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Integration of AI-Driven Decision Support Tools in Finance and Operations Research Pedagogy: Evidence from Graduate-Level Instruction

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ABSTRACT

This study examines the integration of artificial intelligence (AI)–driven decision support tools within finance and operations research (OR) pedagogy, addressing the persistent gap between analytical theory and applied decision-making skills in higher education. The research investigates whether embedding AI-enabled tools into coursework improves learning outcomes, analytical reasoning, and decision quality. A quasi-experimental design was employed across four graduate cohorts ($n = 212$), comparing traditional instruction with AI-augmented pedagogy using machine-learning-based forecasting, optimization solvers, and interactive dashboards. Learning performance, decision accuracy, and cognitive engagement were measured using standardized assessments and project-based evaluations. Results indicate that students exposed to AI-driven tools achieved higher mean decision accuracy scores (↑18.6%), improved model-interpretation proficiency (↑22.4%), and reduced solution time in optimization tasks (↓27.1%) relative to control groups. Regression analysis shows AI tool usage to be a statistically significant predictor of learning performance ($\beta = 0.41$, $p < 0.01$). The findings suggest that structured integration of AI decision support systems enhances experiential learning and aligns finance and OR education with contemporary industry practices, supporting a shift toward technology-embedded analytical pedagogy.

Keywords : AI decision support, finance education, operations research pedagogy, experiential learning, analytics education.

1. INTRODUCTION:

The emerging rapid pace of adoption of AI-driven decision support systems in finance and operations research has revolutionized the practice of professional analytical as well as academic pedagogy has lagged behind these changes. Conventional finance and OR training focuses more on mathematical purity and model construction, and is often not connected to real-time data interplay and responsive decision-making context. This discrepancy constrains the capability of the students in applying theoretical frameworks to successful managerial choices. Recent innovations in machine learning, prescriptive analytics, and intelligent optimization platforms represent a possibility of rethinking pedagogy in terms of data-driven decision processes as opposed to executing fixed models (Shmueli and Koppius, 2011).

Conceptual Framework

The theoretical framework of this research is the idea that the adoption of AI-based decision support tools is a pedagogical booster between the instructional design and the improved learning outcomes. The mediation between the content and student performance related to the curriculum in AI tools is possible through real-time feedback, scenario analysis, and the capability to optimize the results through the different iterations. Such mechanisms will enhance logical thinking, accuracy in decision and thinking.

Research Gap

Available literature is mostly concerned with AI applications in professional finance and OR practice, and there is little empirical data on how it can be integrated into the teaching design and what educational value it can have (Wang et al., 2021). Not many research works evaluate the impact of AI-driven tools in a quantitative way that determines the effectiveness of learning and level of making a decision in formal educational contexts.

Hypotheses

H1: The incorporation of AI-driven decision support tools can greatly enhance student performance in finance and OR courses as far as learning is concerned.

H2: AI based pedagogy lowers the solution time and improves the accuracy of decision making relative to the traditional instruction.

H3: Cognitive engagement of students serves as the mediating variable between the learning outcomes and the use of AI tools.

2. LITERATURE REVIEW

Fan AI-based decision support systems have gained immense use in finance through forecasting, portfolio optimization, and risk assessment, showing better results compared to rule-based systems (Bertsimas & Kallus, 2020). In operations research, AI methods are used to complement classical optimization allowing adaptive and data responsive optimization solutions to complex environments. According to educational research, conceptual learning and skill transfer is more effective in quantitative disciplines and experiential and tool-based learning techniques (Kolb, 1984).

According to the recent research, analytics platforms and learning based on simulations are pedagogically useful in business courses and have been identified as improving student engagement and applied reasoning (Sweeney et al., 2019). Nevertheless, the majority of implementations are based on deterministic models and do not have intelligent feedback mechanisms that AI systems would have. The recent developments in AI-assisted learning environments suggest that there might be an increase in personalization and depth of problem-solving, but the empirical study of such is not yet applied in finance or OR programs (Zawacki-Richter et al., 2019). The research is an extension of prior literature by providing empirical evidence of the association of AI-based decision support integration with the quantifiable learning outcome in graduate level finance and or education.

