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Reconciling Leadership–Diversity Interaction Claims with Published SME Survey Summaries

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Abstract Published small-business surveys often report moderation coefficients, simple slopes, and model fit separately. This methodological secondary analysis examines published summaries from a survey of 350 SME-associated respondents in Pakistan; it does not re-estimate the authors' structural model. If the reported correlations refer to the same standardized scores, an additive two-predictor regression would explain 7.184% of the variance in self-reported success, including 1.906% of shared additive association. If those scores and the published path coefficients also enter one common standardized-score regression, the coefficients imply an interaction-model R^2 of 0.42188, whereas the figure reports 0.444; ordinary three-decimal rounding cannot bridge the gap. Holding the other inputs fixed would require a product coefficient of 0.61525 rather than 0.597. Separately, the three displayed conditional slopes place the mean-diversity evaluation only 6.12% of the way from low to high, although their labels specify equally spaced -1, 0, and $+1$ standard deviations. These are conditional reconciliation diagnostics, not corrected coefficients or evidence that the underlying SmartPLS model was fitted incorrectly: its score definitions, product normalization, coefficient covariance, evaluation points, and respondent structure were unavailable. The reported summaries alone cannot establish an interpretable leadership–diversity complementarity effect.

Index Terms entrepreneurial leadership, perceived diversity, secondary analysis, interaction diagnostics, reporting reconciliation, SME survey

I. Introduction

Diverse teams may give entrepreneurial leaders access to ideas and experience that improve business outcomes. The empirical claim of complementarity is more specific: the association between leadership and an outcome must change with diversity. Positive separate coefficients do not establish that change. Nor can an association measured in a cross-sectional survey establish that a management intervention would produce the same result [1].

The constructs themselves require care. Entrepreneurial leadership instruments assess different dimensions of opportunity-oriented behavior [2]; perceived team diversity can mix team composition with attitudes and organizational practices [3]. Success may include personal satisfaction as well as commercial performance [4]. The survey analyzed here combines respondents in different roles and measures perceived success, rather than audited firm performance [5]. Its published summaries cannot connect a given respondent's score to a verified firm-level outcome.

Checking whether published correlations, coefficients, model fit, and slopes agree under a common-score interpretation is necessary but incomplete. Identifying an inconsistency does not show what would have to differ for the summaries to describe one interaction equation. In particular, a coefficient's units depend on how the product is centered and standardized; the slope also depends on where diversity was evaluated [6], [7]. These choices cannot be inferred from a plotted trend or a significant coefficient.

We use the reported aggregate values to answer three questions: what additive association follows if the published entries refer to common standardized scores; what numerical changes would make the interaction summaries mutually compatible if one input were varied at a time; and which uncertainty statements remain possible without coefficient covariance or moderator support. Each comparison states its assumptions. The aim is to specify the minimum reporting record needed to evaluate the proposed interaction, without fabricating respondent data or treating illustrative reconciliations as re-estimates.

II. Materials and Methodology

This methodological note audits numerical summaries from a published SmartPLS structural-equation analysis; it does not replicate the fitted model. Its analytical dataset contains only the published entries and their locators [5]. Respondent records and the estimation project were unavailable; no new survey or model estimation was undertaken. Other references support the interpretation of the constructs and the analytical methods. The available record does not explain why 20 of the 370 valid questionnaires were excluded. It also does not give the number of participating firms or the number of respondents per firm. Accordingly, 350 is a respondent count, not a firm count or an effective sample size for independent organizational observations. We make no assumptions about exclusion rules, response weights, clustering, or missing-response patterns.

A. Published Scores and Additive Reconstruction

For each construct with m displayed loadings λ_j, the calculations evaluate the average squared loading and the conventional standardized composite-reliability expression:

$$A_\lambda = \frac{1}{m}\sum_{j=1}^{m}\lambda_j^2, \qquad C_\lambda = \frac{(\sum_{j=1}^{m}\lambda_j)^2}{(\sum_{j=1}^{m}\lambda_j)^2 + \sum_{j=1}^{m}(1-\lambda_j^2)}. \quad (1)$$

Eq. (1) assumes standardized indicators and uncorrelated measurement errors. It evaluates the displayed loadings rather than re-estimating a measurement model. For each two-decimal loading, the rounding interval is $\lambda_j \pm 0.005$. All loadings are positive, so the endpoints of the corresponding interval for A_λ follow by squaring the lower and upper endpoints. The resulting ranges test arithmetic compatibility; they do not quantify sampling uncertainty or validate unidimensionality.

