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Development of Basic Science Teachers' adversity scale

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Abstract
This study developed and validated the Basic Science Teachers' Adversity Scale (BSTAdQ) to measure teachers' capacity to cope with professional challenges. Grounded in the four theoretical dimensions of adversity. The initial pool of 100 items was generated and subjected to systematic psychometric evaluation. A sample of 111 public junior secondary school Basic Science teachers in Ibadan, Nigeria, was selected using a multi-stage sampling technique. Data collected were analysed using exploratory factor analysis (EFA), parallel analysis, exploratory graph analysis (EGA), confirmatory factor analysis (CFA), and reliability estimation. Results from parallel analysis and EGA consistently supported a four-factor structure, which was confirmed through EFA following iterative item purification. The CFA results indicated that all items loaded significantly on their respective constructs, supporting convergent validity. The overall model demonstrated an acceptable fit to the data (CFI = 0.825, TLI = 0.805, RMSEA = 0.077, SRMR = 0.084), indicating that the four-factor model adequately represents the underlying structure of the scale. Reliability analysis showed strong internal consistency across all constructs with coefficients exceeding 0.70. The study concludes that the BSTAdQ is a reliable and valid instrument for assessing adversity among Basic Science teachers.
Keywords: Basic Science teachers, Adversity scale, Exploratory Graph Analysis (EGA), Construct validity, Psychometric validation

Introduction
Education remains a critical instrument for national development, and the quality of any educational system is largely determined by the effectiveness of its teachers. Teachers are central to the teaching–learning process, serving as facilitators of knowledge, role models, and implementers of educational policies. As noted by Lian et al. (2012), teachers play a vital role in moulding students' character and directing them toward success, while Berman (2015) emphasized that effective teachers must possess a repertoire of pedagogical skills and attitudes that foster meaningful learning and human relationships. In line with this, effective teachers are those who consistently produce significant student learning gains, reinforcing the assertion that teacher quality directly influences students' academic achievement. This position is further supported by Nigeria's National Policy on Education (2006), which states that no educational system can rise above the quality of its teachers.

Despite the recognized importance of teachers, the Nigerian education system continues to face significant challenges that undermine teaching effectiveness and learning outcomes. Reports indicate a steady decline in educational standards, characterized by poor teaching and learning conditions, moral decadence, examination malpractice, and increasing dropout rates (Federal Ministry of Education, 2006). Scholars such as Ogunsaju (1990) and Blumende (2001) have highlighted the deterioration in educational quality, attributing it to systemic issues including inadequate infrastructure, insufficient instructional materials, and poor teacher welfare. Olaniyan and Israel (2013) further observed that many public schools are plagued by dilapidated facilities, inadequate manpower, and low staff morale due to unfavourable working conditions. These challenges are particularly evident at the basic education level, where foundational learning is expected to occur.

Basic Science teachers, who are responsible for laying the groundwork for scientific literacy, are especially affected by these adverse conditions. Their work environment is often characterized by large class sizes, limited laboratory facilities, inadequate teaching resources, and weak administrative support (Smith, 2025; Wang, 2024). In Ibadan metropolis, these challenges are further compounded by diverse socio-economic conditions and infrastructural limitations, which significantly influence teachers' experiences and effectiveness (Onuka & Emunemu, 2009; Fayemi and Aliyu, 2026). Such adversities not only hinder instructional delivery, but also affect teachers' emotional well-being and job satisfaction, ultimately impacting students' academic outcomes.

In response to these challenges, recent research has increasingly focused on psychological constructs such as resilience and adversity quotient (AQ) as critical determinants of teachers' ability to cope with workplace difficulties. Resilience, defined as the capacity to adapt and thrive despite challenges (Masten, 2018), has been linked to reduced burnout and improved teaching effectiveness (Beltman, Mansfield & Price 2019). Similarly, adversity quotient, as conceptualized by Stoltz (1999), refers to an individual's ability to withstand and overcome adversity. It comprises four key dimensions: Teacher Control (TC), Teacher Ownership (TO), Teacher Reach (TR), and Teacher Endurance (TE). Teacher Control dimension reflects an individual's perceived ability to influence challenging situations, which has been associated with reduced stress and improved coping (Skinner, 2014; Gallagher, Bentley and Barlow, 2014). TO involves taking responsibility for addressing adversity, and promoting proactive problem-solving behaviours (Bowers, 2015; Perera et al., 2018). TR pertains to the extent to which adversity affects other areas of life, with effective containment linked to better psychological well-being (Neff, 2021). TE relates to perceptions of the duration of adversity, where optimism and viewing challenges as temporary enhanced resilience (Carver & Scheier, 2014; Schroder et al., 2017).

