Application of Multilevel Parameter Algorithm to Enhance College Admission and Referral System

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***Abstract*—The admissions processes in Philippine Higher Education Institutions (HEIs) often rely on rigid, score-based criteria that struggle to adapt to unfilled program slots, applicant withdrawals, and equality requirements. These limitations make implementing a consistent referral procedure difficult, compromising fairness and increasing the administrative burden. This study aimed to develop and implement an automated admission and referral system based on the Multilevel Parameter Algorithm (MLPA) to manage prioritization, tie-breaking, and multi-stage referrals, while ensuring adherence to program capacity and policy guidelines. Unlike prior models that remain theoretical, simulation-based, or limited to recommendation stages, this study demonstrates a fully deployed MLPA-based admission and referral system. System quality evaluation by 10 Information and Communications Technology (ICT) professionals using ISO/IEC 25010 indicates excellent ratings across all criteria (overall M = 4.72, SD = 0.06). Meanwhile, functionality testing by 18 admission and staff personnel likewise unanimously validated the operational correctness of the system's core functions. From the applicant side, the system's usability was evaluated by 1287 first-year students from across colleges using the expanded Post-Study System Usability Questionnaire (PSSUQ), which yielded an overall usability of 2.02 (Good Usability), well above the PSSUQ Norm3 benchmark. The result likewise indicates that 255 (17.48%) of the respondents were successfully referred to their second-choice programs. The study demonstrates that an MLPA-based system can uphold fairness and user satisfaction from admission personnel and applicants, offering a replicable model for HEIs seeking to modernize admissions through transparent, data-driven, and equity-oriented digital solutions.**

***Keywords*—multi-level parameter algorithm, tie-breaking rules, equity in admission, referral process optimization, higher education enrollment, college admission system**

I. Introduction

University admissions remain a critical process in higher education, often dominated by test-based and market-oriented approaches that position academic performance as the primary measure of merit. While these systems can be efficient, they are increasingly perceived as restrictive, particularly in developing nations where, according to the report of United Nations Educational, Scientific and Cultural Organization (UNESCO) [1], equity, access, and quality must be carefully balanced. In the Philippines, admission practices in public Higher Education Institutions (HEIs) are shaped by national policies that aim to promote inclusive access.

The Universal Access to Quality Tertiary Education Act (RA 10931) [2] guarantees free tuition and other school fees at state-funded HEIs, shifting the admissions emphasis from exclusivity to broader inclusion. Complementing this, the Commission on Higher Education (CHED) Memorandum Order No. 09, s. 2013 [3] directs HEIs to design admissions and student services considering students' socio-economic backgrounds and circumstantial details.

However, despite these progressive frameworks, many state-funded HEIs continue to use strict, score-based admissions procedures that are ineffective in adapting to real-time developments like applicant withdrawals, unfilled quotas, and late-stage referrals. For instance, Iloilo Science and Technology University (ISAT-U) continues to face persistent challenges in redirecting unadmitted but qualified applicants to programs with available slots, due to the lack of automated support and the administrative burden of manual processing. In such cases, contingency measures like first-come and first-served enrollment are sometimes used, undermining the national policy's intended fairness and inclusiveness.

The limitations of these traditional processes have motivated research into algorithmic and Multi-Criteria Decision-Making (MCDM) approaches for admissions. Existing models such as the Analytic Hierarchy Process (AHP), fuzzy AHP, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the Weighted Sum Model (WSM) have been applied to rank applicants and recommend program placements [4, 5]. Kusuma [6] proposed a stable marriage-based algorithm for public school placements, while Muharram *et al*. [4] applied layered utility theory for teacher candidate selection. However, these applications typically function as simulations or stand-alone recommender systems, not integrated into real admissions workflows. Even in studies implementing functional decision platforms [7], support for dynamic referral logic, quota-based filtering, and multi-round decision-making is still limited.

Emerging frameworks such as Multilevel Parameter Algorithms (MLPAs) present a promising pathway to address these gaps. MLPAs allow prioritization, tie-breaking, and staged referrals by combining quantitative measures with qualitative or policy-driven parameters. While previous research demonstrates MLPA-like decision logic, for example, Kusuma [6] using a stable marriage-based algorithm and Xu *et al.* [7] combining hard and soft parameters for educational placements, these models have rarely been deployed in real-world, policy-constrained, and resource-limited settings.

To address these limitations, emerging frameworks such as the Multilevel Parameter Algorithm (MLPA) provide a more adaptable solution. Unlike traditional MCDM models, MLPA explicitly integrates sequential prioritization, tie-breaking rules, and staged referrals, enabling alignment with policy constraints and institutional capacity. Previous works, such as Kusuma [6], who modeled fairness through stable marriage theory, and Xu *et al.* [7], who combined hard and soft

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parameters for educational placements, demonstrate elements of MLPA-like logic yet do not implement such models in real-world, policy-driven, and resource-limited higher education contexts.

This study responds to that gap by moving beyond theory and simulation to demonstrate an operational MLPA-based admission and referral system in a Philippine state university setting. Accordingly, the study has the following aims:

1) To design and implement an automated admission and referral system that applies MLPA to integrate academic merit, program preferences, and socio-economic factors while enforcing capacity constraints and referral rules;
2) To evaluate the developed system using multiple complementary frameworks: (a) ISO/IEC 25010 for software product quality, (b) the Post-Study System Usability Questionnaire (PSSUQ) for user-perceived usability, and (c) functionality testing through structured test cases to validate operational correctness.

By integrating policy logic directly into the admissions workflow and automating critical placement decisions, this study offers HEIs like ISAT-U a scalable and transparent mechanism for streamlining admissions while upholding equity standards. In doing so, it contributes to improving admissions practice and extending the application of MCDM and MLPA research into policy-driven, resource-constrained environments.

II. Literature Review

Historically, university admissions prioritized academic merit, which is often measured through standardized examinations and prior academic records [8]. While this approach assures that admitted students meet institutional academic standards, it has been demonstrated to disadvantage candidates from low-income households that lack access to quality education and test preparation resources [9, 10].

