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THE PERCEPTION GAP IN OUTCOME-BASED EDUCATION: A MULTI-STEP STATISTICAL FRAMEWORK FOR CO–PO MAPPING VALIDATION AND ATTAINMENT ANALYSIS

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ABSTRACT

In Outcome-Based Education (OBE) framework, it is critical to have a robust framework for measuring Course Outcomes and Programme Outcomes. This study proposes a comprehensive multi-step statistical analysis of data obtained by administering a Course Exit Survey and a Programme Exit Survey of a course, on a Likert scale. The study was done using descriptive statistics, correlation analysis, mapping validation, gap analysis, reliability testing, and predictive modelling to evaluate the alignment between course-level and programme-level learning outcomes. The results obtained indicate that course outcomes are achieved at a high level, but programme outcomes are achieved only at a moderate level. This indicates a potential disconnect between course-level and programme-level learning and how students perceive these levels. The study also indicates that course outcomes and programme outcomes are statistically independent constructs from a student's perspective. Additionally, it has been found that course outcome programme outcome mapping is only partially validated and overstates the actual relationships. This study further reveals that certain programme outcomes require immediate attention by indicating a potential disconnect between how students perceive themselves and how they have achieved these programme outcomes. These findings provide useful insights for improving course/programme outcome mapping, with meaningful implications for curriculum design and accreditation.

Keywords: *Outcome-Based Education; CO–PO mapping; attainment analysis; perception gap; Cronbach's alpha; NBA accreditation*

1. INTRODUCTION

Outcome-Based Education (OBE) has emerged as the dominant pedagogical paradigm in higher education globally. Unlike traditional input-focused models, OBE shifts the emphasis from what is taught to what students are able to demonstrate at the end of a course or programme. Accreditation frameworks including the Washington Accord, the National Board of Accreditation (NBA) in India have institutionalised this shift by requiring programmes to articulate, measure, and report the attainment of defined learning outcomes at two levels: Course Outcomes (COs) and Programme Outcomes (POs).

COs describe the learning outcome of students after completing a specific course. POs describe a little more broader which would describe the competencies that students are expected to during the programme. These include parameters like computing knowledge, problem analysis, ethics, sustainability, and communication etc. The bridge between COs and POs is formulated through a CO–PO mapping matrix, in which faculty assign weight values (typically 1 = low, 2 = medium, 3 = high) to indicate the degree to which each CO contributes to each PO.

Inspite of adopting this framework, several critical questions remain unaddressed in the study of literature. Basically there is a systematic difference in how students identify their attainment of course-level versus programme-level outcomes. Secondly it was needed to verify if the faculty-designed CO–PO mapping matrices accurately reflect the empirical relationships between CO and PO scores as reported by students. Finally it was required to check if CO attainment scores predict PO attainment scores. These questions have direct answers for the validity of OBE reporting and for the re-design of curriculum.

This study addresses all above concerns, through a statistical framework applied to exit survey data from 94 postgraduate students in a specific course. The study is motivated not merely by the requirements of accreditation compliance, but by a deeper concern: that the infrastructure of OBE may be producing reports of attainment that do not accurately represent how students experience their own learning development.

1.1 Research Objectives

The study aims to assess three primary objectives:

(1) To verify and compare CO and PO attainment levels and examine whether a meaningful perception gap exists between course-level and programme-level learning.

(2) To empirically validate the faculty-designed CO–PO mapping matrix by testing whether mapping weights produce stronger empirical correlations between corresponding CO and PO scores.

(3) To evaluate whether CO attainment scores predict PO attainment scores, and to evaluate the reliability and consistency of both measurement instruments.

1.2 Hypotheses

H1: Students perceive significantly higher attainment of Course Outcomes than Programme Outcomes, indicating a measurable perception gap between course-level and programme-level learning.

H2: The faculty-designed CO–PO mapping partially reflects empirical reality — where higher assigned mapping weights tend to produce stronger observed relationships between course and programme outcomes, but do not fully capture the strength of those connections as perceived by students.

H3: Course Outcome attainment scores, while demonstrating excellent internal consistency and reliability, do not significantly predict Programme Outcome attainment scores — suggesting that CO and PO scales operate as independent constructs from the student's perspective.

