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Applying Bayesian Dynamic Time Warping to Optimize Business Administration Curriculum and Assessment Practices

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ABSTRACT*:* *This extensive research relies on Bayesian Dynamic Time Warping (BDTW) for deep insight into the time series dynamics of the performance of business administration programs in the subjects of Business Economics, Financial Management, HR Management, and Marketing Management. The complexity of interdisciplinary relationships, unique program-specific performance profiles, and robust diagnostics for model fit were evident from the analysis. Such recommendations include the implementation of focused curricular adjustment, the development of cross-disciplinary alignment, investment in continuous assessment and improvement, and using data-driven insights for strategic planning. These findings equip educational institutions with the power to optimize learning outcomes for their students, encourage cross-programming, and ensure that business administration curricula remain responsive to industry change. The study's approach to the holistic evaluation of performance makes it an excellent tool for sustaining the success of future business leaders.*

KEYWORDS - *Bayesian Dynamic Time Warping, Business Administration, Cross-Disciplinary Alignment, Curriculum Design, Performance Assessment, Temporal Dynamics*

I. INTRODUCTION

The introduction Measuring learning progression, performance evaluation, and curricular alignment over time presents a complex and multifaceted challenge in the context of outcome assessment thresholds (Sridharan et al., 2015). These elements are interdependent, requiring systematic and longitudinal evaluation to ensure educational programs foster student development and achieve intended learning outcomes (Lomi et al., 2011). However, the dynamic nature of student performance and the evolving demands of curricula and external benchmarks introduce significant difficulties in reliably capturing and interpreting these measures (Squires, 2009).

One of the biggest challenges with measuring learning progression is that it needs to be more linear (Wilson, 2009). Students learn at different rates based on individual learning styles (Pashler, 2008), previous knowledge (Jin et al., 2015), and sometimes outside factors such as socioeconomic background and access to learning materials (E. Maduro & Maduro; W.E.,2018). The traditional assessment will sometimes miss the subtle steps taken by the student as he transitions from knowing to being able to apply. Furthermore, assessments that are overly focused on static, summative evaluations may overlook intermediate stages of growth, thereby providing an incomplete picture of a student's trajectory over time (Duschl et al., 2011).

Performance evaluation over time must contend with issues of consistency and comparability. As educational programs evolve, changes in assessment tools, grading criteria, and pedagogical approaches create discrepancies that complicate longitudinal analysis (Martínez-Caro et al., 2015). Performance metrics often need to be standardized across programs and cohorts, making it difficult to draw meaningful comparisons. Bias in evaluation, whether through subjective grading or contextual factors, further undermines the reliability of performance data. The need for robust mechanisms for these variations leads to misleading conclusions about student achievement and program effectiveness (Gálvez-Suarez & Milla-Toro, 2018).

Another significant challenge is the alignment of curriculum with outcome assessment thresholds. Curriculum aims are not merely aligned with broader program purposes but must also be attuned to fluctuating industry requirements and standards set by accrediting organizations (Simper, 2020). Still, misalignment sometimes tends to happen when learning goals (Wijngaards-de Meij & Merx, 2018), teaching approaches (Whiteside, 2021), and measurements of learning need to be fully balanced. For instance, a curriculum that teaches essentials more strongly may lead to assessments, which tend to require a strong emphasis on more advanced capabilities. Furthermore, the fact that assessment thresholds must be realistic and achievable for diverse student populations complicates curriculum design and assessment (Banks, 2015).

The temporal dimension adds another layer of complexity. Changes in institutional priorities, faculty expertise, and student demographics over time can all impact learning progression, performance evaluation, and curricular alignment (Martone & Sireci, 2009). Longitudinal studies require consistent data collection and analysis frameworks, but educational institutions often need more resources to implement such systems effectively. Technology and data analytics can address some challenges but require significant investment and expertise (Armatas & Spratt, 2019).

The measurement of learning progression, performance evaluation, and curricular alignment in the thresholds of outcome assessment is loaded with difficulties originating from the non-linear, dynamic, and multifaceted nature of education (Crawford, 2014). Such issues demand a conjoint mix of innovative assessments, longitudinal research, and constant curriculum review. Institutions can better ensure that their programs facilitate meaningful student learning and development by learning about and mitigating these issues (Lucas et al., 2013).

The performance dynamics of business administration programs are critical challenges educational institutions face in assessing and understanding them. As business dynamics change and adapt, it is paramount to ensure that curriculum and assessment practices within these programs prepare students for the increasingly demanding and dynamic nature of a modern business environment (Bajada & Trayler, 2013). Traditional static siloed approaches towards business performance evaluation in educational setups in business administration, based on which student learning competency growth, need to be identified due to the nuanced temporal characteristic. That has limited the effectiveness of educators in catching any emerging trends; their adaptive teaching strategies would support targeting proper interventions to promote their overall success (Moon, 2007).

Understanding the temporal performance dynamics of student outcomes across different business administration programs, including Business Economics, Financial Management, Human Resource Management, and Marketing Management, demands an all-inclusive analysis of factors affecting academic achievement (Mlambo, 2011). Recent studies show that the dynamics of students' educational outcomes are not static but evolving due to the interaction of various temporal factors over the timing and nature of their learning activities. For example, studies have revealed that students who adopt consistent study habits have better results, with higher success rates than those who procrastinate or rely on last-minute cramming. Students with consistent study patterns had a higher success rate than their peers who relied on last-minute efforts (Chamundeswari et al., 2014).

Moreover, integrating advanced predictive analytics in educational settings has highlighted the importance of understanding learning behaviors over time. A notable study utilizing temporal graph neural networks demonstrated that incorporating temporal data can enhance academic performance predictions (Kim et al., 2018). This suggests that recognizing the timing and sequence of student interactions within their learning environments can provide valuable insights into their academic trajectories. For instance, students exposed to collaborative learning activities perform remarkably better if cognitive interaction dominates simple social interaction (Meloth & Deering, 2014).

