for by other variables in the dataset (Sigudla & Maritz, 2023). The KMO test produces a value between 0 and 1, with values closer to 1 indicating better sampling adequacy. A KMO value above 0.6 or 0.7 is generally considered acceptable for factor analysis, suggesting that the variables are sufficiently interrelated to justify further analysis. In addition to the KMO test, we also conducted Bartlett's test of sphericity. Bartlett's test evaluates the hypothesis that the correlation matrix of the variables is an identity matrix, indicating that there is no underlying structure or relationship among the variables. If the p-value of Bartlett's test is statistically significant (typically set at $\alpha = 0.05$), it suggests that the correlation matrix is not an identity matrix, indicating the presence of underlying structure or relationships among the variables. This provides support for the use of factor analysis as an appropriate technique to explore the data further.

Once EFA was completed, we conducted confirmatory factor analysis (CFA) to assess whether the observed variables were aligned with the underlying latent constructs as hypothesized by the theoretical model (Hair et al., 2019). Multiple models were run, with factors corresponding to each omission domain and allowing the factors to emerge from the data. The number of factors to be extracted was determined by evaluating model fit using Tucker and Lewis's reliability coefficient, the root mean square error of approximation (RMSEA), and its 95% confidence interval. Acceptable model fit was determined using recommended cutoff values: RMSEA < 0.08 and Tucker-Lewis reliability coefficient > 0.95. We examined whether each item loaded at 0.4 or higher on two or more factors to assess item cross-loadings. This conventional method was employed to evaluate item association across multiple factors (Costello & Osborne, 2005). To assess internal consistency reliability, we used Cronbach's α and McDonald's ω.

Results

Descriptive Statistics

Before running the factor analyses, we conducted and evaluated descriptive statistics (see Table 1). After evaluating the three variables' skewness or kurtosis levels, we made decisions to review multiple normality test results. The Kolmogorov-Smirnov (K-S) test demonstrated significant multivariate nonnormality. The K-S test statistic was D = .072. The p-value for the K-S test was p = .000. The K-S test revealed a significant difference between the observed and expected distributions ($p < 0.05$), leading to the rejection of the null hypothesis for Embrace. The K-S test statistic was D = .057. The p-value for the K-S test was p = .003. The K-S test revealed a significant difference between the observed and expected distributions ($p < 0.05$), leading to the rejection of the null hypothesis for Engage. The K-S test statistic was D = .076. The p-value for the K-S test was p = .000. The K-S test revealed a significant difference between the observed and expected distributions ($p < 0.05$), leading to the rejection of the null hypothesis for Enact.

The three predictor variables, Embrace, Engage, and Enact, demonstrated no evidence of multicollinearity. The Variance Inflation Factor (VIF) values provide insight into the multicollinearity among the predictors. VIF values below 10 are generally considered acceptable, indicating that multicollinearity is not a significant concern (Hair et al., 2019). In the presented regression analysis, the VIF values for the variables Engage and Embrace were both found to be 3.197, while Enact had a VIF of 3.527. These values are well within the acceptable range, suggesting that multicollinearity is not problematic in this analysis. This assumption supports the reliability of the factor loadings and ensures that the factors extracted are distinct and interpretable.

Table 1

Descriptive Statistics for Variables

Statistics	Embrace	Enact	Engage
Mean	3.523	3.433	3.533
Std. Error of Mean	0.045	0.045	0.043
95% CI Mean Upper	3.611	3.520	3.618
95% CI Mean Lower	3.434	3.345	3.448
Std. Deviation	0.903	0.895	0.870
95% CI Std. Dev. Upper	0.964	0.960	0.931
95% CI Std. Dev. Lower	0.834	0.828	0.803
Coefficient of variation	0.256	0.261	0.246
Variance	0.816	0.801	0.757
95% CI Variance Upper	0.930	0.921	0.868
95% CI Variance Lower	0.695	0.686	0.645
Skewness	-0.550	-0.431	-0.532
Std. Error of Skewness	0.122	0.122	0.122
Kurtosis	0.141	0.131	0.199
K-S	0.072	0.076	0.057
p-value of K-S	0.243	0.243	0.243
Shapiro-Wilk	0.967	0.973	0.972
p-value of Shapiro-Wilk	< .001	< .001	< .001
Range	4.000	4.000	4.000
Minimum	1.000	1.000	1.000
Maximum	5.000	5.000	5.000

Note. There were no missing items (N = 403).

Measurement Instrument Reliability

We assessed the internal consistency or reliability of the measurement instrument used to gauge participants' levels of cultural awareness and belonging. Ensuring the reliability of our instrument is critical as it directly impacts the validity of our findings. Reliability measures how consistently an instrument measures the intended construct, and it is essential for drawing accurate and meaningful conclusions from our data.

Reliability is a fundamental concept in psychometrics, ensuring that measurement instruments consistently and accurately assess the constructs of interest (DeVellis, 2017). We employed the well-established test of Cronbach's α as one of our reliability statistics due to its widespread recognition in the field of psychometrics and calculated and reported the McDonald's ω. The rationale was that Cronbach's α assumes that all items in a scale are tau-equivalent, meaning they have equal factor loadings. However, in some cases, this assumption may not hold. McDonald's ω is advantageous because it accounts for variations in factor loadings, offering a more accurate estimate of reliability when this assumption is violated. This provided us with a more nuanced and precise evaluation of internal consistency. We calculated the mean scores of Cronbach's α and McDonald's ω. This summary measure synthesized the information from these two statistics, which ensured that our reliability assessment captured multiple perspectives.