Globally, several universities use market-oriented admissions policies that balance academic criteria with financial viability and institutional branding [11]. In competitive situations, such techniques may result in prioritizing high-fee-paying or overseas students to increase revenue and reputation [12, 13], especially in private or semipublic sectors where financial considerations may outweigh commitments to social inclusion [14].

In contrast, public higher education systems, especially in Southeast Asia, increasingly implement inclusive access policies to reduce educational inequality [15–17]. In the Philippines, Republic Act (RA) 10931 mandates tuition-free education for eligible students in state universities and colleges, requiring consideration of academic credentials and socio-economic status to promote equitable access for marginalized groups [2]. Similarly, CHED Memorandum Order No. 09, series of 2013, emphasizes fairness and equity in admissions by accounting for individual circumstances [3]. Together, these frameworks aim to transform admissions from exclusive to inclusive processes, encouraging institutions to recognize socio-economic diversity alongside academic achievement.

Despite these policy shifts, many public Higher Education Institutions (HEIs) continue to use rigid single-score cutoffs, based on entrance exams or high school grades, with limited flexibility for tie-breaking or alternative program placements. Such practices overlook context-specific factors like financial capacity or geographical location, potentially resulting in inefficiencies and inequities [18]. Moreover, manual admissions processing during peak periods can hinder fair reallocation of seats, leaving some programs under-enrolled while qualified students remain unplaced [19].

These challenges have spurred interest in Multi-Criteria Decision-Making (MCDM) techniques, which enable evaluations based on multiple, often competing, quantitative and qualitative factors [20, 21]. In education, MCDM is particularly useful for balancing academic performance, equity considerations, and institutional priorities [21]. Standard methods include the Analytic Hierarchy Process (AHP), Fuzzy AHP, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Weighted Sum Model (WSM) [18, 20, 21].

The WSM is widely favored for admissions due to its simplicity, transparency, and ease of implementation [22]. By assigning weights to criteria based on importance, WSM produces a composite score that can integrate entrance exam results, GPA, interview scores, financial background, and program preferences. Munir *et al.* [10] highlight the significant influence of socio-economic status on academic performance, and WSM offers a systematic means to incorporate such factors rather than treating them as secondary.

MCDM applications in education include graduate program recommender systems, where candidates are assessed on multiple criteria better to align them with program offerings [18]. Chaube *et al.* [21] note that MCDM enhances transparency and objectivity by enabling institutions to simulate admissions scenarios, adjust weighting configurations, and improve fairness within capacity limits.

However, while MCDM approaches are practical at ranking candidates, they often fail to address operational constraints such as maintaining program quotas, handling hierarchical tie-breaking rules, or managing dynamic referrals. For example, Kustiyahningsih and Aini [5] developed a hybrid Fuzzy AHP–COPRAS model that integrated academic and qualitative factors, achieving ~97% classification accuracy, but did not address real-time operational needs such as capacity control and reallocation mechanisms.

To address these limitations, this study has explored MLPA, which reflects the hierarchical structure of admissions: student-level attributes (e.g., test scores, socio-economic status) are evaluated within program-level constraints (e.g., quotas, priority rules), which operate within institution-wide policies. Unlike descriptive statistical models such as Hierarchical Linear Modeling (HLM) or Bayesian multilevel modeling [23, 24], MLPA uses a procedural, stage-by-stage selection approach, filtering candidates first on academic criteria, then on socio-economic or qualitative factors, followed by preference alignment [6, 25].

MLPA has proven valuable for ensuring structured fairness, priority-based selection, and dynamic seat reallocation. Kusuma [6], for instance, applied a Stable Marriage–based model to public school admissions, incorporating factors like school-home distance, exam ranking, economic status, and preferences. The approach eliminated unmatched candidates, improved geographic fairness by 71.4%, and raised the average exam score of admitted students by 6.6% compared to zone-based models. Similarly, Muharram *et al.* [4] used a multilevel Multi-Attribute Utility Theory (MAUT) framework for teacher candidate selection, integrating academic and personal attributes without explicit quota enforcement or referral mechanisms.

An added advantage of MLPA is its compatibility with rule-based automation, enabling consistent, transparent, and scalable decision-making. Xu *et al.* [7] emphasize that algorithmic approaches enhance responsiveness during postadmission referral cycles, allowing for rapid yet equitable seat redistribution.

Recent research from around the world has looked at how Artificial Intelligence (AI) and automated decision-making systems are increasingly being used in college admissions and other critical educational processes. While these technologies can make tasks like reviewing applications faster and more efficient, they also raise important questions about fairness, transparency, and legal responsibilities.

Studies have found that AI tools can help manage large numbers of applications and speed up evaluation [26, 27]. However, other research has pointed out that these AI systems often reflect existing inequalities and might not work as well for applicants from racial or socio-economic minority groups [28, 29]. This result has led experts to stress the importance of designing AI systems that prioritize fairness, are transparent in making decisions, and include human oversight [26, 29].

From a legal standpoint, using AI in admissions carries risks related to accountability and discrimination. Institutions must address these concerns by creating clear rules, documenting their processes carefully, and designing AI tools that respect individual rights [30]. Overall, while AI can boost efficiency and offer new capabilities—like spotting AI-generated application content or predicting future trends—it is crucial to pair these benefits with strong fairness safeguards and thoughtful policies.

The literature indicates that MCDM and MLPA offer strong foundations for addressing student selection and program placement complexity. However, practical implementations vary widely; some remain conceptual [4], others are simulation-based [6], and only a few operate as decision-support tools without final admissions decisions [7]. Even deployed models, such as that of Kustiyahningsih and Aini [5], often lack the integrated referral and capacity management functions required in policy-intensive environments. Notably, few systems are tailored to the Philippine context, where RA 10931 and CHED MO 09 mandate prioritizing socioeconomically disadvantaged students in tie-breaking situations [2, 3].

This gap underscores the need for applied research integrating multilevel decision algorithms into operational admissions systems in resource-constrained, policy-driven environments. Leveraging MLPA's structural logic can help institutions create transparent, equitable, and capacity-aware admissions processes that balance academic quality and equity objectives.