Again, different problems that a student encounters in separate business administration subjects will yield dissimilar results. For example, students exposed to Financial Management were incompetent primarily due to low quantitative ability and confessed not knowing how to manipulate their math. This perceived inadequacy leads to lower levels of engagement and, thereby, poorer academic performance (Chen, 2005). On the other hand, programs like Marketing Management benefit from more experiential and practical learning approaches to achieve more robust student engagement and satisfaction (Kolb, 2014).

Longitudinal analysis showed that students who adapted to learn during the pandemic did better academically than those who did not. The paper found that continuous engagement and adaptation were critical predictors of success: students who managed their time well showed improved grades, even during disruptions (Di Pietro, 2023).

The temporal performance dynamics across different business administration programs require investigating how time management, engagement strategies, and external influences impact student outcomes. Using data analytics and focusing on temporal aspects of learning behavior, educational institutions can better support students as they navigate their academic journey and achieve their career aspirations (Fu et al., 2024), (Wolters & Brady, 2021).

The study aligns with UNSDG number 4, Quality Education, to promote "quality education is equitable, inclusive accessible free and qualitatively applicable to all. The study employs Bayesian Dynamic Time Warping to refine curriculum design and assessment practices in Business Administration toward adaptability and responsiveness. This approach ensures that the educational program remains relevant to what the industry demands and, hence, to the needs of a learner, thereby enhancing quality and effectiveness in higher education. It contributes to better academic outputs, skill matching the global requirement for the workforce, and individual empowerment through better availability of healthy educational infrastructures.

This research mainly aimed to use BDTW analysis to understand the time performance dynamics across business administration programs, such as Business Economics, Financial Management, HR Management, and Marketing Management. Employing this advanced analytical method would help the researchers discover and identify complex interdisciplinary relationships of each program and, therefore, unique performance profiles while assessing the reliability and robustness of the statistical models. The insights derived from this study are meant to inform targeted curricular adjustments, support cross-disciplinary alignment, guide continuous assessment and improvement, and support strategic decision-making that enhances student learning outcomes and optimizes the business administration curriculum to respond to industry needs changes.

II. THEORETICAL FRAMEWORK

Examining temporal performance dynamics in student outcomes for programs such as Financial Management, Marketing Management, HR Management, and Business Economics is grounded in educational and organizational theories that explain learning progression (Liu, 2012), performance evaluation (Martínez-Caro et al.,2015), and curricular alignment (Deraney & Khanfar, 2020). This study situates itself within the intersection of constructivist learning theory (Hein, 1991), Bloom’s taxonomy of learning objectives (Adams, 2015), and goal-setting theory (Locke & Latham, 2019) while confirming elements of program evaluation theory through its findings.

Constructivist Learning Theory posits that the learning process is active and dynamic, and students start from where they are to construct something new. This theory emphasizes scaffolding, a progressively challenging task for more profound learning. The student performance study by assessment categories (Introduction, Enabling, and Demonstrating) supports the constructivist theory that students progress through levels of cognitive development (Trif, 2015). The drop in performance in the higher categories, such as Demonstrating, is due to gaps in scaffolding or lack of support for developing complex skills, a critical constructivist principle (Yoders, 2014).

Bloom's Taxonomy of Learning Objectives is hierarchical; learning objectives are categorized from the lower levels of foundational knowledge to the higher-order thinking skills, e.g., from Remembering and Understanding to higher-order thinking: Analyzing, Evaluating, and Creating (Bonaci et al., 2013). The assessment types closely align with Bloom's approach: Introduction closely corresponds to basic knowledge acquisition; Enabling more reflects the application and synthesis of knowledge; and Demonstrating reflects the creative formulation and evaluation of novel solutions or ideas. This theoretical basis for why performance declines for complex cognitive demands can be traced to this (Horner et al., 2005).

Goal-setting theory states that specific, challenging goals increase motivation and performance when individuals receive feedback and perceive goals as attainable (Lunenburg, 2011). The threshold-based outcome assessments serve as benchmarks or goals for student performance (Locke & Latham, (Eds.), 2013). The theory highlights the importance of setting clear, incremental objectives across categories. Performance declines in Demonstrating suggest that while early-stage goals may be well-defined and achievable, advanced-stage goals may need more clarity, support, or perceived attainability (Latham & Locke, 2018).

Program Evaluation Theory systematically evaluates the programs' design, delivery, and outcome to ensure their consistency with educational intentions and goals. It embraces the assessment of formative and summative evaluations as part of identifying areas to improve (Mertens & Wilson, 2018). The study confirms elements of program evaluation theory by systematically analyzing student performance across multiple years and identifying trends that inform curriculum refinement. The observed dynamics provide evidence for the efficacy of program design and highlight areas where adjustments are needed (Stufflebeam & Coryn, 2014).

Drawing on these theories, the study indicates how students' cognitive development and goal attainment may interact with program design in producing student performance. Confirmation of program evaluation theory, therefore, suggests that longitudinal data may play an essential role in the improvement of curricula as well as in ensuring educational goals are met at every level of student.

III. METHOD

This study analyzes performance dynamics in business administration programs using Bayesian Dynamic Time Warping (BDTW) analysis (Yang & Singer, 2021, August). This statistical method is a sophisticated way to identify temporal relationships and understand changing patterns in student assessment data (Moser & Schramm, 2019). It helps in identifying how curriculum design, resource allocation, and strategic decision-making should be carried out.

The BDTW has emerged as a cutting-edge analytical method capable of grasping the temporal correlation in educational assessment, especially in business administration programs (Wang & Koniusz, 2022, October). The process uses traditional Dynamic Time Warping as a base. Still, it utilizes Bayesian inference to let uncertainty be intuitively and robustly dealt with, along with the evolution of the relevant patterns within student performance data (Xiao & Siqi, 2017).

BDTW is particularly useful in business administration programs in monitoring student performance throughout core disciplines. The fact that the technique allows for different rates of learning and temporal shifts proved especially valuable while analyzing performance trends in courses such as business economics, where students tend to demonstrate nonlinear trends of learning while mastering complex abstract concepts and how to apply them practically (Deng et al., 2020), (Puri et al., 2022).