The relevance of adversity quotient in education is well documented. Studies have shown that teachers with high AQ demonstrate greater perseverance, adaptability, and effectiveness in managing classroom challenges. Additionally, AQ has been identified as a predictor of academic performance and professional success across various fields, including education (Bautista et al., 2018). However, findings are not entirely consistent, as some studies report a negative relationship between AQ and job performance (Ablaña, Isidro and Cabrera, 2016), suggesting the need for further investigation within specific contexts.

Despite the growing body of literature on adversity and resilience, there remains a significant gap in the development of context-specific instruments for measuring adversity among teachers, particularly in Nigeria. Most existing studies have been conducted in different cultural and educational settings, limiting the applicability of their findings to the Nigerian context. Furthermore, many of the available measurement tools are generalized and do not adequately capture the unique challenges faced by Basic Science teachers in environments such as Ibadan metropolis. As emphasized by Asanza (2025), contextualized research is essential for generating meaningful insights that can inform policy and practice.

The development of a valid and reliable Basic Science Teachers' Adversity Scale is therefore imperative. Such a scale would provide a systematic means of assessing teachers' experiences of adversity and their capacity to cope with challenges. The use of quantitative and psychometric approaches, including techniques such as Rasch measurement modelling, ensures the accuracy, reliability, and validity of the instrument (Combrinck, 2020; Yoon et al., 2015). Additionally, incorporating diverse teacher perspectives through appropriate sampling techniques enhances the generalizability and relevance of the findings (Daugherty and Custer, 2012).

Given the complexity of teaching environments and the multifaceted nature of adversity, a comprehensive and contextually grounded measurement tool is necessary to support educational improvement efforts. Such a tool can inform targeted interventions, guide professional development programs, and assist policymakers in addressing the challenges faced by teachers. Moreover, it can provide insights into how adversity influences teachers' professional competence, instructional practices, and overall effectiveness.

Against this backdrop, this study seeks to develop and validate a Basic Science Teachers' Adversity Scale (BSTAdQ Scale) specifically for use in Ibadan metropolis. The study focuses on operationalizing the four dimensions of adversity quotient—control, ownership, reach, and endurance—within the context of Basic Science teaching. It also aims to establish the psychometric properties of the scale and examine the influence of teachers' demographic and professional characteristics, such as qualification, years of experience, and age, on their adversity quotient. By addressing the identified gaps, this study intends to contribute to the advancement of educational research and practice, particularly in enhancing teacher effectiveness and improving the quality of Basic Science education in Nigeria.

The following research questions were raised to guide this study:

1. What is the underlying factor structure of the Basic Science Teachers' Adversity Scale (BSTAdQ)?
2. To what extent does the BSTAdQ demonstrate construct validity?
3. How well does the proposed measurement model of the BSTAdQ fit the observed data?
4. What is the reliability of the BSTAdQ scale?

Methods

Research Design

This study adopted a quantitative, cross-sectional research design to develop and validate a multi-dimensional measurement scale (Gottert et al., 2021). Data were collected at a single point in time using a structured questionnaire designed to measure the hypothesised constructs. A survey method was deemed appropriate as it allows for the systematic collection of standardized responses across a relatively large sample (Nardi, 2018). The study utilized a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) to capture respondents' perceptions. A total of 111 valid responses were obtained and used for analysis. The research design is consistent with scale development and validation studies, where statistical techniques are employed to examine the dimensionality, reliability, and validity of measurement instruments.

Population

The population of this study comprised all public secondary schools in Ibadan Metropolis, with a specific focus on public junior secondary school Basic Science teachers across both rural and urban settings. This population was selected due to its relevance to the study objectives, particularly in capturing variations in teaching contexts within metropolitan and semi-urban environments.

Sampling Technique and Sample

The sample consisted of 111 Basic Science teachers drawn from public junior secondary schools in Ibadan Metropolis. A multi-stage sampling technique was employed to ensure adequate representation across different geographical contexts. In the first stage, simple random sampling was used to select one Local Government Area (LGA) from the eleven LGAs in Ibadan, which include five urban and six semi-urban LGAs. In the second stage, one sector was randomly selected from the chosen LGA. In the third stage, four wards were randomly selected from the selected sector, comprising two rural (less urbanized) wards and two semi-urban wards to ensure diversity in the sample. Finally, Basic Science teachers within the selected wards were included in the study, resulting in the final sample size of 100 respondents. This procedure ensured a balanced representation of teachers across different settlement types within the metropolis.

Development of the Basic Science Teachers' Adversity Scale (BSTAdv)

The instrument used in this study, the Basic Science Teachers' Adversity Scale (BSTAdv), was adapted from an existing Job Adversity framework and further developed to suit the context of Basic Science teaching. The scale was designed to measure four core dimensions of teacher adversity: control, ownership, reach, and endurance. The initial instrument consisted of 100 items, developed to comprehensively capture these constructs, following established recommendations that initial item pools should be at least three to four times larger than the intended final scale to ensure adequate coverage and internal consistency.

