Predicting Success in Professional Licensure Examinations through Discriminant Function Analysis

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ABSTRACT

The study developed a data-driven predictive model for forecasting graduates' success in professional licensure examinations using Discriminant Function Analysis (DFA). It employed a quantitative, predictive-correlational design to analyze institutional records of 933 graduates from five licensure programs in higher education institutions in the Philippines between 2020 and 2025. Cognitive-academic factors, including fluid intelligence, communication skills, reading comprehension, mathematical ability, professional knowledge, internship performance, and mock board exam performance, as well as contextual factors such as study duration and academic difficulty, were examined using descriptive statistics, independent samples *t*-tests, and DFA. Results revealed that licensure passers significantly surpassed non-passers across all variables ($p < .001$). The discriminant model was statistically significant (Wilks' $\Lambda = 0.430$, $\chi^2 (9) = 781.573$, $p < .001$; canonical $r = 0.755$) and accurately classified 88% of the cross-validated cases. The strongest predictors of licensure success were professional knowledge, mock board exam performance, study duration, and academic difficulty. The research concludes that cognitive mastery and academic persistence are crucial for licensure readiness. The study recommends integrating data-driven and AI-enabled early warning and academic analytics systems to identify at-risk examinees and support timely interventions aimed at optimizing readiness for professional qualifications.

Keywords: Predictive modeling; Discriminant function analysis; Professional licensure examination; Higher education; Academic performance predictors; Artificial intelligence

INTRODUCTION

A critical benchmark used to assess the quality of higher education institutions (HEIs) is the professional licensure examination outcome of the graduates (Gatpandan et al., 2023; Oducado et al., 2019). For the latter, passing the board examination is not only a prerequisite for earning a professional license, but it is also a cutting-edge tool to get a position in employment – a critical gateway for entry into specialized practice across various disciplines. For HEIs, it is a critical performance indicator to earn accreditation, a good reputation, and public trust. Evidence shows a strong direct relationship between licensure exam performance and institutional quality. Therefore, institutional quality assurance efforts should be in place to maintain adequate performance in the board exams (Dator, 2016; Pizarro & Talosig, 2025).

Through the years, fluctuating passing rates across disciplines have sparked global debates concerning the preparedness of graduates and the educational quality of HEIs. The concerning statistics necessitate that institutions identify and understand the determinants of licensure success and address them accordingly as a means of conducting a root-cause analysis of the frequent low passing percentage. This scenario implicates the need for proactive academic measures, such as research and innovation, to provide better results.

In the Philippines, passing rates for various licensure exams have not consistently improved over the long term (Matusalem et al., 2024; Padullon, 2025; Polinar et al., 2020). In 2024, out of 577,844 licensure examinees across all disciplines, 258,331 (45%) failed the examinations (Professional Regulation Commission, 2024). This weakening exam passing rate is a sign of the deterioration of the quality of education. Universities are under increasing pressure to improve licensure exam outcomes, preventing the immediate closure of programs, boosting passing percentages, increasing employability, and enhancing workforce quality (Sicuan et al., 2025).

Primarily, the study examined the factors that predict professional licensure examination outcomes of graduates from Philippine HEIs. Specifically, it aimed to: First, determine the level of cognitive-academic factors of licensure examinees in the areas of fluid intelligence, communication skills, reading comprehension, mathematical ability, professional knowledge, internship performance, and mock board exam performance;

Second, to assess the significance of the difference in the level of cognitive-academic factors between passers and non-passers in the areas of fluid intelligence, communication skills, reading comprehension, mathematical ability, professional knowledge, internship performance, and mock board exam performance; Third, to identify the contextual factors of licensure examinees, specifically in the areas of study duration and academic difficulty; Fourth, to ascertain significance of the difference of contextual factors between passers and non-passers in the areas of study duration and academic difficulty; Fifth, to develop a mathematical model that best predicts professional licensure examination outcomes based on the cognitive-academic and contextual factors; Finally, to formulate innovative intervention program for academic institutions to enhance licensure exam outcomes based on the findings.

This research is based on Albert Bandura's (1986) Social Cognitive Theory, which emphasizes the reciprocal interaction between personal factors, behavior, and environment in shaping learning outcomes. The theory is one of the most widely applied frameworks connecting cognitive, academic, and contextual factors to predict educational engagement and outcomes. It is supported by the works of Zachry et al. (2024), which revealed that intelligence measures predict licensure outcomes, and Dietrichson et al. (2016), which demonstrate that contextual factors, such as time spent schooling and access to quality instruction, create differential opportunities to succeed.

Research demonstrates that students' cognitive abilities and adaptability to contextual changes are foundational to academic performance, resilience, and post-schooling success (Niileksela et al., 2025; Yuan et al., 2024). This demonstrates that while cognitive and academic abilities enable students to manage the complex information processing demands inherent in professional licensing assessments, institutional contexts significantly shape learning outcomes. Studies increasingly support integrated models, which combine cognitive, academic, and contextual factors to thoroughly describe the associations between these factors and their contributions to learning and achievement (Anghel, 2023).

