A Personalized Method for Computing Course and Program Learning Outcome Attainment in Higher Education

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Abstract

This study proposed a personalized outcome evaluation method for Outcome Based Education that traced assessment evidence from course components to Course Learning Outcomes and aggregated them into Program Learning Outcomes to support accreditation oriented quality assurance such as ABET and AUN-QA. A binary linkage matrix identified assessment components contributing evidence to each Course Learning Outcome, ensuring alignment with constructive alignment principles and Bloom's taxonomy. Course Learning Outcome scores were calculated on a normalized scale from zero to one hundred using course grading weights and outcome specific evidence weights, and attainment was determined using a pre-defined threshold. Program Learning Outcome scores were obtained through weighted aggregation of related Course Learning Outcome scores, and results were reported using the Percentage of Program Learning Outcome Completion indicator for clear interpretation. A pilot implementation in one master's program using data from five courses demonstrated high outcome attainment and identified weaker areas, thus providing auditable evidence and practical support for continuous program improvement.

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Course Learning Outcomes (CLO); Program Learning Outcomes (PLO); Personalized Assessment; Quality Assurance.

1 Introduction

Outcome-Based Education (OBE) emphasizes demonstrating students' attainment of intended learning outcomes through explicit alignment between outcomes, teaching activities, and assessment evidence. In this paradigm, courses define measurable Course Learning Outcomes (CLOs) while programs define broader Program Learning Outcomes (PLOs) quality assurance and continuous improvement require that a traceable link from assessment results to outcome attainment must be established [1, 2].

Quality Assurance (QA) frameworks oriented towards international accreditation such as ABET [3] and AUN-QA [4] require programs to define outcomes, and provide systematic auditable evidence of attainment at course and program levels, which feeds back to curriculum improvement cycles.

However, in many implementations, assessment results are aggregated at class or course-grade level [5], and normalization practices can obscure individual students' strengths and weaknesses with respect to specific outcomes. Therefore, instructors could not have any

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actionable diagnostics for targeted support and program managers could lack consistent evidence for evaluating how CLO evidence accumulates into PLO attainment. This refers to a methodological gap: a transparent and reproducible computation which maps heterogeneous assessment components to CLO attainment and then aggregates CLO evidence across courses into PLO attainment at the level of an individual.

To fill the gap in the existing system, the present study proposed a student-level achievement calculation approach which (i) assigned a linkage between the components of student assessment and the CLOs using a pre-defined linkage matrix, (ii) calculated scores for each student using weighted values, and (iii) combined student performance of CLOs to determine scores in PLOs using specific rules. This approach adopted Bloom's Taxonomy to satisfy the constraint of the designed level of cognition of CLOs, enhancing the levels of validity of the approach [6]. This approach aimed to be executed using data provided in the learning management system, providing a mean of reportability in relation to teaching support and quality assurance [2, 7].

The contributions of this paper are:

(1) a unitary computation process to transform the scores of the assessment components into the achievement of the CLOs by the students through the use of linkage matrices and normed weights;

(2) an aggregation rule for determining PLO scores and levels of achievement using weighted average or threshold/proportion methods based on CLO evidence across courses;

(3) outcome-level indicators for the purpose of transparent and continuous quality improvement procedures.

The rest of this document gives the related work and the methodology followed in the project along with the pilot results and implications.

2 Literature Review

OBE focuses upon constructive alignment and involves assessment evidence traceable to learning outcomes rather than the course grades alone [1]. Under the focus of accreditation-based quality assurance, there is also the need to specify learning outcomes through systematic assessment procedures to encourage a correspondence between the course learning outcomes (CLOs) and the learning outcomes in the programs (PLOs) [3, 4].

To ensure the results are valid, it is necessary to design the learning outcomes with cognitive expectations. The revised Bloom taxonomy is a common framework used to align the learning activities to the intended cognitive levels of the learning outcome to avoid misrepresentation of the learning level in the assessment results [6]. In the process of implementing the Outcome-Based Education model, it is essential to ensure that the achievement of CLOs includes valid evidence rather than just the completion results in the test format.