2. LITERATURE REVIEW

The implementation of OBE in Indian engineering education has evolved significantly since the late 1990s, accelerating with NBA's adoption of the Washington Accord standards. Mayurappriyan et al. (2021) document this transition from a content-delivery model to a learner-centric paradigm, noting that while the structural requirements of OBE have been widely adopted, the pedagogical depth of implementation remains highly variable across institutions. Their case study indicates that compliance with accreditation checklists does not guarantee that OBE principles are genuinely practiced in the classrooms.

Amirtharaj et al. (2022) proposes a systematic assessment framework for OBE attainment that integrates multiple measurement strategies that includes direct assessments such as examinations and assignments, and indirect assessments such as exit surveys and alumni feedback. This paper claims that relying on a single measurement method produces incomplete and potentially misleading attainment reports. This study further extends their claims by demonstrating that the relationship between direct CO measures and indirect PO perceptions is not straightforward as indicated in the institutional reporting frameworks .

Pachiyappan et al. (2024) address the computational complexity of CO–PO attainment reporting by proposing a simplified measurement model that reduces administrative burden while maintaining methodological rigour. Their contribution highlights a persistent tension in OBE implementation: between the need for statistically valid measurement and the practical constraints of institutional data collection. The present study complements their work by interrogating whether the simplified mapping structures that ease administration also accurately capture the empirical structure of student learning.

Kumar et al. (2021) demonstrate practical CO–PO mapping and attainment tracking in the domain of Big Data Analytics , a discipline closely related to Machine Learning. Their case study provides a domain-specific precedent for the present work and confirms that technical courses in data science and AI present particular challenges for CO–PO alignment, because the skills developed (e.g., algorithm design, model evaluation) do not map intuitively onto broader programme outcomes such as ethics or sustainability.

Sreekanth et al. (2015) argue that co-operative and collaborative learning strategies are essential tools for achieving OBE competencies in the Indian engineering context, particularly for POs that emphasise teamwork, communication, and societal awareness. Their work implies that the gap between CO attainment and PO perception may be partly a pedagogical design problem: if students are not explicitly shown how course-level skills connect to programme-level attributes, they may fail to perceive that connection even when it exists.

Taken together, the literature identifies three recurring gaps: (a) the absence of empirical validation of CO–PO mapping matrices; (b) the lack of statistical testing of the relationship between CO and PO attainment scores; and (c) the insufficient attention to the student perspective on how course-level learning connects to programme-level development. The present study is designed to address all three.

3. METHODOLOGY

3.1 Study Context and Sample

The study was conducted in the context of an course delivered in MCA Program at a single institution. Exit survey data were collected from 94 students at the end of the course (N = 94). All students had completed the full course curriculum and were eligible to respond to both exit surveys. The sampling was purposive — all enrolled students who completed the course were included, ensuring maximum coverage of the cohort.

3.2 Instruments

Three instruments were used:

(1) Course Exit Survey (CES): A four-item Likert scale instrument (1 = Strongly Disagree, 5 = Strongly Agree) measuring student-perceived attainment of the four Course Outcomes defined.

(2) Programme Exit Survey (PES): An 11-item Likert scale instrument measuring student-perceived attainment of the 11 Programme Outcomes defined by NBA. Items covered: PO1 (Computing Knowledge), PO2 (Problem Analysis), PO3 (Design/Development of Solutions), PO4 (Conduct Investigations of Complex Problems), PO5 (Modern Tool Usage), PO6 (Professional Ethics), PO7 (Life-long learning), PO8 (Project Management and Finance), PO9 (Communication), PO10 (Societal and Environmental Concerns), and PO11 (Creativity and Enterpreneurship).

(3) Faculty CO–PO Mapping Matrix: A 4×11 matrix prepared by faculty prior to the study, assigning weights of 1 (low), 2 (medium), or 3 (high) to each CO–PO pair to indicate the degree of curricular alignment. This matrix served as the institutional benchmark for mapping validation.