The BSTAdv was structured into five sections. Section A captured demographic information of respondents, including gender, school, and highest educational qualification. Sections B to E measured the four dimensions of adversity: Section B (Control), Section C (Ownership), Section D (Reach), and Section E (Endurance), with each section containing 25 items. A five-point Likert scale was used for measurement, with response options tailored to the nature of each construct. For the Control and Ownership dimensions, responses ranged from *Very Low (1)* to *Very High (5)*, while for Reach and Endurance; responses ranged from *Never (1)* to *All the Time (5)*.

To ensure content validity and clarity, the initial 100-item instrument underwent trial testing, during which items were reviewed for relevance, wording, and alignment with the theoretical constructs. Following this, a pilot study was conducted to evaluate the psychometric properties of the scale. The pilot data were subjected to systematic analysis involving measurement purification, assessment of dimensionality, and evaluation of reliability and construct validity. Based on these analyses, poorly performing items, such as those with low factor loadings, weak communalities, or cross-loadings were removed.

The refinement process resulted in a more robust and theoretically coherent scale. The final version of the BSTAdv retained a structured format with four dimensions, each represented by 25 items, ensuring balanced coverage of the adversity construct. The refined instrument was subsequently used for the main study to collect data for further validation and analysis, providing a reliable and valid measure of Basic Science teachers' adversity in the study context.

Data Analysis Procedure

The scale validation process followed a two-stage approach: Exploratory Factor Analysis (EFA), Exploratory Graph Analysis (EGA), followed by Confirmatory Factor Analysis (CFA). All analyses were conducted using R 4.4.2 statistical software, primarily utilizing the psych and lavaan packages.

Exploratory Factor Analysis (EFA)

EFA was conducted to identify the underlying factor structure and refine the measurement scale (El-Den et al., 2020). Maximum likelihood (ML) extraction with oblimin rotation was employed, allowing for correlated factors (Jafarnezhad, 2025). Prior to factor extraction, the suitability of the data for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. Initial results indicated inadequate sampling adequacy, necessitating item refinement (Shrestha, 2021).

An iterative item purification process was implemented to improve the factor structure. Items were evaluated and removed based on the following criteria: (1) factor loadings below 0.40, (2) communalities (h^2) below 0.30, and (3) substantial cross-loadings (≥ 0.30 on multiple factors) (Khawaja and Armstrong, 2005). After each iteration, EFA was re-run to reassess the structure. This process resulted in a reduced and more coherent set of items with improved psychometric properties. Parallel analysis was conducted to determine the appropriate number of factors, and results supported a four-factor solution, which was consistent with the theoretical model.

The final EFA solution demonstrated acceptable model fit and interpretability, with most items loading strongly on their respective factors and minimal cross-loadings. Sampling adequacy improved significantly (KMO = 0.80), and Bartlett's test was significant ($p < .001$), confirming the appropriateness of factor analysis.

Exploratory Graphical Analysis (EGA)

Following the exploratory factor analysis (EFA) and parallel analysis, an Exploratory Graphical Analysis (EGA) was conducted as an additional robustness check to support the identified factor structure (Sheykhangafshe et al., 2024). EGA employs network-based modelling to estimate data dimensionality by detecting clusters of items using partial correlations (Shi et al., 2025). In this study, EGA was used after the EFA refinement process to validate the number of dimensions suggested by parallel analysis and to assess whether the retained items formed coherent and distinct clusters.

Confirmatory Factor Analysis (CFA)

Following EFA, CFA was conducted to validate the refined factor structure. A four-factor measurement model was specified, with each item loading on its respective latent construct (TC, TO, TR, TE) (Steenkamp & Maydeu-Olivares, 2023). CFA was performed using the maximum likelihood estimation method. Model fit was evaluated using multiple indices, including the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) (Sathyanarayana & Mohanasundaram, 2024). Acceptable model fit was determined based on commonly recommended thresholds

(CFI and TLI ≥ 0.90, RMSEA ≤ 0.08, SRMR ≤ 0.08).

Reliability and Validity Assessment

The reliability and validity of the constructs were assessed following CFA. Internal consistency was evaluated using Cronbach's alpha and composite reliability (CR), with values above 0.70 considered acceptable (Izah et al., 2023). Convergent validity was assessed through standardized factor loadings (≥ 0.50) and average variance extracted (AVE ≥ 0.50). Discriminant validity was evaluated by comparing the square root of AVE with inter-construct correlations and, where necessary, using the heterotrait–monotrait ratio (HTMT) criterion.