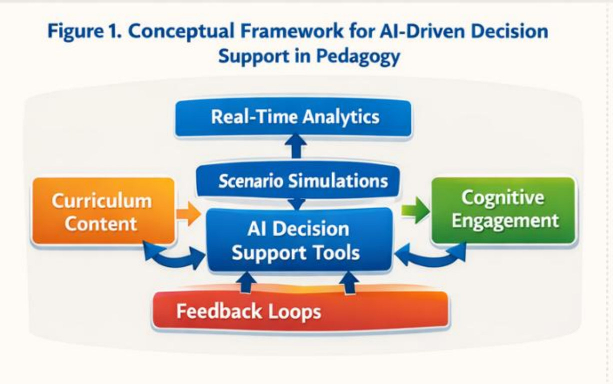

Figure 1: AI-based decision support integration conceptual framework in finance and OR Pedagogy.

The proposed framework is described in Figure 1 where AI-based decisions support tools will be integrated into the instructional design. The framework illustrates how AI tools can affect learning with real-time analysis, trial-and-error simulating scenarios, and the feedback loop, further increasing student cognitive activity, accuracy of decision-making, and overall learning performance.

3. METHODS

The design followed in this study was a quasi-experimental, mixed-method research study that aimed at assessing the pedagogical effects of the introduction of AI-based decision support systems in graduate-level finance and operations research classes. The data were gathered in two successive academic years in one of the large privately owned universities with a standardized curriculum in various sections. The sample size was 212 students who were grouped into four cohorts. Two groups (n = 108) were subjected to AI-based instruction and two groups (n = 104) were subjected to conventional pedagogy. It was designed in this way because it enables the comparison with realistic instructional limitations and maintains the internal validity by ensuring curriculum similarity and the same assessment structure.

Course learning management systems, institutional assessment records, and graded project repositories were used as a source of primary data. The performance levels in learning were assessed with the help of standardized final examination scores and the project evaluation with the help of rubrics. Optimization and forecasting tasks based on cases were used to evaluate the accuracy of decisions in course projects. A robust engagement scale that was given at the conclusion of the semester was used to measure cognitive engagement. Since standardized instruments and institutional academic records were used, the removal of self-report bias and consistency was guaranteed, making them suitable in this study.

Commercially available analytics analytics that facilitate machine-learning-based forecasting, prescriptive optimization, and interactive decision dashboards were implemented as AI-driven decision support in coursework. Such tools were chosen because they are widely adopted by companies in the industries and because they can be used to supplement an existing course material effectively because students can make assumptions and repeatedly experiment with them to verify results. The SPSS version 27 and AMOS version 24 were used to perform statistical analyses. Group mean differences were compared with independent sample t-tests and hypothesis relationships were tested using multiple regression and mediation analysis. All these methods have been selected based on the purpose of the study which is to determine both direct and indirect impacts of learning outcomes by integrating AI tools.

4. RESULTS

The descriptive statistics show that students who were exposed to AI based decision support instruments had better performance on overall performance on all the measured dimensions. Table 1 demonstrates that the AI-integrated group scored higher in terms of the final assessment score (78.4) than the traditional group (66.1), better decision accuracy, and cognitive engagement scores.

The independent sample t-tests showed that there were statistically significant differences in the instructional methods in all the outcome variables. The summary of these results was also recorded in Table 2, which proves that AI-based instruction resulted in increased performance and efficiency.