The term "fluid intelligence" was coined by psychologist Raymond Cattell (1963), who distinguished it as the ability to reason and solve new problems independently of previously acquired knowledge. This type of intelligence has had a significant impact on aptitude research, as exemplified by the Raven's Standard Progressive Matrices (SPM), which is considered a measure of fluid intelligence, encompassing abstract reasoning, problem-solving, and pattern recognition (Raven, 2000; Wongupparaj et al., 2015). Research in education and psychology demonstrates that students with higher fluid intelligence tend to achieve better results in scientific and mathematics-related assessments, which are cognitively similar to the demands of many licensure examinations (Zerbini et al., 2017).

Studies have found that early assessments, which include communication skills focused on developing oral and written English communication, along with reading comprehension, professionalism, and reasoning, strongly predict later success on standardized board exams. Cadosales et al. (2023) reported that language and communication proficiency correlate with licensing examination performance; thus, passers tend to be more proficient in communication than non-passers. Students with unsatisfactory or borderline communication-related grades were more likely to perform poorly on subsequent board exams, indicating a clear link between communication arts proficiency and examination outcomes (Strowd et al., 2022).

In the field of teacher education, there is consistent evidence that higher reading comprehension levels are linearly associated with academic achievement and licensure exam performance (Bansiong & Balagtey, 2020). The literature suggests that students with strong reading comprehension abilities are better equipped to understand and analyze exam questions, leading to higher success rates (Asilestari et al., 2025; Makiling et al., 2025). According to Clinton-Lisell et al. (2022), reading comprehension, coupled with a high college GPA, which reflects overall academic achievement, forms a key component in performing well on high-stakes exams.

Research consistently shows that mathematical ability, including logical and critical thinking skills, plays a significant role in exam performance. Studies suggest that individuals with strong math skills are more likely to develop enhanced reasoning abilities that extend beyond mathematical contexts (Cresswell & Speelman, 2020). Braak et al. (2021) posited that math-proficient students are more likely to succeed in technical board exams.

Mastery of professional education subjects, also known as professional knowledge, is a strong indicator of success on licensure exams. Atadjanov (2018) and Makiling et al. (2025) found that achievements in professional education courses are among the most significant predictors of performance on the professional teacher licensure examination. This underscores the importance of mastering professional subjects to ensure readiness for licensure examinations.

Internship performance is a significant predictor of success on the board exam (Sears et al., 2017). This idea is supported by Banua (2017), who reported that related learning experiences, such as practicum, have a significant influence on licensure examination outcomes. This suggests that higher grades in practicum courses reflect better preparedness in licensure exams.

Mock board exam performance is another determinant of the actual licensure exam outcome, as mock board tests are designed to simulate the conditions and content of the real examination. Martin (2015) and Martin et al. (2017) found a strong correlation between pre-board performance and actual board exam outcomes. This finding highlights the value of formative high-stakes assessments in predicting readiness.

Contextual factors refer to environmental and institutional variables that influence educational outcomes outside of innate cognitive and academic abilities. These include attributes such as time taken to graduate, academic challenges, and other background characteristics that shape the learning context (Bronfenbrenner, 1979; Wang & Sheikh-Khalil, 2014). These factors help explain variations in academic and professional performance by accounting for external influences and support systems available to students (Ortiz-de-Villate et al., 2021; Vermunt, 2005).

Extended time to graduation can impact performance on licensure exams. Aiken et al. (2020) demonstrated that prolonged time to degree completion is associated with lower academic performance, which in turn affects licensure exam outcomes. Academic difficulty, as measured by the number of repeated subjects enrolled, is strongly associated with an increased risk of attrition and academic failure (Karalar et al., 2021). Palmer et al. (2020) and Domiano (2018) theorized that repeated courses are associated with a higher risk of failing the licensing exam, indicating academic struggles during the undergraduate program.

Previous studies in education and psychology have utilized Discriminant Function Analysis (DFA) to classify students based on academic achievement (Divjak & Oreški, 2009; Labad et al., 2019), admission test performance (Gaylo et al., 2022), and licensure examination performance (Alipio, 2020; Tamayo, 2015). Comparisons with other machine learning and statistical classification techniques, such as logistic regression, support vector machines, and neural networks, show that discriminant analysis can often match or even exceed their performance (Cazarez, 2022). For instance, a study comparing logistic regression, discriminant analysis, and K-nearest neighbor algorithms in predicting student retention and success found that discriminant analysis was highly effective and easy to interpret for institutional decision-making (Rowtho, 2017). Its use and feature selection for more complex machine learning models ensure model interpretability and practical relevance in educational settings (Thaher et al., 2021).

By recognizing the various predictors of success through the application of mathematical modeling, HEIs can proactively address student needs. Data-driven interventions based on these insights can contribute to higher passing rates and elevate institutional credibility. These efforts will contribute to institutional rankings, program accreditation, and student recruitment, while ensuring the professional readiness of graduates and the quality of the workforce.