On a practical level, achievement of the outcome can be calculated either by threshold rules (pass/fail) or by a continuous process, which provides a deeper diagnosis on the outcome level. Because assessors are often combining a range of different elements such as examinations, assignments, or projects, there must be a clear process of weighing and normalizing in order to be able to arrive at a pass/fail measure of each component, a necessary first step toward determining achievement on a CLO. Therefore, it follows on a program level, PLO achievement can be aggregated across a range of courses, either by a process of weighted averages or a formulaic measure, which seems to support a process for continuous improvement toward a quality process required for and anticipated by accreditation. Nevertheless, a lack of clear specification in the computation process may make it difficult to achieve a consistent measure.

Some universities in Viet Nam have also put in practice the tools using the OBE framework for assessments and reports of CLOs. For example, the information given in the CLO framework is offered at a class or test group level in the case of Ton Duc Thang University [8]. The indicators are given in a graphical format but can be aggregated in a manner that affects the ability to make student- or CLO-specific interpretations in the case of Lac Hong University [9].

Indeed, there emerged a methodological gap in current practices. There remained a need for a transparent and reproducible calculation in which divergent scores for the assessment components are converted into CLO achievement scores for individuals before summarizing CLO achievement scores in courses to PLO achievement scores based on weighted schemes. This problem is addressed in this study by proposing a method.

3 Materials and Methods

3.1 Notation and data model

This study models outcome attainment at the individual student level by tracing assessment evidence from course assessment components to CLOs, and subsequently aggregating CLO evidence across courses to PLOs. Let i denote a student, c a course, j a CLO in course c, k a PLO, and a an assessment component in course c (e.g., midterm, final, assignment, project). All assessment scores are normalized to a common scale of 0-100 to ensure comparability across components and courses.

We define the index sets as follows:

$$i \in 1, \dots, N, c \in 1, \dots, C, j \in 1, \dots, J_c, k \in 1, \dots, K, a \in 1, \dots, A_c. \qquad (1)$$

For each student i, course c, and assessment component a, the observed component score is denoted by:

$$s_{i,c,a} \in [0,100]. \qquad (2)$$

To explicitly represent which assessment components provide evidence for each CLO, we introduce a binary linkage variable (CLO – component linkage matrix):

$$\gamma_{c,j,a} = \begin{cases} 1, & \text{if component } a \text{ provides evidence for CLO } j \text{ in course } c, \\ 0, & \text{otherwise.} \end{cases} \qquad (3)$$

The linkage $\gamma_{c,j,a}$ is derived from the course assessment design (Table 1) and reflects constructive alignment, i.e., only assessment components that are intended to measure a given CLO are allowed to contribute evidence to that CLO. In addition, $\gamma_{c,j,a}$ is constructed to respect the intended cognitive level of each CLO based on Bloom's taxonomy, thereby supporting the validity of interpreting component scores as outcome evidence.

Table 1 The matrix between CLO and assessment groups.

CLO	Midterm (30%)	Final (40%)	In-class (20%)	Presentation (10%)
CLO1	X	X	X	-
CLO2	X	X	-	X
CLO3	-	X	X	X

In summary, the minimal data required to apply the proposed method consist of: (i) normalized component scores $s_{i,c,a}$, (ii) the CLO – component linkage matrix $\gamma_{c,j,a}$, and (iii) the course and program outcome definitions (CLO and PLO sets). The subsequent sections build upon this data model to compute CLO scores and attainment at the student level, and to aggregate CLO evidence into PLO attainment in a transparent and reproducible manner.

3.2 Computing CLO score for each student

In order for an attainment of a CLO, on an individual student basis, to be calculated, a structured consolidation of evidence taken from various assessment components must occur. In light of various assessment components having different contributions towards a course grade and towards different CLOs, there will now be two levels of weighting involved: course grading weights, and evidence weights for individual CLOs.

First, for each course c, a set of course grading weights is defined for its assessment components:

$$\alpha_{c,a} \geq 0, \sum_{a=1}^{A_c} \alpha_{c,a} = 1, \qquad (4)$$

where $\alpha_{c,a}$ represents the proportion of the total course grade allocated to assessment component a, as specified in the course syllabus (e.g., midterm 30%, final 40%, assignments 20%, project 10%).