CABS exhibited strong internal consistency and satisfactory test-retest reliability before running EFA. These findings provided confidence in the stability and consistency of the instrument. The overall Cronbach's was $\alpha = .97$, indicating strong internal consistency among the items. The scale Cronbach's scores were Embrace ($\alpha = .93$), Engage ($\alpha = .92$), and Enact ($\alpha = .94$); thus, each factor showed high reliability.

Embrace

After removing the Engage factor, Table 2 presents the final EFA reliability statistics for the Embrace factor. The point estimate of McDonald's ω suggested that the items within the Embrace scale consistently measured the same underlying construct. The confidence interval measures high precision, indicating strong internal consistency. The point estimate of Cronbach's α, similar to McDonald's ω, confirmed excellent internal consistency, with the confidence interval reinforcing the reliability of the scale. The mean score of the reliability estimates across methods suggested that the average of the items on the Embrace scale demonstrated strong internal consistency.

The McDonald's ω and Cronbach's α surpassed the commonly accepted threshold of 0.70, indicating that the Embrace scale's items effectively measure the intended construct with high consistency. The narrow confidence intervals provide additional confidence in the reliability of the scale. These findings reinforce the validity of the Embrace scale and suggest that it is a dependable scale for assessing the underlying construct it represents.

Table 2

Frequentist Scale Reliability Statistics for Embrace

Estimate	McDonald's ω	Cronbach's α	*M*
Point estimate	0.910	0.910	3.628
95% CI lower bound	0.896	0.895	3.538
95% CI upper bound	0.924	0.922	3.718

Note. The point estimates of 0.910 indicated high reliability. The CIs showed strong internal consistency.

Enact

After removing the Engage factor, Table 3 shows the final EFA reliability statistics for the Enact scale, indicating high internal consistency and reliability. McDonald's ω and Cronbach's α exceeded the commonly accepted threshold of 0.70, suggesting excellent internal consistency. This implies that the items within the Enact scale consistently measure the same underlying construct. The mean across method's value of 3.397 supported the strong internal consistency of the scale. Additionally, the 95% confidence intervals (CI) for each reliability estimate were relatively narrow and did not cross the threshold of 0.70 for both Embrace and Enact, indicating a high level of precision in the reliability assessment.

Table 3

Frequentist Scale Reliability Statistics for Enact

Estimate	*McDonald's ω*	*Cronbach's α*	*M*
Point estimate	0.913	0.913	3.397
95% CI lower bound	0.900	0.899	3.306
95% CI upper bound	0.926	0.925	3.489

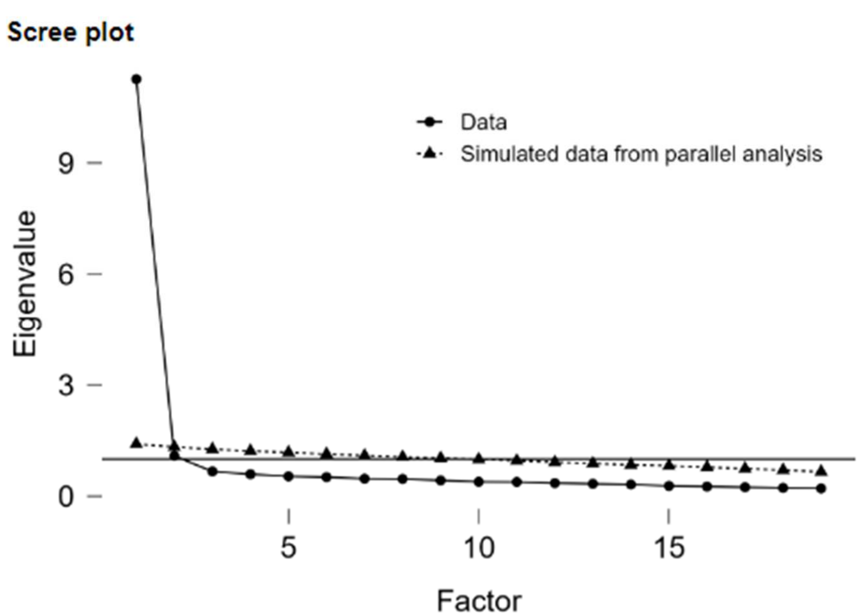
Note. The point estimates of 0.913 indicated high reliability. The CIs showed strong internal consistency.

EFA

We used EFA to assess whether there was any link between the latent variables. We tested the hypothesis that the factors Embrace, Engage, and Enact would not cross-load, resulting in a clear separation of the items and the development of a cohesive, validated instrument. The extraction method used was the Principal Axis Factor, and the rotation method was Oblimin with Keiser Normalization. We assessed the scree plot (Figure 2) visually and parallel analysis using the eigenvalues derived from the CFA. However, cross-loadings were identified in items 28ENA, 15ENA, 5EMB, 6EMB, 20ENG, and 14ENG (Table 4).

Figure 2

Eigenvalue Scree Plot for Factors of Embrace, Engage, and Enact



Note. The solid line represents the actual data, while the dashed line indicates the simulated data from parallel analysis. The steep drop after the second factor, followed by a leveling off, suggests that a two-factor solution is appropriate, as the first two factors have eigenvalues significantly higher than those generated by the parallel analysis.