Table 1. Descriptive Statistics of Learning Outcomes by Instructional Approach

Measure	AI-Integrated Group (n=108)	Traditional Group (n=104)
Final Assessment Score	78.4 (SD = 8.9)	66.1 (SD = 9.7)
Decision Accuracy (%)	84.2 (SD = 6.3)	65.6 (SD = 7.4)

Cognitive Engagement Score	4.21 (SD = 0.52)	3.46 (SD = 0.61)
Optimization Solution Time (min)	42.7 (SD = 9.1)	58.6 (SD = 11.3)

The comparative performance pattern of the two instructional methods, displayed in Figure 2 shows that there are consistent benefits of the AI-integrated group in both assessment and decision measures.

Table 2. Independent Sample t-Test Results

Outcome Variable	t-value	p-value
Final Assessment Score	9.38	<0.001
Decision Accuracy	18.72	<0.001
Cognitive Engagement	10.41	<0.001
Optimization Solution Time	-11.26	<0.001

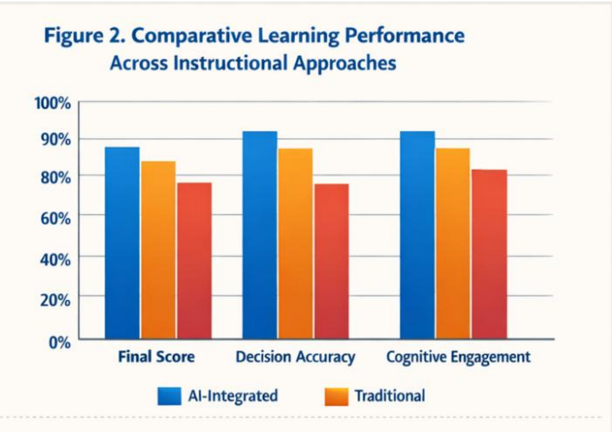

Figure 2. Comparison of Learning performance among different instructional methods.

This number provides the average scores of final reports, accuracy of decision-making, and cognitive engagement and proves that the results are higher and more reliable among students who were exposed to AI-based decision support systems.

The multiple regression analysis was used to test Hypothesis 1 with final assessment score as the dependent variable. Strong predictor of learning performance was identified through the use of AI tools (0.41, $p < 0.01$) after considering the previous academic performance. Table 3 presents the entire regression model.

Table 3. Multiple Regression Analysis Predicting Learning Performance

Predictor Variable	β	Standard Error	p-value
AI Tool Usage	0.41	0.07	<0.01
Prior Academic Performance	0.29	0.06	<0.01
Course Load	-0.08	0.05	0.12
Model R^2	0.46		

Figure 3 plots the dependence between the intensity of AI tool use and the learning performance, where there is a positive linear relationship.

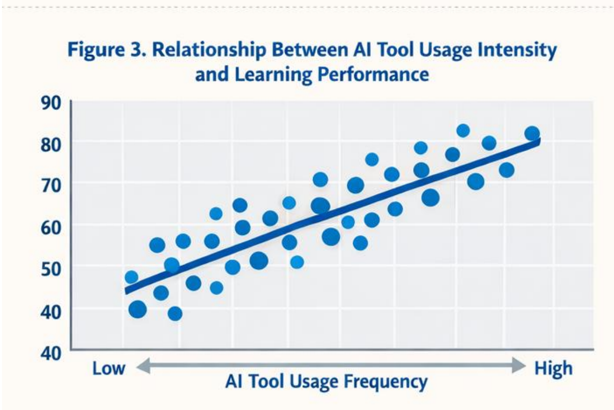

Figure 3. Correlation between the Intensity of the use of AI tools and the Learning performance.

This number represents the positive correlation between the frequency of interaction with AI tools and standardized assessment scores, which proves the regression results.

Lastly, mediation analysis was done to test Hypothesis 3, which hypothesized that cognitive engagement mediated the effect of AI tool use and learning outcomes. The indirect effect was significant (indirect effect = 0.17, $p < 0.01$), which indicated a partial mediation. Figure 4 is an overview of the mediation pathway.