III. Materials and Methods

This study employed a combination of developmental and descriptive research designs. Developmental research is widely used in instructional technology, as it involves not only the creation of a product but also the documentation of its development process and the evaluation of its final form [31]. The study adopted the prototyping model to guide the iterative design and implementation of an automated admission and referral system based on the Multi-Level Parameter Algorithm (MLPA).

The descriptive component involved evaluating the developed system using multiple complementary instruments: the ISO/IEC 25010:2011 software quality model, the Post-Study System Usability Questionnaire (PSSUQ), and Functionality Testing. These instruments assessed the system's software quality characteristics, usability, user satisfaction, and functional correctness. The statistical treatment employed was the computation of the mean to interpret evaluation data.

A. Research Participants

The study engaged three groups of participants to evaluate the developed admission and referral system across different quality, usability, and functionality dimensions.

The first group comprised 10 Information and Communications Technology (ICT) professionals purposively selected from ISAT-U. Purposive sampling allowed the inclusion of individuals who could provide informed, relevant feedback due to their roles and experience [32]. These participants included personnel from the Management Information Systems (MIS) Office, program coordinators, and faculty members involved in admissions processes. Their role was to assess the system using the ISO/IEC 25010. Their selection was based on professional expertise and direct engagement in institutional data management and admissions workflows, ensuring that the feedback reflects technical and operational perspectives.

The second group comprised 18 purposively selected participants, including program heads, deans, faculty members, and personnel from the Office of Student Affairs and Services (OSAS) and the MIS Office. Their inclusion was based on their familiarity with admissions workflows and role as intended system end-users. Consistent with Ref. [32], purposive sampling was applied to ensure that the study included individuals with operational expertise and policy knowledge. Their evaluation focused on functionality testing, verifying whether the system correctly enforced institutional policies, referral rules, and program-level requirements.

The third group focused on usability and user-friendliness testing. A total of 1,287 first-year students participated through voluntary response sampling with stratification, as they self-selected to respond to an online invitation. While participation was voluntary, the researcher monitored the responses to ensure proportional representation from each college within the university, thereby strengthening the representativeness of the findings. Voluntary response sampling is commonly used in educational research where large populations are involved, and although it carries the risk of self-selection bias, stratification by subgroups can improve balance across participant characteristics [33]. First-year students were chosen because they had already used the system during their admission application, enabling them to provide meaningful feedback on its usability using the System Usability Questionnaire (PSSUQ) instrument.

By combining purposive sampling for expert evaluators and functionality testers with voluntary sampling for student users, the study ensured a balance of technical, operational, and end-user perspectives. This multi-perspective evaluation strengthened both the validity and applicability of the findings.

B. Data Gathering Instruments

The study developed a structured survey instrument for evaluating the system's quality with two main sections. The first step is to gather respondents' profiles, including names, institutional affiliations, positions, educational backgrounds, and fields of expertise, to confirm the professional Suitability of the participants. The second served as the system evaluation tool, applying the ISO/IEC 25010:2011 quality model, a globally recognized software assessment framework [34]. The study assessed the system using six quality characteristics: functional Suitability, performance efficiency, usability, Reliability, security, and maintainability. Responses were recorded on a 5-point Likert scale, with the verbal interpretation presented in Table 1. This approach ensured a standardized and structured evaluation consistent with international software quality assessment practices.

Table 1. Likert five-point scale range interpretation

Point	Scale range	Interpretation
5	4.50–5.00	Excellent
4	3.50–4.49	Very Satisfactory
3	2.50–3.49	Satisfactory
2	1.50–2.49	Good
1	1.00–1.49	Poor

The study also used PSSUQ to measure the system's perceived usability and user satisfaction. The PSSUQ is a validated instrument widely used in numerous usability studies and demonstrates strong internal reliability [35]. The respondents rated their experiences of the system on a 7-point Likert scale, where 1 = "Strongly Agree" (most positive) and 7 = "Strongly Disagree" (least positive). Lower scores indicate better usability, with the scale ranges interpreted as shown in Table 2.

Table 2. Scale range and interpretation of PSSUQ results

Scale range	Interpretation
5.01–7.00	Very Poor Usability
4.01–5.00	Poor Usability
3.01–4.00	Moderate Usability
2.01–3.00	Good Usability

The study expanded the PSSUQ instrument with two items. The first asked the respondents whether they were referred successfully by the system, and the second sought their feedback or suggestions about the system. Answering these two items was voluntary.

Table 3. PSSUQ Norm3 benchmark means [35]

Dimension	Norm3 Mean
System Usefulness	2.82
Information Quality	3.02
Interface Quality	2.49
Overall Usability	2.82

The study used the normative averages (Table 3) reported by Lewis [35], commonly called PSSUQ Norm3, to benchmark the PSSUQ results.

The third instrument used in this study is Functionality Testing, which assessed whether the system performed its intended processes according to design specifications. Functionality testing is a standard part of software validation as it ensures that each feature operates correctly and consistently in line with institutional requirements [36, 37].

Testing a feature involves using a test case, and the testers filled out the test case form with the actual test data they used and the result obtained, indicating either a "Pass" or a "Fail" criterion for the feature being tested. For this purpose, the study developed six structured test cases for the system's core functions, including data management, scheduling, notifications, analytics and reporting, user management, and referral mechanism.

C. Research Procedure

The study followed the prototyping model in developing the MLPA-based system. A prototype served as an early functional version of the software, enabling user feedback and iterative refinement before full implementation. The study selected this approach because of its ability to incorporate user-specific requirements and address needs that might not emerge during the initial design [38]. The model consisted of the following phases: requirements gathering, quick design, prototype development, user evaluation, prototype refinement, and final product development. This study has chosen this model to ensure that end-user feedback is continuously integrated throughout the development cycle, leading to a more effective and user-centered system.

1) Requirements gathering

The process began with a thorough analysis of ISAT-U's admissions and referral workflows. The researcher collected the data through document review, informal interviews with admissions personnel, and consultations with ICT staff, admissions encoders, and program coordinators from various colleges, including the Office of Student Affairs and Services and the MIS Office. Finally, the researcher examined the institutional policies, CHED guidelines, and challenges associated with manual referral processing in detail.