This study addresses the persistent gap in research that calls for exploring predictive modeling techniques and developing analytical tools to enhance student success. There is a limited body of research that applies predictive models using various data to forecast licensure exam outcomes. Most existing studies tend to rely on individual academic metrics or qualitative data, often neglecting the comprehensive integration of cognitive assessments, detailed academic records, and contextual variables. This study incorporates a multidimensional set of continuous cognitive-academic and contextual factors to develop a robust predictive model explicitly tailored to licensure exam outcomes across programs, advancing both theoretical understanding and practical applications in educational assessment and workforce development.

The study addresses the United Nations Sustainable Development Goals (SDGs) 4 – Quality Education and 8 – Decent Work and Economic Growth. The ability of the HEIs to identify factors and develop models that will help them predict the success of their graduates in passing professional licensure exams contributes to ensuring the attainment of sustainable, inclusive, equitable, responsive, and quality education, while preparing graduates for the workforce and in due course contributing to higher employment rates, a competent labor market and a sustainable economic growth.

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METHODOLOGY

Research Design

This study employed a quantitative predictive-correlation research design using secondary data to model licensure examination outcomes based on cognitive-academic and contextual factors using Discriminant Function Analysis (DFA), a statistical method designed to classify cases, i.e., to determine whether a student is likely to pass or fail the professional licensure examination based on available institutional data.

DFA has proven its efficacy in educational contexts, particularly when the objective is to predict group membership based on multiple predictors. DFA is used when the dependent variable is categorical (e.g., pass/fail) and the independent variables are metric or continuous. Ojating (2022) emphasized the applicability of discriminant analysis in educational statistics, noting its capacity to address multivariate problems and classify observations effectively.

Dataset and Sampling Technique

The study examined the academic records of 933 licensure examinees from the five academic programs of the University of Mindanao and UM Tagum College, the largest higher education institutions in terms of population in Region 11, Philippines, who took the licensure examination between 2020 and 2025. The year range encompasses a complete cycle of graduates during and after the pandemic disruptions, ensuring that the model accounts for variations in academic delivery. The five academic programs include: Bachelor of Elementary Education (BEEd), Bachelor of Secondary Education (BSEd), Bachelor of Science in Criminology (BSC), Bachelor of Science in Accountancy (BSA), and Bachelor of Science in Psychology (BSP). Table 1 presents the dataset's profile.

Table 1. Profile of the examinees included in the dataset

Dataset Profile	Category	Number	Percentage
Campus	UM Main	412	44.16
	UM Tagum	521	55.84
	TOTAL	**933**	**100**
Program	BEEd	25	2.68
	BSEd	185	19.83
	BSC	644	69.02
	BSA	51	5.47
	BSP	28	3.00
	TOTAL	**933**	**100**
Outcome	Pass	469	50.27
	Fail	464	49.73
	TOTAL	**933**	**100**

Convenience sampling was employed, as the dataset consisted of institutional records, which are the only legitimate sources of licensure exam and scholastic performance data. The examinees included in the study are those who have complete institutional records of the identified cognitive-academic and contextual factors, those who graduated from any of the five identified licensure programs, those with licensure examination results officially released by the Philippine Professional Regulation Commission (PRC), and those who took the examination for the first time within the study period.

Research Instrument

The study utilizes the following secondary institutional data to measure the cognitive-academic and contextual factors:

Percentile score obtained in Raven's Standard Progressive Matrices (SPM) scale, a non-verbal mental ability test that measures abstract reasoning, was used to quantify fluid intelligence.

The Purposive Communication (also known as Communication Arts subject) final grade was the source of the data on communication skills.

Final grade in the Reading Comprehension subject, assessing the graduate's proficiency in understanding and analyzing written text, was the basis of the measure of the reading comprehension.

Final grade in Mathematics in the Modern World (also known as Mathematical Operations or Basic Math subject in the old curriculum) was used to measure mathematical ability.

The arithmetic mean of the final grades in the professional education courses required by the respective curriculum of each academic program was obtained to quantify professional knowledge.

Final rating obtained in the on-the-job/practicum course was the basis for the internship performance

The result from the achievement test or pre-board exam administered before the actual board exam was used to represent mock board exam performance.

The total duration, in academic years, from the student's initial enrolment in the degree program to the date of graduation, was captured to denote study duration.

The total count of academic subjects the student was required to retake due to initial non-passing marks, indicating academic struggles during the undergraduate program, was used to measure academic difficulty.

Board examination outcomes of the graduates labelled as "Pass" or "Fail" were based on the results obtained from the Professional Regulation Commission (PRC) through printed lists.

Data Gathering Procedure

Since the data were sourced from school records, a formal request letter was submitted to the offices of the Vice President for Academic Affairs, Campus Director, and College Dean. After securing the approval to conduct the study, the data collection process commenced. The Records and Admission Center (RAC) provided academic records, including communication arts grades, reading comprehension grades, general mathematics grades, professional education courses general averages, practicum course grades, number of years to graduate, and number of repeated courses, through individual examinees' Student Permanent Records (SPRs). The Program Heads of the academic programs involved in the study provided the mock board exam results. The fluid intelligence scores were obtained from the Raven's SPM results, which are stored at the Guidance Services and Testing Center (GSTC). The licensure examination outcomes were extracted manually from the official PRC examination results obtained from the Quality Management Office (QMO) of the university.