Second, for each CLO j in course c, CLO-specific evidence weights are defined over the assessment components that provide evidence for that CLO:

$$\beta_{c,j,a} \geq 0, \sum_{a:\,\gamma_{c,j,a}=1} \beta_{c,j,a} = 1, \quad (5)$$

where $\beta_{c,j,a}$ reflects the relative importance of assessment component a in measuring CLO j. These weights allow instructors to distinguish components that provide stronger or weaker evidence for a given CLO, even when multiple components are linked to the same outcome.

Given the normalized component score $s_{i,c,a}$ and the CLO – component linkage $\gamma_{c,j,a}$ defined in Section 3.1, the CLO score of student i for CLO j in course c is computed as:

$$\mathrm{CLO}_{i,c,j} = \frac{\sum_{a=1}^{A_c} \left(\alpha_{c,a}\, \beta_{c,j,a}\, \gamma_{c,j,a}\right)\, s_{i,c,a}}{\sum_{a=1}^{A_c} \alpha_{c,a}\;\beta_{c,j,a}\, \gamma_{c,j,a}}. \quad (6)$$

In this formulation, $\alpha_{c,a}$ captures the contribution of each assessment component to the overall course evaluation, $\beta_{c,j,a}$ captures the strength of the component as evidence for CLO j, and $\gamma_{c,j,a}$ ensures that only assessment components explicitly aligned with CLO j contribute to its score. The normalization in the denominator guarantees that $\mathrm{CLO}_{i,c,j}$ remains on the same 0-100 scale regardless of the number of contributing components.

This weighted and normalized computation provides a transparent mechanism for translating heterogeneous assessment scores into CLO-level attainment that is both interpretable and auditable. In contexts where simplicity is preferred, either the course grading weights $\alpha_{c,a}$ or the CLO-specific weights $\beta_{c,j,a}$ may be omitted; however, the combined formulation is retained in this study to preserve consistency with course grading policies while allowing fine-grained control over CLO evidence allocation.

3.3 CLO attainment decision (threshold rule)

After finding the CLO score for the student as discussed in Section 3.2, the ensuing step would be to decide whether the student has satisfied the related CLO. In outcome-oriented evaluation, this can be done by comparing the evaluated CLO score with the learning outcome threshold.

For each course c and CLO j, an attainment threshold is defined as:

$$\tau_{c,j}^{\mathrm{CLO}} \in [0,100], \quad (7)$$

where $\tau_{c,j}^{\mathrm{CLO}}$ represents the minimum score required for a student to be considered as having achieved CLO j. The threshold value is typically determined by the program or faculty in accordance with institutional quality assurance policies and the expected difficulty level of the course. In practice, common threshold values include 50/100 or 60/100.

Based on this threshold, a binary CLO attainment indicator is defined for each student i:

$$I_{i,c,j}^{\mathrm{CLO}} = \mathbb{1}\left(\mathrm{CLO}_{i,c,j} \geq \tau_{c,j}^{\mathrm{CLO}}\right), \quad (8)$$

where $\mathbb{1}(\cdot)$ is the indicator function, returning 1 if the condition is satisfied and 0 otherwise. Thus, $I_{i,c,j}^{\mathrm{CLO}} = 1$ indicates that student i has achieved CLO j in course c, while $I_{i,c,j}^{\mathrm{CLO}} = 0$ indicates non-achievement.

As a generally accepted practice for quality assurance, the threshold-level decision rule leads to a clear interpretable standard for the attainment of the CLOs, which facilitates consistent reporting and aggregation of the CLO evidence at the program level. Moreover, the binary output facilitates the easy calculation of the proportions for the attainment of the outcomes.

3.4 Aggregating CLO evidence into PLO score

PLOs, as stated, encapsulate higher-order skills, which are usually the result of aggregation of various learning outcomes from numerous courses. Therefore, the achievement of the PLO has to be inferred based on the aggregated performance of the various relevant CLOs.

To explicitly model the relationship between CLOs and PLOs, a CLO-PLO linkage variable is defined as:

$$m_{c,j,k} \in \{0,1\}, \quad (9)$$

where $m_{c,j,k} = 1$ indicates that CLO j of course c contributes evidence toward PLO k, and $m_{c,j,k} = 0$ otherwise. This linkage is derived from the curriculum mapping process and reflects the intended alignment between course-level outcomes and program-level outcomes, as typically documented in accreditation materials.