2) Quick design

The researcher prepared the preliminary design to capture the system's essential features, including applicant data management, program preference handling, quota enforcement, and referral logic. The study extended the existing admissions database schema to support referral processes. The design included a centralized data repository; scheduling for the University Admission Test (UAT), aptitude tests, and interviews; real-time applicant notification; admission data reporting; user management; and automated referral mechanisms. Lastly, the researcher prepared the Mock-up interfaces and flowcharts to visualize workflows and facilitate early stakeholder validation.

3) Prototype development

The study developed the prototype using a PHP–MySQL technology stack, where PHP handled the admission rules, referral logic, and multilevel tie-breaking algorithms. At the same time, MySQL managed data storage and retrieval. On the client side, the study used JavaScript with jQuery to provide interactivity, and Bootstrap 5 ensured a responsive and user-friendly interface across devices. The system integrated several third-party libraries to extend functionality, including PHPMailer for automated email notifications, FPDF for generating PDF reports, and Chart.js for data visualization.

An initial functional prototype incorporated the MLPA's core ranking and referral logic. The first version focused on essential functionalities, enabling immediate demonstration and feedback collection.

4) User evaluation

The prototype was presented to the selected participants for quality evaluation using the ISO/IEC 25010 quality model and for functionality testing of its features. For each evaluation process, the researcher obtained a distinct request for approval to evaluate the Office of the Vice President for Academic Affairs, given the involvement of personnel directly engaged in admissions operations. The researcher provided the participants with a printed copy of their respective evaluation instruments and briefed them on the study objectives, participation rights, and confidentiality safeguards. Completed forms were collected, encoded, and analyzed using the Statistical Package for the Social Sciences (SPSS). The study also used SPSS in the tabulation and computation of means.

Meanwhile, for functionality testing, the evaluation results were processed manually. The researcher also gathered additional qualitative feedback through direct interaction with participants to guide refinements. The usability evaluation by first-year students occurred months after they used the system in the admission process and did not influence the prototype design process.

Prototype Refinement

Based on evaluation results and feedback, the system underwent minimal modifications. These included user interface enhancements and adjustments to the referral process output, specifically revising the transfer of computed UAT, aptitude, and interview scores from first- and second-choice programs to more clearly reflect applicant eligibility during referral stages.

5) Final product development

The refined version was finalized, and all planned features were implemented. The completed system automated the admissions and referral process, integrating academic merit, socio-economic considerations, and enrollment capacity controls into a unified operational platform.

6) Multi-level parameter algorithm

The Multilevel Parameter Algorithm governs the admissions decision-making process across multiple stages: ranking, tie-breaking, and referral. The algorithm was mathematically modeled to reflect current practices in Philippine higher education institutions, particularly under policy frameworks such as RA 10931, to ensure transparent, merit-based, and policy-compliant outcomes.

Level 1: Ranking of Applicants using Weighted Sum Model (WSM)

Applicants are first evaluated, which integrates multiple academic and eligibility criteria into a single composite score:

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{ij} \tag{1}$$

With n = 4 (UAT, Aptitude, Interview, GPA), where w_j denotes the assigned policy weight and x_{ij} represents the applicant's score for criterion j. The scoring function expands to:

$$\text{CombinedScore}_i = w_1 \cdot \text{UAT}_i + w_2 \cdot \text{Aptitude}_i + w_3 \cdot \text{Interview}_i + w_4 \cdot \text{GPA}_i \tag{2}$$

where:

- UAT_i = University Admission Test score
- Aptitude_i = Program-specific aptitude score
- Interview_i = Interview rating (if applicable)
- GPA_i = General weighted average from high school
- w_1, w_2, w_3, w_4 = Assigned weights
- CombinedScore_i = Total score used for ranking

Applicants are sorted in descending order by their CombinedScore, subject to program capacity N_p and minimum passing score PassingScore_p. The pool of qualified applicants for program p is defined as:

$$P_p = \{\ \mid CombinedScore_i \geq PassingScore_p\} \tag{3}$$

Each applicant $i \in P_p$ is assigned a comparator vector:

$$\tau p(i) = (\text{CombinedScore}_i, \text{UAT}_i, \text{Aptitude}_i, \text{Interview}_i, \text{GPA}_i, -\text{FamilyIncome}_i, r_j) \tag{4}$$

where r_j is a random tie—break key and the negative income ensures lower—income applicants are favored. Sorting P_p lexicographically by $\tau p(i)$ produces a deterministic, policy-compliant ranking:

$$sort_{\text{desc}}(P_p, \tau_p) \tag{5}$$

The descending lexicographic order ensures that applicants with a higher combined score come first, those tied are resolved using tie breakers, and random tie resolution is used if applicants match all criteria. The top N_p applicants from this sorted list are admitted: if applicants matched in all of the criteria. The top N_p applicants from this sorted list are admitted:

$$\text{Selected}_p = \text{Top}N_p\ (sort_{\text{desc}}(P_p, \tau_p)) \tag{6}$$

The lexicographic comparator rp_i ensures deterministic resolution of ties at capacity limits. The ranking rules are:

1) Combined Score: $i > j$ if $\text{CombineScore}_i > \text{CombinedScore}_j$
2) UAT Score: Used if Combined Scores are equal
3) Aptitude Score: Used if above remain equal
4) Interview Score: Next comparison criterion
5) GPA: Higher GPA ranks higher
6) Family Income: Lower income is preferred
7) Randomization: Final tie resolution

Level 2: Referral and Second-Round Evaluation

Applicants not admitted to their first-choice program but meeting institutional standards are evaluated for referral to their second choice. The referral score uses the same WSM approach, with weights adjusted for the second-choice program q:

$$\text{ReferralScore}_i = w_1' \cdot \text{UAT}_i + w_2' \cdot \text{Aptitude}_i + w_3' \cdot \text{Interview}i + w_4' \cdot \text{GPA}_i \tag{7}$$

where wk' are adjusted according to the second program's criteria. Referral occurs if:

- Program q has remaining capacity C_q;
- Applicant meets cutoff score T_q;
- Applicant is not already admitted elsewhere