Data Analysis Procedure

The statistical tools employed in this study were Mean, Standard Deviation, independent samples *t*-test, and DFA. The dependent variable of the study constituted the licensure exam outcomes (Pass = 0, Fail = 1). The independent variables included the cognitive-academic and contextual factors. All variables were entered and validated in SPSS prior to analysis.

Several statistical assumptions were employed prior to performing the discriminant analysis to ensure the robustness and suitability of the model. Following the guidelines of Hair et al. (2019) and Tabachnick and Fidell (2019), these assumptions include sample size adequacy, multivariate normality, homogeneity of variance-covariance matrices, absence of multicollinearity, and the absence of outliers. In summary, the data were deemed suitable for DFA to identify predictors of licensure outcomes among examinees.

Ethical Considerations

Ethical clearance from the University of Mindanao Ethics Review Committee (UMERC) was obtained prior to collecting the relevant information. Since the data to be collected was historical in nature and no interaction with respondents was ever required, the UMERC issued an Exemption Certificate to proceed with the data gathering. Ethical standards were strictly observed by ensuring the anonymity of data prior to analysis. The data were solely for research purposes, and access was limited to the researchers. Necessary permissions and clearances were secured from the concerned offices prior to data collection. Data privacy and confidentiality were maintained throughout the research process.

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RESULTS AND DISCUSSION

Descriptive Statistics of Cognitive-Academic Factors

Table 2 presents the cognitive-academic factors of the examinees. The results show that licensure passers demonstrated a higher level of fluid intelligence compared to non-passers. This supports the argument of Feraco et al. (2024), which emphasized that high fluid intelligence is evident in individuals who excel in educational settings.

Table 2. Level of licensure examinees' cognitive-academic factors

Factor	Outcome	Mean ($\bar{x}$)	SD	Descriptive Equivalent
Fluid Intelligence	Pass	79.32	16.91	Above Average
	Fail	62.98	22.62	Average
	Overall	71.20	21.55	Average
Communication Skills	Pass	87.07	5.17	Very Good
	Fail	81.56	4.50	Good
	Overall	84.34	5.58	Good
Reading Comprehension	Pass	86.00	5.40	Very Good
	Fail	80.24	4.65	Average
	Overall	83.14	5.80	Good
Mathematical Ability	Pass	86.05	6.14	Very Good
	Fail	80.17	4.99	Good
	Overall	83.13	6.32	Good
Professional Knowledge	Pass	87.44	3.98	Very Good
	Fail	81.14	3.36	Good
	Overall	84.30	4.84	Good
Internship Performance	Pass	94.89	2.46	Distinction
	Fail	93.37	3.35	Distinction
	Overall	94.14	3.03	Distinction
Mock Board Exam Performance	Pass	80.87	8.55	Good
	Fail	70.02	9.01	Fail
	Overall	75.48	10.32	Average

Legend: Fluid Intelligence: $\geq$95 = Intellectually Superior; 90-94 = Definitely Above Average; 75-89 = Above Average; 50-74 = Average; 25-49 = Below Average; 10-24 = Low; $\leq$9 = Very Low

Others: 96-100 = High Distinction; 90-95 = Distinction; 85-89 = Very Good; 80-84 = Good; 75-79 = Average; <75 = Fail

Licensure examinees who passed performed better than those who did not in terms of oral and written English communication. The results align with the peer reviews and meta-analyses in general education settings, which identified written and oral communication as central to successful test performance (Jang et al., 2024). This further supports the existing literature, which suggests that licensure passers possess better communication skills than non-passers.

The passers achieved a higher reading comprehension level than the non-passers. The disparity in reading comprehension levels was reinforced by Acuning et al. (2023), who confirmed a significant positive correlation between reading comprehension and academic performance, including test performance, among students, signifying that students with higher reading comprehension levels tend to achieve better academic results.

The mathematical ability of licensure exam passers exceeds that of the non-passers. This result is supported by Braak et al. (2021), who found that foundational skills, such as mathematical proficiency, are linked to improved performance in technical board exams.

In the area of professional knowledge, the licensure passers demonstrated a higher level of professional knowledge compared to the non-passers. In multiple studies from the Philippines, researchers found that stronger averages and performance in professional education subjects predicted a higher likelihood of passing the licensure exam. This makes professional knowledge a significant predictor of licensure success (Ferrer, 2024). Mendez

(2025) also argued that graduates with a stronger general average in their professional courses have a clear advantage in the licensure examination, explaining why it is a key determinant of licensure exam success.

For internship performance, passers and non-passers had the same level of distinction. Though on-the-job training performance was among the factors significantly related to licensure exam performance in teacher education, criminology, and other programs (Dionio et al., 2025; Igdon et al., 2024), several studies demonstrate that internship performance can often predict, but not as strongly as other academic indicators (Terry et al., 2017). A relationship exists between internship performance and board examination success, although it is not entirely uniform across all disciplines or settings (Sears et al., 2017). This can explain the high internship performance ratings of both passers and non-passers.