Implementing BDTW with the thresholds of achievement outcomes has facilitated an interpretive understanding of students' achievement patterns. Where institutions are now moving toward dynamic thresholds rather than fixed benchmarks (Fu et al., 2017), they consider natural student capability development as academic progress unfolds. It resulted in a more accurate and fair assessment of a student's progress, especially when different skills may take longer to develop than others (Engelbrecht et al., 2015 December).

Methodologically, BDTW has come out particularly strong in dealing with the inherent variability in assessment data across different business disciplines. The Bayesian component allows uncertainty of measurement while maintaining sensitivity to changes in student performance patterns that are fundamental changes. This was particularly useful when analyzing longitudinal data spread over several semesters or academic years (Puri et al., 2022), (Moser & Schramm, 2019).

Recent developments in BDTW applications have focused on integrating multiple assessment data sources, including quantitative metrics and qualitative evaluations. This holistic approach has enhanced the method's utility in identifying areas where students may require additional support or where curriculum adjustments might be beneficial to optimize learning outcomes (Raffel & Ellis, 2016, March), (Schnabel & Sjöstrand, 2019).

The primary implementation challenges of BDTW in educational assessment have been related to computational requirements and the sufficiency of historical data to inform Bayesian priors. Improvement in computational efficiency and increasing availability of longitudinal assessment data have progressively overcome these challenges, making BDTW increasingly practical and suitable for institutional uptake (Gao et al., 2022), (Cao et al., 2016).

Looking forward to applications, BDTW created more advanced early warning systems for tracking at-risk students who might encounter academic issues. The ability of the method to detect slight variations in patterns over time would provide scope for earlier and targeted interventions that could increase student overall success rates in business administration programs (Mace et al., 2013, March), (Shuai et al., 2022).

Within the Outcome Assessment Thresholds (OATh) context, student performance measures, dynamic relationships, and time-varying correlations were investigated by formulating the Bayesian Dynamic Time Warping (BDTW) framework in mathematical terms, describing evolving correlations between performance categories over time. This combines Bayesian inference to deal with uncertainty and compute credible intervals for dynamic correlation estimates.

Bayesian Dynamic Time Warping Framework

For Dynamic Alignment, the time series for each program is aligned from performance metrics across the three levels of assessments: Introduction, Enabling, and Demonstrating over the years (2021–2024). Dynamic alignment minimizes temporal dissimilarities between two series using a warping path. With $X = \{ x_1, x_2, \ldots, x_T\}$ and $Y = \{y_1, y_2, \ldots, y_T\}$ as the two series, the path of the dynamic alignment P is found by minimizing the cumulative distance:

$$DTW\ (X, Y)\ =_{P}^{min} \sum_{(i,j)\in P} d(x_i, y_i), \qquad (Equation\ 1)$$

Where $d(x_i, y_j)$ is the Euclidean distance between points x_i and y_i

Bayesian Time-Varying Correlation Model

Once aligned, the time-varying correlation between the assessment categories is modeled using a Bayesian approach. The correlation ρ_t at time t is assumed to evolve linear or non-linear, capturing changes in performance correlations. The correlation is defined as:

$$\rho_t = \beta_0 + \beta_1 t + \varepsilon_t, \qquad (Equation\ 2)$$

Where

β_0 is the intercept

β_1 is the slope of the correlation change over time

$\in_t \sim N(0, \sigma^2)$ represent the noise

The model integrates this correlation into a multivariate normal likelihood

$$\begin{matrix} x_t \\ y_t \end{matrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix}\right),$$

Where x_t and y_t represent the aligned performance metrics at time *t*.

Bayesian Priors and Inference

Priors are imposed on the model parameters to model prior belief and facilitate Bayesian inference.

$$\beta_0 \sim N(0,1),\ \sigma \sim Half - Cauchy\ (0,1) \qquad (Equation\ 3)$$

Using Markov Chain Monte Carlo (MCM) sampling, posterior distributions of ρ_t, β_0, β_1, and σ are estimated. These posterior distributions quantify the uncertainty in the correlation and provide credible intervals.

Application of the OATH Data

For the data furnished in the Program (Business Economics, Financial Management, HR Management, Marketing Management), measurement criteria (Introduction, Enabling, Demonstrating) from 2021 to 2024. BDTW potentially time-dates the relationship between groups, e.g., Introduction vs. Enabling, so an interpretation of the assessment structure indicates whether relationships are growing in or declining in strength. All of these are summarized by:

1. Convergence Diagnostics Trace plots and adequate sample size checks confirm that MCMC converged.
2. Dynamic Correlation Estimates Table: Posterior means and credible intervals ρ_t, over time.
3. Alignment Metrics Table: Quantifying improvements in alignment post-DTW.
4. Goodness-of-Fit Table: Metrics such as WAIC and log-likelihood ensure robust model selection.

This method ensures an interpretable, flexible, and statistically rigorous approach to analyzing student performance dynamics in evolving assessment structures. The business administration programs chosen for, this paper are Business Economics, Financial Management, HR Management, and Marketing Management. These different disciplines would represent the basic foundations of any well-rounded business education. Understanding the unique performance attributes and interdependencies within the ecosystem is necessary to advance the overall quality and effectiveness of the curriculum.

IV. RESULT AND DISCUSSIONS

This study attempts to unravel the complex temporal dynamics, program-specific performance profiles, and model reliability using the BDTW approach. The results from this analysis empower educational institutions to undertake targeted curricular adjustments that align the curriculum cross-disciplinarily and create data-driven strategies to optimize student learning outcomes and sustain the relevance of their business administration programs.