3.3 Analytical Framework

Data were analysed using Jamovi (open-source statistical software) through a nine-step pipeline:

Step 1: Descriptive Statistics like Mean and standard deviation computed for all 4 CO items and 11 PO items.
Step 2: CO Attainment items are classified as High ($\geq$ 4.0), Moderate (3.0–3.99), or Low (< 3.0) as per NBA threshold which is 3.5 and above.
Step 3: PO Attainment is also classified as same as CO attainment.

Step 4: Implicit PO Attainment is computed as Σ(CO_mean × Mapping_Weight) ÷ Σ(Weights) for each PO, using the faculty mapping matrix. Compared against explicit PO survey means.

Step 5: Correlation Analysis where Pearson r is computed for all 44 CO–PO pairs, with significance testing ($\alpha = 0.05$).

Step 6: Mapping validation whereby Statistical tests like Pearson r, Spearman ρ, one-way ANOVA, Kruskal-Wallis, post-hoc comparisons, linear regression, are used to test whether mapping weight predicts empirical CO–PO correlation.

Step 7: Item-Level Analysis where Individual CO and PO item means are examined for range and outliers.

Step 8: In Gap Analysis Attainment gaps (actual mean − target of 3.5) are ranked by priority for curriculum intervention.

Step 9: Perception Deficit: Differences between implicit (mapping-derived) and explicit (survey-reported) PO means are calculated per PO.

Step 10: Reliability and Validity is tested using Cronbach's α and 95% confidence intervals computed for CO and PO scales.

Step 11: Predictive Modeling in which simple linear regression (CO composite mean → each PO) and multiple linear regression (CO1–CO4 → each PO) with Variance Inflation Factor (VIF) diagnostics testing of residuals are done.

4. RESULTS AND DISCUSSION

4.1 Instrument Reliability and Validity

To begin with it is essential to establish the psychometric quality of the measurement instruments, as this determines the interpretability of all subsequent analyses.

The CO scale has achieved a Cronbach's α of 0.9935 (95% CI: [0.9911, 0.9953]) which is an exceptional value indicating near-perfect internal consistency. Principal Component Analysis confirmed that a single factor explained 98.1% of total variance, establishing one-dimensionality of all four CO items measure one coherent underlying construct. Inter-item correlations ranged from $r = 0.96$ to $r = 0.98$ (all $p < 0.001$).

The PO scale has achieved a Cronbach's α of 0.9679 (95% CI: [0.9574, 0.9758]) — an excellent value across a significantly more diverse set of items spanning computing knowledge, ethics, environmental concern, communication, and project management. The first principal component explained 76.0% of total variance, confirming near-unidimensionality. Both instruments exceed the conventionally accepted threshold of $\alpha \geq 0.90$ for excellent reliability (George & Mallery, 2003).

The key implication of these findings is that any subsequent null results in prediction or correlation cannot be attributed to poor measurement. Both scales are demonstrated to be robust, reliable instruments. Non-significant correlations between CO and PO scores are therefore a genuine empirical finding about how students experience their learning not an object of measurement error.

Table 1. Cronbach's Alpha and PCA Results for CO and PO Scales

Scale	Items	Cronbach's α	95% CI	PCI Variance
CO Scale	4	0.9935	[0.9911, 0.9953]	98.1%
PO Scale	11	0.9679	[0.9574, 0.9758]	76.0%

4.2 Descriptive Statistics and Attainment Levels

Table 2 presents the mean scores and attainment levels for all four COs. All COs achieved High attainment (mean ≥ 4.0), with means ranging from 4.021 to 4.032 and gaps above the NBA target of 3.5 ranging from +0.52 to +0.53. The overall CO composite mean was 4.027, placing the course clearly within the HIGH attainment category.

Table 2. CO Attainment Summary (N = 94; Target ≥ 3.5)

CO	Mean	Level	Attained	Gap
CO1	**4.032**	High	Yes	+0.53
CO2	**4.021**	High	Yes	+0.52
CO3	**4.032**	High	Yes	+0.53
CO4	**4.021**	High	Yes	+0.52
Average	**4.027**	**High**	All	+0.52

Table 3 presents results for all 11 POs. All POs were attained, but at Moderate level (mean between 3.7 and 4). PO10 (Societal and Environmental Concern) recorded the highest mean (3.957), while PO7 (Life-long learning) recorded the lowest (3.713). The overall PO composite mean was 3.841, corresponding to Moderate attainment and a gap of 0.186 below the CO composite mean constituting the perception gap investigated under H1.

