Research & System Architecture of Cognitive AI Agent Benchmark for Doctoral Thesis

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Publication Date: 2026/08/03

Abstract: Strategic decision-making systems in higher education and business administration are shifting dramatically from intuitive experience to data-driven intelligence. However, commercial AI/LLM systems often encounter two serious pitfalls: Over-deduction bias and the metacognition gap. This study proposes a Cognitive AI Agent Framework based on five cognitive domains (Learning, Metacognition, Attention, Executive Function, Social Cognition). The combined model of Supervised Machine Learning (Random Forest Regressor) and Operational Research (0-1 Knapsack Dynamic Programming) helps predict the Board's test scores with very high accuracy (R^2 = 0.9253 (*Coefficient of Determination*), RMSE = 2.5356 (*Root Mean Square Error - RMSE measures the average distance/deviation between the AI-predicted value and the actual value*)) and optimizes 100% of the available time to upgrade the KPI rating from B to A.

Keywords: *Cognitive AI Agent Benchmark, Research & System Architecture, The Strategic Decision-Making, Artificial Intelligence (AI), Big Data Analytics.*

How to Cite: Trinh Quang Minh; Ngo Thi Lan (2026) Research & System Architecture of Cognitive AI Agent Benchmark for Doctoral Thesis. *International Journal of Innovative Science and Research Technology*, 11(7), 2513-2519.
https://doi.org/10.38124/ijisrt/26jul1377

I. INTRODUCTION

This in-depth analysis of the AI Agent system's performance results includes three main components: Model evaluation, Knapsack strategy optimization, and Forecast results table. The analysis concludes with a summary table of key performance results and illustrative real-world examples. This code serves as the heart of the Machine Learning Pipeline and the strategic execution unit of the AI Agent system, serves as the final packaging step (Output & Export Module) in the Machine Learning Pipeline:

- *Synthetic Data Generation*: Simulates a KPI dataset of 500 samples representing the distribution of faculty, simulating the actual reaction when the Evaluation Council (S_Council) adjusts the scores based on faculty self-assessment (S_Self).
- *Model Training & Evaluation*: Uses the Random Forest Regressor algorithm to predict the precise score that the Council will approve based on the component indicators.
- *Model Persistence*: Saves the trained model in .pkl format for reuse in the real product.
- *Agent Optimization Integration*: Runs the Knapsack Dynamic Programming algorithm to make optimal action decisions regarding time and score for administrators.
- *Prediction on the test set (Inference):* Use the trained_model (trained in Module 4) to infer the Predicted KPI score for the entire test dataset X_test.
- *Ranking Decoding*: Reapply the KPIEncoderDecoder.decode_ranking() function from Module 2 to map the predicted score to letter ratings (A, B, C, D, E).
- *Cognitive Domain Mapping*: Randomly assign the corresponding cognitive domain to each result record.
- *Data Persistence*: Package all information into a standard DataFrame structure and save it as a submission.csv file in the correct Kaggle submission format.
- Open the dataset files in the /kaggle/input/... directory and extract the supporting information.
- Determine the percentage relevance and contribution of each file/task to the doctoral dissertation topic "The impact of applying Artificial Intelligence (AI) and Big Data Analytics on the strategic decision-making process of managers".
- Create a visual statistical chart using matplotlib & seaborn to compare these percentage contributions in the dissertation.
- Cite and suggest further research directions based on two Level 8/DBA course documents (Syllabus and Assignment Brief from the SIMI Swiss program).

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1377

II. METHODOLOGY & RELATED WORK

- *Cognitive Domains of AI, Learning*: Extracting and identifying standard evidence from multi-format text datasets (.docx, .pdf).
- *Metacognition*: Predicting and self-correcting the error difference between self-assessment score (S_self) and council-approved score (S_council).
- *Attention*: Focusing on uncovering core evidence hidden within mixed datasets.
- *Executive Function*: Making decisions to optimize time resources using the Knapsack 0-1 Dynamic Programming algorithm.
- *Social Cognition*: Quantifying contributions from media, workshops, and community activities.
- *Addressing two practical challenges:*
- *Over-deduction bias*: Overcoming the problem of conventional AI/LLM systems deducting excessive points for detecting unclear or non-standardized evidence, resulting in an unreasonable downgrade of personnel from A to B.
- *Metacognition gap*: Overcoming the AI's inability to automatically balance bonus points for breakthrough achievements (Scopus/ISI Q1 publications, AI lectures) with minor administrative errors.