The correlation calculation uses only the three off-diagonal entries from the Fornell–Larcker block. Its diagonal entries are square roots of average variance extracted, so they are replaced by ones when forming a correlation matrix. HTMT values are not substituted for correlations; they serve a different measurement purpose [8]. In particular, the displayed interaction–success HTMT of 0.664 is not treated as the correlation between the product score and success. The resulting numerical matrix is

$$R = \begin{pmatrix} 1 & 0.267 & 0.222 \\ 0.267 & 1 & 0.204 \\ 0.222 & 0.204 & 1 \end{pmatrix}, \qquad (L, D, Y) \text{ ordering}. \quad (2)$$

All regression interpretations of this matrix are conditional on its entries referring to the same standardized scores. This qualification matters because ordinary score correlations, latent correlations, and correlations adjusted for measurement error need not coincide. Latent-factor and observed-score results can differ even when variable names coincide [9]. The calculations therefore establish implications of a specified covariance interpretation, not a reconstruction of the unavailable estimation project.

Additive association and reliability sensitivity. Writing $A = R_{1:2,1:2}$ and $r = (0.222, 0.204)^\top$, the standardized additive regression identities are

$$b_A = A^{-1}r, \qquad R_A^2 = r^\top A^{-1}r. \quad (3)$$

The shared and unique components are calculated from the two single-predictor squared correlations. Specifically, $U_L = R_A^2 - r_{DY}^2$, $U_D = R_A^2 - r_{LY}^2$, and $C = r_{LY}^2 + r_{DY}^2 - R_A^2$. The two-predictor Shapley allocations are $\phi_L = U_L + C/2$ and $\phi_D = U_D + C/2$. Averaging the incremental contribution across the two possible entry orders gives the same allocations [10]. Neither the shared component nor a Shapley allocation estimates a multiplicative interaction.

Reliability is examined through an explicitly conditional attenuation calculation. Alpha does not estimate all kinds of reliability without assumptions, and the printed statistics do not supply a full measurement model [11]. Accordingly, two separate sets of printed coefficients are used as sensitivity inputs: alpha values $(0.90, 0.84, 0.92)$ and composite reliabilities $(0.91, 0.88, 0.93)$ in the order (L, D, Y).

For each set ρ, the off-diagonal correlations are transformed as

$$R_{ij}(t) = \frac{R_{ij}}{\sqrt{\rho_i^t\rho_j^t}}, \qquad i \neq j, \quad R_{ii}(t) = 1, \quad 0 \le t \le 1. \quad (4)$$

The endpoint $t = 0$ retains the displayed correlations; $t = 1$ applies full classical attenuation adjustment under independent errors and fixed reliabilities. Intermediate values index the strength of that assumption, not a probability or an estimated degree of measurement error. Positive definiteness is checked before applying Eq. (3). This exercise would be inappropriate as a further correction if the used correlations already incorporated the same adjustment; its role is to expose assumption dependence rather than identify a preferred latent correlation matrix.

B. Interaction Compatibility and Reconciliation

Consider the additive predictors and a standardized product score P in a common ordinary least squares equation,

$$\begin{aligned} Y =& b_L L + b_D D + b_P P + \varepsilon, \\ \mathrm{Cov}(\varepsilon, L) &= \mathrm{Cov}(\varepsilon, D) = \mathrm{Cov}(\varepsilon, P) = 0. \end{aligned} \quad (5)$$

With $a = r_{LD}$, the first two normal equations imply product correlations $q_L = (r_{LY} - b_L - ab_D)/b_P$ and $q_D = (r_{DY} - ab_L - b_D)/b_P$. The third implies $r_{PY} = b_L q_L + b_D q_D + b_P$. Substitution into $R_I^2 = b_L r_{LY} + b_D r_{DY} + b_P r_{PY}$ eliminates all three unavailable product correlations and gives the necessary identity

$$R_I^2 = 2b_L r_{LY} + 2b_D r_{DY} - b_L^2 - b_D^2 - 2ab_L b_D + b_P^2. \quad (6)$$

The identity applies only when the correlations, coefficients, and coefficient of determination describe the same scores, standardization, predictors, and estimation equation. It is not a universal identity linking any numbers appearing in a structural-equation report. Distinct score solutions or a differently normalized interaction can invalidate that comparison without establishing which displayed quantity should be changed.

The normal equations explain the restriction. Given the main coefficients and the three available correlations, the first two equations determine the required correlations between the standardized product and its constituents. The third then determines the product–outcome correlation. These quantities fix R_I^2; it cannot be chosen independently. The argument requires finite covariances and residual orthogonality, without a distributional assumption.

To show the size of a possible reconciliation, write Eq. (6) as $R_I^2 = B + b_P^2$, where B contains the five non-product inputs. If these five inputs and the displayed R_I^2 are held fixed, the positive product coefficient required by the common-score identity is

$$b_P^{\mathrm{req}} = \sqrt{R^2_{I,\mathrm{printed}} - B}. \tag{7}$$

This is a conditional repair calculation, not an estimate. We also maximize B over the 2^5 corners of the five three-decimal rounding intervals, then combine it with the lower rounding endpoint of the printed R^2 to obtain the smallest positive product coefficient compatible with those bounds. An admissible coefficient must still correspond to a feasible standardized product and to the same estimation sample.