Since not all CLOs contribute equally to a given PLO, a non-negative contribution weight is assigned to each CLO-PLO linkage:

$$w_{c,j,k} \geq 0, \qquad (10)$$

where $w_{c,j,k}$represents the relative importance of CLO $j$in course $c$as evidence for PLO k. These weights are defined by the program council or quality assurance (QA) team to ensure consistency with program objectives and accreditation requirements [3, 4].

Given the CLO scores computed in Section 3.2, the PLO score of student i for PLO k is calculated as a weighted average of the contributing CLO scores:

$$\mathrm{PLO}_{i,k} = \frac{\sum_{c=1}^{C} \sum_{j=1}^{J_c} w_{c,j,k}\ m_{c,j,k}\, \mathrm{CLO}_{i,c,j}}{\sum_{c=1}^{C} \sum_{j=1}^{J_c} w_{c,j,k}\ m_{c,j,k}}. \qquad (11)$$

In fact, a more correct formulation for defining CLO includes only those CLOs that can be k add to the score, while the normalization part of the denominator ensures that the results remain comparable across students as well as programs irrespective of the number of contributing CLOs. This approach enables a fine-grained analysis of the results based on the performance of the students at the Program level by having the attainment of the PLOs as well as the CLOs on the same scale with respect to scores.

3.5 PLO attainment decision

After computing the continuous PLO score $\mathrm{PLO}_{i,k}$in Section 3.4, the next step is to determine whether student $i$has achieved PLO k. In practice, programs may adopt different attainment rules depending on the strictness required by the curriculum and quality assurance policies. This study supports two commonly used decision rules: a score-threshold rule and a proportion-based rule.

3.5.1 Score-threshold rule

Under the score-threshold rule, each PLO k is assigned an attainment threshold:

$$\tau_k^{\mathrm{PLO}} \in [0,100]. \qquad (12)$$

A student is considered to have achieved PLO $k$if the computed PLO score meets or exceeds this threshold:

$$I_{i,k}^{\mathrm{PLO}} = \mathbb{1}\big(\mathrm{PLO}_{i,k} \geq \tau_k^{\mathrm{PLO}}\big), \qquad (13)$$

where $\mathbb{1}(\cdot)$ is the indicator function that returns 1 if the condition is satisfied and 0 otherwise. This rule provides a direct and interpretable attainment decision while retaining $\mathrm{PLO}_{i,k}$ as a continuous metric for benchmarking and longitudinal analysis.

3.5.2 Proportion-based rule (CLO achievement proportion)

In some programs, a PLO may be considered achieved if a student attains a sufficient proportion of the CLOs linked to that PLO, acknowledging that certain CLOs may play a supplementary role. Let $\rho_k \in (0,1]$denote the minimum required proportion of achieved CLOs for PLO k. Using the CLO attainment indicator $I_{i,c,j}^{\mathrm{CLO}}$ defined in Section 3.3, the proportion-based attainment decision is defined as:

$$I_{i,k}^{\mathrm{PLO}} = \mathbb{1}\left(\frac{\sum_{c=1}^{C} \sum_{j=1}^{J_c} m_{c,j,k}\ I_{i,c,j}^{\mathrm{CLO}}}{\sum_{c=1}^{C} \sum_{j=1}^{J_c} m_{c,j,k}} \geq \rho_k \right). \qquad (14)$$

This rule is particularly useful when a program aims to emphasize breadth of competency attainment across multiple CLOs, rather than relying solely on the weighted average PLO score. In practice, typical values for ρ_k include 0.6 or 0.7, depending on program expectations.

3.5.3 Practical usage and consistency

The score-threshold rule (Eqs. (12)-(13)) supports continuous reporting and comparison across cohorts, while the proportion-based rule (Eq. (14)) supports flexible attainment decisions when PLO evidence consists of multiple CLOs with varying instructional roles. Both rules are compatible with accreditation-oriented documentation practices, provided that thresholds τ_k^{PLO} and proportions ρ_k are defined consistently and approved through the program's QA governance process [3, 4].