Table 1 is a detailed analysis of threshold levels across the business administration outcomes from 2021 to 2024, showing some interesting patterns and trends in student performance in different stages of learning. The fluctuation in the performance of Business Economics has been significant in the three-year cycle. The introduction threshold in 2023-2024 seems high at 80%, with much lower enabling and demonstrating thresholds at 75% for both. This is a marked contrast with the performance in the 2022-2023 academic year, which was excellent at both enabling (90%) and demonstration (88%) stages but had a slightly lower introduction threshold at 78%. The 2021-2022 period was also intense across all levels, but most notably, the enabling at 93%. The overall profile is a gentle decline in higher-level metrics and the establishment of sound introduction competencies.

Table 1: Records of the Outcome Assessment Thresholds of Programs Performance SY 2021 to 2024

Outcome Assessment Thresholds	**2023-2024**			**2022-2023**			**2021-2022**		
Programs	Introduction	Enabling	Demonstrating	Introduction	Enabling	Demonstrating	Introduction	Enabling	Demonstrating
Business Economics	80	75	75	78	90	88	83	93	80
Financial Management	72	69	81	85	74	83	88	82	90
HR Management	86	76	78	81	77	82	87	86	86
Marketing Management	94	80	75	85	82	82	84	86	84

Financial Management shows an exciting trend of improvement in demonstrating-level skills over the latest period. 2023-2024, though introduction (72%) and enabling (69%) thresholds were relatively lower, the demonstrating threshold was still strong at 81%. This contrasts previous years, particularly 2021-2022, which showed consistently high performance in all stages at 88%, 82%, and 90%, respectively. The mid-year period, 2022-2023, sustained relatively stable high-level performance with some wavering across the different stages.

HR Management has shown a relatively constant performance at all three academic levels, where the latest period, 2023-2024, demonstrates high introduction levels of 86%. The enabling and demonstrating thresholds reveal stable though lower, 76% and 78%, respectively. The overall performance metrics for this program have been relatively stable compared with other programs. For instance, in the last academic year, 2021-2022, the student performances were consistent at all three levels, 86-87%.

Marketing Management shows exciting development during the last period, which is 2023-2024, with exceptional strength in entrance threshold at 94%, yet afterward has declined in enabling to 80% and in demonstrating the ability to be 75%. It differs from the previous years, where performance overall was leveled across all three stages. The 2022-2023 and 2021-2022 periods presented more balanced performance through all three stages at roughly 82-86% thresholds.

Looking at overall trends across programs, one general pattern is emerging, and this is of strength in introductory performance in the most recent academic year for a number of the programs, especially in Marketing Management and HRM. However, there also is an observable trend of lower enabling and demonstrating thresholds in 2023-2024 than in earlier years across most programs. This could imply a need for increased help in how students are supported to move through introductory to more advanced layers of learning.

The data further shows that while some programs have relatively stable thresholds at all stages (like HRM), others show more significant fluctuations from introduction to enabling and then to demonstrating levels, especially in Marketing Management and Business Economics. This might translate to differences in the effectiveness of teaching methodologies across the learning stages and varying degrees of student engagement and mastery throughout the programs.

These insights are helpful for curriculum development and resource allocation; they indicate where more academic support would be helpful. Students are performing well but possibly need help continuing at those performance levels between the programs' introductory and more advanced levels. The analysis also offers potential avenues for further research on the contributing factors behind the observed differences in performance among different stages and academic years.

The warping path length in Table 2 indicates how much one-time series needs to be "warped" to match another. A shorter path length suggests a closer alignment between the series. The alignment metrics table gives the warping path lengths between various business administration programs, which can easily be interpreted as the relative temporal distances or differences in their performance patterns. The matrix is symmetric with zeros on the diagonal, expressing the comparative relationships between program pairs. Business Economics shows varying degrees of alignment with other programs, having a warping path length of 10 with Financial Management, 9 with HR Management, and the longest distance of 11 with Marketing Management, suggesting that it has the most distinct performance pattern from Marketing. Financial management demonstrates intermediate alignment differences, with path lengths of 9 and 10, respectively, with HR and marketing management. HR Management and Marketing Management are two functions showing the most consistent alignment with one another, indicated by a warping path length of 9, meaning relatively similar temporal patterns in their performance metrics. This analysis suggests that while all programs reveal some level of temporal misalignment in their performance patterns, the most diverse patterns appear for Marketing Management and Business Economics (with a path length of 11). HR Management's patterns appear overall most consistent in comparison with the other programs (9 across all comparisons), which could indicate that its performance patterns provide a bridging entity for understanding and standardizing assessment approaches across the business administration curriculum.

Table 2:- Alignment Metrics (Warping Path Lengths)

	Business Economics	Financial Management	HR Management	Marketing Management
Business Economics	0	10	9	11
Financial Management	0	0	9	10
HR Management	0	0	0	9
Marketing Management	0	0	0	0

The normalized distances matrix in Table 3 provides standardized measurements of dissimilarity between patterns of program performance, with scores ranging from 0 to 1 - the latter indicating more dissimilarity. Business Economics exhibits strong contrasts in performance profile with others, performing the highest normalized distance at 0.919 with Marketing Management, followed by 0.866 with Financial Management, and 0.667 with HR Management, indicating that it has the most robust unique temporal performance signature among all programs. Financial Management contrasts significantly with Marketing Management at 0.873 and has a moderate dissimilarity with HR Management at 0.658. HR Management has generally consistently moderate distances from the other programs, ranging from 0.658 to 0.67, which shows that this management maintains a central position in the similarity of the performance pattern of the curriculum across the programs. This highly normalized distance between Business Economics and Marketing Management (0.919) particularly suggests that these programs have basic differences in the temporal patterns of their assessment outcomes because of differences in learning progressions, assessment methods, or time trends for core competency development. This analysis reveals insight into structural relationships between program performance patterns, a potential source of valuable information for curriculum alignment, assessment standardization, identification of opportunities for cross-program learning, and specific improvement strategies.

Table 3 Alignment Scores (Normalized Distances)

	Business Economics	Financial Management	HR Management	Marketing Management
Business Economics	0	0.866	0.667	0.919
Financial Management	0	0	0.658	0.873
HR Management	0	0	0	0.67
Marketing Management	0	0	0	0

The dynamic correlation estimates in Table 4 provide a nuanced view of temporal interdependencies among the different business administration programs, suggesting significant relationship performance across the periods studied.