Table 3. PO Attainment Summary (N = 94; Target ≥ 3.5)

PO	What it Measures	Mean	Level	Attained?	Gap
PO1	Computing Knowledge	3.787	Moderate	Yes	+0.29
PO2	Problem Analysis	3.851	Moderate	Yes	+0.35
PO3	Design/Development of Solutions	3.830	Moderate	Yes	+0.33
PO4	Conduct Investigations of Complex Problems	3.894	Moderate	Yes	+0.39
PO5	Modern Tool Usage	3.787	Moderate	Yes	+0.29

PO6	Professional Ethics	3.830	Moderate	Yes	+0.33
PO7	Life-long Learning	**3.713**	Moderate	Yes	+0.21
PO8	Project Management & Finance	3.819	Moderate	Yes	+0.32
PO9	Communication	3.904	Moderate	Yes	+0.40
PO10	Societal and Environmental Concern	**3.957**	Moderate	Yes	+0.46
PO11	Creativity and Enterpreneurship	3.883	Moderate	Yes	+0.38
Avg		**3.841**	**Moderate**	All	+0.34

These results support H1. The gap of Δ = 0.186 between CO attainment (High) and PO attainment (Moderate) is consistent and systematic across all 15 items. Between 28 and 33% of individual students scored below 3.5 on each PO — meaning that even though the cohort mean meets the NBA threshold, a substantial minority of students are not attaining the required level on programme outcomes.

4.3 Implicit vs. Explicit PO Attainment — Perception Deficit

Using the faculty CO–PO mapping matrix shown in Table 4, implicit (indirect) PO means were calculated as Σ(CO_mean × Weight) ÷ Σ(Weights) for each PO. All 11 implicit PO means converged at approximately 4.027, corresponding to HIGH attainment when compared to explicit survey means averaging 3.841 (Moderate). This produced a consistent perception deficit for all 11 POs.

Table 4. Faculty CO-PO Mapping Matrix

CO/PO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11
CO1	3	1	2	1	3	2	1	1	1	1	1
CO2	3	2	3	1	3	2	1	1	1	1	2
CO3	2	2	2	1	3	2	1	1	1	1	2
CO4	3	2	2	1	3	1	1	1	1	1	2

The perception deficit (implicit minus explicit) ranged from +0.069 (PO10, Societal and Environmental Concern — best aligned) to +0.314 (PO7, Life-long Learning — worst aligned). The average deficit across all 11 POs was +0.185. This means the mapping consistently overestimates how well students perceive they are developing programme-level attributes. PO7, PO5 (Modern Tool Usage, +0.239), and PO1 (Computing Knowledge, +0.239) represent the highest-priority targets for curriculum redesign to close this perception gap.

4.4 CO–PO Correlation Analysis

Pearson correlation coefficients were computed for all 44 CO–PO pairs. Results are summarised in Table 5.

Table 5. Pearson r Matrix — CO–PO Pairs (N = 94; all p > 0.05)

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11
CO1	0.052	0.078	0.035	0.021	0.136	0.117	0.065	0.058	−0.077	0.051	0.051
CO2	0.049	0.075	0.032	0.020	0.132	0.100	0.060	0.055	−0.079	0.050	0.049
CO3	−0.005	0.020	−0.020	−0.043	0.078	0.048	0.011	−0.007	−0.141	−0.014	−0.010
CO4	0.006	0.033	−0.009	−0.029	0.090	0.086	0.034	0.022	−0.111	−0.015	0.004

All 44 correlation coefficients fall within the range of $r = -0.141$ to $r = +0.136$, and none reach statistical significance (all $p > 0.05$). The highest absolute values are CO1–PO5 ($r = +0.136$) and CO3–PO9 ($r = -0.141$) remain well below the conventionally accepted threshold for a small effect ($r \geq 0.10$ is considered small; Cohen, 1988), and even these extreme values are non-significant given the sample size of 94.