Each of the six printed inputs $(a, r_{LY}, r_{DY}, b_L, b_D, b_P)$ is allowed to vary independently by 0.0005. The derivative signs of Eq. (6) remain fixed throughout this box, so evaluating its 64 corners supplies its extrema. These bounds are compared with the three-decimal interval $[0.4435, 0.4445]$ for the displayed ES-node value. An augmented correlation matrix is also checked for positive definiteness. That matrix check is necessary for covariance feasibility but does not prove that a random-variable product with the required higher-order moments exists.

Slope spacing and product normalization. A linear interaction yields a conditional slope that is affine in the moderator [6]. Therefore, slopes evaluated at any three equally spaced moderator values satisfy

$$s_- + s_+ - 2s_0 = 0. \tag{8}$$

For displayed slopes $s = (s_-, s_0, s_+)$, the contrast $\Delta = s_- + s_+ - 2s_0$ quantifies disagreement with this restriction. The smallest possible maximum absolute change across the three values needed to reach an affine triplet is $|\Delta|/4$. This follows because the absolute coefficients of the contrast sum to four, and equal-magnitude changes with alternating signs attain that lower bound. Four-decimal rounding changes the contrast by at most 0.0002.

A consistent shift or rescaling of the moderator leaves Eq. (8) unchanged. Unspecified centering therefore cannot explain a nonzero contrast at equally spaced evaluation points. Possible explanations would include unequal evaluation spacing, estimates from different equations, or a transcription difference. Sampling uncertainty does not remove the identity: slopes calculated from one fitted linear interaction, using the same coefficients and units, must satisfy it.

If the three reported slopes were instead evaluated at unequally spaced points on one affine slope curve, the middle point would occupy the fraction

$$f = \frac{s_0 - s_-}{s_+ - s_-} \tag{9}$$

of the low-to-high moderator interval, assuming $s_+ \neq s_-$. Equally spaced points require $f = 1/2$. A different value describes how unequally spaced the evaluation points would have to be; it does not recover those points from the publication.

Conditional slopes also depend on product normalization. Let centered, unit-variance L and D form

$$\begin{aligned} P &= \frac{LD - \mathbb{E}[LD]}{\kappa}, \\ \kappa &= \sqrt{\mathrm{Var}(LD)} > 0, \\ s(z_D) &= b_L + \frac{b_P}{\kappa} z_D. \end{aligned} \tag{10}$$

The effective coordinate $u = z_D/\kappa$ then gives $s(u) = b_L + b_P u$. A value $u = 1$ is not generally one standard deviation above mean diversity. Moreover, $\kappa^2 = \mathbb{E}[L^2D^2] - a^2$ requires a fourth joint moment, while product correlations involve third joint moments. The three pairwise correlations alone do not determine these quantities. The analysis therefore retains u rather than assigning unsupported respondent-level diversity values to a slope plot. Interpreting an interaction requires information about the observed moderator support and functional form [7].

Taking the displayed SDs conditionally as coefficient standard errors, $\sigma_L = 0.067$ and $\sigma_P = 0.083$, let $c = \mathrm{Cov}(\widehat{b}_L, \widehat{b}_P)$. Positive semidefiniteness gives $|c| \leq \sigma_L \sigma_P$. For fixed u,

$$\begin{aligned} \mathrm{Var}\{\widehat{s}(u)\} &= \sigma_L^2 + u^2\sigma_P^2 + 2uc, \\ (\sigma_L - |u|\sigma_P)^2 &\leq \mathrm{Var}\{\widehat{s}(u)\} \leq (\sigma_L + |u|\sigma_P)^2. \end{aligned} \tag{11}$$

Thus an outer envelope for pointwise normal-reference 95% intervals is $s(u) \pm 1.96(\sigma_L + |u|\sigma_P)$. It accounts only for the missing covariance under the specified coefficient scales. It is not a simultaneous confidence band, a recovered bootstrap interval, or an allowance for uncertainty in κ, reliability, or model selection. This separation of identified restrictions from assumption-dependent sets follows the logic of partial identification [12].

C. Missing Coefficient Covariance and Reproducibility

Rounding intervals and uncertainty intervals answer different questions. The former contain values compatible with printed precision and have no confidence level. The latter combine normal-reference sampling intervals across an admissible covariance set. Neither supplies the missing sampling design. In particular, the respondent count is not used to construct additive-regression standard errors when clustering and score construction are unknown.