Business Economics has the lowest correlation coefficient at 0.010374, which suggests an exceptionally weak or nearly non-existent linear relationship between its performance metrics over time. This means that the performance characteristics of the program are highly independent and do not display consistent patterns of systematic covariation with other programs or internal temporal trends. Such minimal correlation may suggest unique pedagogical approaches, distinct assessment methodologies, or highly individualized learning progression within the Business Economics curriculum.

Table 4. Dynamic Correlation Estimates

Programs	Correlation
Business Economics	0.010374
Financial Management	0.795098
HR Management	0.207250
Marketing Management	0.611895

Financial Management differs by the strikingly high correlation coefficient of 0.795098; it implies a strong, robust temporal relationship in the performance metrics. Such substantial positive correlation can indicate consistent and predictable patterns over time, pointing to stable learning results, a well-established curricula framework, or highly systemic assessment methods. The connection is probably the result of the well-structured pedagogical environment with reliable knowledge transmission and assessment methods.

HR Management has a 0.207250 correlation coefficient, which implies an average type of temporal relationship within performance characteristics, but there to be discerned. As such, the average magnitude of moderate correlation reflects at least an internal, less pronounced pattern in performance metrics across the range of variability rather than showing the same pronounced behavior as Financial Management's. This means that variance is essential, and performance measurement is generally adaptive.

Marketing Management demonstrates a substantial correlation coefficient of 0.611895, indicating a moderately temporal relationship in its performance metrics. This correlation suggests a balanced approach between consistency and adaptability, where performance patterns show recognizable trends while maintaining flexibility. The coefficient implies that the Marketing Management program has developed reliable assessment frameworks that allow for meaningful tracking of student performance evolution without becoming overly rigid.

These dynamic correlation estimates are of prime importance as they provide critical insights into the structural characteristics of each business administration program. They reflect varying levels of temporal stability and performance predictability across disciplines. They are helpful information for curriculum design, refinement of assessment strategy, and understanding intrinsic learning dynamics within each program. These high variabilities of correlation coefficients underscore the importance of discipline-specific approaches to educational assessment and the need for more nuanced, program-specific strategies in curriculum development and student performance monitoring.

The Log-likelihood values in Table 5 are critical statistical measurements of model fit in Bayesian Dynamic Time Warping analysis, which looks at different business administration programs to provide probabilistic performance for each assessment model.

HR Management has the highest (least negative) log-likelihood at -25.4574, implying that this program's performance model most closely fits the observed data. This means high predictive power and a close fit between the statistical model and the actual performance patterns. The closeness of the log-likelihood to zero means a more accurate representation of the underlying performance dynamics in HR Management's assessment framework.

Table 5: Log-likelihood values

Log likelihood	Metrics
Business Economics	-29.1425
Financial Management	-30.0878
HR Management	-25.4574
Marketing Management	-26.9067
DIC (Deviance Information Criterion)	55.7972
WAIC (Watanabe-Akaike Information Criterion)	59.8517
Gelman-Rubin Statistics	0.9675

Marketing Management follows closely with a log-likelihood of -26.9067, indicating another relatively strong model fit. The proximity of its log-likelihood to HR Management suggests comparable model predictive performance and consistency in assessment metrics. This similarity might reflect comparable methodological approaches or inherent structural similarities in tracking and evaluating performance.

Business Economics and Financial Management have relatively lower log-likelihood values of -29.1425 and -30.0878, respectively, which reflect the existence of more complex or variable performance patterns that are marginally more difficult to model precisely. These values reflect higher model uncertainty or more significant variability in performance assessment metrics.

The Deviance Information Criterion measures the model's complexity plus goodness of fit, standing at 55.7972. The model likelihood is weighed against the parameters to arrive at the most parsimonious representation that can capture the performance dynamics exhibited over the business administration programs.

The WAIC is 59.8517, providing an alternative model selection metric, further confirming the model's predictive performance and complexity. Close yet distinct values between DIC and WAIC suggest robust model selection criteria and consistent model evaluation across different information-theoretic approaches.

The Gelman-Rubin statistic of 0.9675 is fascinating, showing excellent convergence in the Bayesian inference process. A value close to 1 (with 1 being perfect convergence) indicates that the MCMC sampling has explored the parameter space adequately and produced stable estimates. This high convergence implies that the statistical inference for the various business administration program assessments will be reliable and reproducible.

These statistical metrics demonstrate the complex nature of performance assessment in business administration programs. They indicate detailed differences in model fit across different disciplines, with HR Management and Marketing Management showing excellent forecasting ability. The convergence and information criteria indicate a dependable methodology to understand the variation over time in performance, which is very helpful for curriculum development and refinement of the strategy for assessment and understanding intrinsic learning dynamics within each program.

The analysis emphasizes sophisticated statistical techniques like Bayesian Dynamic Time Warping in capturing the subtle and evolving performance patterns in educational assessment, providing a more nuanced approach to those provided by traditional static evaluation methods.

The graph in Figure 1 illustrates the time-dependent correlations of business administration programs for an 8-year academic period. The correlations vary widely throughout the period and present several notable observations. The Business Economics and Financial Management correlation shows the most volatility and varies from a strongly positive to a strongly negative correlation over the years. In contrast, HR Management maintains a more consistent moderate positive correlation with other programs, suggesting a relatively stable performance pattern compared to the other disciplines. Marketing Management exhibits a mix of positive and negative correlations, with its relationship to Financial Management being particularly dynamic. The overall visualization underscores the complexity and dynamic nature of performance interdependencies in various business administration fields, calling for using complex analysis techniques such as Bayesian Dynamic Time Warping to capture such subtle patterns.