3.6 PLO attainment decision

Although immediate scores of CLO and PLO assessments result in precise quantitative data of result achievement, there would also need to be additional summary metrics in order for transparent reporting and interpretation of outcome data at both individual and programmatic assessments. In this particular research study, there would also need to be a "Percentage of PLO Completion" metric.

For each student i and PLO k, PPC is defined as the percentage of CLOs linked to PLO k that have been achieved by the student. Using the CLO – PLO linkage $m_{c,j,k}$ (Section 3.4) and the CLO attainment indicator $I_{i,c,j}^{\mathrm{CLO}}$ (Section 3.3), PPC is computed as:

$$\mathrm{PPC}_{i,k} = 100 \times \frac{\sum_{c,j} m_{c,j,k}\ I_{i,c,j}^{\mathrm{CLO}}}{\sum_{c,j} m_{c,j,k}}. \qquad (19)$$

By construction, $\mathrm{PPC}_{i,k} \in [0,100]$, where higher values indicate a greater proportion of required CLO evidence satisfied for PLO k. Unlike weighted PLO scores, PPC provides an intuitive measure of outcome coverage, making it suitable for visual reporting and diagnostic analysis.

To provide an overall view of outcome completion at the individual level, an aggregate PPC across all PLOs is defined as:

$$\mathrm{PPC}_i = \frac{1}{K}\sum_{k=1}^{K} \mathrm{PPC}_{i,k}\,. \qquad (20)$$

This program-level indicator provides an overall assessment of progress towards program outcomes for a student, and it will be used in results for comparing patterns of attainment.

Transparency in reporting at the level of outcomes based on PPC indicators enables feedback for students and teachers as well as helping in acquiring continuous quality improvements during the accreditation process.

4 Results

4.1 Pilot setting and report completeness

The proposed outcome computation was piloted in one master's program using assessment data from five courses delivered to a single class. The cohort size for the exported report is 26 students (26 records). Among these, 6 students have missing PPC entries ("-") because they transferred to another program.

The program specifies 10 PLOs (PLO1–PLO10), each decomposed into indicators. For each student i and outcome k, PLO completion is summarized using the Percentage of PLO Completion $\mathrm{PPC}_{i,k}$ and the overall completion index PPC_i defined in Eqs. (19)-(20). This enables results to be directly traceable to the CLO attainment evidence and CLO-PLO mapping described in Section 3.

4.2 Student-level PLO completion profiles (PPC)

For the 20 students with complete PPC values, the overall completion index PPC_i exhibits high attainment with notable dispersion:

- Mean $\mathrm{P\bar{P}C} = 86.0$
- Median $= 100.0$
- Minimum $= 0.0$, Maximum $= 100.0$

A majority of students show full outcome evidence coverage: 11/20 students (55%) achieved $\mathrm{PPC}_i = 100$. Meanwhile, a small subset presents substantial gaps: 2/20 students (10%) have $\mathrm{PPC}_i < 50$, and one additional student is at approximately $\mathrm{PPC}_i \approx 70.2$. These cases demonstrate that the PPC-based reporting can identify students who require targeted support at the outcome level, without conflating missing data from transferred students with underachievement.

At the PLO level, cohort mean PPC values remain above 80 across all outcomes, but differences are observed:

- Highest mean PPC: PLO5 (90.0); PLO1 and PLO3 (both 89.7)
- Lowest mean PPC: PLO6 (82.1) and PLO7 (82.1)

This indicates that evidences linked to PLO6 and PLO7 are the least complete on average in the pilot class, suggesting these outcomes as priority targets for diagnostic review.

4.3 Outcome-level diagnosis for program improvement

Because $\mathrm{PPC}_{i,k}$ is computed from CLO attainment indicators $I^{\mathrm{CLO}}_{i,c,j}$ and the CLO-PLO linkage $m_{c,j,k}$ (Eq. (19)), low PPC values can be traced back to specific CLO evidences and, ultimately, to assessment components through $\gamma_{c,j,a}$ and the CLO score computation (Eq. (6)). In practical QA workflow, the program council can start from the weakest PLOs (here, PLO6 and PLO7 by mean completion), then identify which linked CLOs contribute most to incompleteness, and review whether the issue is due to assessment design, insufficient evidence coverage in the five pilot courses, or threshold settings.