Results

Item Refinement

The initial measurement model comprised a pool of 100 items distributed across four theoretical constructs (Control, Ownership, Reach, and Endurance) which were subjected to exploratory factor analysis (EFA) using maximum likelihood extraction with oblimin rotation. Preliminary diagnostics, including a low Kaiser–Meyer–Olkin (KMO) value and weak factor structure, indicated poor sampling adequacy and substantial cross-loadings among items. To address these issues, an iterative item refinement process was undertaken to improve the psychometric quality of the scale.

Items were systematically evaluated and removed based on established statistical criteria, including low factor loadings (< 0.40), low communalities ($h^2 < 0.30$), high cross-loadings (≥ 0.30 on multiple factors), and weak inter-item correlations. This process was conducted sequentially, with EFA re-run after each iteration to reassess the evolving factor structure. Through this rigorous purification procedure, items that did not contribute meaningfully to a clear and interpretable structure were eliminated, while efforts were made to retain those that were theoretically relevant.

In addition to statistical thresholds, refinement decisions were guided by theoretical considerations to ensure that each retained item aligned conceptually with its intended construct. Items exhibiting inconsistent loading patterns or poor conceptual fit were critically reviewed and removed where necessary. Attention was also given to item complexity, ensuring that retained items demonstrated strong unidimensionality, with primary loadings on a single factor.

As a result of this iterative process, 26 items were retained from the original 100-item pool (25 items per construct initially developed: Teacher Control, Teacher Ownership, Teacher Reach, and Teacher Endurance), forming a more parsimonious and psychometrically sound instrument, with retained items distributed as Teacher Control (4 items), Teacher Ownership (8 items), Teacher Reach (8 items), and Teacher Endurance (6 items). The refined scale demonstrated improved factor loadings, stronger communalities, reduced cross-loadings, and enhanced overall structure, culminating in a well-defined four-factor solution. This final item set was deemed appropriate for subsequent confirmatory factor analysis (CFA) to further validate the measurement model.

Research Question One: What is the underlying factor structure of the Basic Science Teachers' Adversity Scale (BSTAdQ)?

KMO and Bartlett's Test

The sampling adequacy and sphericity tests indicate that the refined dataset (BS_clean3) is now highly suitable for factor analysis. The overall Kaiser–Meyer–Olkin (KMO) value of 0.80 falls within the "meritorious" range, demonstrating that the variables share sufficient common variance to justify factor extraction. Additionally, all individual item MSA values exceed the minimum threshold of 0.60, with many above 0.80, confirming that each retained item contributes meaningfully to the factor structure. The Bartlett's Test of Sphericity is also highly significant ($\chi^2(325) = 1265.30$, $p < .001$), indicating that the correlation matrix is not an identity matrix and that there are adequate inter-item correlations for factor analysis. Taken together, these results show a substantial improvement from the initial dataset and provide strong statistical support for proceeding with factor analysis, confirming that the data refinement process has successfully achieved acceptable sampling adequacy and structural validity.

Parallel Analysis

The parallel analysis scree plot provides strong empirical support for the retention of four factors in the dataset. This conclusion is based on the comparison between the eigenvalues from the actual data and those generated from

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both simulated and resampled datasets. Specifically, the first four observed eigenvalues clearly exceed the corresponding eigenvalues from the random data, indicating that these factors explain more variance than would be expected by chance. After the fourth factor, the observed eigenvalues fall below the simulated thresholds, suggesting that any additional factors are likely due to random noise rather than meaningful underlying structure. The sharp decline in eigenvalues followed by a levelling-off pattern further reinforces this interpretation, consistent with the scree test. In summary, the parallel analysis confirms that a four-factor solution is both statistically justified and theoretically appropriate, supporting the factor structure identified in the exploratory factor analysis and providing a robust basis for proceeding to confirmatory factor analysis (CFA).