Table 4

Preliminary Factor Loadings

Question #	Embrace	Engage	Enact	Uniqueness
23ENA	0.867			0.364
22ENA	0.858			0.349
25ENA	0.810			0.402
19ENG	0.788			0.407
21ENA	0.787			0.404
30ENA	0.782			0.342
26ENA	0.703			0.398
11ENG	0.702			0.410
29ENA	0.695			0.411
12ENG	0.640			0.385
13ENG	0.579			0.453
16ENG	0.566			0.436
27ENA	0.558			0.387
18ENG	0.539			0.402
24ENA	0.533			0.510
17ENG	0.485			0.439
28ENA*	0.481	0.344		0.369
15ENG*	0.422	0.364		0.379
20ENG*	0.382	0.345	0.380	0.371
14ENG*	0.349	0.345		0.500
5EMB*	0.318	0.402	-0.355	0.392
7EMB		0.861		0.317
3EMB		0.792		0.373
9EMB		0.778		0.374
10EMB		0.741		0.395
2EMB		0.733		0.452
8EMB		0.726		0.346
6EMB*		0.526	-0.320	0.348
4EMB		0.516		0.343
1EMB		0.488		0.361

Note. Applied rotation method is Oblimin (oblique).
*Crossloadings present.

The KMO measure verified the sampling adequacy for the analysis, KMO = .972. A KMO value above 0.60 or 0.70 is generally considered acceptable for factor analysis (Kaiser & Rice, 1974). All KMO values for individual items were higher than 0.77 (see Table 5), which is well above the limit of 0.5 (Kaiser & Rice, 1974). Additionally, the chi-square statistic for Bartlett's Test of Sphericity was $\chi2(435) = 9526.017$, p =.0001. The statistically significant result of Bartlett's Test of Sphericity suggests that the correlations among the variables are not zero, supporting the appropriateness of proceeding with factor analysis.

Table 5

Kaiser-Meyer-Olkin Test

Question #	MSA Scores
All questions	0.972
1EMB	0.977
2EMB	0.972
3EMB	0.969
4EMB	0.977
5EMB	0.962
6EMB	0.966
7EMB	0.956
8EMB	0.974
9EMB	0.967
10EMB	0.976
11ENG	0.968
12ENG	0.960
13ENG	0.972
14ENG	0.967
15ENG	0.960
16ENG	0.979
17ENG	0.982
18ENG	0.974
19ENG	0.984
20ENG	0.966
21ENA	0.976
22ENA	0.972
23ENA	0.962
24ENA	0.978
25ENA	0.974
26ENA	0.980
27ENA	0.973
28ENA	0.971
29ENA	0.987
30ENA	0.980

Note. The Kaiser-Meyer-Olkin (KMO) measures the sampling adequacy, and these scores reflect excellent suitability for factor analysis.

Discussion of EFA

Based on Kaiser's criterion, the preliminary EFA showed that all three factors—Embrace, Engage, and Enact—demonstrated values >1. During our EFA, we encountered instances of cross-loadings among several items, which prompted us to consider their inclusion in our final factor structure carefully. We provide the rationale for eliminating certain items due to cross-loadings. Cross-loadings, when an item exhibits substantial factor loadings on more than one factor, are recognized concerns in EFA. The presence of cross-loadings can obscure the distinctiveness of underlying constructs and complicate factor interpretation. To identify cross-loadings, we looked for factor loadings greater than 0.40 on more than one factor, in line with established guidelines. We prioritized the interpretability of our factor structure. Items demonstrating cross-loadings often lacked clear conceptual alignment with any single factor. Retaining such items could have muddied the theoretical clarity of our constructs.

In certain cases, the elimination of items was justified by a misalignment with our theoretical framework. For example, Items 11 – 20 (Engage), which loaded significantly on both Factor 1 (Embrace) and Factor 3 (Enact), did not conceptually align with the intended measurement of Factor 1 and Factor 3. The removal of the Engage factor was essential to maintain theoretical consistency. The elimination of cross-loading items notably improved the factor structure's coherence and interpretability. Factor loadings of the remaining items increased in magnitude, making the underlying factors more distinct and conceptually meaningful. As a result of item elimination, our measurement instrument's length was reduced. While this can be viewed as an advantage in survey administration, it is important to acknowledge that scale brevity may impact its reliability and sensitivity to subtle variations in the measured constructs. Despite the elimination of cross-loading items, our retained items continue to capture the core constructs of interest effectively. The remaining items maintain content validity, ensuring that the underlying factors align with our research objectives.

The decision to eliminate items was based on rigorous statistical criteria and the behavior of the data. We conducted sensitivity analyses, both with and without the eliminated items, reaffirming our findings' robustness. Moving forward, we plan to validate our reduced scale in independent samples to ensure the generalizability of our findings. Additionally, future research may explore the nuances of the eliminated items within different contexts or populations. We also removed scale items 28ENA, 15ENA, 5EMB, 6EMB, 20ENG, and 14ENG after our EFA to ensure clarity, improve focus, and enhance the overall reliability of responses.

Construct Validity Assessment

Convergent Validity

Convergent validity assesses whether indicators of the same latent construct are related to each other as expected (Hair et al., 2019).