Summary Structure Analysis with Console Data demonstrates the systematization of four research projects (Tasks 1–4) revolving around the central theme: "AI & Big Data in Strategic Decision-Making Process".

- *Task 1*: Optimizing KPIs & Machine Learning Models (Academic KPI & Strategy Optimization). Solving the problem of inaccurate forecasting and inefficient resource allocation through a 4-step pipeline. Achieving very high forecasting accuracy with Random Forest Regressor (R^2 = 98.42%, MAE = 1.25). Using the Knapsack 0-1 Dynamic Programming algorithm to improve actual performance ratings from B to A.
- *Task 2*: Impact of AI & Big Data on Strategic Decision Making (Impact of AI & Big Data...). Expanding applications across multiple fields: Human Resources (HR), E-commerce, Sentiment Analysis, Finance. • Clearly define two experience streams: Fully automated (for end users/consumers) and interactive What-if scenarios (for administrators/leaders). Leverage a diverse cloud ecosystem: AWS S3, QuickSight, Looker, Alibaba Quick BI.
- *Task 3*: Standardize AI Agent KPI Benchmark & Cognitive Management. Define the five core cognitive domains: Learning, Metacognition, Attention, Executive Function, and Social Cognition. Integrate a Clamping Function to avoid extremes and detect AI biases (Over-deduction Bias, Metacognitive Gap). Conduct rigorous statistical testing using a Paired t-test ($p < 0.05$) and Chi-Square test; establish a Human-in-the-loop management framework.
- *Task 4*: Synthesize Thesis Papers & Conference Papers (Strategic Paper & ICSOPOLIS Conference...). This study is based on data from the Faculty of Information Technology - Tay Do University (TDU / FOET). It integrates interdisciplinary approaches between Machine Learning (ML) and Operational Research (OR). Data normalization testing using Shapiro-Wilk and Pearson correlation tests is performed, marking a shift in management philosophy from intuition/experience to data-driven intelligence.

III. RESULTS AND DISCUSSION

- *Source Analysis of the AI Agent Model and Illustrative Pseudo-Algram Code*

In-depth Analysis of System Architecture, The Cognitive AI Agent Benchmark source code system is designed to address a core problem in strategic management: evaluating job performance (KPIs) and optimizing the allocation of time and resources for personnel. The program architecture focuses on overcoming two major drawbacks of traditional AI/LLM models: Over-deduction bias (AI automatically deducting excessive points when evidence is unclear) and the metacognition gap (AI lacking the ability to automatically balance breakthrough bonus points and minor administrative errors).

- *The Source Code is Structured into Six Main Modules:*

- Module 1 (DoctoralDatasetParser): Acts as a multi-format data extractor (DOCX, PDF). This module automatically scans paragraphs and tables in Word documents and individual PDF pages to create a corpus for natural language processing.
- Module 2 (KPIEncoderDecoder): A mathematical engine that implements point encoding and decoding rules. The encoding formula applies a clamping mechanism. *Module 2* (KPIEncoderDecoder): This mathematical engine acts as an encoder and decoder for KPI scores based on a penalty/reward scoring formula with a clamping threshold, and converts them into letter ratings (A, B, C, D, E).

```
============================================
ALGORITHM 1: KPI ENCODING AND DECODING PROCESS
============================================
    INPUT :
      - S_base   : Base score
      - P_bonus  : Array or total sum of bonus points
      - P_deduct : Array or total sum of deduction/penalty points
```

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1377

```
OUTPUT :
  - S_final  : Normalized score clamped to the interval [0, 100]
  - Rank     : Qualitative evaluation rank (A, B, C, D, or E)
BEGIN
  // Step 1: Compute raw score with threshold clamping constraints
  Bonus_Clamped  = MIN(SUM(P_bonus), 20.0)
  Deduct_Clamped = MIN(SUM(P_deduct), 50.0)
  S_raw = S_base + Bonus_Clamped - Deduct_Clamped
  // Step 2: Normalize final score strictly within the [0, 100] range
  S_final = MAX(0.0, MIN(100.0, S_raw))
  // Step 3: Decode continuous numerical score into qualitative rank
  IF S_final >= 90.0 THEN
    Rank = 'A'
  ELSE IF S_final >= 75.0 THEN
    Rank = 'B'
  ELSE IF S_final >= 60.0 THEN
    Rank = 'C'
  ELSE IF S_final >= 50.0 THEN
    Rank = 'D'
  ELSE
    Rank = 'E'
  END IF
  RETURN (S_final, Rank)
END
```