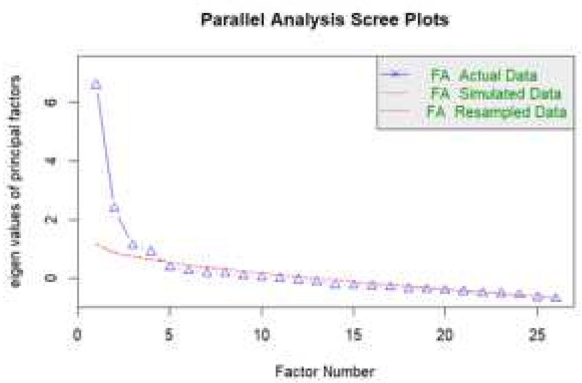

Figure 1: Scree Plot showing a 4-factor structure

Table 1: Factor Loadings for Four-Factor Model

Item	ML1	ML2	ML3	ML4
TC3	—	—		0.75
TC17	—	—		0.69
TC18	—	—		0.42
TC24	—	—		0.81
TO3	—	0.48	—	—
TO13	—	0.59	—	—
TO14	—	0.55	—	—
TO16	—	0.48	—	—
TO21	—	—	—	0.49
TO23	—	0.68	—	—
TO24	—	0.70	—	—
TO25	—	0.67	—	—
TR8	0.53	—	—	—
TR9	0.61	—	—	—
TR12	0.55	—	—	—
TR13	0.81	—	—	—
TR14	0.58	—	—	—
TR15	0.62	—	—	—
TR17	0.60	—	—	—
TR22	0.56	—	—	—
TE12	0.47	—	—	—
TE13	—	—	0.80	—
TE14	—	—	0.60	—
TE15	—	—	0.63	—
TE17	—	—	0.60	—
TE24	0.48	—	—	—

Exploratory Graph Analysis

The exploratory graph analysis (EGA) reveals a clear and interpretable four-cluster structure, supporting the results of the parallel analysis and confirming a four-factor dimensionality for the Basic Science Scale. The network grouped the items into four distinct communities, with relatively dense and stronger positive connections within each cluster and weaker, more diffuse connections between clusters, indicating good internal coherence of each latent dimension and clear separation across constructs. Specifically, the red, blue, green, and orange communities represent four stable latent dimensions, where items within each group tend to cohere strongly and align closely with their respective factors, while cross-cluster edges are comparatively weaker, suggesting limited overlap between constructs. The stability of these communities and the visual clarity of separation provide strong empirical support that the scale is best represented by a four-factor solution, consistent with the earlier parallel analysis and reinforcing the structural validity of the measurement model prior to confirmatory factor analysis.

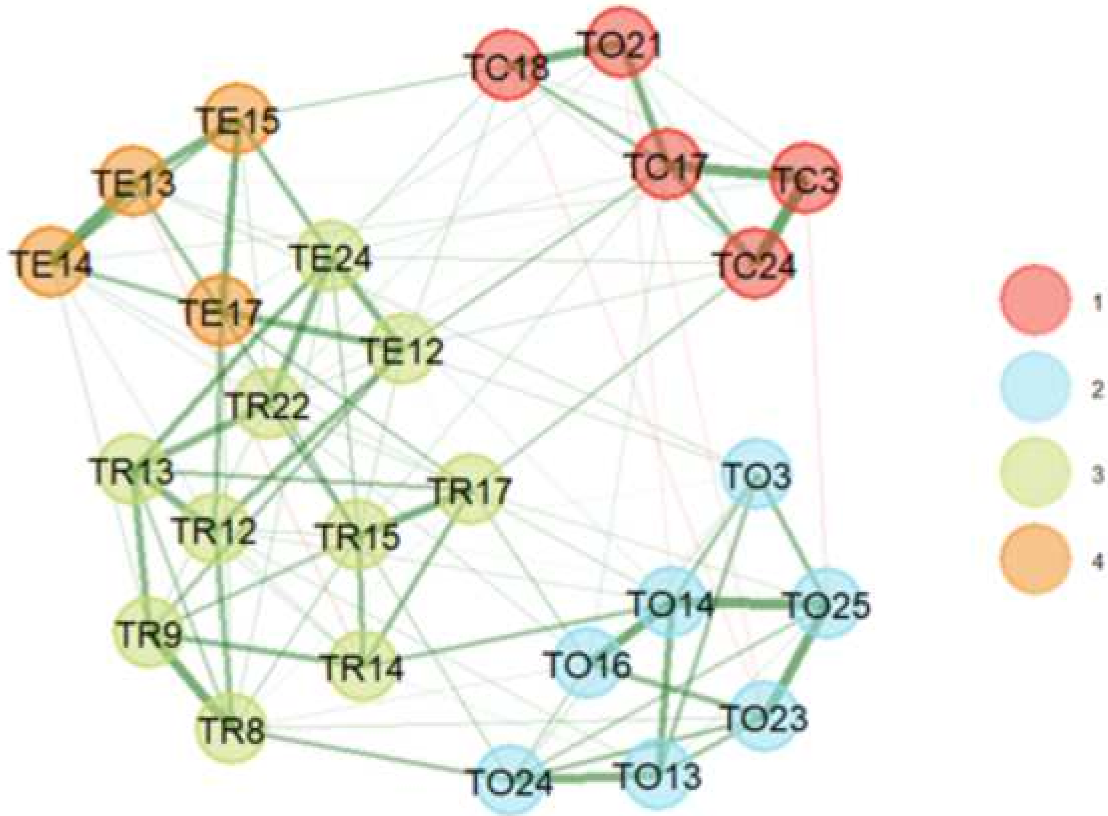

Figure 2: Exploratory Graph Plot

Research Question Two: To what extent does the BSTAdQ demonstrate construct validity?
Confirmatory Factor Analysis