Coefficient-to-SD ratios are compared with printed test statistics while allowing three-decimal rounding in both numerator and denominator. Normal-reference probabilities and symmetric Wald intervals are calculated only as diagnostic reference values. They do not replace an undocumented bootstrap procedure. Statistical-reporting research motivates these arithmetic checks without implying intent or misconduct [13].

Supplementary File S1 contains the transcribed inputs, source locators, calculation scripts, derived tables, and figure-generation code. Automated checks cover the covariance identities, variance partitions, rounding bounds, and boundary equations. Figures show aggregate entries or mathematical functions; none represents reconstructed respondents. The calculations are retrospective; no analysis plan was preregistered.

III. Results

A. Measurement and Additive Associations

The 24 retained loadings span 0.59–0.79 for EL, 0.51–0.85 for TD, and 0.79–0.86 for ES. Figure 1 preserves questionnaire order within each construct, making the omitted TD3 label and the wider spread of TD loadings easy to see. The narrower ES range describes the displayed indicators; it does not establish greater substantive importance or stronger content validity.

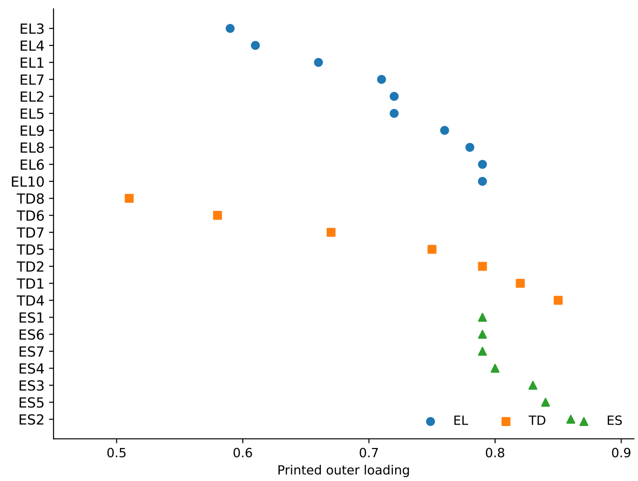

Figure 1: Loadings of the 24 tabulated indicators, grouped by construct and shown in questionnaire order. Dots and labels reproduce the two-decimal entries; horizontal stems aid comparison and are not uncertainty intervals. EL: entrepreneurial leadership; TD: perceived team diversity; ES: subjective entrepreneurial success.

The TD items mix perceived backgrounds and cultural differences with equal opportunity, organizational policies, market understanding, and benefits attributed to diversity. The resulting score is broader than team composition. The relatively low loadings for TD8 and TD6 do not by themselves justify removing those items: doing so would change the content represented by the scale.

The ES items concern perceived success, control, work–family balance, pride, employment provision, fulfillment, and optimism. Several are written from a business operator's perspective. Since owners, supervisors, managers, and employees may interpret them differently, the absence of role-specific results limits the interpretation of the combined score. It should not be read as a measure of revenue growth.

The small measurement discrepancies are compatible with rounding (Table 1). For ES, the displayed loadings yield $A_\lambda = 0.66377$, but admissible loading precision allows values up to 0.67194 and thus a printed AVE of 0.67. The calculated composite reliabilities also agree closely with 0.91, 0.88, and 0.93. This supports the arithmetic plausibility of the summaries under Eq. (1); it does not independently verify the factor structure.

Table 1: Loading-based arithmetic.

Construct	Items	Printed AVE	A_λ	Rounding range	C_λ
EL	10	0.51	0.51309	0.50599–0.52025	0.91259
TD	7	0.52	0.51813	0.51105–0.52525	0.87985
ES	7	0.67	0.66377	0.65565–0.67194	0.93245

Rounding cannot explain the item-count differences. TD9 and TD10 appear in the appendix, while the loading table stops at TD8 and omits TD3. The document does not establish whether these differences arose during administration, estimation, or presentation. Restricting the calculations to the 24 visible entries makes that uncertainty explicit.

1) Variance allocation

The correlation matrix is positive definite, with eigenvalues 0.73137, 0.80558, and 1.46305. Interpreted as correlations among common standardized scores, it yields additive coefficients of 0.18039 for EL and 0.15584 for TD, with $R^2_A = 0.07184$. Both partial associations are positive. Their signs say nothing about whether the leadership slope changes with diversity.

The first three rows of Table 2 sum to the additive total. The Shapley rows allocate that same total by averaging incremental contributions over both predictor entry orders; they are not additional components. EL receives 55.34% of the explained variance, equivalent to 3.975% of total ES-score variance. Figure 2 uses total outcome variance as the denominator throughout.

Table 2: Additive variance allocation.