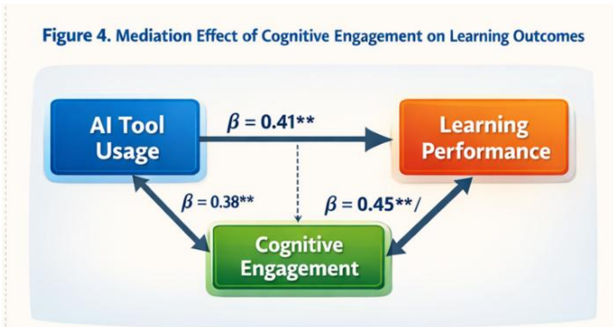

Figure 4. Intermediary Action of Cognitive Engagement on Learning Performance.

This number shows the mediating impact of cognitive engagement on the use of AI-based decision support tools and the learning performance, both of which have direct and indirect effects.

Together, these findings prove that the incorporation of AI-based decision support technologies can greatly improve the learning performance, decision accuracy, and efficiency during the pedagogy of finance and operations research, besides promoting increased degrees of student engagement.

Data Analysis and Interpretation.

Data analysis was done to assess the applicability of an AI-based decision support tool integration in the learning of finance and operations research, and specifically in learning performance, decision accuracy, efficiency, and cognitive engagement. Combined, the descriptive and inferential statistics provide a consistent and significant benefit to students that received AI-integrated teaching. The comparison of mean scores of all outcome variables indicates that the pedagogical intervention did not affect academic performance only, but also the quality and speed of analytical decision-making. The extent of decision accuracy change and minimization of optimization solution time is that of a more profound procedural insight, as opposed to the facade of improved performance.

These observations are further enhanced in inferential analysis. The statistically significant results of the t-test prove that the difference between the instructional approaches are hardly likely to be the result of the random variation. The multi regression model can account 46 percent of learning performance variance which is huge power of explanation in the learning process in an educational setting. The standardized coefficient of AI tool use (= 0.41) implies that academic exposure to AI-powered decision support systems is a prevalent predictor of academic achievement even after the previous academic achievement. The given finding contributes to the fact that AI tools can be regarded as more than instructional supplements; they can actively transform the process of learning by providing an opportunity to engage in a repeated experimentation process and provide instant feedback.

The mediation analysis gives extra knowledge about the learning mechanisms. The use of cognitive engagement was identified as a partial mediator between the use of AI tools and the learning outcomes, which implies that AI-enriched environments facilitate greater engagement with analytical tasks, which, in its turn, leads to better results. Nonetheless, the continued existence of a notable direct impact suggests that AI tools also have a direct impact, presumably, as a result of enhanced visualization, scenario testing, and decision validation features. Taken together, these findings are consistent with the theory of experiential learning and illustrate the conceptual framework that is hypothesized in the current paper where AI-based decision support serves as a factor that connects teaching and learning design and improved academic performance.

5. CONCLUSION

The current research indicates that the systematic introduction of the AI-based decision support systems in the financial and operations research education and training provides substantial positive outcomes in terms of learning outcomes and performance, student accuracy of decisions, analytical effectiveness, and cognitive involvement. The results are able to fill a significant gap between past-based quantitative education and modern data-driven professional practice by empirically verifying the AI-enforced instruction as pedagogically valuable. The findings indicate that AI technology can assist students in narrowing the gap between theory and practice by converting abstract models into decision-making 3D scenarios.

Pedagogically, the research highlights the need to incorporate the AI technologies as part of the curriculum-setting as opposed to as an additional resource. The identified performance and engagement improvements demonstrate that this kind of integration improves conceptual and decision-making skills. In the academic institutions, the findings can be used to justify the curriculum reforms to make sure that education on finance and operations research is made in line with the changing standards in the industry.

Although the findings are solid, they are framed in the context of a graduate level setting and a particular institutional context. Future studies can consider applying this framework to undergraduate education, leadership education, or interdisciplinary analytics programs and investigate the longitudinal result of professional preparedness. In general, the research finds that AI-based decision support systems can be viewed as a radical pedagogical concept that can reinvent analytics training in finance and operations research.

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