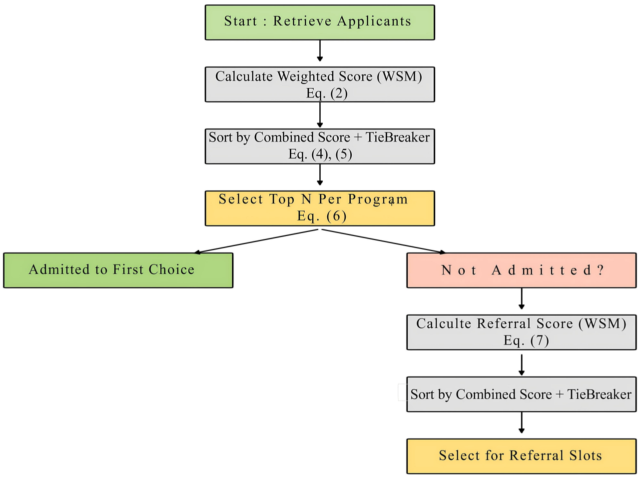

Fig. 1. Flowchart of the multi-level parameter algorithm.

Fig. 1 presents the formal flowchart of the Multilevel Parameter Algorithm implemented in the developed admission and referral system. The diagram outlines the sequential processes, beginning with the input of applicant data and computation of the combined score, followed by the two-level allocation procedure. Each allocation stage applies the passing score filter, lexicographic tie-breaking, and capacity-based selection before moving unallocated applicants to their next preferred program.

IV. Result and Discussion

Implementing the Multilevel Parameter Algorithm (MLPA) in the admission and referral processes of a state-funded Higher Education Institution (HEI) yielded positive results. This section presents key findings and explores their significance across operational, quality, and policy areas.

A. *Centralized Data and Application Interface*

The system's centralized data repository effectively consolidates applicant information, from personal to academic to socio-economic attributes, in a single system (Fig. 2). Consistent with the findings of Abughazalah *et al.* [39], centralized data offers integration, effectiveness, simplicity, and rapid information access. Such an approach also allows one to adopt a university-wide data-sharing model as demonstrated by Dandan *et al.* [40]. This fundamental architecture supports the MLPA's seamless integration of multi-criteria evaluation components.

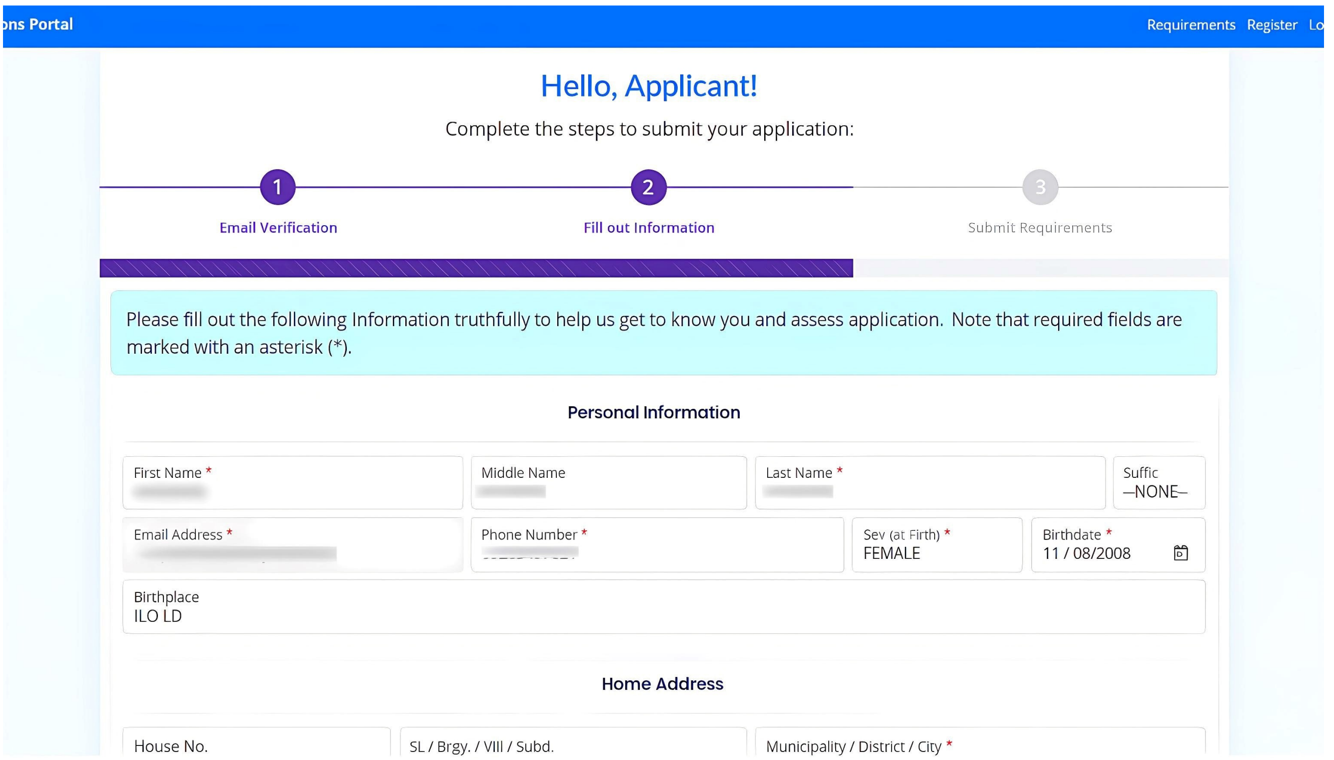

Fig. 2. Applicant application form.

B. *Applicant Ranking and Tie-Breaking Procedures*

Fig. 3 shows the overall ranking of applicants based on composite scores derived from MLPA. In the event of tied scores, the lexicographic hierarchy from University Admission Test score, aptitude, interview, GPA, and income is followed. This structured tie-breaking enhances fairness by applying a deterministic, rule-based sequence to resolve applicant ranking ties. Such approaches reflect principles in matching theory and school choice mechanisms, particularly those employing structured matching rules such as the Gale–Shapley [41] deferred acceptance algorithm, which guarantees stable outcomes through clearly defined priority hierarchies. The result indicates that the system outperforms conventional, nonsystematic approaches that may unintentionally reduce equity.