Component	Proportion of total ES variance	Percentage
Unique EL	0.03022	3.022
Shared additive association	0.01906	1.906
Unique TD	0.02255	2.255
Total additive association	0.07184	7.184
Unexplained by this additive equation	0.92816	92.816
Shapley allocation to EL	0.03975	3.975
Shapley allocation to TD	0.03208	3.208

The shared component reflects overlap in the variation associated with correlated predictors. Such overlap can occur in a strictly additive model. Conversely, an interaction can exist when additive correlations are small. The 1.906% shared component therefore neither establishes nor rules out complementarity.

These allocations are specific to a model with EL and TD alone. "Unique EL" means variation associated with leadership after linear adjustment for perceived diversity, not after adjustment for firm age, finance, industry, or managerial experience. The unexplained 92.816% includes measurement variation, omitted associations, and any nonlinear structure not captured by this equation.

Standardized path coefficients cannot be read directly as percentages of explained variance. In particular, coefficients of 0.158 and 0.597 do not mean 15.8% and 59.7% of outcome variance. Variance attribution depends on predictor correlations and an explicit allocation rule or model comparison.

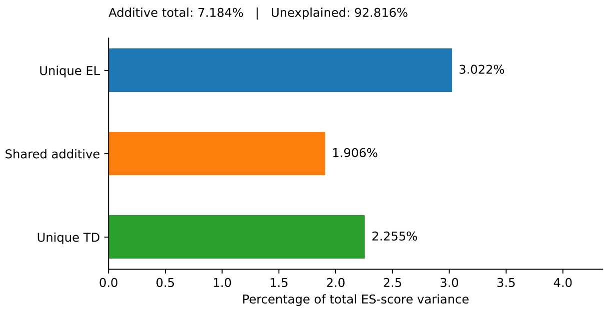

Figure 2: Additive variance decomposition for leadership and perceived diversity. The upper bar shows the explained and unexplained proportions of total ES-score variance. The lower bars expand the three components of the explained total on a separate, clearly labeled scale. Shared variance is explanatory overlap, not an interaction effect.

2) Reliability sensitivity

Applying the full alpha-based attenuation assumption raises additive R^2 from 0.07184 to 0.08679; using composite reliability raises it to 0.08410. Both transformed matrices remain positive definite. The corresponding EL coefficients are 0.19069 and 0.19104, and the TD coefficients are 0.17350 and 0.16850. These are conditional calculations under fixed reliabilities, not new estimates from respondent records.

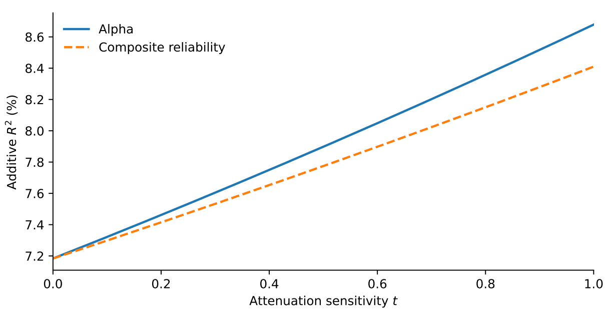

Figure 3: Additive R^2 under the reliability sensitivity path in Eq. (4). At $t = 0$, the displayed correlations are unchanged; at $t = 1$, the alpha or composite-reliability inputs determine a full independent-error attenuation adjustment. Curves show assumption-dependent calculations, not confidence limits.

Across the sensitivity path in Figure 3, additive R^2 increases smoothly and remains below 9%. The separation of the curves reflects the reliability inputs, particularly for TD. It does not select either reliability coefficient as the correct one.

Independent errors are essential to this calculation. Correlated response tendencies across leadership, diversity, and success would require a different model, and an adjustment would be redundant if the used correlations already incorporated it. Nor can attenuation correction recover unmeasured dimensions of success. The sensitivity analysis shows how the additive total depends on specified assumptions; it does not resolve those assumptions.

B. Interaction Summaries and Reconciliation Requirements

Using

$$b_L = 0.158, \quad b_D = 0.085, \quad \text{and} \quad b_P = 0.597$$

in the common standardized-score equation, Eq. (6) requires $R_I^2 = 0.42188038$. Allowing every three-decimal input to vary within its rounding interval produces $[0.42090957, 0.42285267]$. This interval does not overlap $[0.4435, 0.4445]$, the interval associated with the displayed ES-node value of 0.444. The smallest separation between those intervals is approximately 0.02065.

The intervals in Figure 4 cannot be reconciled by ordinary rounding under a common standardized regression. That condition is unverified, however. Different score solutions or additional model terms could make the comparison inapplicable. The calculation calls for clarification of the estimation output; it does not justify substituting 0.42188 for the used 0.444.