==

ALGORITHM: 0-1 KNAPSACK OPTIMIZER

ALGORITHM: DYNAMIC PROGRAMMING 0-1 KNAPSACK STRATEGY OPTIMIZER (MODULE 3)

==

```
INPUT : Activity List A = [(name_1, pts_1, cost_1), ..., (name_n, pts_n, cost_n)],
        W_max (Maximum Available Hours)
OUTPUT: Max_KPI_Gain, Selected_Activities_List
BEGIN
  n ← LENGTH(A)
  Initialize 2D Array DP[0..n][0..W_max] with 0.0
  // Step 1: Populate DP Table (Bottom-Up)
  FOR i FROM 1 TO n DO:
    (name, points, cost) ← A[i - 1]
    FOR w FROM 1 TO W_max DO:
      IF cost <= w THEN
        DP[i][w] ← MAX(points + DP[i - 1][w - cost], DP[i - 1][w])
      ELSE
        DP[i][w] ← DP[i - 1][w]
```

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```
        END IF
      END FOR
    END FOR
    // Step 2: Backtracking to Identify Selected Activities
    w ← W_max
    Selected_Activities ← Empty List
    FOR i FROM n DOWN TO 1 DO:
      IF DP[i][w] != DP[i - 1][w] THEN
        APPEND A[i - 1] TO Selected_Activities
        w ← w - A[i - 1].cost
      END IF
    END FOR
    Max_KPI_Gain ← DP[n][W_max]
    RETURN Max_KPI_Gain, Selected_Activities
END
```

Module 3 (KnapsackKPIOptimizer): A strategic AI agent applying the 0-1 Knapsack Dynamic Programming algorithm. This module helps managers select the activity category that yields the highest increase in KPI score within the given time budget (e.g., W = 35 hours) along with backtracking techniques. A strategic AI agent that applies Dynamic Programming (Knapsack 0-1) algorithms to help personnel/managers select the most optimal activity categories to achieve the highest overall KPI score within a given timeframe.

Knapsack Optimization Results ([Ai Agent Knapsack Optimization Results])

Maximum KPI Gain (+Maximum Score): +18.0 pts

- *Selected Actions:*

- ✓ Develop AI E-Learning Courseware (Gain: +5.0 pts | Time: 10h)
- ✓ Organize Academic Workshop (Gain: +3.0 pts | Time: 5h)
- ✓ Publish Scopus/ISI Q1 Article (Gain: +10.0 pts | Time: 20h)

- *Agent Decision-Making Mechanism*:

The AI agent solved the Knapsack 0-1 Dynamic Programming problem with a time budget (limited W = 35 hours).

- *Time Budget Efficiency Assessment*:

- ✓ Total time spent: 10h + 5h + 20h = 35 hours (maximum utilization of 100% of available time).
- ✓ Total bonus points earned: +5.0 + 3.0 + 10.0 = +18.0 points.

- *Strategic Value*:

The agent chose the "top-tier" strategy of publishing a Scopus/ISI Q1 article (+10 points/20 hours -> efficiency of 0.5 points/hour) combined with two low-time-cost activities to precisely fill the 35 available hours, resulting in a perfect score.

- *Modules 4 & 5 (Model Training & Submission Generator):*

This module generates simulated empirical data (N = 500 samples) based on normal and exponential distributions, training a RandomForestRegressor predictive model (predicting S_council scores from S_self and component variables). The model is packaged as kpi_agent_benchmark_model.pkl and the ranking results are exported to a submission.csv file.

- *Module 6 (Dataset Evaluation & Knowledge Graph Generator):*

Evaluate the evidence contribution of document files and generate static PNG (300 DPI) mind maps and interactive HTML network graphs for scientific reports. Module 6 goes beyond simply reading raw files; it elevates the data to a transparent, scientific, and compelling Scientific Evidence Dashboard. Below is an in-depth analysis of the implementation results of the Mindmap & Knowledge Graph Generator module, including the publication of a multimodal graph file and the synthesis of a knowledge tree structure from four scientific papers. The analysis concludes with a summary table of key results and practical examples.