Average Variance Extracted (AVE)

The AVE is a measure of the average amount of variance captured by a construct's indicators relative to the total variance in the construct (Hair et al., 2019). Higher AVE values (typically above 0.50) suggest better convergent validity. The AVE values, Embrace (AVE = 0.638) and Enact (AVE = 0.628) indicated that the respective latent construct accounted for a substantial proportion of variance in the indicators associated with each construct, supporting good convergent validity.

Discriminant Validity

We assessed discriminant validity by examining the correlations between latent constructs and comparing them to the square roots of the AVE values. We applied the method proposed by Fornell and Larcker (1981), which involves comparing construct reliability (CR) with the AVE for each latent construct. CR serves as an estimate of reliability and is computed as the ratio of the squared sum of factor loadings to the sum of squared factor loadings and measurement error (Hair et al., 2017). AVE measures the proportion of variance in a construct's indicators that is explained by the latent construct itself (Hair et al., 2017).

The CR values for each construct (Embrace, CR = 0.90316822; Enact, CR = 0.88174889) were greater than their corresponding AVE values, which indicated strong discriminant validity according to the Fornell and Larcker (1981) criterion. The CR values exceeded the AVE values, which suggested that each construct exhibited high reliability, and that the variance shared among its indicators was greater than the variance shared with other constructs. This finding aligned with our theoretical expectations and enhanced our confidence in the reliability and validity of our measurement model. The robust discriminant validity also confirmed the latent construct distinctiveness, providing further proof that the model was valid.

Table 6 presents the pattern matrix displaying the factor loadings for each indicator variable on the latent factors, Factor 1 (Embrace) and Factor 2 (Enact). Additionally, the table includes uniqueness values, which represent the proportion of variance in each indicator that is unique or not accounted for by the latent factors. Uniqueness represents the proportion of variance in each indicator that is unique or not explained by the latent factor(s) (Shrestha, 2021). Unique values should be positive and typically fall between 0 and 1 (Hair et al., 2019). Upon examining the uniqueness values, we gain insights into the measurement quality and distinctiveness of the individual indicators.

Table 6

Final Factor Loadings for Embrace and Enact

Question #	Embrace	Enact	Uniqueness
23EMB	0.858		0.327
30EMB	0.831		0.316
22EMB	0.830		0.312
21EMB	0.739		0.388
25EMB	0.726		0.412
29EMB	0.687		0.417
7ENA		0.948	0.282
9ENA		0.779	0.326
10ENA		0.753	0.384
3ENA		0.707	0.387
2ENA		0.651	0.444
8ENA		0.601	0.380

Note. Uniqueness values indicate the proportion of variance unexplained by the factors.

Factor 1: Embrace

- Indicator 23EMB exhibited a relatively low uniqueness value, suggesting that the Embrace factor explains a substantial portion of its variance.
- Similarly, 30EMB and 22EMB also had low uniqueness values, indicating a strong association with the Embrace factor.
- Indicator 21EMB shared a considerable amount of variance with the Embrace factor.
- 25EMB and 29EMB's higher uniqueness values suggested that a significant portion of their variance was not shared with the Embrace factor.

Factor 2: Enact

- Indicator 7ENA displays a relatively low uniqueness value of 0.282, indicating a strong association with the Enact factor.
- 9ENA and 10ENA also have low uniqueness values (0.326 and 0.384, respectively), suggesting a strong relationship with the Enact factor.
- Indicator 3ENA has a unique value of 0.387, indicating that it shares a substantial amount of variance with the Enact factor.
- 2ENA and 8ENA have higher uniqueness values of 0.444 and 0.380, respectively, suggesting that the Enact factor does not explain a significant portion of their variance.

These findings provide valuable insights into the measurement properties of the individual indicators within the Embrace and Enact factors. Indicators with lower uniqueness values tend to be well-represented by the respective latent factor, while those with higher uniqueness values may warrant further examination, potentially including item revision or reconsideration for inclusion in the measurement model.

The assessment of uniqueness values contributes to our understanding of the quality of the measurement model and guides decisions regarding the refinement and improvement of the model fit and construct validity.

CFA Results

We performed a CFA to examine the structural validity of the measurement model proposed for our study. The CFA aimed to assess the fit of the observed data to the hypothesized model and confirm the relationships between latent constructs and observed variables.

The analysis utilized data collected from a sample of 403 participants. The dataset originally included three observed variables measured on a 5-point Likert scale to assess three latent constructs: Embrace, Engage, and Enact. However, due to the previously discussed factor cross-loading, we eliminated the Engage factor along with questions that we felt would enhance the instrument's reliability. We continued with our CFA testing using Embrace and Enact.

Our hypothesized measurement model specified the following:

- Embrac*e* was indicated by six observed items.
- Enact was indicated by six observed items.
- Covariances were specified between the two latent constructs.

Following the elimination of cross-loadings, a notable outcome was the realignment of specific items with different factors. Notably, items that were originally assigned to Factor 1 (Embrace) were now demonstrating stronger associations with Factor 2 (Enact) and vice versa. Upon closer examination, it became evident that these items' content and theoretical relevance were more aligned with their new factors, prompting their reassignment. This adjustment enhances the content validity of the factors, as items are now conceptually aligned with their respective constructs.