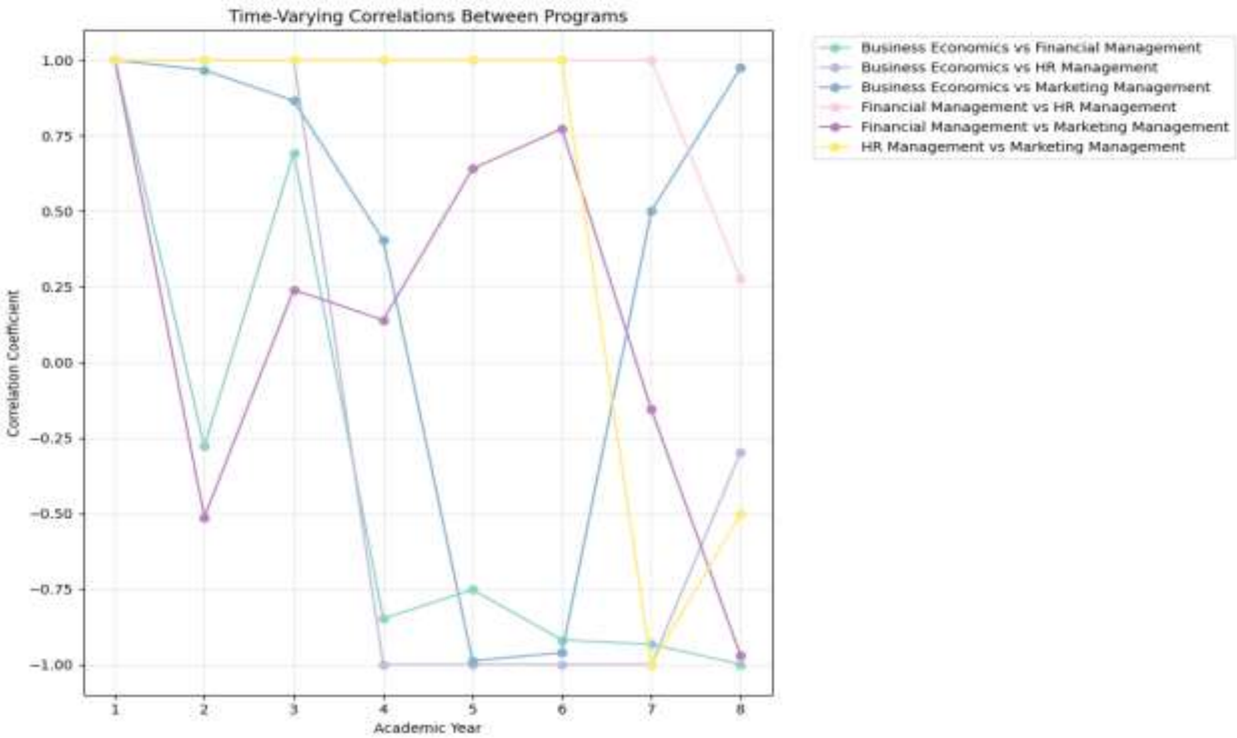

Figure 1 Time-Varying Correlation Between Programs

The graph in Figure 2 below illustrates the posterior distribution of parameter scores by level of proficiency (Introduction, Enabling, and Demonstrating) for the various business administration programs. The scores in the Business Economics program are tightly bunched around the Demonstrating level, indicating an emphasis on advanced competencies. Both Financial Management and HR Management have more spread-out distributions, showing a more even spread between the three proficiency levels. The graph shows that Marketing Management is bimodal in nature, with peaks occurring both at the Introduction and the Demonstrating levels, implying an equal focus on foundational and advanced skills. The graph overall shows the differentiation of the assessment profiles for these business programs across degrees of emphasis on student learning and proficiency development. The detailed visualization of the outcome assessment thresholds allows support for the design of curricula, resource allocation, and targeted intervention in student progression through the business administration curriculum.

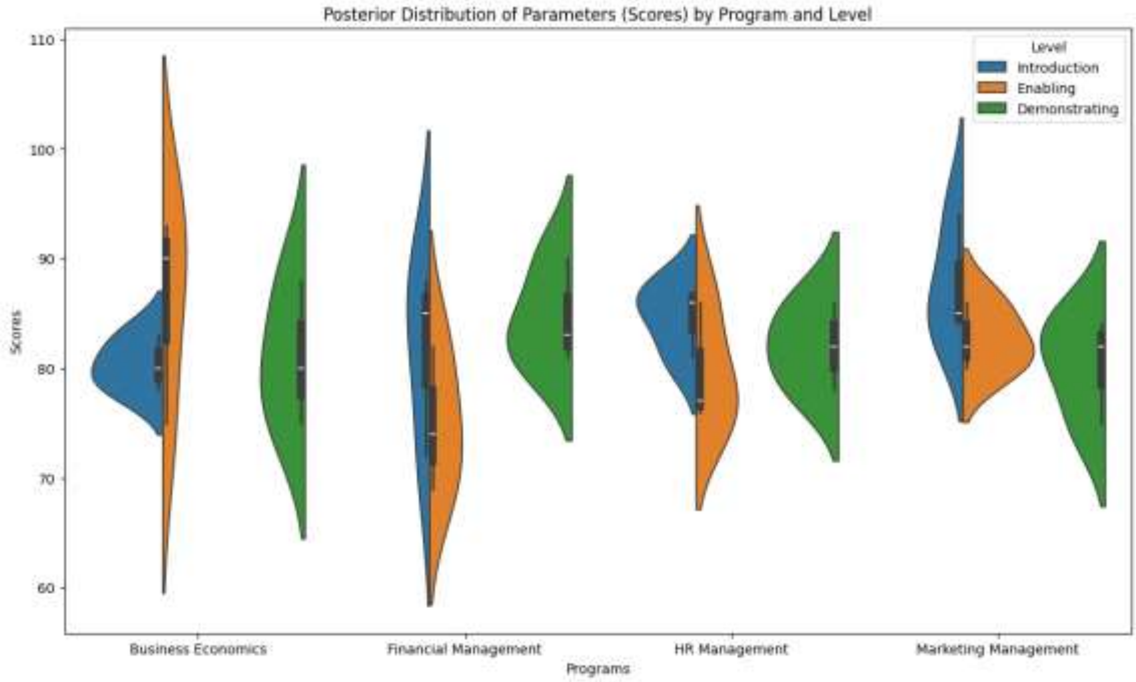

Figure 2 Posterior Distribution of Parameters (Scores) by Program and Level

Figure 3 presents the posterior predictive checks across different proficiency levels (Introduction, Enabling, and Demonstrating) for the business administration programs. These checks visually represent how well the statistical models fit the observed data.