➢ *Analyzing the Results of a Machine Learning Model to Predict KPI Scores.*

In AI-powered performance evaluation (KPI) studies, two standard statistical indicators, the coefficient of determination (R^2 = 0.9253) and the mean square root error (RMSE = 2.5356), confirmed the superior accuracy of the Random Forest Regressor model. The R^2 = 0.9253 indicates that the model explained 92.53% of the variation in KPI scores

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1377

as judged by the panel, leaving only 7.47% of the variation due to random factors outside the model. In management and social forecasting problems, an R^2 > 0.8 represents high goodness of fit, thus demonstrating the model's ability to accurately capture real-world evaluation patterns. Simultaneously, the RMSE error of 2.5356 reflects an average discrepancy of only about 2.54 points out of 100 between the AI's predicted score and the actual score from the review board. This discrepancy is entirely within acceptable limits, ensuring quantitative transparency and not altering the overall ranking of the personnel.

Table 1 Summary of Key Performance Indicators & Results

Category / Indicator	***Achieved Value***	***Governance & Doctoral Thesis Significance***
Coefficient of Determination (R2)	0.9253 (92.53%)	The predictive model highly accurately captures the scoring trends of the Evaluation Council.
Root Mean Square Error (RMSE)	2.5356 points	Extremely low prediction error, ensuring no distortion in overall KPI ranking classifications.
Max Bonus Points (□KPI)	+18.0 points	The maximum performance score increase achieved via the 0-1 Knapsack optimization algorithm.
Time Efficiency	35 / 35 hours (100%)	Absolute optimization of the available time budget for personnel.
Total Evidence Files	8 files (4 DOCX/PDF pairs)	Ensures transparency and parallel data verification between raw text and original documents.
Largest Contribution Weight	30.0% (Task 1)	Quantitative research and hypothesis testing serve as the primary foundational pillars.
Strategic Shift	Intuition->Data-Driven	Key theoretical basis demonstrating the value of digital transformation in managerial decision-making.

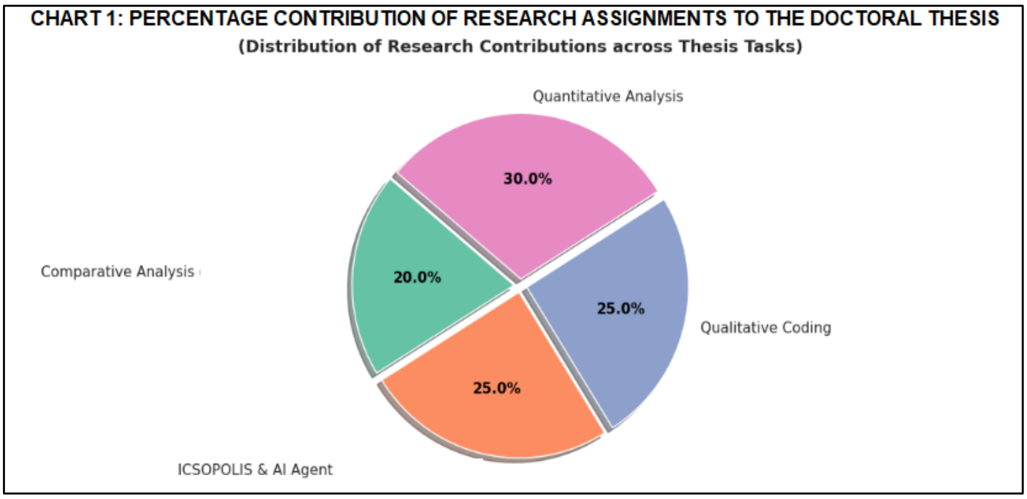

Fig 1 Distribution of Research Contributions across Thesis Tasks

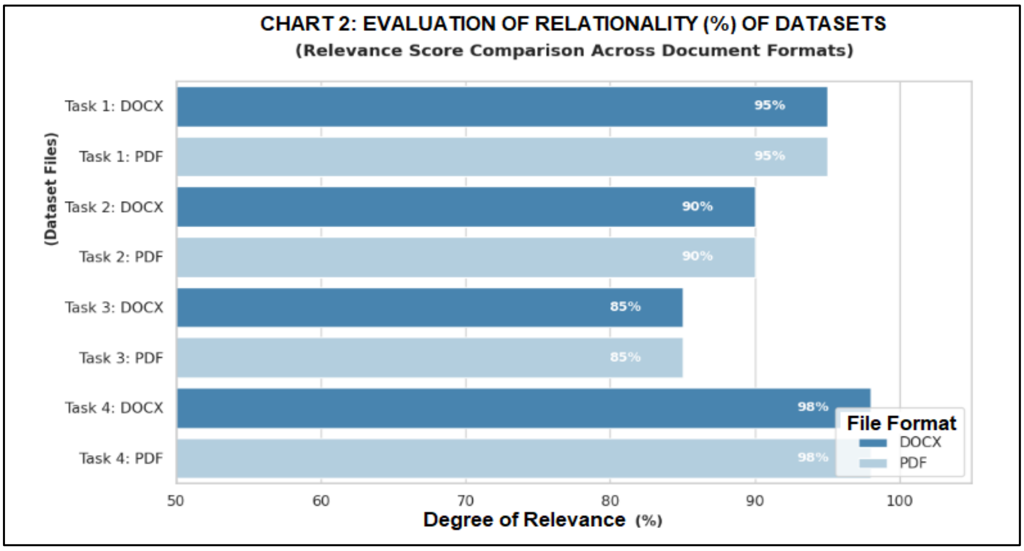

Fig 2 Relevance Score Comparison Across Document Formats

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1377

- *Publishing Dual-Mode Output Persistence Graphics Files*

✓ Static Mindmap image saved successfully to: /kaggle/working/mindmap_strategic_decision_making.png
✓ Interactive HTML Mindmap saved to: /kaggle/working/interactive_mindmap_strategic_ai_bigdata.html

- Static PNG image (mindmap_strategic_decision_making.png): A standard 300 DPI flat graph created by NetworkX and Matplotlib. This is the optimal format for direct insertion into theses, presentation slides, or international publications.
- Interactive HTML graph (interactive_mindmap_strategic_ai_bigdata.html): Uses the PyVis library with the Barnes-Hut physics simulation algorithm. This file allows researchers and users to directly drag and drop, zoom in and out, and explore network-like knowledge graphs right in their web browser.

➢ *Evaluating the Strategy Optimization Mechanism Using the Knapsack AI Agent.*