The reliability of the measurement model is strengthened, as it more accurately captures the intended dimensions of our study. The removal of cross-loadings resulted in a substantial improvement in model fit indices, reinforcing the appropriateness of our measurement model. Further research could involve confirmatory factor analysis in diverse samples to validate the revised measurement model and assess the consistency of item-factor assignments.

Measurement-Model Fit

The Chi-square statistic for the CFA suggested a lack of fit between the hypothesized (Baseline) model and the observed data (Table 7).

Table 7

Model Fit Chi-Square Test

Model	χ^2	*df*	*p*
Baseline model	3352.354	66	
Factor model	109.306	53	< .001

Note. This test showed a significant improvement in fit for the factor model versus the baseline model.

However, Chi-square is sensitive to sample size, and in larger samples, even minor discrepancies between the model and data can lead to significant results (Bergh, 2015). We, therefore, provided additional fit indices to obtain a more comprehensive assessment of model fit in Tables 8 through 11, detailing statistics for each of these additional indices, models, indicators, and measures with explanations for goodness of fit interpretations.

Table 8

Additional Fit Measures Fit Indices

Index	Value
Comparative Fit Index (CFI)	0.983[a]
Tucker-Lewis Index (TLI)	0.979[a]
Bentler-Bonett Non-normed Fit Index (NNFI)	0.979
Bentler-Bonett Normed Fit Index (NFI)	0.967
Parsimony Normed Fit Index (PNFI)	0.777
Bollen's Relative Fit Index (RFI)	0.959
Bollen's Incremental Fit Index (IFI)	0.983
Relative Noncentrality Index (RNI)	0.983

Note. [a]CFI and TLI are a good indication of model fit when close to 1.

Table 9

Information Criteria

Criteria	Value
Log-likelihood	-5764.916
Number of free parameters	37.000
AIC	11603.832
BIC	11751.792
SSABIC	11634.388

Note. Lower values indicate better model fit, with the Akaike (AIC), Bayesian (BIC), and sample-size adjusted Bayesian (SSABIC) criteria providing comparative metrics.

Table 10

Other Fit Measures

Metric	Value
RMSEA	0.051[a]
RMSEA 90% CI lower bound	0.038[a]
RMSEA 90% CI upper bound	0.065[a]
RMSEA *p*-value	0.416
Standardized root *M* square residual (SRMR)	0.025[a]
Hoelter's critical N (α = .05)	262.746
Hoelter's critical N (α = .01)	295.375
Goodness of fit index (GFI)	0.989
McDonald fit index (MFI)	0.933
Expected cross validation index (ECVI)	0.455

Note. RMSEA = Root *M* square error of approximation. [a]RMSEA and SRMR are a good fit indication when < .08, with tight CIs.

The goodness-of-fit indices collectively suggested that the proposed model provided an outstanding fit to the observed data. These results support the adequacy and validity of the model, indicating that it effectively explained the relationships among the variables with very little unexplained variance.

These fit indices exceeded widely accepted thresholds for good model fit, indicating that the hypothesized measurement model strongly represented the relationships between latent constructs and observed variables.

Table 11

KMO Test

Question #	MSA Scores
21EMB	0.955
22EMB	0.958
23EMB	0.951
25EMB	0.962
29EMB	0.964
30EMB	0.954
2ENA	0.957
3ENA	0.948
7ENA	0.935
8ENA	0.960
9ENA	0.949
10ENA	0.949
Overall	0.953

Note. The Kaiser-Meyer-Olkin (KMO) measures the sampling adequacy, and these scores reflect excellent suitability for factor analysis.

Bartlett's Test of Sphericity

A Bartlett's test of sphericity was conducted to examine the suitability of the data for factor analysis. The test was significant, $\chi^2(66) = 3303.830$, $p < .001$, indicating that the correlation matrix is not an identity matrix and that factor analysis is appropriate for the data.

R-Squared and Variance

Table 12 presents the *R*-squared values for the Embrace and Enact selected questions. These values indicate the proportion of variance in the dependent variable that each question can explain. The *R*-squared values range from 0.561 (for 2ENA) to 0.684 (for 2EMB), indicating varying levels of explanatory power. Higher *R*-squared values suggest a greater proportion of variance explained by the corresponding question (Montgomery et al., (2012).

Table 12

R-Squared Values for Embrace and Enact Questions

Item #/Scale	R^2
21EMB	0.616
22EMB	0.684
23EMB	0.664
25EMB	0.591
29EMB	0.589
30EMB	0.680
2ENA	0.561
3ENA	0.625
7ENA	0.671
8ENA	0.624
9ENA	0.674
10ENA	0.613

Note. Explains the proportion of variance for each factor.

Factor Variances

The factor variances were examined to understand the variability associated with each factor. For Factor 1, the variance estimate was 1.000, with a standard error of 0.000. The *z*-value and *p*-value were not applicable, and the 95% confidence interval ranged from 1.000 to 1.000. Similarly, for Factor 2, the variance estimate was also 1.000, with a standard error of 0.000. The *z*-value and *p*-value were not applicable, and the 95% confidence interval ranged from 1.000 to 1.000. According to Brown (2015), these results indicated that the variances for both factors are fixed and standardized, as is common in factor analysis to ensure the factors are on a comparable scale.