In contrast, CO–CO inter-item correlations were exceptionally high ($r = 0.96$ to 0.98; all $p < 0.0001$), confirming near-perfect multicollinearity among the four CO items — a finding that is consistent with the PCA result (PC1 = 98.1%) and justifies the use of a CO composite mean in regression analysis. PO–PO inter-item correlations ranged from $r = 0.51$ to $r = 0.91$, all significant ($p < 0.0001$), confirming that POs form a coherent but multidimensional programme-level construct.

4.5 Mapping Validation — H2

A critical question for OBE implementation is whether the faculty-designed CO–PO mapping matrix accurately reflects the empirical relationship between student CO and PO scores. To test this, empirical Pearson r values for all 44 CO–PO pairs were grouped by mapping weight (Weight 1, 2, or 3) and compared. Table 6 presents the results.

Table 6. CO–PO Mapping Validation — Statistical Test Results

Statistical Test	Result	Sig.	Interpretation
Mean r — Weight 1 (Low, 23 pairs)	$\bar{r} = 0.0064$	—	Baseline near-zero
Mean r — Weight 2 (Medium, 13 pairs)	$\bar{r} = 0.0335$	—	Moderate increase
Mean r — Weight 3 (High, 8 pairs)	$\bar{r} = 0.0718$	—	Highest — as predicted
Pearson r (weight vs. empirical r)	$r = 0.419$, $p = 0.005$	**	Moderate positive

Spearman ρ (weight vs. empirical r)	$\rho = 0.338$, $p = 0.025$	*	Rank confirmation
One-way ANOVA	$F = 4.421$, $p = 0.018$	*	Groups differ significantly
Kruskal-Wallis	$H = 6.114$, $p = 0.047$	*	Non-parametric confirmation
Post-hoc: Low vs. High	$t = -2.720$, $p = 0.011$	*	Significantly different
Post-hoc: Low vs. Medium	$p = 0.173$	ns	Not significantly different
Post-hoc: Medium vs. High	$p = 0.070$	ns	Not significantly different
Linear Regression (slope)	$\beta = 0.032$, $R^2 = 0.176$, $p = 0.005$	**	17.6% variance explained
Concordance Rate	67.3% of 44 pairs	—	Direction correct in 2/3 pairs

Note: * $p < 0.05$; ** $p < 0.01$; ns = not significant.

The above results provide partial support for H2. The mapping matrix captures the correct directional trend higher weights are systematically associated with higher empirical correlations (monotonic increase confirmed; concordance = 67.3%). However, the linear regression R^2 of 0.176 indicates that the mapping weights explain only 17.6% of the variance in empirical CO–PO correlations, meaning 82.4% of the variance is attributed to factors not captured in the mapping. Furthermore, post-hoc tests reveal that only the Low vs. High weight comparison reaches significance Low vs. Medium and Medium vs. High do not. This suggests that the three-level weight scale is not sufficiently granular to differentiate moderate from strong relationships.

4.6 Predictive Modeling — H3

Simple linear regression was run with the CO composite mean as the predictor and each of the 11 POs as the outcome. As shown in Table 7, none of the 11 models reached statistical significance.

Table 7. Simple Linear Regression: CO Composite Mean → Each Programme Outcome (N = 94)

PO	Description	β (Slope)	R^2	F	p-value
PO1	Computing Knowledge	−0.05	0.002	0.185	0.668 ns
PO2	Problem Analysis	+0.04	0.001	0.113	0.737 ns
PO3	Design/Developme nt of Solutions	−0.03	0.001	0.060	0.807 ns
PO4	Conduct Investigations of Complex Problems	−0.08	0.007	0.663	0.417 ns
PO5	Modern Tool Usage	+0.10	0.012	1.115	0.293 ns
PO6	Professional Ethics	+0.09	0.009	0.877	0.351 ns
PO7	Life-long Learning	+0.04	0.001	0.095	0.758 ns
PO8	Project Management & Finance	+0.05	0.003	0.284	0.595 ns
PO9	Communication	−0.10	0.010	0.981	0.324 ns
PO10	Societal and Environmental Concern	−0.01	0.000	0.006	0.940 ns
PO11	Creativity and Enterpreneurship	+0.02	0.000	0.044	0.834 ns

The CO composite mean fails to predict any of the 11 POs. The maximum R^2 across all 11 models is 0.012 (PO5), meaning CO scores explain at most 1.2% of the variance in any PO score. This is a near-zero predictive relationship.