The overall mock board exam performance of the passers was at a good level; however, a failure level was recorded for the non-passers. Studies have shown that students who practice self-assessment or engage in mock exams improve their metacognitive awareness and calibrate performance expectations more accurately as they progress, leading to better alignment between expected and achieved outcomes on high-stakes tests (Osterhage et al., 2019). This finding explains why high mock board exam scores are associated with passing outcomes and lower ones are associated with failure outcomes.

Significance of the Difference in the Level of the Cognitive-Academic Factors

An independent samples t-test confirmed statistically significant differences ($p < .001$) across all cognitive-academic factors, as shown in Table 3. The most considerable mean differences were recorded in professional knowledge ($t = 26.165$) and mock board exam performance ($t = 18.865$), signifying that these variables most strongly distinguish successful examinees. These findings reinforce that scholastic aptitudes, which combine cognitive and academic factors, are significantly different between successful and unsuccessful examinees, making these factors critical predictors of licensure examination outcomes (Bellen et al., 2018; Kuncel et al., 2004; Reynolds et al., 2021).

Table 3: Significance test of the difference in the level of cognitive-academic factors between passers and non-passers

Variable	***T***	***Df***	**Mean Difference**
Fluid intelligence	12.482*	857.203	0.758
Communication skills	17.406*	916.406	0.990
Reading comprehension	17.441*	913.842	0.991
Mathematical ability	16.069*	897.230	0.931
Professional knowledge	26.165*	908.457	1.300
Internship performance	7.882*	849.568	0.500
Mock board exam performance	18.865*	931.000	1.051

*p < .001

3.3 Descriptive Statistics of Contextual Factors

Table 4 reveals apparent variations between passers and non-passers of the licensure examination in terms of the number of years spent to complete the degree and the number of repeated courses throughout the degree completion.

Table 4. Descriptive statistics of the licensure examinees' contextual factors

Factor	**Outcome**	$\bar{x}$	**SD**	**Descriptive Equivalent**
Study duration	Pass	4.35	0.40	Slightly delayed

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	Fail	5.28	0.87	Moderately delayed
	Overall	4.81	0.82	Slightly delayed
Academic difficulty	Pass	0.72	1.66	Low academic difficulty
	Fail	7.47	6.02	Moderate academic difficulty
	Overall	4.08	5.55	Low academic difficulty

Legend: Study duration: ≤4.0 = On-time; 4.01-4.99 = Slightly delayed; 5.00-5.99 = Moderately delayed; 6.00-6.99 = Severely delayed; ≥7 = Critically delayed

Academic difficulty: 0 = No academic difficulty; 1-5 = Low academic difficulty; 6-10 = Moderate academic difficulty; 11-20 = High academic difficulty; ≥21 = Very

High academic difficulty

Passers had an average of 4.35 years of degree completion (SD = 0.40), while non-passers completed their degree programs in 5.28 years (SD = 0.87). The result reinforces the claim of Aiken et al. (2020), who demonstrated that a prolonged time to degree completion is associated with lower academic performance; thus, non-passers had a longer study duration than passers. A recent US-based study found that students who required additional time to complete the training years often had a higher risk of underperforming on their board-qualifying or licensing exams (Mercedes et al., 2024). This suggests that timely graduation is beneficial for licensure success.

The academic difficulty distinguished passers from non-passers, with passers exhibiting fewer academic difficulties than the non-passers. On average, the non-passers had more recurring subjects, which is reflective of academic difficulty, with an average of about seven repeated courses (SD = 6.02). Passers, in general, did not have to retake courses. The result is supported by substantial evidence from multiple independent studies indicating that a student's history of repeating courses is associated with a decreased likelihood of success in board examinations (Domiano, 2018; Palmer et al., 2020). Thus, repeated courses are associated with a higher risk of failing the licensing exam, indicating the need for early intervention and targeted support for at-risk students.

Significance of the Difference in the Level of Contextual Factors

Table 5 presents the results of the independent samples *t*-test, which were performed to determine the significance of the difference between passers and non-passers in terms of contextual factors.

Table 5. Significance test of the difference in the level of contextual factors between passers and non-passers

Variable	***T***	***df***	**Mean Difference**
Study duration	–21.165*	650.014	–1.142
Academic difficulty	–23.293*	532.250	–1.216

*p < .001

The result indicates that passers and non-passers exhibited clear distinctions across contextual education factors, namely, study duration and academic difficulty. Thus, study duration and academic difficulty are essential factors in distinguishing successful from the unsuccessful examinees (Bagabir et al., 2021; Reynolds et al., 2021; Varpio et al., 2017).

Development of a Mathematical Model that Predicts Licensure Examination Outcomes

A model predicting licensure outcomes based on cognitive-academic and contextual factors was generated using Discriminant Function Analysis (DFA) with nine predictor variables: fluid intelligence, communication skills, reading comprehension, mathematical ability, professional knowledge, internship performance, mock board exam performance, study duration, and academic difficulty. The resulting discriminant function identifies which linear combination of variables distinguished passers from non-passers of the licensure examination.