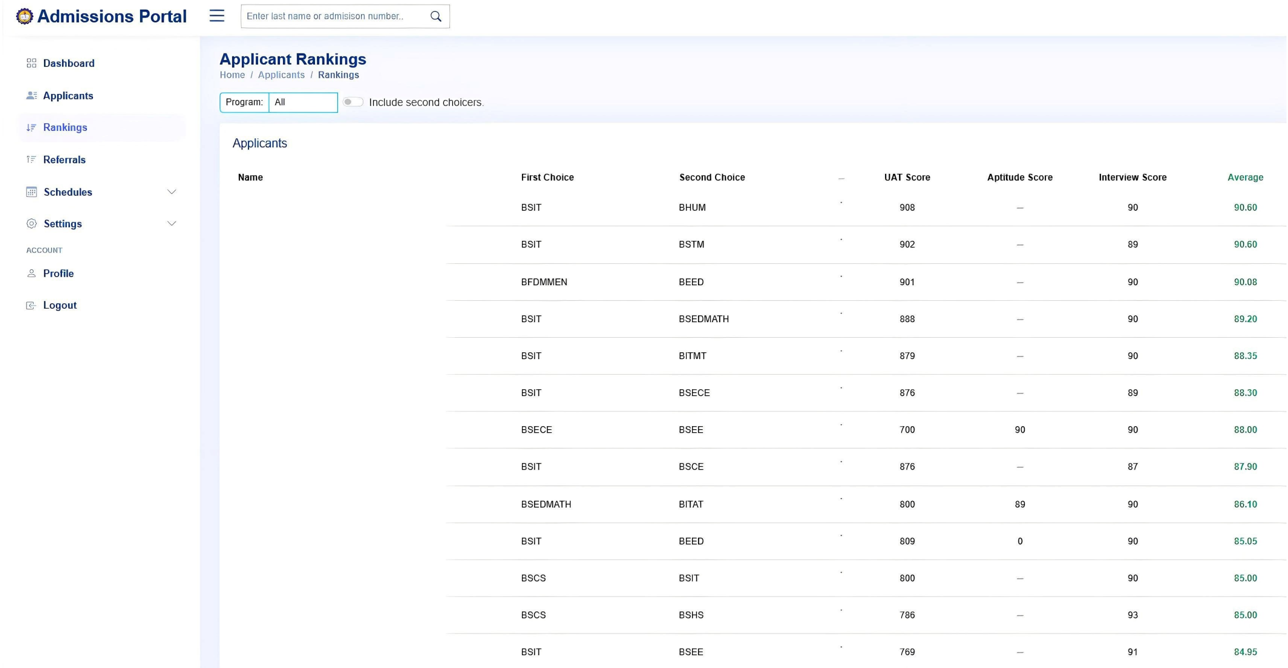

Fig. 3. The ranking of applicants.

C. Referral Management and Capacity Enforcement

Referral processing (Table 4) demonstrates the algorithm's enforcement of program capacity and structured placement of applicants into their second-choice program. This stage operationalizes complex decision-making, enabling data-driven seat assignment and resource optimization. Consistent with matching theory as described by Dogan *et al.* [42] and Abdulkadiroğlu *et al.* [43], the list reflects the effective implementation of the mathematical representation of the lexicographic ordering governed by the hierarchy of criteria and strictly capped by capacity.

Table 4. List of Referred Applicants (May 9, 2025)

Admission ID	UAT	Aptitude	Interview	Ave.	Referred To
2025-7751-A	771	56	25	79.68	BITWFT
2025-1592-A	792	95	71	81.56	BITCUL
2025-3910-A	788	90	63	80.44	BFDMMEN
2025-0636-A	752	23	30	79.56	BITAD
2025-1625-A	761	49	11	80.68	BSHS
2025-3577-A	792	21	15	82.16	BITAFT
2025-7143-A	785	13	73	79.20	BITHVAC
2025-5089-A	786	0	68	79.88	BITMT
2025-0905-A	794	99	54	83.32	BITAT
2025-5318-A	758	47	47	80.44	BITET
2025-5022-A	756	4	56	79.48	BITCT

D. Software Quality Assessment Using ISO/IEC 25010

1) Product quality evaluation using ISO/IEC 25010

a) Demographic profile of respondents

Table 5 shows that the selected population sample is comprised of respondents with deep institutional insight, 40% of whom hold strategic administrative roles, and is balanced by technically profiled staff. Meanwhile, the educational qualifications ranged from bachelor's to doctoral levels. This high level of intellectual qualification, paired with their respective institutional roles and diversity of expertise, enhances the evaluation's validity and supports the credibility of the assessment on both strategic and operational dimensions.

Table 5. Profile of respondents

Characteristic	Category	Frequency	Percentage
Position Held	Department Head	3	30
	Programmer	1	10
	Director	1	10
	Encoder	2	20
	Dean Staff	3	30
Educational Attainment	Bachelor's Degree	6	60
	Master's Degree	3	30
	Doctorate Degree	1	10

b) Software quality evaluation

The system achieved an overall quality rating of $M = 4.72$ ($SD = 0.06$) across ISO/IEC 25010 dimensions (Table 6), a performance classified as Excellent. This suggests strong user satisfaction and confirms that the system successfully meets high-quality standards. It further suggests that the system is highly functional and meets the specific needs of its users [44], leading to increased user satisfaction and adoption [45].

Table 6. Overall result of software evaluation based on ISO 25010

ISO 25010 Criteria	Mean	SD
Functional Suitability	4.77	0.51
Performance Efficiency	4.63	0.57
Usability	4.72	0.13
Reliability	4.80	0.00
Security	4.72	0.05
Maintainability	4.70	0.05
Overall	4.72	0.06

Reliability received the highest score among the specific quality attributes ($M = 4.80$, $SD = 0.00$), indicating unanimous consensus regarding the system's dependability and fault tolerance. These results align with Panduwiyasa *et al.* [46], who noted that systems with excellent reliability achieve faster recovery times and foster higher levels of user satisfaction, which is a critical factor in resource-constrained environments. Moreover, the result signifies the system's conformance to the reliability guidelines established by the Software Improvement Group [47].