At the student level, PPC profiles support targeted advising by identifying which outcomes remain incomplete. At the cohort level, PPC summaries provide an interpretable measure of outcome evidence coverage that can be tracked across future intakes, supporting continuous improvement and accreditation-aligned reporting.

5 Conclusion

This paper presented a transparent, auditable method to compute learning outcome attainment at the individual student level by tracing assessment evidence from course assessment components to Course Learning Outcomes (CLOs), and aggregating CLO evidence across courses to Program Learning Outcomes (PLOs). The method was grounded in Outcome-Based Education and constructive alignment, where only assessment components explicitly linked to a CLO contribute to its computed score through the linkage matrix $\gamma_{c,j,a}$ and a two-layer weighting scheme $\alpha_{c,a}$ and $\beta_{c,j,a}$. CLO attainment was then determined using a threshold rule, and PLO scores were derived as weighted aggregations of CLO evidence using the curriculum mapping $m_{c,j,k}$ and contribution weights $w_{c,j,k}$. To support interpretable reporting, the paper further defined outcome-level indicators such as $\mathrm{PPC}_{i,k}$, enabling direct linkage between reported completion patterns and underlying CLO attainment evidence.

Pilot testing was done in a masters level course by using data from five courses and an exported file of 26 student records. The PPC outcome data was incomplete in six student records because the students transferred to another class, and the other records included complete PPC data at the cohort level. The pilot test suggests that it is possible and feasible to generate outcome data at the student level and also identify those outcomes that have relatively low rates of completion.

There are two implications of the proposed approach for practice. Firstly, the approach offers an auditable and reusable computation process, which is supported by documentation principles formalized for accreditation purposes, including proof of achievement of outcomes and progress towards continuous improvement. Secondly, the approach offers outcome-level diagnostics at the individual student and cohort level which will allow the teacher and the respective program councils to trace back the identified gaps to the respective CLOs and components.

However, there are also certain limitations that need to be taken into consideration. First, only one program is targeted by this pilot, as well as only certain numbers of courses, due to restrictions imposed by the lack of data available regarding students who transfer into the institution. Currently, only the quantitative component scores and achievement levels are emphasized by this implementation, even where certain outcomes are better assessed by more qualitative methods, such as rubrics, portfolios, or observation-based assessment. Future development will target full implementation across multiple cohorts, programs, as well as involve more qualitative measures regarding data governance rules, such as privacy as well as LMS tools.

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Phương pháp cá nhân hóa trong tính toán mức độ đạt được chuẩn đầu ra môn học và chuẩn đầu ra chương trình trong giáo dục đại học

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Tóm tắt Nghiên cứu này đề xuất phương pháp đánh giá chuẩn đầu ra theo hướng cá nhân hóa trong Giáo dục dựa trên chuẩn đầu ra (OBE), truy vết dữ liệu từ các thành phần đánh giá của học phần đến chuẩn đầu ra học phần (CLO), sau đó tổng hợp CLO qua nhiều học phần để suy ra chuẩn đầu ra chương trình (PLO), phục vụ đảm bảo chất lượng và kiểm định (ABET, AUN-QA). Ma trận liên kết nhị phân xác định thành phần nào thực sự cung cấp bằng chứng cho từng CLO, phù hợp nguyên tắc liên kết dạy học, đánh giá và mức nhận thức theo Bloom. Điểm CLO được tính trên thang 0-100 theo công thức chuẩn hóa, kết hợp trọng số theo đề cương và trọng số bằng chứng cho CLO, rồi áp dụng ngưỡng để quyết định đạt/không đạt. Điểm PLO được tổng hợp có trọng số từ các CLO liên quan; báo cáo dùng chỉ số PPC để trực quan hóa mức hoàn thành. Thử nghiệm trên một chương trình thạc sĩ với dữ liệu 5 học phần (26 bản ghi) cho thấy mức hoàn thành nhìn chung cao và giúp nhận diện các PLO yếu. Phương pháp tạo bằng chứng minh bạch, hỗ trợ chẩn đoán cá nhân và cung cấp đầu vào cho cải tiến liên tục.

Từ khóa Chuẩn đầu ra học phần (CLOs); chuẩn đầu ra chương trình (PLOs); đánh giá cá nhân hóa, đảm bảo chất lượng.