Categorization of Participants

The examinees were classified into two groups according to their licensure outcome: Pass and Fail. The group centroids from the discriminant analysis were 1.144 for the Pass group and -1.156 for the Fail group. The data revealed a clear separation between groups on the discrimination axis, justifying the creation of a two-group predictive model.

The group centroid provided insight into the discriminant scores associated with each classification. The cut-score, computed as the midpoint between the two centroids, is approximately zero.

$$C = \frac{1.144 + (-1.156)}{2} = -0.006 \approx 0$$

From this result, the categorization rule can be defined as:

If $D \geq 0$, then the examinee is predicted to pass the exam; If $D < 0$, then the examinee is predicted to fail the exam, where D is the discriminant score.

3.5.2 Discriminating Power of Cognitive-Academic and Contextual Factors

Table 6 presents the test of equality of group means, including significance tests for the cognitive-academic and contextual educational factors in the study. Results showed that all factors used in the analysis have a significant relationship with the professional licensure examination outcomes of the examinees. This means that fluid intelligence, communication skills, reading comprehension, mathematical ability, professional knowledge, internship performance, mock board exam performance, study duration, and academic difficulty all correlate with performance on licensure examinations.

Table 6. Test of equality of group means, including a significance test for cognitive-academic and contextual factors

Factor	Wilks' Lambda	F	df_1	df_2
Cognitive-Academic				
Fluid Intelligence	.856	156.275*	1	931
Communication Skills	.755	302.518*	1	931
Reading Comprehension	.754	303.717*	1	931
Mathematical Ability	.783	257.653*	1	931
Professional Knowledge	.577	683.372*	1	931
Internship Performance	.937	62.333*	1	931
Mock Board Exam Performance	.723	355.900*	1	931
Contextual				
Study Duration	.674	451.106*	1	931
Academic Difficulty	.630	547.574*	1	931

* $p < .001$

The results imply that every cognitive-academic and contextual variable significantly differentiates passers and non-passers at the univariate level. Thus, each of these cognitive-academic and contextual educational factors is useful for classifying licensure outcomes (Reynolds et al., 2021), justifying the inclusion of all nine variables in the discriminant analysis. The Wilks' Lambda test for the discriminant function was significant, $\Lambda = 0.430$, $X^2(9) = 781.573$, $p < 0.001$, confirming that the set of predictors effectively differentiates between pass and fail outcomes.

The Predictive Model

Table 7 displays the unstandardized canonical coefficients that complete the discriminant function used to predict licensure outcomes. The results reveal that professional knowledge and performance in mock board examinations are strong predictors of success in the licensure exam, as these variables had the highest coefficients. These major predictors can be interpreted meaningfully in relation to Bandura's construct of self-efficacy within his Social Cognitive Theory. Professional knowledge and mock board exam performance reflect mastery experiences, which are the most influential sources of self-efficacy. Repeated success in domain-specific tasks strengthens an individual's beliefs in performing well in similar evaluative contexts. As examinees demonstrate mastery of professional knowledge and proficiency in simulated licensure environments, their confidence and persistence are reinforced, increasing the likelihood of actual licensure success. Additionally, a pattern of progression, manifested by timely graduation and resolved remediation, adds predictive value (Bagabir et al., 2021). The negative coefficient indicates that as the score on a predictor increases, the overall discriminant score decreases, suggesting lower success in licensure exams. The study duration showed to be the dominant negative predictor, indicating that for every one-unit increase in the number of years taken to graduate, D decreases by 0.233.

Table 7. Unstandardized canonical coefficients of cognitive-academic and contextual factors

	Unstandardized Coefficient
(Constant)	–19.439
Fluid Intelligence	.010
Communication Skills	.030
Reading Comprehension	.031
Mathematical Ability	.008
Professional Knowledge	.074
Internship Performance	.044
Mock Board Exam Performance	.053
Study Duration	–0.233
Academic Difficulty	–0.062

These negative coefficients – study duration and academic difficulty – undermine self-efficacy by exposing students to repeated failure experiences. These experiences result in diminished academic momentum, weakened confidence, and increased test anxiety, heightening the chances of failing the licensure examinations. From this theoretical lens, licensure outcomes are not solely cognitive achievements but manifestations of self-belief acquired through academic experiences (Bandura, 1986).

The idea underlying the DFA is to develop a linear combination, F, of n variables as $F = \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n$ with values for $\beta_1, \beta_2, \ldots, \beta_n$ chosen to maximize the difference between groups and to minimize the difference within groups. Based on the coefficients in Table 7, the discriminant function predicting licensure outcomes is:

D = -19.439 + 0.010 (Fluid intelligence) + 0.030 (Communication skills) + 0.031 (Reading comprehension) + 0.008 (Mathematical ability) + 0.074 (Professional knowledge) + 0.044 (Internship performance) + 0.053 (Mock board exam performance) – 0.233 (Study duration) – 0.062 (Academic difficulty)

The model had an Eigenvalue of 1.325, which accounted for 100% of the discriminating power in the analysis. The canonical correlation for the function was $r = 0.755$, indicating a strong relationship between the discriminant scores and group membership. Squaring the canonical correlation ($r^2 = 0.570$) indicates that approximately 57.0% of the variance in the discriminant scores is explained by the licensure outcome.