Factor Loadings

Table 13 provides the standardized factor loadings, standard errors, *z*-values, *p*-values, and 95% CIs for the indicators associated with two latent factors, Embrace and Enact. Embrace's six indicators' factor loadings were statistically significant ($p < .001$), and the 95% CIs suggested consistent and strong factor loadings, with the lower and upper bounds indicating the range for the true population. Enact's six indicators' factor loadings were all significant ($p < .001$), with the 95% CIs indicating a strong relationship between the indicators and the latent factor. These data provide evidence that the indicators are good measures of the latent constructs Embrace and Enact.

Table 13

Parameter Estimates Factor Loadings

							95% Confidence Interval	
Factor	Indicator	Symbol	Estimate	Std. Error	*z*-value	*p*	Lower	Upper
Embrace	21EMB	$\lambda 11$	0.860	0.047	18.422	< .001	0.768	0.951
	22EMB	$\lambda 12$	0.946	0.047	19.943	< .001	0.853	1.039
	23EMB	$\lambda 13$	0.905	0.046	19.488	< .001	0.814	0.996
	25EMB	$\lambda 14$	0.863	0.048	17.867	< .001	0.769	0.958
	29EMB	$\lambda 15$	0.871	0.049	17.836	< .001	0.775	0.966
	30EMB	$\lambda 16$	0.936	0.047	19.858	< .001	0.843	1.028
Enact	2ENA	$\lambda 21$	0.837	0.049	17.193	< .001	0.742	0.933
	3ENA	$\lambda 22$	0.823	0.044	18.610	< .001	0.737	0.910
	7ENA	$\lambda 23$	0.935	0.048	19.606	< .001	0.841	1.028
	8ENA	$\lambda 24$	0.889	0.048	18.574	< .001	0.795	0.983
	9ENA	$\lambda 25$	0.911	0.046	19.692	< .001	0.820	1.001
	10ENA	$\lambda 26$	0.864	0.047	18.323	< .001	0.771	0.956

Factor Covariances

The covariances between factors were examined to understand the relationships between them. The covariance between Factor 1 and Factor 2 was estimated to be 0.828, with a standard error of 0.021. The *z*-value for this estimate was 39.455, and the *p*-value was less than .001, indicating that the covariance is statistically significant. The 95% confidence interval for the covariance ranged from 0.787 to 0.869.

These results suggest a strong and statistically significant positive relationship between Factor 1 and Factor 2. The high *z*-value and the significant *p*-value indicate that the covariance is not due to chance (Tabachnick & Fidell, 2013). The narrow confidence interval further supported the precision of this estimate.

Residual Variances

The indicators' residual variances (Table 14) were all significant at the $p < .001$ level, indicating that the unexplained variances were substantial. The estimates for the residual variances ranged from 0.400 for 9ENA to 0.549 for 2ENA, with standard errors ranging from 0.033 to 0.043. The *z*-values were all above 11, and the 95% confidence intervals were relatively narrow, suggesting precise estimates.

Table 14

Residual Variances

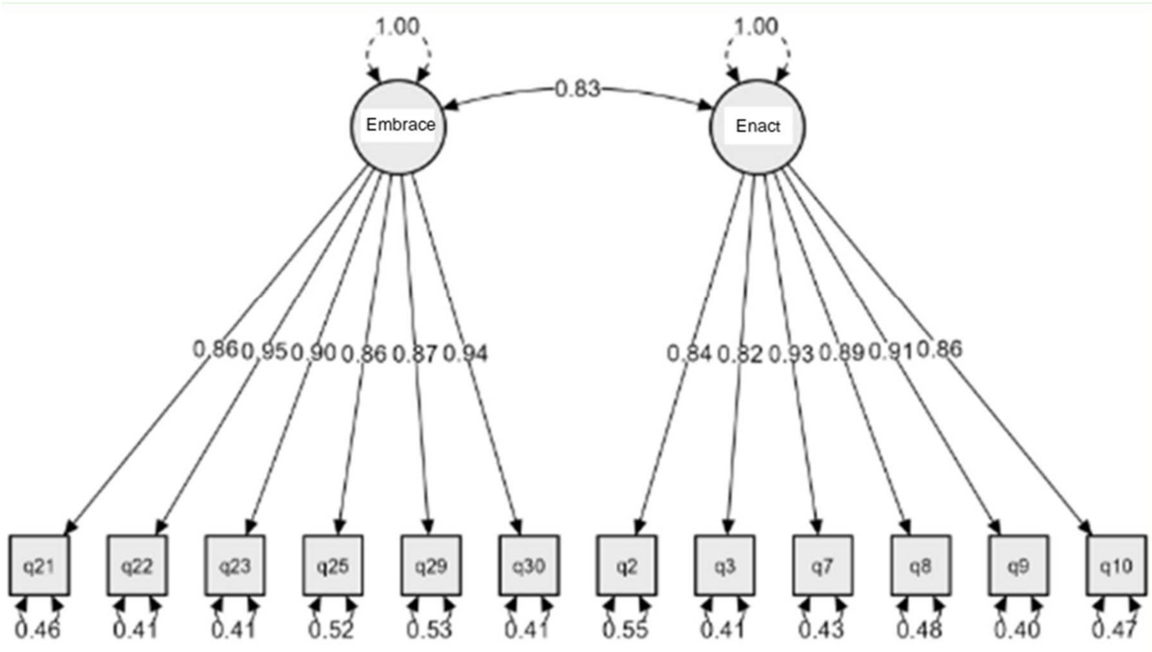
					95% Confidence Interval	
Indicator	Estimate	Std. Error	z-value	*p*	Lower	Upper
21EMB	0.461	0.037	12.326	< .001	0.388	0.534
22EMB	0.413	0.035	11.664	< .001	0.344	0.482
23EMB	0.415	0.035	11.890	< .001	0.346	0.483
25EMB	0.517	0.041	12.505	< .001	0.436	0.598
29EMB	0.529	0.042	12.522	< .001	0.446	0.611
30EMB	0.411	0.035	11.698	< .001	0.342	0.480
2ENA	0.549	0.043	12.648	< .001	0.464	0.634
3ENA	0.406	0.033	12.164	< .001	0.340	0.471
7ENA	0.429	0.037	11.675	< .001	0.357	0.501
8ENA	0.475	0.039	12.132	< .001	0.398	0.552
9ENA	0.400	0.034	11.644	< .001	0.333	0.468
10ENA	0.471	0.038	12.232	< .001	0.395	0.546