The confirmatory factor analysis (CFA) supports a four-factor measurement model consisting of Control, Ownership, Reach, and Endurance, with all indicators loading significantly on their intended latent constructs ($p < .001$). Standardized factor loadings are generally moderate to high, indicating acceptable convergent validity. For Control, loadings range from 0.551 to 0.769, with strongest contributions from TC17 (0.769) and TC3 (0.743), suggesting these items are strong indicators of the construct. Ownership shows more variability, with loadings ranging from 0.516 to 0.711; TO14 (0.711) and TO25 (0.681) perform best, while TO3 (0.516) is comparatively weaker but still acceptable. Reach demonstrates consistently strong loadings (0.538–0.714), particularly TR15 (0.714) and TR13 (0.703), indicating good construct representation across items. Endurance also shows solid loadings (0.561–0.728), with TE17 (0.728) and TE12 (0.681) as the strongest indicators. Overall, the measurement model demonstrates acceptable convergent validity, as most standardized loadings exceed the commonly recommended threshold of 0.50.

In terms of discriminant validity, the latent correlations suggest mixed results. Control is weakly related to Ownership ($r = 0.059$, not significant), but shows moderate associations with Reach ($r = 0.415$) and Endurance ($r = 0.544$). Ownership, Reach, and Endurance are strongly interrelated, particularly Reach and Endurance ($r = 0.766$), which may indicate conceptual overlap or limited discriminant validity among these constructs. Ownership also correlates substantially with Reach ($r = 0.464$) and Endurance ($r = 0.378$), further suggesting that these constructs, while distinct, are closely connected within the model.

Regarding indicator reliability and error structure, most items show acceptable residual variances, though some indicators (e.g., TC18, TO3, TR14) exhibit relatively higher error proportions, indicating weaker explained variance. Nonetheless, the majority of items show adequate shared variance with their latent

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constructs.

In Summary, the CFA results indicate that the four-factor model is psychometrically acceptable at the indicator level, with strong evidence of convergent validity. However, the high inter-factor correlations, specially between Reach and Endurance, suggest potential discriminant validity concerns, which may warrant further model refinement (e.g., examining higher-order factor structures or item overlap).

Research Question Three: How well does the proposed measurement model of the BSTAdQ fit the observed data?

Model Fit

The confirmatory factor analysis (CFA) model shows suboptimal overall fit based on multiple fit indices. The chi-square statistic is significant ($\chi^2 = 448.05$, df = 269, $p < .001$), indicating that the model-implied covariance matrix differs significantly from the observed data. While this result is common in models with moderate sample sizes (N = 111) and multiple parameters, it still suggests some degree of model misfit. The incremental fit indices fall below recommended thresholds: CFI = 0.825 and TLI = 0.805, both of which are below the conventional cut-off of 0.90 (or 0.95 for a well-fitting model). This indicates that the hypothesized four-factor structure does not improve the fit sufficiently over a null (independence) model. Similarly, the RMSEA = 0.077 suggests a mediocre to borderline fit, as values below 0.06 are typically considered good and values up to 0.08 indicate acceptable but not strong fit. The SRMR value of 0.084 slightly exceeds the commonly accepted threshold of 0.08, further reinforcing evidence of modest misfit at the item level. In summary, the model demonstrates some acceptable features, particularly a reasonable RMSEA, but it does not achieve strong fit across indices. The pattern of results suggests that the measurement structure is plausible but not optimal.

Standardized factor loading

Item	Control	Ownership	Reach	Endurance
TC3	0.743	—	—	—
TC17	0.769	—	—	—
TC18	0.551	—	—	—
TC24	0.710	—	—	—
TO3	—	0.516	—	—
TO13	—	0.587	—	—
TO14	—	0.711	—	—
TO16	—	0.587	—	—
TO23	—	0.597	—	—
TO24	—	0.617	—	—
TO25	—	0.681	—	—
TR8	—	—	0.650	—
TR9	—	—	0.707	—
TR12	—	—	0.634	—
TR13	—	—	0.703	—
TR14	—	—	0.538	—
TR15	—	—	0.714	—
TR17	—	—	0.617	—
TR22	—	—	0.653	—
TE12	—	—	—	0.681
TE13	—	—	—	0.575
TE14	—	—	—	0.561
TE15	—	—	—	0.630
TE17	—	—	—	0.728
TE24	—	—	—	0.678

Research Question Four: What is the reliability of the BSTAdQ scale?