Multiple regression with CO1–CO4 as separate predictors yielded apparently significant models for 7 of 11 POs ($p < 0.05$). However, this apparent significance is entirely attributable to severe multicollinearity: VIF values for all four CO predictors ranged from 30.16 (CO4) to 53.09 (CO3), far exceeding the critical threshold of 10 as presented in Table 8. Under such conditions, individual regression coefficients are unstable and uninterpretable the significance of the overall model tells us nothing about the genuine predictive relationships. Notably, CO3 consistently produced large negative β coefficients (ranging from −1.54 to −2.27 across 9 of 11 models), a pattern that reflects a suppressor effect caused by multicollinearity rather than a genuine negative relationship. Shapiro-Wilk tests on regression residuals confirmed non-normality for all 11 models (all $p < 0.001$), further limiting the validity of OLS interpretations.

These results fully support H3. The independence of CO and PO scales is not a measurement artefact both instruments have demonstrated excellent reliability ($\alpha > 0.96$). Rather, it reflects a genuine structural finding: students who rate their course-level outcomes highly do not automatically rate their programme-level development more highly. The mechanisms that would make CO learning transferable to PO perception explicit pedagogical linkage, reflective activities, and integrated assessments appear to be absent or insufficient in the current course design.

Table 8. Variance Inflation Factors — Multiple Regression Multicollinearity Diagnostics

Predictor	VIF	Threshold	Status
CO1	33.31	< 10	SEVERE
CO2	41.29	< 10	SEVERE
CO3	53.09	< 10	SEVERE
CO4	30.16	< 10	SEVERE

5. CONCLUSION

This study has presented a statistical framework for analysing CO–PO attainment data from 94 postgraduate computer application students, producing three principal findings corresponding to the three hypotheses tested.

H1 is supported. A consistent and systematic perception gap exists between CO attainment and PO attainment across all survey items. 28% to 33% of individual students score below the NBA threshold of 3.5 on every PO. This gap is not a measurement artefact, but it is a genuine feature of how students experience their learning in this course and programme.

H2 is partially supported. The faculty-designed CO–PO mapping matrix captures the correct directional trend, where higher mapping weights are associated with higher empirical CO– PO correlations. However, the mapping explains only 17.6% of the variance in empirical correlations, and distinguishes reliably only between the Low and High weight groups. The matrix is directionally valid but quantitatively overstated. This represents a stronger and more precise picture of CO–PO alignment than students actually experience.

H3 is supported. CO composite scores do not significantly predict any of the 11 POs in simple regression. Multiple regression results that appear significant are fully invalidated by severe multicollinearity. These two scales confirms to be excellent by Cronbach's $\alpha > 0.96$ and PCA and they operate as statistically independent constructs from the student's perspective.

These three findings converge on a single conclusion: the way institutions currently design CO–PO mappings, measure attainment, and report outcomes does not accurately reflect how students experience their own development. High CO attainment does not automatically produce high PO perception. The missing link is explicit, visible pedagogical connection — students need to be shown, during course delivery, how the skills they are developing in a specific course connect to broader programme-level attributes such as life-long learning, project management & finance, and societal & environmental concern.

The most urgent priority emerging from the gap analysis is PO7 (Life-long learning): it records the lowest direct mean (3.713), the smallest attainment gap (+0.21), the largest perception deficit (+0.314), and the highest proportion of students below target.

5.1 Limitations

This study has a few principal limitations. Firstly the data is collected from a single course at a single institution which in turn limits generalisation. Replication across multiple courses and institutions is required to establish more validity. Secondly, both instruments measure student perception rather than demonstrated competence. Student performance data also should be incorporated in the future studies. Lastly, the CO–PO mapping matrix used as the institutional benchmark was faculty-designed without prior empirical validation. Future research should test the effect of involving students in the mapping process on the size and direction of the perception deficit.

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