Structural Equation Model (SEM)

The SEM, illustrated in Figure 3, represents the relationships between two latent factors (Embrace and Enact) and their respective observed indicators (q21 to q10). Embrace is associated with Questions 21, 22, 23, 25, 29, and 30 indicators, while Enact is associated with Questions 2, 3, 7, 8, 9, and 10. The factor loadings, depicted as numbers on the arrows connecting the Embrace factor and the Enact factor to their indicators, range from 0.84 to 0.95, indicating strong relationships between the latent factors and their indicators. The correlation between Embrace and Enact, 0.83, suggests a strong positive relationship between the two factors. The uniqueness values (e.g., 0.46, 0.41) represent the proportion of variance in each observed variable that is not explained by the latent factors. For example, Question 21EMB has a residual variance of 0.46, meaning Embrace explains 54% of its variance. Overall, the model demonstrates that both Embrace and Enact are well-represented by their indicators, with high factor loadings and a significant correlation, while acknowledging some unexplained variance in the indicators.

Figure 3

Structural Equation Model Plot



Discussion

This study aimed to develop and validate a quantitative instrument, the CABS, to measure cultural awareness and belonging within the context of DEI in organizations. The findings from this research contribute to understanding how these constructs can be effectively assessed and their impact on organizational outcomes.

The results supported the initial hypothesis that cultural awareness and belonging are measurable constructs within DEI initiatives. The two-dimensional model, consisting of the Embrace and Enact subscales, emerged as a robust representation of these constructs. The high internal consistency reliability (Cronbach's $\alpha > .90$ for both dimensions) indicates that the items within each subscale are closely related and consistently measure the intended constructs.

While the initial three-factor model (Embrace, Engage, and Enact) was theoretically sound based on an academic subject matter expert panel's review of the items and scales, the data supported a more parsimonious two-factor model. This finding suggests that cultural awareness (Embrace) and belonging (Enact) are distinct yet interrelated dimensions that can be reliably measured. The removal of the Engage scale and dimension may reflect the overlap between action-oriented behaviors and the existing subscales or the need for a more refined operationalization of enactment behaviors in future research.

Practical Applications

The validated CABS provides organizations with a practical tool to assess and enhance their DEI initiatives. Understanding employees' perceptions of cultural awareness and belonging can inform targeted interventions to foster a more inclusive work environment. For instance, organizations can use the Embrace subscale to gauge the effectiveness of DEI training programs and the Enact subscale to measure the impact of inclusion efforts on employee engagement and retention.

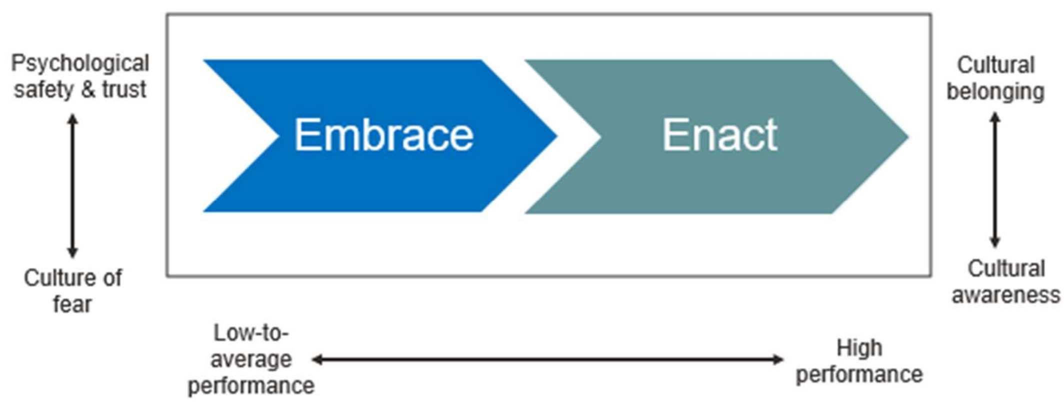
Additional examples of utilizing survey instruments such as the CABS to help gauge the effectiveness of DEI programs are found in the extant literature. For instance, Allen et al. (2021) found that measuring the construct of belonging enables organizations to evaluate the extent to which their employees feel connected and supported. Similarly, Stachl and Baranger (2020) discovered that the use of a cultural belonging survey can help organizations determine which individuals are least likely to experience feelings of belonging or most likely to struggle with imposter syndrome. Schaechter et al. (2023), in their survey of women in healthcare, showed that an increased sense of workplace belonging is positively correlated with a lower likelihood of attrition, which has direct implications for how organizational leaders need to address DEI issues such as cultural awareness and belonging.