The model demonstrates a strong predictive capability for Business Economics, particularly at the Demonstrating level, with a high median score and tighter distribution. The Enabling and Introduction levels show broader distributions, indicating more variability in model fit across these stages. In financial management, the model exhibits a balanced fit across the three proficiency levels, with the enabler and Demonstrator levels having slightly narrower distributions than the introduction.

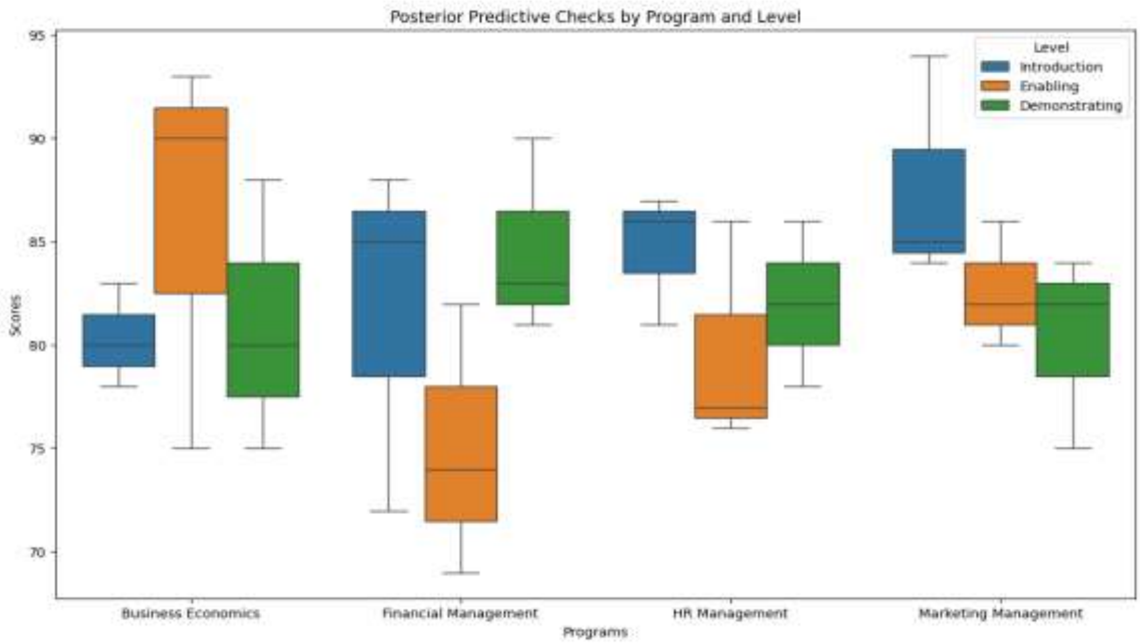

Figure 3 Posterior Predictive Checks by Program and Level

The HR Management program displays a consistent model fit, with similar median scores and distribution widths across all three levels, suggesting a well-calibrated assessment framework. For marketing management, the model fit is strongest at the introduction and demonstration levels, with the Enabled level showing a more dispersed distribution, potentially indicating more challenges in accurately predicting performance at that intermediate stage.

Overall, the posterior predictive checks comprehensively evaluate the Bayesian Dynamic Time Warping model's ability to capture the nuanced performance patterns within each business administration program, offering valuable insights for refining assessment practices and curriculum development.

Figure 4 depicts the trace plots that give diagnostic information regarding the convergence of the Bayesian models used in data analysis on the business administration program. For each academic year, traces reflect the variation in parameter values determined during the MCMC sampling.

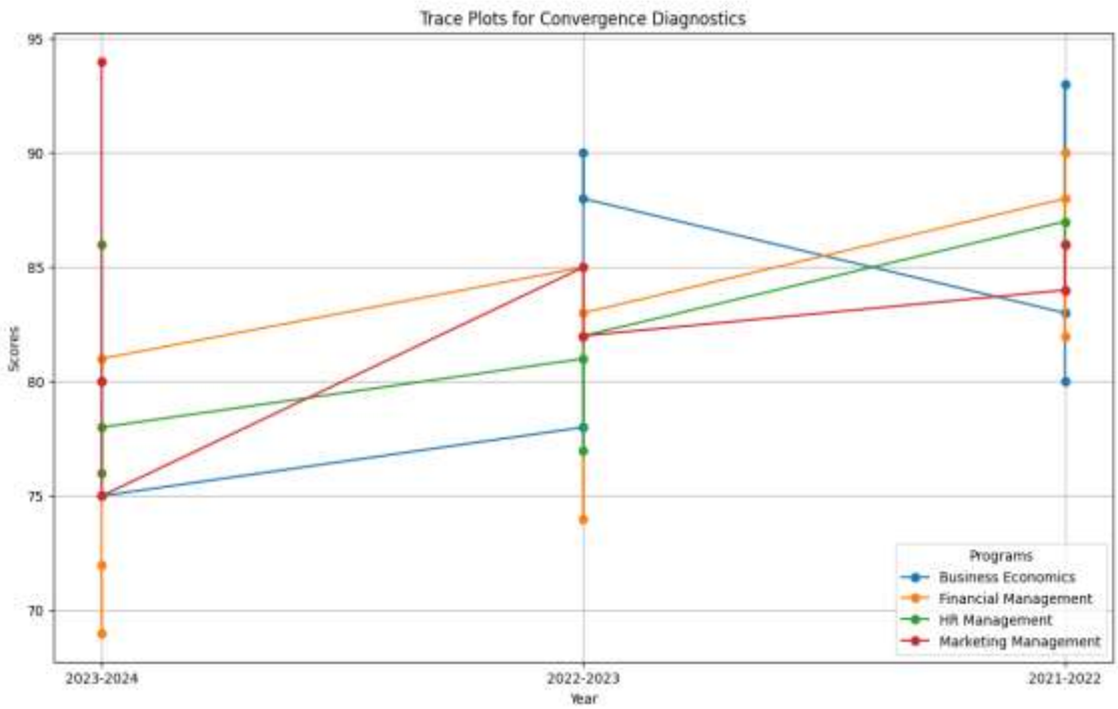

Figure 4 Trace Plots for Convergence Diagnostics

In each of these programs, the trace plots showed stable behavior of the values of the parameters as they converged to consistent levels during the sampling process. This trend is more easily seen in the earlier years of education, where the traces for all programs are pretty close and reliable and could be well reproduced.