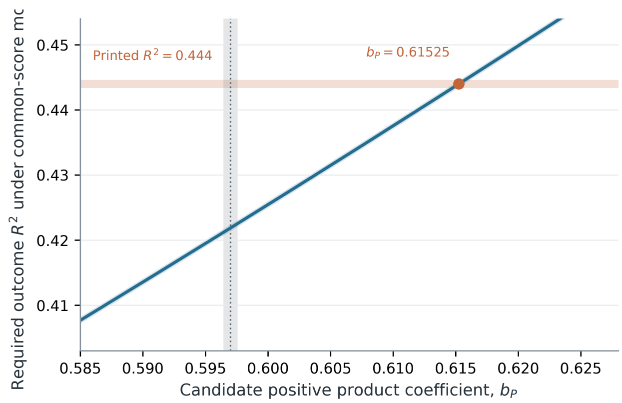

Figure 4: Common-score $R^2 = B + b_P^2$ across candidate positive product coefficients. The light envelope varies the five other printed inputs across their rounding intervals; the vertical line marks $b_P = 0.597$ and the horizontal band the printed $R^2 = 0.444$ interval. The crossing near $b_P = 0.615$ is a conditional reconciliation scenario, not a corrected estimate or a fitted model.

At the printed point values, Eq. (7) requires $b_P^{\text{req}} = 0.61525$ if the five other inputs and $R_I^2 = 0.444$ are fixed. This exceeds the displayed 0.597 by 0.01825. Allowing the five other inputs to vary throughout their rounding boxes and taking the lowest R_I^2 that still prints as 0.444 requires $b_P \geq 0.61454$, outside the printed coefficient interval $[0.5965, 0.5975]$. Figure 4 shows

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this conditional requirement across candidate product coefficients. It does not establish which, if any, printed value should change.

The required product correlations are 0.06919 with L, 0.12867 with D, and 0.61887 with Y. The resulting four-variable correlation matrix is positive definite, with minimum eigenvalue 0.36152. Thus the implied correlations pass a covariance-feasibility check, although they cannot accompany the displayed R^2 under Eq. (5).

The rounding bounds allow all six inputs to vary independently. Since the derivative signs are fixed over this box, evaluation of its 64 corners gives the extrema exactly for the specified intervals. The disagreement does not depend on a random search or numerical seed. It would require different underlying entries or a different interpretation of the reported model to be resolved.

Positive definiteness is not sufficient to show that the additional variable can be constructed as the stated product. Product correlations depend on third joint moments, and product variance depends on a fourth joint moment. Centering the constituents does not generally make their product uncorrelated with them; standardizing the constituents does not give the product unit variance. Those moment conditions remain unverified.

Conditional-slope spacing. The displayed slopes at low, average, and high diversity are 0.1561, 0.2065, and 0.9791. Their endpoint-implied midpoint is 0.5676, which differs from the displayed middle value by 0.3611. Equivalently, the contrast in Eq. (8) equals 0.7222. Allowing independent four-decimal rounding leaves this contrast between 0.7220 and 0.7224, far from zero.

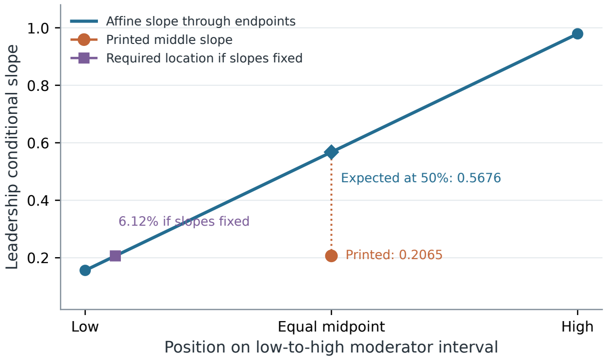

Figure 5: The published low, mean, and high slopes on a normalized low-to-high moderator axis. At the stated equally spaced midpoint $x = 0.5$, the endpoint line requires slope 0.5676, not the reported 0.2065. On the same affine line, a slope of 0.2065 occurs at $x = 0.06124$, illustrating the unequal spacing needed if all three slope values are correct.

Figure 5 shows both the midpoint required by the two endpoint slopes and where the displayed middle slope would sit if the moderator evaluations were uneven. To make the triplet affine, at least one printed slope must change by 0.18055 or more in absolute value. This minimax bound quantifies the disagreement without identifying an erroneous entry. Eq. (9) yields $f = 0.06124$ for the reported triplet: the middle value would have to sit only 6.12% of the way from low to high, compared with 50% under the printed -1, 0, $+1$ standard deviation labels. Unequal spacing or separate fitted equations could explain the numbers, but either requires an explicit record of the actual model and evaluation points.

For the low-diversity row, slope/SE is 2.6503 rather than the printed 3.6151 (Table 3). The symmetric normal-reference interval is 0.0407–0.2715, compared with the printed 0.0819–0.1103. These entries do not match an ordinary Wald calculation. An asymmetric or bias-corrected interval need not equal the reference interval or contain the point estimate, so the interval discrepancy requires documentation of the procedure before a stronger conclusion can be drawn.