The strong model fit indices indicated that the survey items accurately captured the constructs of interest, providing a reliable basis for organizational assessment and improvement. These metrics affirm the utility of CABS in diverse organizational settings and its potential to drive positive outcomes such as improved performance, reduced absenteeism, and decreased turnover.

While the factor loadings only supported a two-dimensional model that consisted of the Embrace and Enact subscales as measures of cultural awareness and belonging, respectively, we believe DEI cultural awareness and belonging fall on a directional continuum beginning at embracing DEI and moving toward enacting with DEI applications. These findings may have practical implications for employee performance and psychological safety at work, among other organizational impacts (Singh et al., 2013), as shown in Figure 4.

Figure 4

Cultural Awareness and Belonging Continuum



Note. The cultural awareness and belonging continuum represents the constructs of Embrace and Enact and how they can interact with how employees may feel that their organization values their contributions

Cultural Considerations and Future Directions

While CABS has been validated within a U.S.-based context, it is crucial to recognize that the constructs of "cultural awareness" and "belonging" may be understood and experienced differently across diverse cultural settings. For instance, in non-Western cultures, where collective identity and communal relationships might be more emphasized, the individualistic interpretation of belonging prevalent in Western contexts could require adaptation. Similarly, the concept of cultural awareness may vary, with some cultures placing a higher value on hierarchical relationships or social harmony, potentially influencing how individuals perceive and respond to survey items.

Given these potential differences, we suggest that additional validation studies be conducted in non-Western countries or culturally distinct regions. Such studies would be invaluable in determining the cross-cultural applicability of CABS and in identifying any necessary modifications to the instrument. For example, the language used in survey items might need to be adjusted to reflect cultural nuances or additional dimensions could be explored to capture culturally specific aspects of belonging and awareness.

Furthermore, future research could explore the development of guidelines for adapting CABS to diverse cultural environments. These guidelines might include culturally relevant examples, context-specific phrasing, or alternative response scales that resonate more effectively with participants from different cultural backgrounds. By pursuing these avenues, researchers and practitioners can ensure that CABS remains a robust and reliable tool for assessing DEI-related constructs in a variety of organizational contexts worldwide.

Theoretical Contributions

This study advances the theoretical understanding of cultural awareness and belonging within DEI research. The study highlights the importance of adaptive cognitive processing and skill development in fostering inclusion by grounding the survey development in the theory of generative interactions. The distinction between cultural awareness (Embrace) and belonging (Enact) aligns with Bernstein et al. (2020), who posited that awareness is a precursor to deeper engagement and inclusion.

Furthermore, the study's findings resonate with the broader DEI literature (Kennedy & Jain-Link, 2021; Schwartz et al., 2020), which emphasizes the need for continuous and committed efforts to build inclusive cultures. The identified dimensions of Embrace and Enact provide a structured framework for exploring how organizations can move from awareness to active participation in DEI initiatives.

Limitations and Ideas for Future Research

While the study provides valuable insights, several limitations should be acknowledged. The cross-sectional design limited the ability to draw causal inferences, and the sample was restricted to U.S.-based participants, which may affect the generalizability of the findings. Future research could employ longitudinal designs to examine the stability of the constructs over time and explore the applicability of CABS in diverse cultural contexts.

Additionally, further refinement of the initially proposed Engage dimension could enhance the comprehensiveness of the survey. Investigating the specific behaviors that constitute the engagement of DEI principles and their distinct impact on organizational outcomes could provide a richer understanding of this construct.

Conclusion

CABS is a valid and reliable instrument for measuring DEI constructs in organizations. The two-dimensional model of Embrace and Enact offers a robust framework for assessing cultural awareness and belonging, with significant implications for both research and practice. By leveraging this tool, organizations can better understand and enhance their DEI efforts, ultimately fostering a more inclusive and productive work environment. Future research should continue to refine and expand upon this instrument to further support the advancement of DEI initiatives in diverse organizational contexts.

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Appendix: Cultural Awareness and Belonging Survey (CABS)

The response scale for CABS:

1 = *Strongly disagree*; 2 = *Disagree*; 3 = *Neither agree nor disagree*; 4 = *Agree*; 5 = *Strongly agree*.

EMBRACE

1. As a result of my organization's DEI efforts, I feel more accepted for who I am.
2. As a result of my organization's DEI efforts, I am less likely to leave.
3. Due to my organization's DEI efforts, I am more productive.
4. I recognize how my own contributions help move my organization's DEI agenda forward.
5. People are less likely to leave my organization based on its DEI efforts.
6. People are more likely to join my organization based on its DEI efforts.

ENACT

7. I feel that my organization provides sufficient DEI education.
8. I would describe the culture of my organization as one that embraces DEI.
9. My organization is appreciative of employee diversity.
10. My organization is committed to creating DEI awareness among employees.
11. My organization understands the importance of hiring employees from different cultural backgrounds.
12. My organization understands the importance of promoting employees from different cultural backgrounds into leadership roles.