Construct	Cronbach's α	McDonald's ω	ω2	ω3	AVE
Control	0.784	0.794	0.794	0.798	0.497
Ownership	0.807	0.812	0.812	0.813	0.391
Reach	0.855	0.857	0.857	0.859	0.434
Endurance	0.810	0.809	0.809	0.802	0.419

The reliability analysis indicates that all four constructs demonstrate acceptable to strong internal consistency. Cronbach's alpha values range from 0.784 (Control) to 0.855 (Reach), all exceeding the commonly recommended threshold of 0.70, suggesting that the items within each construct consistently measure the same underlying concept. Similarly, McDonald's omega coefficients (ω = 0.794–0.857) confirm strong composite reliability and provide a more robust estimate of internal consistency, particularly for latent variable models. The alternative omega coefficients (ω2 and ω3) show very similar

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values, further reinforcing stability in reliability estimates across methods. However, the Average Variance Extracted (AVE) results present a more nuanced picture of convergent validity. While Control approaches the acceptable threshold (AVE = 0.497), slightly below the recommended 0.50 cut-off, Ownership (0.391), Reach (0.434), and Endurance (0.419) all fall below the ideal level. This indicates that although the constructs are internally consistent, they explain less than 50% of the variance in their indicators, suggesting moderate rather than strong convergent validity. In summary, the measurement model demonstrates good reliability but mixed convergent validity, implying that while the constructs are stable and consistent, some indicators may not strongly represent their underlying latent variables.

Discussion of findings

The present study set out to develop and validate the Basic Science Teachers' Adversity Scale (BSTAdQ), and the findings provide important insights into both the dimensionality and psychometric robustness of the instrument. The combination of parallel analysis and exploratory graph analysis (EGA) offered strong and converging evidence for a four-factor structure, representing Teacher Control, Teacher Ownership, Teacher Reach, and Teacher Endurance. This aligns closely with the theoretical foundation of adversity constructs originally conceptualized in the adversity quotient literature (Stoltz, 1997), thereby supporting the structural validity of the scale. The use of EGA alongside traditional factor retention techniques represents a methodological advancement, as recent studies have emphasized the superiority of network-based approaches in detecting latent dimensions with greater accuracy and stability (Golino & Epskamp, 2017; Christensen & Golino, 2021). The convergence of parallel analysis and EGA in this study strengthens confidence in the retained four-factor solution and addresses longstanding concerns about over- or under-extraction of factors in exploratory research (Hayton et al., 2004).

The confirmatory factor analysis (CFA) results further support the plausibility of the four-factor model, particularly at the indicator level, where all items demonstrated statistically significant and generally moderate-to-high loadings. This is consistent with recommendations in scale development literature that emphasize the importance of achieving loadings above 0.50 to establish adequate convergent validity (Hair et al., 2019). However, despite acceptable item-level performance, the overall model fit indices (CFI = 0.825, TLI = 0.805, RMSEA = 0.077, SRMR = 0.084) indicate only moderate fit. This pattern is not uncommon in newly developed scales, especially those measuring complex psychological constructs across multiple dimensions (Worthington & Whittaker, 2006). Similar studies in educational and psychological measurement have reported initial CFA models with suboptimal fit, often requiring further refinement or the exploration of higher-order or bifactor structures (Brown, 2015; Marsh et al., 2014). Thus, while the current model is theoretically sound, the findings suggest the need for continued refinement, particularly in addressing item redundancy or conceptual overlap.

A key issue emerging from the CFA results is the presence of relatively high inter-factor correlations, especially between Teacher Reach and Teacher Endurance. This raises concerns regarding discriminant validity, as correlations exceeding 0.70 may indicate that constructs are not sufficiently distinct (Fornell & Larcker, 1981). While some degree of association among adversity dimensions is theoretically expected, given that they represent interrelated coping mechanisms, the magnitude observed here suggests potential conceptual overlap. Comparable findings have been reported in resilience and adversity-related scales, where constructs such as persistence, coping, and emotional endurance often show substantial intercorrelations (Connor & Davidson, 2003; Smith et al., 2008). This may reflect the inherently multidimensional yet interconnected nature of adversity. Nonetheless, future studies may consider testing alternative models, such as second-order or hierarchical factor structures, to better account for these relationships.

In terms of reliability, the BSTAdQ demonstrates strong internal consistency across all four constructs, with Cronbach's alpha and McDonald's omega values exceeding recommended thresholds. This is consistent with best practices in psychometric validation, where reliability coefficients above 0.70 are considered acceptable for research purposes (Nunnally & Bernstein, 1994). The consistency of omega estimates further strengthens confidence in the scale, given its robustness in latent variable contexts (Dunn et al., 2014). However, the average variance extracted (AVE) values indicate only moderate convergent validity, as most constructs fall below the 0.50 benchmark. This suggests that, although items are consistent, they may not capture sufficient variance from the underlying constructs, a limitation also noted in early-stage scale development studies (Hair et al., 2019). Such findings highlight the importance of ongoing item refinement and validation across different samples.