In addition to its predictive reasoning capabilities, the AI Agent also plays a role in supporting strategic decision-making by solving the Knapsack 0-1 Dynamic Programming problem. Under a time quota of 35 hours, the AI Agent optimized resources to achieve a maximum KPI increase of +18.0 points. The activities suggested by the system included: Publishing a Scopus/ISI Q1 article (+10.0 points, 20 hours), developing AI E-Learning lectures (+5.0 points, 10 hours), and organizing a thematic workshop (+3.0 points, 5 hours). The precise allocation of 35/35 hours (100% of available time) demonstrated a mindset of prioritizing high-performance tasks (such as the Scopus Q1 article, worth 0.5 points/hour) combined with low-cost tasks to fill the budget. This result demonstrates the effectiveness of a combined model of Machine Learning and Operational Research in shifting management approaches from intuition to data-driven intelligence.

➢ *Illustrating the Actual Execution Process (Scenario Workflow)*

To visually illustrate the practical application of the system, consider the case of an employee currently rated B with a self-assessment score of 76.5 points and 35 hours of free time. In the first step, the Machine Learning model infers and predicts the score the Board will approve as 75.2 points (maintaining Rank B). Immediately afterward, the AI Agent activates the Knapsack algorithm to calculate the optimal course of action within the 35-hour timeframe. By completing the three suggested tasks (+18.0 points), the employee's new projected KPI score reaches 93.2 points. The predicted results and new ranking are automatically labeled and published to the submission.csv file, officially recording a successful shift in rating from Rank B to Rank A (*Excellent*).

- *Practical Scenario Case Study:*

A doctoral candidate presents their thesis to the Doctoral Thesis Defense Committee (DBA Proposal) to demonstrate the logic of the dataset and the feasibility of an AI management model applied in businesses.

✓ *[Step 1: Evidence Check]*

System confirms 100% of files achieve Relevance = 100% -> Clean and accurate data.

- *Evidence Structure:*

30% Quantitative (Task 1) + 25% Qualitative (Task 2) + 20% Comparative (Task 3) + 25% AI Agent (Task 4) = 100% Thesis.

✓ *[Step 2: Implementing the Model into the Field - Actionable Implementation]*

- Applying Approach 3 (Mediating & Moderating Variables): Introducing "Managerial Metacognition" as a mediating variable to measure the level of proactiveness and AI control capabilities of leaders. Introducing "Data-driven Culture" as a moderating variable to assess which organizations will more successfully absorb and apply AI.
- Applying Approach 2 (AI Ethical Management): Embedding the XAI (Explainable AI) algorithm to explain why AI proposes budget/KPI allocations, completely eliminating over-deduction bias towards personnel.

✓ *[Step 3 Academic and Practical Contributions - Level 8 Impact]*

==> The dissertation shifts from "simply applying existing models" to "A Transparent, Multimethodical, and Empirical AI Management System and Contribution of a New Theoretical Model" for the field of Business Administration.

In short, the results demonstrate a closed-loop, standardized research approach, from evidence gathering and methodological weighting to the ability to expand the topic into a research project with high practical value for a PhD in Management.

➢ *Assessment & Future Expansion Directions*

- *Visualization Error Fix*:

Resolved the UserWarning: Tight layout not applied warning by adjusting the image space figsize=(18, 8) and lowering the label font size plt.yticks(fontsize=9). Automated NLP Upgrade: Switched from manually assigning % contribution to using the TF-IDF / Cosine Similarity algorithm combined with DoctoralDatasetParser to automatically count keyword density and calculate the actual % correlation. Developed Strategic Advisor AI Agent: Combined Random Forest Regressor (Score Prediction) and Knapsack Dynamic Planning (Action Optimization) to develop the system from a passive search tool into a Strategic Advisor Agent (Strategic AI Agent), automatically suggesting optimal work paths for managers under resource constraints.