Maintainability was rated at $M = 4.80$ ($SD = 0.42$), suggesting the system is structured to facilitate easy updates, corrections, and adaptations. This result supports long-term system evolution and aligns with the observations of Peters and Aggrey [44], who found that systems with high maintainability scores tend to require lower adaptation effort, facilitate smoother upgrade processes, and ultimately reduce the total cost of ownership over the system's lifecycle.

Performance Efficiency, while still Excellent at $M = 4.63$ ($SD = 0.57$), scored lower than reliability and maintainability. This implies faster response times and efficient resource utilization, but with some room for optimization. The result is consistent with Pereira *et al*. [48], who found that achieving high performance efficiency improved availability and reliability.

Meanwhile, the system's usability score of $M = 4.72$ ($SD = 0.13$), which is equivalent to Excellent, demonstrates its high levels of effectiveness, efficiency, and overall user satisfaction. The result is consistent with Sivaji *et al*. [49], who stress that addressing usability issues improves user experience and increases engagement.

Functional Suitability was rated $M = 4.77$ ($SD = 0.51$), implying completeness, accuracy, and alignment with user tasks. A high score implies that the system directly improved operational efficiency and data accuracy [50], fosters stakeholder confidence and regulatory compliance [51], correlates with enhanced user satisfaction and system adoption [52], and provides evidence that academic systems can deliver measurable educational process efficiencies [53].

2) Usability evaluation using PSSUQ

a) Demographic profile of respondents

A total of 1,287 first-year students participated in the PSSUQ survey (Table 7), representing all university colleges. The distribution of respondents reflects broad institutional coverage, ensuring that usability feedback captured students' perspectives across diverse academic disciplines. Female respondents comprised a slight majority, indicating balanced gender participation. The CIT had the highest representation, while students from the CAS and CEA contributed meaningfully to the sample, providing insights from technical and non-technical programs.

Table 7. Profile of PSSUQ respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	526	40.87
	Female	761	59.13
College	CCI	212	16.47
	CAS	94	7.30
	CIT	573	44.52
	COE	290	22.53
	CEA	123	9.56

This diversity of respondents strengthens the generalizability of the usability findings, as it reflects how students from varied academic and technological backgrounds experienced and evaluated the admission and referral system.

b) Usability evaluation results

The developed admission and referral system's usability was assessed using PSSUQ, and the result is shown in Table 8.

The system's overall usability score is 2.02, reflecting "Good Usability", as lower scores indicate higher satisfaction. This rating is considerably better than the PSSUQ Norm3 benchmark of 2.82 [35], suggesting that students were more satisfied with the system than average benchmarks reported in prior studies.

Table 8. Overall result of software evaluation using PSSUQ

PSSUQ Criteria	Mean	Description
System Usefulness (SYSUSE)	1.95	Very Good Usability
Information Quality (INFOQUAL)	2.14	Good Usability
Interface Quality (INTERQUAL)	1.99	Very Good Usability
Overall Usability	2.02	Good Usability

The System Usefulness (SysUse) subscale achieved a mean of 1.95, outperforming the Norm3 Mean of 2.82. These findings show that students found the system effective and easy to use for completing admission tasks. Prior research has shown that high usefulness ratings strongly correlate with user acceptance and trust in new educational technologies [53]. For admission systems, the result indicates that the system design successfully addressed core functional requirements while reducing the learning curve for first-time users.

The Information Quality (InfoQual) subscale scored 2.14, slightly higher than the other subscales but still below the Norm3 benchmark 3.02. This result indicates that while students generally found the system information clear, the study could improve error messages and documentation. Research consistently highlights that clarity of feedback and documentation significantly affects user efficiency and satisfaction [54, 55]. Thus, enhancing the system's feedback mechanisms could further strengthen user confidence and reduce reliance on external support.

The Interface Quality (InterQual) subscale had a mean of 1.99, again outperforming the Norm3 Mean of 2.49. This result indicates that students perceived the interface as visually pleasant and consistent. Interface quality influences emotional engagement and willingness to continue using educational systems [53, 56]. The system's positive interface evaluation suggests it provides an intuitive and appealing user experience, which is especially important for first-year students adapting to new institutional systems.

The students' high rating of the system was achieved even though the respondents came from diverse academic strands and varying levels of ICT proficiency. This result highlights the system's inclusiveness and accessibility, similar to earlier findings that usability plays a decisive role in user satisfaction and adoption in higher education settings [53, 57]. These findings provide strong evidence of its readiness for institutional deployment.

c) Referral outcome

Table 9. Referred applicants by college

College	Total Referred	Percentage
CCI	41	3.19
CAS	17	1.32
CIT	79	6.14
COE	79	6.14
CEA	9	0.70
Total	225	17.48

The system successfully referred 225 students (17.48%) to their second-choice programs (Table 9), demonstrating the effectiveness of the MLPA-based system in optimizing program slot utilization and maintaining fairness in student placement. This outcome underscores the system's capacity to reduce manual intervention in the referral process, ensure equitable opportunities for qualified applicants, and minimize unfilled slots, the key indicators of efficiency and inclusivity in the admission process.

3) System features evaluation using functional testing

The system's features were tested by 18 university personnel directly involved in the admission process. The respondents consisted of three department heads, three staff personnel from distinct dean offices, and three from the Management Information System (MIS)—one programmer, one director, two admission encoders, and the MIS director.

Functionality testing examined seven critical workflows of the admission and referral system (Table 10). It is essential to software validation, ensuring that each feature works as designed and meets user expectations [37, 38]. All 18 evaluators unanimously rated every test case as passed, indicating the prototype's reliable execution of its specified processes. This unanimous pass proves the system's technical correctness and operational readiness, a fundamental precondition for user trust and organizational adoption [37]. When domain experts validate that the core modules behave as intended, the institutions face fewer deployment surprises and can move more confidently from pilot to scale [58].