Classification Accuracy of the Model

The classification results further demonstrate the effectiveness of the discriminant function derived from the predictor variables, which correctly classify examinees into their actual licensure examination outcomes (Pass or Fail). The table presents two sets of results: the original and the cross-validated classification. Both of which

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indicate the predictive accuracy of the developed model. These results are shown in Table 8. The predictive accuracy of the model is demonstrated in the appendix.

Table 8. Classification results for original and cross-validated cases

Licensure Outcome	Predicted Pass (%)	Predicted Fail (%)
Pass (Original)	91.0	9.0
Fail (Original)	14.2	85.8
Pass (Cross-Validated)	91.0	9.0
Fail (Cross-Validated)	15.1	84.9

Model accuracy in classifying: original cases: 88.4%, cross-validated cases = 88%

Among 469 actual passers, 91.0% (427) were correctly classified as Pass, while 9.0% (42) were misclassified as Fail. Among the 464 actual non-passers, 85.8% (398) were correctly classified as Fail, while 14.2% (66) were misclassified as Pass. The model achieved an accuracy of 88.4% in classifying the original cases and 88% in classifying cross-validated cases. This means that, using the dataset on which the model was built, the discriminant function shows high accuracy and strong classification power.

Implications and Proposed Innovative Intervention Program

The study posits that professional licensure examination outcomes can be predicted by cognitive-academic predictors, including fluid intelligence, communication skills, reading comprehension, mathematical ability, professional knowledge mastery, internship performance, and mock board exam performance, as well as contextual educational predictors, such as study duration and academic difficulty. This suggests that interventions designed to enhance examination outcomes must be multidimensional, strategically addressing intellectual preparedness and structural supports that help students advance.

Based on this theory, an innovative intervention program entitled Artificial Intelligence-driven Readiness, Intervention, and Support for Examination Success (AI-RISES) is proposed to help institutions improve licensure examination outcomes. AI-RISES is an institutional innovation that incorporates the intervention programs designed to strengthen licensure examination outcomes. This innovation utilizes early detection through data-driven analytics and targets aligned support and academic interventions for students at risk. Anchored on the discriminant-based predictive model developed in this study, the innovative program employs an AI-powered Early Warning and Students at Risk Identification System (AEWSRIS) that analyzes students' cognitive-academic and contextual educational profiles. These analytics guide the deployment of the four strategic intervention components: the Licensure Readiness Enhancement Program (LREP), the Academic Consistency and Monitoring System (ACMS), the Cognitive Development Initiatives (CDI), and the Contextual Support and Retention Program (CSRP). Together, these integrated systems establish an adaptive and comprehensive institutional mechanism for ensuring licensure examination readiness and improving professional licensure outcomes.

Table 9. Proposed intervention program for higher educational institutions

Component	Rationale	Objective	Strategy Highlights
AI Early Warning and Student at Risk	The discriminant model demonstrated a predictive	Identify students at risk early, recommend	Automatic computation of discriminant scores,
Identifying System (AEWSRIS)	accuracy of 88.4%. An AI system operationalizes this into an automated and actionable institutional tool to improve licensure outcomes.	targeted interventions, and monitor progress through analytics.	Risk level classification (High, Moderate, Low), Intervention recommendations that target specific needs of the student, and Dashboards for faculty advisers, deans, and program heads

Licensure Readiness Enhancement Program (LREP)	Mock board exam performance and mastery of professional knowledge were the strongest predictors of licensure success. Students often lack long-term preparation and only receive review support before graduation. LREP builds consistent, curriculum-aligned mastery and provides students with targeted practice based on their identified areas of weakness.	Enhance students' domain-specific mastery through continuous diagnostic testing, modular review sessions, and simulated licensure exams.	Regular mock board mini-assessments, Faculty-led competency mastery sessions, and Department-generated review modules
Academic Consistency Monitoring System (ACMS)	Academic difficulty and study duration were strong negative predictors of licensure outcomes. Students with repeated courses often do not receive timely intervention.	Enhance academic consistency by monitoring student performance, providing guidance on course loads, and minimizing subject repetition.	Schedules consultations with academic advisers, Mandatory attendance in tutorial and mentoring sessions, and Progress reports at the end of every term.
Cognitive Development Initiatives (CDI)	Cognitive abilities, including reasoning, comprehension, and analytical thinking, contribute to licensure success. These skills may not be intentionally enhanced throughout the degree program.	Strengthen general cognitive abilities that support licensure examination tasks.	Problem-solving and reasoning seminars, Reading comprehension mastery workshops, Program-based analytical simulation tasks, and Adaptive learning modules
Contextual Support and Retention Program (CSRP)	Contextual educational factors and other noncognitive factors, such as financial stress, psychosocial issues, and time management problems, often disrupt study progression and can lead to delays in completing the degree program	Provide personal, financial, emotional, and academic support to address contextual barriers affecting student performance.	Guidance counseling, Peer monitoring, Study skills and time management workshops, Referral to scholarship and financial assistance units, and Wellness and mental health programs