Table 3: Conditional-slope arithmetic.

Diversity label	Slope	SE	Slope/SE	Symmetric 95% reference interval
Low	0.1561	0.0589	2.6503	0.0407–0.2715
Average	0.2065	0.0412	5.0121	0.1257–0.2873
High	0.9791	0.0568	17.2377	0.8678–1.0904

A positive interaction coefficient also need not imply a positive leadership slope throughout the moderator range. Resolving the slope table and documenting the observed range are necessary before describing leadership as positively associated with success at all diversity levels.

C. Conditional-Slope Uncertainty with Missing Covariance

On the effective coordinate u, the conditional estimate is $s(u) = 0.158 + 0.597u$. The missing coefficient covariance is bounded by ± 0.005561. Eq. (11) therefore yields the outer pointwise interval envelope displayed in Figure 6. At $u = -1$, 0, and 1, the slope estimates are -0.439, 0.158, and 0.755, with outer intervals $[-0.733, -0.145]$, $[0.02668, 0.28932]$, and $[0.461, 1.049]$, respectively.

At each fixed u, the shaded envelope in Figure 6 contains all normal-reference intervals allowed by the coefficient-covariance bound. Its lower edge is positive when $u > -0.03512$, and its upper edge is negative when $u < -0.66614$. Between these boundaries, the envelope includes zero. These are pointwise statements about interval signs, not simultaneous confidence statements or probabilities of benefit.

The boundaries cannot yet be located on the observed diversity scale. Because $u = z_D/\kappa$, the coordinate $u = -1$ is not necessarily the low-diversity evaluation point. The product standard deviation κ, the centering convention, and the observed moderator range are needed to make that translation. Labels such as "low diversity" would give the present envelope an unsupported empirical meaning.

At $u = 0$, the product coefficient drops out of the slope and its covariance with the main coefficient is irrelevant. Away from zero, the maximum standard error increases as $\sigma_L + |u|\sigma_P$. This explains the symmetric widening of the

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envelope; it makes no assumption that respondents' diversity scores are symmetrically distributed.

The envelope remains conditional on the coefficient and standard-error interpretation. It cannot resolve the R^2 disagreement or validate the slope table. Its limited purpose is to show the uncertainty attributable to missing coefficient covariance while holding the equation, scales, and remaining inputs fixed.

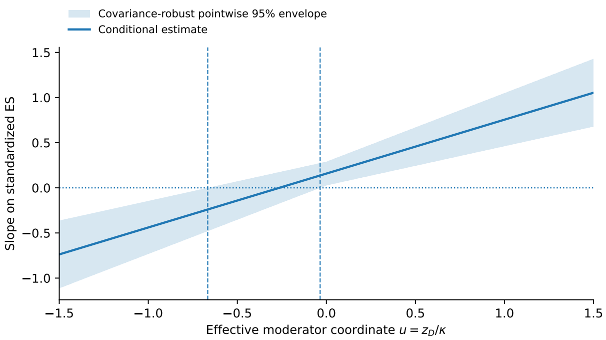

Figure 6: Conditional slope $s(u) = 0.158 + 0.597u$ and the outer envelope of pointwise normal-reference 95% intervals over $|c| \leq 0.005561$. Vertical lines mark where the outer interval touches zero. The illustrative coordinate range is not an observed diversity range; $u = z_D/\kappa$ depends on unknown product normalization. Shading is not a simultaneous confidence band.

D. Test-Statistic Arithmetic

The ratios of the four displayed coefficients to their SDs are 2.3582, 2.0506, 1.2687, and 7.1928 in the order EL–ES, EL–TD, TD–ES, and the interaction–ES path. Three-decimal rounding can accommodate the printed test statistics for three rows, but not the EL–TD value of 3.470. For that row, the admissible ratio interval is approximately 2.0314–2.0701. The discrepancy therefore cannot be dismissed as ordinary rounding if the SD column represents the denominator of the displayed test.

The EL–TD comparison in Figure 7 identifies the clearest ratio discrepancy. A separate issue appears in the TD–ES row: the ratio 1.2687 gives a two-sided normal-reference probability of 0.2046 rather than the printed 0.028. A different reference distribution or testing procedure would need to be documented before that probability could be assessed.

These checks do not establish that an association is absent. Estimates, uncertainty, measurement, and design must be considered together [14]; an interval containing zero is not evidence of equivalence [15]. The narrower finding is that the printed entries do not permit a consistent reconstruction of the conventional tests.