Table 10. Summary of the functionality test based on test cases

No.	Features	Number of Responses	
		Passed	Passed
1	Centralized admission data repository	18	100%
2	Exam and interview scheduling	18	100%
3	Notifications and result dissemination	18	100%
4	Analytics and reporting of admission data	18	100%
5	User account and access management	18	100%
6	Automated referral mechanism	18	100%
	Average	18	100%

The result is favorable for empirical models of technology acceptance, which show that perceived performance and system reliability positively influence behavioral intention to use and organizational uptake [59]. Therefore, the unanimous expert approval not only signals technical success and alignment with institutional workflows but is also well-positioned for broader deployment.

With the unanimous expert approval, the result signals technical success and meaningfully increases the likelihood of institutional acceptance.

E. Quantitative Policy Alignment

Beyond software quality, the results demonstrate how well the MLPA system aligns with national equity mandates such as RA 10931 and CHED Memorandum Order No. 09. By applying income-sensitive tie-breaking rules and enforcing program quotas, the system ensured that applicant placements followed institutional and government policies.

During ISAT-U's 2025 admission cycle, the system successfully assigned every available program slot without exceeding the set quotas, achieving 100% compliance with capacity limits. More importantly, evidence from the PSSUQ survey indicated that 225 students confirmed being successfully referred to their second-choice program after not gaining admission to their first choice. This result highlights the system's ability to operationalize referral logic to preserve fairness and expand opportunities for disadvantaged applicants, whereby previous systems might otherwise have excluded them.

Although the study did not collect baseline data from prior manual admissions, existing studies indicate that traditional score-based systems often lead to underutilized program slots and reduced access for low-income or marginalized applicants. Centralized and rigid admission mechanisms can leave eligible students unassigned or create vacant seats [60] while unequal selection structures tend to reinforce socio-economic stratification and limit diversity in higher education [61–63].

F. Comparative Analysis with Existing Approaches

While the primary objective of this study was to design, implement, and evaluate an admissions and referral system using the Multilevel Parameter Algorithm (MLPA), it is helpful to contrast its operational outcomes with baseline approaches commonly applied in the literature. Traditional score-based admissions, widely practiced in Philippine state universities, rank applicants solely by test or GPA results and often struggle to handle tie-breaking, quota compliance, and referral logic. In contrast, Multi-Criteria Decision-Making (MCDM) methods such as AHP and TOPSIS allow for weighted evaluations of multiple criteria [22]. However, these models are usually applied in simulation studies and lack built-in support for dynamic referrals or strict capacity enforcement [5, 6].

Compared to manual admissions, the MLPA system enhances fairness by applying socio-economic tie-breaking instead of relying on arbitrary, first-come, first-served rules. It improves efficiency by automating quota enforcement and referrals that would otherwise require intensive manual effort. Against AHP and TOPSIS, MLPA goes beyond ranking accuracy by embedding multi-stage decision rules that ensure policy compliance with RA 10931 and CHED directives. While this study did not perform a direct experimental benchmark against AHP or TOPSIS, the deployed MLPA system demonstrates superior Suitability for real-world, policy-driven admissions where fairness and compliance are necessary.

G. Limitations and Future Work

This study was primarily concerned with designing, implementing, and evaluating an MLPA-based admission and referral system. While the results indicate that the system meets high ISO/IEC 25010 standards and performed well in usability (PSSUQ) and functionality testing, several limitations remain.

First, the study did not benchmark MLPA against other established admission models such as AHP, TOPSIS, or stable marriage-based approaches. Although the study validated the system's correctness, fairness, and compliance with institutional policies, the absence of comparative testing limits conclusions about MLPA's relative efficiency or policy alignment advantages.

Second, the evaluation did not include formal performance testing under large-scale, high-load conditions. Stress testing with thousands of concurrent applicants would provide valuable insights into execution time, throughput, and system stability. Such profiling is essential to confirm the system's scalability and reliability in real-world deployment across admission cycles.

Finally, while this study incorporated expert evaluators, applicant feedback through the PSSUQ survey, functionality testing with admissions staff, and broader longitudinal testing across multiple admission cycles and institutions would provide more substantial evidence of transferability and adoption.

V. Conclusion

This study demonstrated the design, implementation, and evaluation of an operational admission and referral system based on the Multilevel Parameter Algorithm (MLPA). Unlike prior models that remain theoretical, simulation-based, or limited to recommendation stages, this study deployed the system in an actual institutional setting. Comprehensive testing through ISO/IEC 25010, PSSUQ, and functionality validation confirmed the system's technical reliability, usability, and fairness, affirming its readiness for institutional implementation.

By embedding institutional policy rules, program quotas, and socio-economic tie-breakers into a structured algorithmic framework, the system advances Multi-Criteria Decision-Making (MCDM) and MLPA research beyond conceptual models. It demonstrates that an MLPA-based system can simultaneously achieve algorithmic fairness and operational efficiency in resource-constrained, policy-driven contexts such as Philippine HEIs. Importantly, the combination of ISO-based technical validation, PSSUQ usability insights, and functionality verification provides strong evidence of technical soundness and practical viability for institutional deployment.

The findings suggest broader implications: MLPA-driven systems can help HEIs modernize admissions by reducing manual workload, ensuring capacity compliance, and promoting equity-driven transparency. While this study was limited to one institution, the model offers replicability for other HEIs and potential adaptability to graduate admissions or multi-institutional settings.

The researcher recommends adapting the system to other admission cycles where similar capacity and fairness constraints apply, like graduate admissions. Future work could enhance MLPA by integrating artificial intelligence and machine learning for predictive admissions, such as forecasting applicant withdrawals or slot vacancies. Cross-institutional and cross-country applications and large-scale comparative studies with AHP, TOPSIS, or stable-matching algorithms would provide deeper insights into MLPA's robustness, scalability, and fairness across diverse policy contexts. Finally, future research should include performance testing to evaluate how the system handles large-scale applicant loads, focusing on execution time, scalability, and responsiveness under typical peak admission conditions. Such an assessment will be essential for verifying the system's efficiency and reliability in real-world institutional deployments.

Conflict of Interest

The author declares no conflict of interest.

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