Implementation Challenges and Ethical Safeguards of the Intervention Program

The implementation of AI-RISES necessitates careful consideration of ethical standards. While the program has the capacity to identify at-risk students, flagging students as “at risk” may inadvertently lead to stigmatization, lowered expectations, or self-fulfilling prophecies if not handled sensitively. To mitigate these risks, AI-generated risk classifications should be institutionalized as support indicators rather than punishing or deficit labels. The program is primarily aimed at supporting, rather than condemning, students. The classification system should be accessible only to authorized academic personnel and accompanied by informed consent mechanisms. Additionally, institutions must ensure that AI models are regularly calibrated and audited for bias, accuracy, and fairness. The innovative intervention works not only with predictive accuracy but also emphasizes student dignity, confidentiality, respect, and developmental support.

Limitations and Future Research

Based on the study's findings, the following recommendations are proposed.

Higher education institutions are encouraged to integrate data-driven decision-making systems, such as artificial intelligence, not only to identify at-risk students and provide targeted support long before graduation, but also as frameworks for developing educational policy.

Future studies may consider incorporating non-continuous and psychosocial variables such as family and socioeconomic backgrounds, study habits, and academic motivation, which are strongly supported by educational and psychological theories, to enhance the model. Furthermore, subsequent research may employ alternative or complementary statistical approaches, including binary logistic regression, multinomial regression, or more advanced machine learning algorithms such as random forests, support vector machines, or neural networks to improve model precision and classification accuracy.

It is also recommended that future investigations adopt a longitudinal and multi-institutional design to strengthen the external validity and generalizability of findings. To complement quantitative modeling, qualitative inquiries may also be conducted to capture the lived experiences of students who are at risk of failing the licensure examination, thereby refining the predictive model.

CONCLUSION

This study examined the predictive capacity of cognitive-academic and contextual factors on professional licensure examination outcomes using discriminant function analysis. The strongest positive and negative predictors were professional knowledge and study duration, respectively. Passers had higher fluid intelligence, reading comprehension, and professional knowledge levels, performing better in terms of communication, problem-solving, and pre-board exams than the non-passers. The findings consistently affirm that licensure success is a multifaceted construct shaped by both cognitive, academic, and contextual factors, supporting Bandura's Social Cognitive Theory and other studies emphasizing the roles of cognitive, academic, and contextual factors in shaping an individual's success. These findings suggest that licensure readiness is not merely a terminal outcome of review preparation, but a cumulative process shaped by sustained positive academic engagement.

The discriminant model revealed that, aside from professional knowledge, mock board exam performance and study duration are strong discriminators. The significant Wilks' Lambda and substantial canonical correlation further confirm that the linear combination of predictors provides a robust separation between passers and nonpassers. The high level of model accuracy supports the feasibility of employing predictive analytics in academic contexts to identify students who are at heightened risk of failing the professional licensure examination, demonstrating that data-driven models contribute to broader institutional goals of academic excellence, student success, and professional readiness.

The study's findings provide a robust and sustainable empirical foundation for developing effective and innovative institutional intervention. It can help identify at-risk students and provide targeted support as early as possible. This encourages HEIs to explore the integration of artificial intelligence and learning analytics as tools and frameworks for developing educational policy.

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APPENDIX

Model Predictive Validity Check

To check the predictive validity of the model, two cases were extracted. Case 13 got the following data: fluid intelligence = 90; communication skills = 86; reading comprehension = 83; mathematical ability = 83; professional knowledge = 86; internship performance = 86; mock board performance = 86; study duration = 5; and academic difficulty = 0. Similarly, case 698 was obtained for the actual gathered data. It got the following data: fluid intelligence = 75; communication skills = 81; reading comprehension = 75; mathematical ability = 87; professional knowledge mastery = 80; internship performance = 87; mock board performance = 73; study duration = 5; and academic difficulty = 6.

Sample data of the present study using the final model

Variables	Model's Coefficients	Predicted Licensure Exam Outcome of Case 13	Predicted Licensure Exam Outcome of Case 698
Fluid intelligence	.010	.900	.750
Communication skills	.030	2.580	2.430
Reading comprehension	.031	2.573	2.325
Mathematical ability	.008	.664	.696
Professional knowledge	.074	6.364	5.920
Internship performance	.044	3.784	3.828
Mock board exam performance	.053	4.558	3.869

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Study duration	–.233	–1.165	–1.165
Academic difficulty	–.062	0.000	–.372
Constant	–19.439	–19.439	–19.439
D		**0.819**	**–1.158**

Using the final mathematical model, the discriminant score D clearly identified case 13 as a "pass" because its value, 0.819, is greater than the cut-score 0. Case 698 was also correctly classified as "fail", with a $D = –1.158$, which is less than 0. This presents the predictive power of the developed mathematical model, which predicts licensure examination outcomes based on the cognitive-academic and contextual educational factors.