IV. Discussion

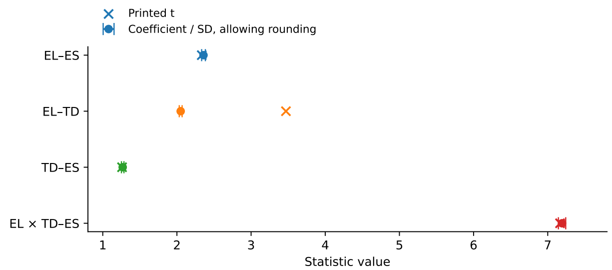

Figure 7: Coefficient/SD ratios, with rounding intervals, compared with the test statistics. Circles show calculated ratios and crosses show printed values; three-decimal rounding cannot reconcile the EL–TD row. The comparison treats the SD column as the denominator of the test statistic. EL, TD, and ES are defined in Figure 1.

A. What the Reconciliation Calculations do and do not Settle?

Table 4 organizes the key numerical conflicts as conditional requirements. The published R^2 can be made compatible with the displayed coefficients by changing the product coefficient under a particular common-score model; the reported slopes can lie on one affine curve by changing their middle coordinate. Neither exercise selects an authentic replacement value. A different score solution, model specification, or output column could make an individual calculation inapplicable. A positive definite four-variable correlation matrix is necessary for the reconstructed covariance but does not prove that an interaction product with the required higher moments was formed.

Table 4: One-input reconciliation diagnostics. Required values hold the other relevant inputs fixed and are not corrected estimates.

Check	Printed	Required
Interaction R^2	0.444	0.42188
Product b_P	0.597	0.61525
Middle slope	0.2065	0.5676
Middle location	50%	6.12%
EL–TD t	3.470	2.0506

The t row presumes $t = \beta/\mathrm{SD}$. Resolving any row requires source scoring and estimation output.

The measurement record adds a substantive constraint. The retained diversity indicators combine perceived backgrounds with inclusion practices and expected benefits; entrepreneurial success was self-reported by people in different firm roles. To interpret the interaction, a reader would need the retained item map and role-specific response structure, together with product-score construction, coefficient covariance, and the moderator evaluation points. A full reanalysis would also require the respondent-to-firm mapping to assess dependence, moderator support, missingness, and influential observations [7]. The published summary cannot supply these records.

The global fit statistics and significance markers do not substitute for this record. The estimated-model SRMR of 0.066 and NFI of 0.820 concern model fit rather than agreement of coefficient and slope entries. The first-factor contribution of 22.2% does not rule out common response processes among self-reported constructs [16]. Moreover, resolving coefficient covariance would narrow one uncertainty statement but could not address confounding or identify the effect of changing leadership or team composition [17].

B. Limits and Next Evidence

All figures and tables here are transcriptions or calculations from one publication. Respondent records, firm identifiers, estimation settings, retained-item decisions, product normalization, coefficient covariance, and exact slope evaluation points were unavailable. The sample is a convenience sample within one province; 350 is a respondent count, with no demonstrated count of independent firms. No model was fitted to reconstructed individuals. Rounding intervals reflect reporting precision, while the conditional normal-reference slope envelope reflects a specific interpretation of two displayed SDs. Neither interval represents uncertainty from the sampling design or a corrected bootstrap analysis.

The next empirical step is to obtain the original scoring syntax, item-level response matrix, respondent-to-firm identifiers, estimation configuration, complete coefficient covariance or bootstrap draws, and the exact points used to compute the simple slopes. An analyst could then refit one declared model, check the conditional-slope identity, display the observed moderator distribution, and compare in-sample associations across respondent roles. If the goal is causal guidance, that would still require an appropriate design and explicit assumptions beyond the arithmetic checks [1].

V. Conclusion

If the published correlations refer to common standardized scores, they imply a limited two-predictor additive association with subjective success; they do not establish leadership–diversity complementarity. If those scores, coefficients, and R^2 further describe one standardized regression, their printed values cannot all hold within three-decimal rounding. Under that conditional interpretation, holding all other inputs fixed would require a product coefficient of 0.61525 instead of 0.597. The reported conditional slopes would require either a middle slope of 0.5676 or evaluation points different from their equal-spacing labels. These values are mathematical diagnostics, not revised estimates or proof of an error in the original fitted model. Establishing the actual interaction requires the score construction, estimation output, and respondent-level data specified above.

Data and Code Availability

The transcribed published entries, numerical provenance, derived files, and scripts required to reproduce all calculations and figures are provided with the manuscript as Supplementary File S1. The original article is cited as Reference [5]. Individual respondent-level records and the original fitted-model outputs were not available for the present analysis.

Conflicts of Interest

The author declares that there are no conflicts of interest related to this work.

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Declaration of Generative AI and AI-Assisted Technologies in the Preparation of the Manuscript

Generative artificial intelligence tools were used solely to assist with language editing, revision, and improvement of the manuscript's presentation. The author reviewed and verified all AI-assisted content and takes full responsibility for the accuracy, integrity, and final content of the manuscript.

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