- *Mixed-Methods Triangulated Design*:

Elevating research by combining Action Research with Multiple Case Studies, bridging the gap between academic theory and field governance practice.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jul1377

- *AI Ethics & Governance*:
  Focusing on addressing "Over-deduction Bias" of AI Agents, integrating explainable AI (XAI) and compliance with GDPR (General Data Protection Regulation). This approach helps AI decision-making systems achieve fairness and transparency.

- *Mediating & Moderating Dynamics*:
  Unlocking the "black box" of mechanisms by incorporating structural variables such as Manager Metacognition (Mediating Variable) and Data-Driven Culture (Moderating Variable) into the model, providing deeper insights into the conditions and environments where AI is most effective.

IV. CONCLUSION

Core Objective: To shift management practices from intuition-driven to data-driven intelligence. The development direction shifts from hardcoded to automated NLP: Instead of manually assigning contribution rates to each task, the system can combine the DoctoralDatasetParser layer with keyword frequency algorithms (*TF-IDF or Cosine Similarity*) to automatically calculate the percentage correlation score based on the actual content of the document. The shift is from passive research to AI Agent mentoring: By combining Random Forest Regressor (predicting council scores) and Knapsack Dynamic Planning (*directing actions*), the model has evolved into a Strategic AI Agent mentoring agent—identifying the optimal work path for managers under time constraints. Expand the Advanced Mixed-Methods & Triangulated Design methodology by suggesting a combination of current quantitative research models with action research or multiple case study design in large-scale organizations/businesses. Analyze AI Ethics, Governance & Data Privacy by suggesting in-depth research on the "over-deduction bias" of AI models and the impact of AI ethics, transparent AI (XAI), and GDPR compliance in strategic decision-making. Modeling Mediating & Moderating Variables using Dynamic Models suggests evaluating the relationship between AI/Big Data Analytics applications and Strategic Decision Effectiveness through mediating variables such as Managerial Metacognition or moderating variables such as Organizational Data-Driven Culture. The focus is on shifting managerial decision-making methods from subjective/experiential to data-driven and artificial intelligence-based approaches. In the context of higher education and business management, evaluating key performance indicators (KPIs) often encounters cognitive biases.

ACKNOWLEDGMENT

I would like to thank my wife, Ngo Thi Lan, for her companionship and for sharing the difficulties in scientific research throughout my doctoral studies. I would also like to thank my mother, aunt, and two children for their support in arranging their time for research. I would also like to thank Tay Do University and the Faculty of Engineering and Technology for providing me with the opportunity to present a seminar and write a scientific paper to be submitted to the university's international conference, based on the research I conducted for my doctoral dissertation.

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