One of the key contributions of this study lies in its rigorous and iterative scale purification process. Unlike many studies that rely solely on exploratory and confirmatory factor analysis, this research integrates multiple modern techniques, including parallel analysis, EGA, and iterative item refinement, to enhance the robustness of the measurement model. This approach aligns with recent calls for more comprehensive validation frameworks in scale development (Boateng et al., 2018). Furthermore, the contextualization of the adversity construct within Basic Science teaching represents a novel contribution to the literature, as most existing adversity and resilience scales are either generic or focused on student populations. By tailoring the instrument specifically to teachers, this study addresses a critical gap and provides a tool that can be used to better understand how educators respond to professional challenges.

Summarily, the findings demonstrate that the BSTAdQ is a promising instrument with solid theoretical grounding, acceptable reliability, and emerging evidence of validity. While the four-factor structure is well supported, issues related to model fit and discriminant validity suggest the need for further refinement and cross-validation. Future research should focus on testing the scale in larger and more diverse samples, exploring alternative model specifications, and examining predictive validity in relation to teacher outcomes such as performance and well-being. Despite these limitations, the study makes a significant methodological and empirical contribution to scale development in educational research.

Conclusion

This study developed and validated the Basic Science Teachers' Adversity Scale (BSTAdQ) as a multidimensional instrument for assessing teachers' capacity to cope with professional challenges. Through a rigorous and iterative process involving exploratory factor analysis (EFA), parallel analysis, exploratory graph analysis (EGA), and confirmatory factor analysis (CFA), a four-factor structure—Control, Ownership, Reach, and Endurance—was empirically established and theoretically justified. The convergence of multiple analytical techniques provided strong support for the dimensionality of the scale, while reliability indices indicated that the instrument possesses satisfactory internal consistency. Although the CFA results demonstrated acceptable indicator loadings and moderate model fit, issues related to discriminant validity and overall model fit suggest that the scale, while promising, is still evolving. Overall, the BSTAdQ represents a valuable contribution to educational measurement by providing a context-specific tool for assessing adversity among Basic Science teachers.

Limitations of the Study

Despite its contributions, this study has several limitations. First, the sample size (N = 111), though adequate for exploratory analysis, is relatively small for robust confirmatory factor analysis and may have contributed to the suboptimal model fit indices. Second, the study was geographically limited to public secondary schools in Ibadan, which may restrict the generalizability of the findings to other regions or educational contexts. Third, the relatively high inter-factor correlations observed, particularly between Reach and Endurance, indicate potential overlap among constructs, suggesting that the conceptual distinctiveness of some dimensions may require further refinement. Additionally, some items exhibited moderate communalities and lower average variance extracted (AVE), implying that certain indicators may not strongly capture their underlying constructs. Finally, the study relied solely on self-report data, which may be subject to response bias such as social desirability or common method variance.

Recommendations

Based on the findings of this study, the following recommendations are proposed:

- The Basic Science Teachers' Adversity Scale (BSTAdQ) should be further validated using larger and more heterogeneous samples to enhance its generalizability and improve the stability of the measurement model.
- Items with relatively weak factor loadings or high error variances should be reviewed, refined, or reworded to strengthen convergent validity and improve overall model fit.
- Given the observed inter-factor correlations, future studies should examine alternative measurement models, such as higher-order or bifactor structures, to better represent the relationships among the dimensions of adversity.
- Educational administrators and policymakers are encouraged to utilize the BSTAdQ as a diagnostic tool to assess teachers' adversity levels and inform the design of targeted professional support and intervention programmes.
- Future research should incorporate qualitative approaches, such as interviews or focus group discussions, to provide deeper insights into teachers' lived experiences and further inform the refinement and contextual relevance of the scale.

Suggestions for Future Research

Future studies should extend the validation of the BSTAdQ by conducting cross-validation across different populations, such as teachers from other subject areas, private schools, or different cultural contexts. Longitudinal studies are also recommended to examine the stability of the factor structure over time and to assess how adversity evolves across different stages of teachers' careers. Additionally, future research should investigate the predictive validity of the scale by examining its relationship with relevant outcomes such as teacher performance, job satisfaction, burnout, and student achievement. There is also a need to explore alternative modelling approaches, including structural equation modelling with higher-order constructs, to address the observed discriminant validity concerns. Finally, incorporating mixed-methods designs could enrich understanding and strengthen the theoretical and empirical foundation of the BSTAdQ.

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