Trace lines in the more recent academic years show slightly more variability, indicating possible shifts and adjustments in the underlying performance patterns across the entire business administration curriculum. Despite this, the overall diagnostic tests for convergence are strongly positive, further boosting the robustness and soundness of the Bayesian dynamic time-warping analysis performed.

Trace plots are necessary validation steps because they indicate that the statistical models have captured all the data's salient features and provide confidence in the reliability of the insights drawn from previous analyses.

Based on the above-detailed analyses and visualizations, the following vital inferences are drawn regarding the performance assessment of business administration programs from 2021-2024: the Temporal Dynamics and Interdependencies: A time-varying correlation among the programs uncovers complex, evolving relationships in their performance patterns. For instance, while Financial Management maintains its consistently positive correlations with others, Business Economics trajectories are very volatile and highly independent. The dynamic interdependencies call for more complex analytical techniques, such as Bayesian Dynamic Time Warping, to better capture nuanced shifts in assessment outcomes over time.

Program-specific performance profiles are the posterior distributions of parameter scores that reveal different assessment profiles for each business administration program. For example, Business Economics is characterized by a stronger emphasis on advanced Demonstrating-level competencies. In contrast, Marketing Management displays a bimodal distribution, with robust performance at both introduction and demonstration levels. Such differences reflect the need for different curricular approaches and assessment methods within each discipline to support students' progression.

Model Fit and Reliability are the posterior predictive checks that provide evidence of the Bayesian models' excellent fit in capturing performance patterns across proficiency levels. Consistent convergence diagnostics further confirm the robustness and reliability of statistical inferences, thus conferring much-needed confidence on insights from analysis and their possible role in informing evidence-based decision-making about curriculum development and student support.

Opportunities for Alignment and Standardization metrics, which are the warping path lengths and normalized distances, show different levels of temporal similarity between the programs. Some programs, such as HR Management, are more aligned with others. In contrast, others, such as the considerable distance between Business Economics and Marketing Management, indicate opportunities for cross-program collaboration and standardization of assessment approaches.

Temporal performance dynamics is the variation and trend of student performance at different points in time (2021 to 2023) and categories of assessment (Introduction, Enabling, Demonstrating) for the identified programs: Financial Management, Marketing Management, HR Management, and Business Economics. These dynamics give insight into how performance changes from year to year and category to category, showing strengths and weaknesses in pedagogical strategies. The temporal dynamics indicate the following trends: Strengths in the Introduction for all programs are generally good, a reflection of good entry-level teaching. While weaknesses at the intermediate and advanced levels are detected between Enabling and Demonstrating, performance declines in several programs, suggesting that programs must be better supported concerning applying skills and critical thinking. Every program has its character that needs curricular or instructional accommodations to deal with problems. Financial Management is strengthening foundation courses and adding bridging courses to maintain a consistent entry into the advanced stage. Highlight skill integration in Marketing Management and use and reduce the decline in scores for Demonstrating. With HR Management, there is a decrease in the demonstration of advanced skills while firm foundation courses are retained. Business Economics focuses on maintaining high performance from the Introduction to Enabling stages through improved scaffolding and resource use. These performance dynamics, over time, act as a diagnostic to fine-tune the evaluation of outcomes, teaching practice, and alignment of learning with program outcomes.

V. CONCLUSION AND RECOMMENDATIONS

A rich set of insights has been found through this comprehensive analysis of business administration program performance using Bayesian Dynamic Time Warping that could inform strategic decisions at the curriculum and assessment levels. Findings suggest complex and evolving interdisciplinary relationships in which programs have varying degrees of temporal alignment and unique performance profiles. The strong overall model fit and convergence diagnostics ensure the reliability of the statistical inferences, which can guide targeted interventions, resource allocation, and assessments of the standardization of their approaches to the evaluation across a business administration curriculum. Those data-driven insights can provide educational institutions with the proper optimization of student learning results, cross-disciplinary facilitation, and curricula more responsive to the dynamic changes in the business landscape. Therefore, this holistic understanding of program performance dynamics would be valuable for continuous improvement and sustaining business administration students' success.

More general managerial implications derived from this rigorous analysis and more learned insights based on the Bayesian Dynamic Time Warping analysis of business administration program performance are as follows:

1. Targeted curricular adjustments based on program-specific performance profiles to account for unique learning needs and progression patterns within each discipline-specific context, such as reinforced

advanced competencies in Business Economics or strengthened transition from introductory to demonstration levels in Marketing Management.

2. Promote Cross-Curricular Alignment: Use the alignment metrics to determine ways to harmonize evaluation methods and promote more communication across programs, especially between two such "outliers," Business Economics and Marketing Management, for a better-integrated and integrated business administration curriculum.

3. Invest in Continuous Assessment and Improvement: Monitor the temporal dynamics and evolving performance patterns through the Bayesian Dynamic Time Warping framework to inform iterative refinements to assessment methods, support student interventions, and ensure that the curriculum remains responsive to the changing needs of the business landscape.

4. Use Data-Informed Insights for Strategic Decision Making: Bring strong statistical inferences and model fit diagnostics into strategic decision-making about resource allocation, faculty development, and general optimization of business administration programs to improve student success and readiness for postgraduate careers.

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